

2.21.99 Sun FT **Sturm:** $\log_2^+ X$

01 More random Models: In STSO. But, using \log_2^+ at $\frac{1}{2}$ Four part at $\rightarrow 80$!
Using \log_2^+ and integrals to get N_i would probably push attention from function.
Expected value of N_i out further.

But Entropy with my version of \log_2^+ maybe easier because it has constant values for long intervals of size. We don't have to integrate to ∞ : only out to where \log_2^+ become constant. We can then just mult $\int_0^{\infty} 2^k \log_2^+ R$ by that constant.

07 This is easily computed: its just $1 - \int_0^{\infty} 2^k \log_2^+ R dK$.

2) For x, y d.f. Perhaps have width of d.f. be uniform betw. $0 \leq 1$

$$\frac{2\pi N(1-N)}{R}$$

is uniform betw. $0 \leq 1$, for constant R : this is $\propto R^{\frac{1}{2}}$.

Then maybe $R \rightarrow R+1$ or $R \rightarrow R-1$ see 36.28 - 37.01

$$\therefore P(R) \propto \frac{1}{R^{\frac{3}{2}}}$$

$$\frac{d}{dR} = -\frac{3}{2} R^{-\frac{5}{2}}$$

of course could become $\log_2^+ \propto \frac{1}{R}$ is uniform betw. $0 \leq 1$ (almost as well) so $P(R) \propto \frac{1}{R^2}$

or try $\frac{1}{R} \frac{1}{\ln R} \left(\frac{1}{\log_2 R} \right)^2$ which converges. (This is like $2^k \log_2^+ R$ $\rightarrow 0.01 - 0.07$)

19 $\int \frac{1}{R} \left(\frac{1}{\ln R} \right)^2$: P 203, G&P: 2.721 (2) $\int \frac{\ln^m x dx}{x} = \frac{\ln^{m+1} x}{m+1}$

$$\text{if } m = -2 \Rightarrow \frac{\ln^{-1} x}{-1} = \left(-\frac{1}{\ln x} \right) d \frac{1}{\ln x} = -\frac{1}{(\ln x)^2} \cdot \frac{1}{x} dx$$

So it converges, but $-\frac{1}{\ln x}$ doesn't work for $\int_{20}^{\infty} \frac{1}{x \ln x} = \frac{1}{\ln x} \Big|_{20}^{\infty} = 0 + \frac{1}{\ln 20}$ ok.

$$\frac{d}{dx} (\ln \ln x)^{-1} = \frac{-1}{(\ln \ln x)^2} \cdot d(\ln \ln x) \quad \Big| \quad d(\ln \ln x) = \frac{1}{\ln x} \cdot \frac{1}{x}$$

$$\frac{d}{dx} \left(\ln(\ln \ln x) \right)^{-1} = \frac{-1}{(\ln \ln \ln x)^2} \cdot \frac{d(\ln \ln \ln x)}{dx} \quad \Big| \quad \frac{d(\ln \ln \ln x)}{dx} = \frac{1}{\ln \ln x} \cdot \frac{1}{\ln x}$$

So probly $\frac{d}{dx} (\ln^m x)^{-1} = -\frac{1}{x} \cdot \frac{1}{\ln x} \cdot \frac{1}{\ln \ln x} \dots \left(\frac{1}{\ln^m x} \right)^{-2}$

Monotonicity:
 $\frac{d(\ln^{(m)} x)}{dx} = \left(\ln^{(m-1)} x \cdot \ln^{(m-2)} x \dots \ln x \cdot x \right)^{-1}$

But $\ln^m x \neq \lim_{k \rightarrow \infty} \ln^k x$. (!) \odot

So $G' \propto R^c$. I want $\int_0^{\infty} G'(R) dR$: So G' is constant for $R > \infty$.

I have to get G' more divergent: mult by Normal constants: $\prod \left(\frac{A_i! B_i!}{N+1!} \right)^{-1}$

No! I want Expected value of N_i .

So that stuff about $\frac{1}{x}$ being only appreciated from direction " Source " a scale m x direction: false. x^N can be expanded by α in x direction $\rightarrow \frac{x^N}{\alpha^N}$; this contracts it by α^N in x direction. The stuff about $\int_0^{\infty} x^N dx$ is also wrong. We will usually integrate from sum of $\alpha \int_0^{\infty} f(x) dx = 1$.

ON The Approx of t integers: (not approx of t roots before $1 \leq n$)

T. approx of n positive integers in w.r.t. a reference unc, M_0 . $P(N) = \sum_{m|N} 2^{-1} (S(N))$
 $S(N)$ is the n th prim that will cause N to print N & stop. — of $P_1(N) = e^{-S(N)}$
 $S'(N)$ being the k th best solution.

$P_1(N) \approx 2^{-\log_2^*(N)}$ is meant to be an approx to $P_1(N)$. $P_1(N)$ has the property of converging

→ that $\int_0^x P_1(x) dx$ converges very slowly, but it does converge.

$\int_0^x P_M(x) dx$ converges more slowly than any recursive function.

($P_M(x)$ is, itself partial recursive) ← NO! — it's incomputable — which is not a function P.R.

$P_1^a(N) \equiv \alpha^{\log_2^*(N)}$: As α goes from 1 to e , $\int_1^x P_1^a(x) dx$ converges more and more slowly.

.13 for $P_1^e(x)$, $\int_0^x P_1^e(x) dx$ does not converge.

To show ~~the~~ divergence of .13:

$\ln^* x = \text{distance } \ln x + \ln \ln x + \ln \ln \ln x + \dots$; we only take positive terms.

so from $x = 1$ to e : $e^{\ln^* x} = x \cdot \ln x$
 e to e^e : $e^{\ln^* x} = x \cdot \ln x \cdot \ln \ln x$
 e^e to e^{e^e} : $e^{\ln^* x} = x \cdot \ln x \cdot \ln \ln x \cdot \ln \ln \ln x$
 etc.

So $e^{\ln^* x}$ is integrable in closed form from 1 to e — transform to e^e when $e^e \leq x < e^{e^e}$, etc.

for each of these intervals, e integrals; $e - p = e$

I.E. for each interval, the $\ln x$ goes from some value to that value plus e

So $\int_1^{\infty} e^{\ln^* x} dx = 1 + (1+1) + \dots = \infty$

for $1 < \alpha < e$, $t \rightarrow \infty$ does not hold, so S converges slowly.

Consider $f(x) = x^{1-\epsilon}$ $\int_0^x f(x) = \frac{x^{2-\epsilon}}{2-\epsilon}$ which converges slowly for small $\epsilon > 0$.

Here $\frac{1}{x \ln x \ln x}$ converges more slowly than $\frac{1}{x} \cdot \frac{1}{k^\epsilon}$ for any $\epsilon > 0$.

$\int_0^x \log_2^* x dx$ converges very slowly for $\alpha \in [e, \infty)$ (small $\epsilon > 0$).

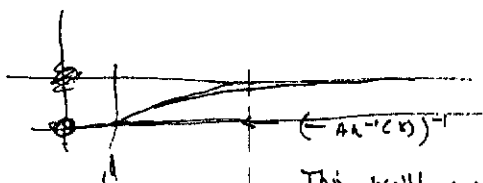
The $\log_2^* x$ is not analytic (it is piecewise analytic), it is Primitive Recursive.

→ A. Non-P.R. function that can converge more slowly: slowly consider Ackermann func. $A_k(x)$

$A_k^{-1}(x)$ is its inverse: it approaches ∞ as $x \rightarrow \infty$, but very slowly.

$\{A_k^{-1}(x)\}^{-1} \rightarrow 0$ as $x \rightarrow \infty$, but very slowly.

If we take $\frac{d}{dx} \cdot \{A_k^{-1}(x)\}^{-1}$ and integrate it, it will approach some constant from below, very slowly.



underlying $\{A_k^{-1}(x)\}^{-1}$ is a discontinuous function so its derivatives are δ func's between (and stretches at zero) to counteract units, we can mod of $A_k(x)$ by making it piecewise linear, or by using \rightarrow more complex "Spline"

This will give us a function N that converges, but very slowly —

$$\log^* x$$

More slowly than any Prim. Rec. function. Th. way to prove this: If there were any prim. rec. function that converged more slowly than t , one could show, then we could construct a prim. rec. function that \uparrow more rapidly than $A(t(x))$; — which is impossible.

[NB. T. way that $A(t(x))$ should not be prim. rec., i.e. that $A(t(x))$ increased faster than any prim. rec. function]. [See Kleene's Book for discn]

Just as \log^* is a total rec. func. based on $A(t(x))$ a factor than any prim. rec. func —

It is itself a total rec. func. ~~but~~ $P_n(x)$ can converge even slower, because it is not recursive.

07 ~~is a total rec. func.~~ I don't know if $P_n(x)$ is the most slowly converging total point. There are functions that \uparrow slower than any recursive function. (in some sense). \rightarrow See .26 (1st proof)

10 Definition of "slow convergence"; Say $\lim_{x \rightarrow \infty} f(x) = A$.

Then if $f(x)$ converges slowly, $|f(x) - A|$ will $\rightarrow 0$ but very slowly.

By look We can look at how fast $A - f(x) \rightarrow 0$ as $x \rightarrow \infty$.

We can compare 2 functions $f(x)$ & $g(x)$ on how fast t corresponding func $\rightarrow 0$.

f beats g if $\exists x_0 \rightarrow$ for $x > x_0$ $A - f(x) > B - g(x)$ $B \equiv \lim_{x \rightarrow \infty} g(x)$.

22 $\left(\frac{1}{\log_a^{(m)} x}\right)^{1+\epsilon}$ approaches zero converges more rapidly. Then $\frac{1}{\log_a^{(m)} x} > \left(\frac{1}{\log_a^{(m+1)} x}\right)^2 > \left(\frac{1}{\log_a^{(m+2)} x}\right)^4 > \dots$ for all values of ϵ $0 < \epsilon < 1$.

So 55.01 = 56.22 gives a perspective on how ~~fast~~ $\log^* x$ is as $x \rightarrow \infty$.

~~is~~ in approx to $P_n(x)$ with respect to behavior for large x .

$P_n(x)$ is within constant factor below say 2 times, ~~the~~ P_{n+1} & P_{n+2} .

26 For $m \in \mathbb{N}$, is an open Q \rightarrow to whether \exists a p.r. function converges more slowly than $P_m(x)$: Suppose there were such a function: T. p.r. funcs are effectively enumerable. \uparrow could simulate new function, \rightarrow This could probly be used to show that no p.r. funct (or any rec. func) could \rightarrow its limit signally more slowly than $P_m(x)$.

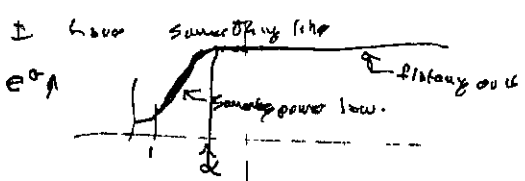
A second Q about $P_n(x)$ is the horizontal scaling factor.

I think this is much more simple than convergence rates. For all func's P_n this scaling factor \rightarrow machine dependent. For any $P(x) \rightarrow \int_0^{\infty} P(x) dx = 1$, then $\int_0^{\infty} P(\alpha x) dx = 1/\alpha$.

The function $P(\alpha x)$ is stretched out in the x direction by a factor, α .

Consider $P(x) = \frac{1}{x^2 + 1}$: The value of A gives us a horizontal "scale factor"

In My present approach to the Stein problem, before I apply δ n -prp of R ,



The important thing is not how our δ n -prp of $P(R)$ behaves as a $\text{fun } \alpha$ (by R), but how it behaves for $1 < R < \alpha$.

α is, of course, a priori unknown, so

It would ~~seem~~ that ~~we are probably~~ choice of α (behavior on $[1, \alpha]$) will influence our result favorably!

Well, as we want. of data (i.e. N) to α (i.e. N) should be important, then N w. modif. of t $[M_i]$ is, here a picture that has to be interpreted differently from t of N w. natural variation of t $[M_i]$. In this second case, usually R would \downarrow as $N \uparrow$, but would settle down to some finite value as $N \rightarrow \infty$ - in which case t α would be ~~less~~ important.

In present case, if α is ~~can~~ (i.e. S.A) can be any thing between 0. & 1. ~~we could look at~~ use from diff. t deriv. a sequence of previous years t_i is. A uniform d.f. in α or α^2 should be ~~not~~ bad.

Uniform d.f. means $P(R) \propto \frac{1}{R^2}$. uniform in α means $\frac{dP}{dR} = \frac{1}{R^2}$

Look at $E X_i$ for $\frac{1}{R^2}$ & $\frac{1}{R}$. See what occurs as $N \uparrow$ (w. some $[M_i]$ set)

Also, look at Crush ~~Model~~ Model. See if t α is t same. It should map very closely to t Juplaca Model (i.e. Bernoulli Model).

Another approach: Actually generate M_i data Monte Carlo using some

$(2 \times 3) + 2 \times 5 = 40$

known X, y or (R, \bar{X}) : then using some N, generate M_i associated M_i . See how well t "true" R, \bar{X} fits t data, as compared to other R, \bar{X} .

19: 56.22 The integration of $\log^* X$ is not easy at all! Only easy if $\alpha = 1$! - so how diff

20 Ribs do $\alpha = 2$? He tells him in his paper. "Annuities from for integers ... 1983 (I have) - P 429-30

P 424 at end of paper expects $\log^* X$ does not converge for $\alpha \geq 2$ (at least convergence is uncertain) seems unlikely for $1/\alpha$ will be "edge".
I don't know if Ribs knows this for sure.

23 I did have an idea that t summation for α could be chopped into t summation for e .

Then ~~for~~ each interval of X in which $\log^* X$ ~~is~~ went from ~~an~~ integer n , to $n+1$, could be mapped into a similar interval for $\log^* X$. - by a simple mult factor of α relative constant or both.

Start w. $(X \ln X)^{-1}$ v.s. $(X \log_\alpha X)^{-1}$ they differ by $\frac{1}{\ln \alpha}$.

$(X \ln X \cdot \ln \ln X)^{-1}$ " $(X \log_\alpha X \log_\alpha \log_\alpha X)^{-1} = \left(X \frac{\ln X}{\ln \alpha} \cdot \frac{\ln \ln X}{\ln \alpha} \left(\frac{\ln X}{\ln \alpha} \right) \right)^{-1}$
 $= \left(X \frac{\ln X}{\ln \alpha} \frac{1}{\ln \alpha} (\ln \ln X - \ln \ln \alpha) \right)^{-1}$

Unclear t for how to integrate this \rightarrow

But it ~~is~~ is possible to show it converges for $\alpha < e$.

Say $\alpha = 1 + \epsilon$. Will it converge?

So it seems likely that

$\alpha \rightarrow 1$, $\log_{1+\epsilon}^* X$ will converge:

for $\epsilon = 0$, $\log_1 X = \infty$ so ϵ must. $\log_{1+\epsilon}^* X = \infty$ i.e. $\frac{1}{\log_{1+\epsilon}^* X} = 0$ But I'm not

at all sure! I'd have to calculate look into this ~~more~~ in more detail.

$\alpha \rightarrow 1 \Rightarrow \log_{1+\epsilon} X \rightarrow \infty$ $(1+\epsilon)^x = X$
 $\ln_{1+\epsilon} X \approx \frac{\ln X}{\epsilon}$ $e^{\epsilon X} = X$; $e^{\epsilon} = 1+\epsilon$
 Note $\ln(1+\epsilon) \approx \epsilon$ so $\frac{\ln X}{\ln(1+\epsilon)} \approx \frac{\ln X}{\epsilon}$ $\rightarrow X = \frac{\ln X}{\epsilon}$

37 \rightarrow In Ribs paper of 120, he shows how to integrate $\frac{1}{2} (\log^* X)$ from $(1, \infty)$, it might be possible (a fact is likely) that one could find way to integrate $\alpha^t (-\log_\alpha^* X)$. \rightarrow (58.07)

38 Another approach: Consider for ϵ intervals mapping into α intervals: discussed on 23-30 would it be possible to show X interval for α is at least $(\log_\alpha X)^k$ times smaller than α interval (k is: no. of log iterations for that interval) \rightarrow (58.01) spec

01 R2: 57.38: Well, not so easy! Th. Convergence intervals for α & α differ considerably in "x" values. In general, $\ln^* x > \log_{\alpha}^* x$ if $\alpha < e$.

Proby $\int_1^{\infty} x^{-\alpha} (\log_{\alpha}^* x) dx$ converges for $\frac{1}{e} < \alpha < e$: i.e. behavior of $\log_{\frac{1}{2}} x$ and $\log_{\alpha} x$ is pretty much the same except for sign.

for $\alpha < 1$, hvr. the defn of $\log_{\alpha}^* x$ has to be modified — so only use positive terms are included.

So we only have to ^{show} convergence for $1 < \alpha < e$.

07: 57.37 from Riss (57.25): say $g(x) = \log_{\alpha} x = \frac{1}{\ln \alpha} \ln x = \beta \ln x$ ($\beta = \frac{1}{\ln \alpha}$)

say $(g^{(k)}(x))$ is k-th iterated \log of x.

then $\frac{d}{dx} \log^{(k)} x = \frac{1}{x} \beta \ln(\log^{(k-1)} x) = \beta \frac{1}{\log^{(k-1)} x} \frac{d}{dx} (\log^{(k-1)} x)$

$\therefore = \beta^k \frac{1}{\log^{(k)} x \cdot \log^{(k-1)} x \cdots x} = \beta^k \alpha^{-k} (\log^{(k+1)} x)^{-1}$ for a certain x range.

This all has to be checked out carefully!

which probably makes it easy to interpret or exactly? So why did Riss. have to use upper & lower bounds to get an approx of known summation, hvr.

45

While it just isn't to show that $\int_0^{\infty} x^{-\alpha} \log_{\alpha}^* x$ converges for $1 < \alpha < e$, getting a n exact sum. can be useful.

Also, if suspect. But what Riss was after, was a prior for the integers!

So these integrals are used by him to find upper & lower bounds on the sum.

Of course, for $\alpha = 2$, there is a much easier way to do it — but I think it

converges more slowly than Riss' function

On the other hand a good prior for $x \rightarrow \infty$ would be useful — if its what I suspect to need for STEIN!

(loop) $f_k(x)$ is faster than any (any loop) from rec. funct. (can we derive a 3 loop funct. that is significantly faster than $f_k(x)$?)

I want to stop working on this problem, write a summary of results obtained, dem of what seem to be main problems, a list of open problems along w. possibl. approaches for each.

- 1) 2 related problems (a) applied for $1, 2, \dots, \infty$
 (b) " " $1 < x < \infty$

2) ~~Alp~~ Alp gives (incomputable) form: ~~series~~ call it $P_0(n)$ (for integers).

Main constraints on $P_0(x)$: (a) its a \downarrow funct of x . (b) $\sum_{n=1}^{\infty} P_0(n) = 1$

(c) we'd like $S(x) = \sum_{i=1}^x P_0(i)$ to converge ~~to~~ as slowly as possible, since $\sum_{i=1}^x P_0(i)$ converges more slowly than any recursive function. (See 55.10 for data of "slow convergence")

3) For any recursive $P(n)$, we can always modify $P(n)$ to converge more slowly, by removing some P from small n and adding it out to P for large n .

3.5) If one uses $P(x) \propto \log^* x$, then $P(x)$ converges for $x \ll e$: its ~~at~~ $\log^* x$ converges more slowly

4) Riss proposes a ~~function~~ funct for $P(n)$ that is prim. rec. Funct that are not prim. rec. (e.g. Ak function is funct based on it) can converge more rapidly than any prim. rec. fun., and ~~does~~ modulus of t .

Ak funct can be made that converges more slowly than any prim. rec. fun.

5) Whether there is a best funct is in sup sense a "best" $P_0()$ is unclear. Probably ~~there is~~ no best among recursive funts

6) Can one define (in sup sense) a $P(n)$ based on partial recursive funts, $P_0(n)$ is incomputable w/ partial recursive.

7) For a discussion of ~~the~~ ~~redundant~~ ~~proof~~ The ~~fact~~ that Ak's funct is more rapid than any prim. rec. funct was ~~at~~ ~~first~~ ~~used~~ ~~to~~ ~~show~~ ~~that~~ ~~it~~ ~~is~~ ~~the~~ ~~first~~ ~~known~~ ~~non-prim. rec. function known to be non-prim. rec.~~

That $\log^* x$ is prim. rec. follows from Peter's deemo. That all prim. rec. funts are expressible by simple loops & compositions of funts.

For deemo. & proofs & refs for 24 ff see Kleene's "Intro to Meta Mathematics"

8) For a discussion of how good Riss' function is as an approx to $P_0(n)$ - see 55.21-56.22

9) T. forgoing is all on behavior of $P(n)$ for large n . For most applns, (5 Riss points out) ~~to~~ ~~differ~~ ~~between~~ $2^{\log^* n}$ and $\frac{1}{(\log^* n)^2}$ is not very much.

10) For most t , imp. Q is behavior for small n . Any $P(n)$ can be normalized by something like $\frac{1}{x} P(xn)$ to yield a convergent $P(n)$, ~~to~~ ~~with~~ ~~significantly~~ ~~different~~ ~~beh.~~ ~~for~~ ~~low~~ ~~n~~ . In fact, $P_0(n)$ (Pr. Alp function) can do this also, by changing reference machines - (for large n , t has t behavior is within constant factor).

for $d = e - \epsilon$
 it converges
 very slowly
 for $d = e$
 Also $\frac{1}{n^{1+\epsilon}}$
 converges slowly
 for discussion
 integration of
 $x^d - (\log^* x)$
 See 57.19-27
 58.02-15

24

36

.01 As I saw it, w.s.t. applies for STEIN: I'm really worried about relative wk. for small v.s. large n .

~~Approximation~~ ~~5890339~~

N399: I'd forgotten this, but 55.23 shows that $\sum_{n=1}^{\infty} dx e^{-n^2 x} = 1 + 1 + 1 + \dots = \infty$.

Levin mentioned this divergence is of π . time, I didn't know how to prove it — I think I had proved it in "CLEVELAND" when I was analyzing $e^{-n^2 x}$.

$$\int_0^{\infty} dx e^{-n^2 x} = \frac{1}{n}$$

($\frac{1}{n} \rightarrow (n^{(a)})$ is $\ln x + \ln \ln x + \dots$ n times (or less if i becomes imaginary).)

Random Musings on STEIN Problem!

T. final soln that \leq STEIN cost var. w/ μ_1 & μ_2 1 to 4 error var. of 5 of 1 to 2.

u. w. wts μ_1 & μ_2 resp. $\mu_1 = 1$ $\mu_2 = 1$
 I find 9 to 1 mix have been better. 130:10

0.265 0.290 400
 25 810
 1.156 0.259 0.265 0.278
 83 26

$\bar{\mu} = .25$ gives σ^2 of $\frac{.25 + .75}{45} = 4.16 \times 10^{-3}$

$\sqrt{\sigma^2} = .0645$. so S of $\bar{\mu}$ would be $\approx .0322$

$R = G = 0$
 $\text{Var}(G - G_1) / 142$
 $G_1 = G$

$\frac{1}{15 \times 16}$

STEIN 61.8%

from Stein 50

Gives slope on log of $\ln R$ v.s. G . ($G = \ln(\frac{G}{G_1})$)

May slope is ≈ 4.5 at $R \approx 9.5$

Pool is at $R \approx 829.4$: $G = -468.666625$

we see down μ_1 $G \rightarrow$ down .86 from positive $R = G_1$ $e^{.86} = 2.36$

$G = 16M$ (≈ 100) is $-468.68.08957$: down .0191 from pool.

20 **SAD** T. applied \rightarrow for whatever μ_1 w/ of $\bar{\mu}$ should be independent of n .

So say for $n=1$ we will have values μ_1 & μ_2 for $\mu_1 = \mu_2$ resp: $c + d \leq 1$.

Give a uniform error, so μ_1 estimate $\approx (\bar{\mu} + (1-c)n\mu_1) / (c + (1-c)n)$

so $\bar{\mu}$ is always handicapped by factor n (noise), i.e. σ^2 of each player

24 **SN** No matter how much data one has, a player can be so badly selected, that prodn. results will be very bad!

Does this Maxm apply in my choice of a priors for R in t. Stein problem?

A reasonable guess for the μ_1 prior (mean σ^2 of the entire new data set) \leftarrow (mean σ^2 of the players). Why didn't I get this in a more vigorous approach to STEIN?

21 In combining 2 p.d.s sometimes one convolutes & sometimes one multiplies. T. results are quite different (Multiplying narrows the result. Convul. broadens the result.)

22 Trouble is, w. the form d.f. I can't convolute since I have to stay on interval (0,1).

23 Re: (24) To get an idea about actual a priori is, pretend that I have data for previous yrs.

Re: (31-33) Instead of convoluting μ_1 & μ_2 , I've been multiplying them!

Multiplication gives $\frac{1}{\sigma_1^2 \sigma_2^2} = \frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}$; $e^{-\frac{\mu^2}{2\sigma_1^2}} + e^{-\frac{\mu^2}{2\sigma_2^2}}$; x^2 coeff. in expansion $\approx \frac{x^2}{2\sigma_1^2} + \frac{x^2}{2\sigma_2^2}$

Convul. gives σ^2 total = $\sigma_1^2 + \sigma_2^2$

2.28.99 SMART STEIN.

So in Gaussian case: $\bar{u}, s^2, \mu_i, \sigma_i^2$. We have only 4 data pts, rather than $k \cdot n$. See 1 (6.32-120.40 for worked ex. 6.2.03

T. pc of μ_i observed $\{u_i\}$: \rightarrow constant factor

0.03 $\frac{1}{S} \prod_{i=1}^k e^{-\frac{1}{2} \frac{(u_i - \bar{u})^2}{s^2}} \prod_{i=1}^k \frac{1}{\sigma_i} e^{-\frac{1}{2} \frac{(u_i - \mu_i)^2}{\sigma_i^2}}$

0.04 $= \frac{1}{S} \cdot \frac{1}{\sigma_i} \cdot \exp\left\{-\frac{1}{2} \left(\sum_{i=1}^k \frac{(u_i - \bar{u})^2}{s^2} + \frac{(u_i - \mu_i)^2}{\sigma_i^2} \right)\right\}$

0.05 $s^2 = \frac{1}{k} \sum_{i=1}^k (u_i - \bar{u})^2 \quad \sum_{i=1}^k 1 = k$

0.07 $G = \ln(0.04) = -\frac{1}{2} k \ln(s^2) - \frac{1}{2} \left(\sum_{i=1}^k \frac{(u_i - \bar{u})^2}{s^2} + \frac{(u_i - \mu_i)^2}{\sigma_i^2} \right)$

$\frac{d}{ds^2} = \frac{1}{2} k \frac{1}{s^2} - \frac{1}{2} k + \frac{1}{2}$

$u_i - \bar{u} = u_i - (2\bar{u} + (1-\alpha)\mu_i) = (1-\alpha)(u_i - \mu_i)$

$\frac{(u_i - \mu_i)^2}{\sigma_i^2} = \frac{(u_i - \bar{u})^2}{\sigma_i^2}$

$\frac{d(0.07)}{ds^2} = -\frac{1}{2} \frac{k}{s^2} + \frac{1}{2} = 0 \Rightarrow s^2 = \frac{k}{2}$

Actually, $\bar{u} = \frac{\sum_{i=1}^k u_i}{k}$
 Does $s^2 = \frac{1}{k} \sum_{i=1}^k (u_i - \bar{u})^2$? No! $s^2 = \frac{1}{k} \sum_{i=1}^k (u_i - \mu_i)^2$

$\frac{d(0.08)}{ds^2} = \frac{1}{1-\alpha} + \frac{1}{2} k + \frac{1}{2} \alpha^2 = 0$ \rightarrow all terms but $\frac{1}{1-\alpha} > 0$ so $\alpha < 0$ - unphysical!
 So α is a function of k & A only!

$\frac{1}{1-\alpha} + \frac{1}{2} k + \frac{1}{2} \alpha^2 = 0$ $\Rightarrow \alpha^2 + k\alpha + 2 = 0$ (looks like cubic eq.)

$\frac{d(0.07)}{ds^2} = -\frac{1}{2} k \frac{1}{s^2} + \frac{1}{2} = 0$

$s^2 = \frac{\sum_{i=1}^k (u_i - \mu_i)^2}{k}$
 $\mu_i - \mu_i = 2\bar{u} + (1-\alpha)\mu_i - \mu_i = 2(\bar{u} - \mu_i)$

from 0.07 $\frac{d(0.07)}{ds^2} = -\frac{1}{2} k \frac{1}{s^2} + \frac{1}{2} = 0$

$\frac{1}{1-\alpha} + \frac{1}{2} k + \frac{1}{2} \alpha^2 = 0$ $\Rightarrow \alpha^2 + k\alpha + 2 = 0$

$\frac{1}{1-\alpha} = \frac{2A}{k}$ $\Rightarrow \alpha = 1 - \frac{k}{2A}$

$\frac{1}{k} \sum_{i=1}^k \left(\frac{u_i^2}{\sigma_i^2} - \frac{2u_i \bar{u}}{\sigma_i^2} + \frac{\bar{u}^2}{\sigma_i^2} \right) = \frac{1}{k} \left(\sum_{i=1}^k \frac{u_i^2}{\sigma_i^2} - \frac{2\bar{u}}{k} \sum_{i=1}^k \frac{u_i}{\sigma_i^2} + \frac{\bar{u}^2}{k} \sum_{i=1}^k \frac{1}{\sigma_i^2} \right)$

1.01 Look at $\frac{A}{K} = 62.26 R$; say $\sigma_i = 2.11$. $\frac{A}{K}$ will be max for $\alpha > 1$. So $\frac{K}{A} < 1$

$2(1-\alpha) = \frac{A}{K} = \alpha$ ~~$2 - 2\alpha = \alpha$~~ $2\alpha - 2 + \alpha = 0$

$2 = \frac{1 \pm \sqrt{1 + 4\alpha}}{2}$

$ax^2 + bx + c$; $x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$

say $\alpha = \frac{1}{2}$; $\alpha \neq 1$ or $\alpha = 0$.

$\mu_i = \alpha \bar{\mu} + (1-\alpha)\mu_j$

So soln is root only if $\alpha < \frac{1}{2}$.

For $0 < \alpha < 1$; $2(1-\alpha)$ has max at $\alpha = 0.5$; it's always smaller than 2.



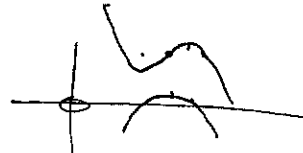
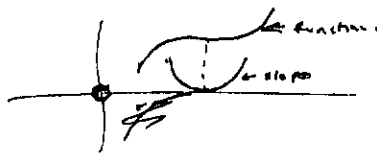
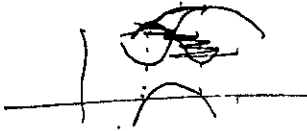
So $\frac{A}{K}$ has to be > 4 for real soln to α !

and if α is a soln, then $1-\alpha$ is a soln!

So if α is a solution for $\bar{\mu}$ then $1-\alpha$ is also a good w.f. for μ_j .

Well, while there may be 2 solns, 1 can be max, the other min.

when $\alpha = 0.5$, it's neither max nor min, but an inflection pt!



This is definitely not behaving in a Reasonable Manner!

Going through again

$S^2 = \beta \cdot (1-\alpha) = (62.26R)$

from 62.07: ~~$\frac{A}{K} = \frac{2\alpha}{1-\alpha}$~~

$\frac{d}{d\alpha} = -\frac{1}{2} K \beta \rightarrow K(1-\alpha) - \frac{1}{2} K \frac{2\alpha}{(1-\alpha)^2}$

$= -\frac{1}{2} K \beta - K(1-\alpha) - \frac{1}{2} K \frac{2\alpha}{(1-\alpha)^2}$

$\frac{d}{d\alpha} = \frac{+K}{1-\alpha} \Rightarrow \alpha = A = 0$

$\mu_i - \bar{\mu} = \alpha(\bar{\mu} - \mu_j)$
 \downarrow
 $\frac{\sum (\mu_i - \bar{\mu})^2}{N} = \frac{\sum (\mu_i - \mu_j)^2}{N} \alpha^2$

In baseball case:

$\sigma_i^2 = \frac{\mu_i^2 (1-\mu_j^2)}{N}$

$A = \frac{\sum (\bar{\mu} - \mu_i)^2}{\sum \mu_i^2 (1-\mu_j^2)}$

$\alpha = \mu_i$ $\bar{\mu} = 2.65$

$A = \beta + \frac{((\bar{\mu} - \alpha)^2) \beta}{\alpha(1-\alpha)}$

$A = A \cdot N / K$

$A = 45/18$

$\frac{A}{K} = 1.091104$; so no real soln! - Root Complex!

from ST 4

Try a form for $G(z)$ $0.03 \rightarrow .07$: $G(z)$ eduction of z .

$.03 \rightarrow s^{-k} \cdot \frac{1}{s^2} e^{-\frac{1}{2} \frac{(u_i - \bar{u})^2}{\sigma^2}} \quad | \quad z = u_i$

$.07 \rightarrow -\frac{k}{2} \ln(s^2) - \frac{1}{2} \frac{\sum (u_i - \bar{u})^2}{\sigma^2} = SS$

$\bar{u} = \frac{1}{N} \sum u_i$

$S^2 = \frac{1}{2} \sum (u_i - \bar{u})^2 - N \bar{u}^2$

Use $S^2 = \frac{1}{2} \sum (u_i - \bar{u})^2$ in form.
 -0.22 is now CO : float $\frac{1}{2} \sum (u_i - \bar{u})^2$
 will be $\frac{1}{2} \sum (u_i - \bar{u})^2$

$u_i = z \bar{u} + (1-z) u_i$

$SS = \sum \frac{u_i^2 (1-u_i)}{N}$
 $k = 18; N = 45$

ST 64.809

I got Max at $z=0$

$G = .59$
 $z=0$, If \downarrow manually, $dy/dz = -9.22$ at $z=0$.
 $z=0$ is symmetric about $z=0$

$z=0$ means $u_i = 1$ for $u_i \in Z$
 $U = \bar{u} = .265$
 $(z = u_i): z = z \cdot U + (1-z) z$
 $SS = z \cdot (1-z) \cdot N$

so $z = -1$ gives same G as $z = +1$.
 wrong formula for $S^2 \equiv SS$.

See why using $\sum (SS = SS + z^2 + z^2)$
 from $SS = SS/N - N \bar{u}^2$

your peak is $z = 0$ (likely) $\Delta = +.011$

Apparently $\frac{1}{2} \sum (u_i - \bar{u})^2$ is quite small compared to $N \bar{u}^2$ term.

I had factor of $\frac{k}{2}$ inverted!

change $\frac{1}{2}$ to $\frac{k}{2}$

Now monotonic \uparrow from $z=0$ to 1

This time the peak is at $z = 1.01$ maybe.
 There may be a singularity near $z = 1$
 for $z = 1.01$ or 1.001 it says "illegal point, call"

$.991 \rightarrow 127.49$
 $.994 \rightarrow 128.194$
 $\rightarrow 174.05$

o.k.! $S^2 = \frac{1}{2} \sum (u_i - \bar{u})^2 - N \bar{u}^2$ can be < 0
 so $(N S^2)$ is troublesome!

T. formula for S^2 is wrong!
 $\bar{u}_z = \bar{u}' = \bar{u}$

$U = .2653889$

Trouble may be due to my not using exactly \bar{u} .
 using \bar{u} more as \bar{u}

$A = 1.00001$ gives illegal point call.
 $A = 1$ doesn't
 $A = 1.049$ doesn't
 $A = 1.049$ is illegal.
 $A = 1.095$ is illegal.
 $G = 51.66$
 1.0448 illegal
 1.0449 illegal
 1.04499 legal $G = 173.149$
 1.04499 illegal
 1.04499 illegal

I got from .99 to .998, w. illegal .999
 $z = 1$ was left at 179.14 a very sharp peak.

$G \sim 12$ for $A = .99$ or $(.0)$
 The actual peak was $A < 1$. (very slight excess).
 $A = 1$ means all wt. on \bar{u} .

well, it seems clear that there is a potential singularity at $A = 1$. This corresponds to $(1-z) = 0$.
 which is all wt. on $u_i = \bar{u}$. If $(1-z) = 0$, $S^2 = \frac{1}{2} \sum (u_i - \bar{u})^2$ (i.e. $G = 0$) $\rightarrow 0$. so $S^{-k} \rightarrow \infty$.
 It's a simple pole; it don't know if $f(x)$ has a simple pole at $x = 0$.

3.1.99 SMART STom

So this looks like a problem w. ~~binomial~~ binomial distribution. at $R(x+y) \rightarrow \infty$. $R \rightarrow \infty$ corresponds to $(1-\alpha) = 0$.

A poss. error in the Gaussian stuff here: α is small $\bar{\mu}$ was known $\hat{\alpha} = \frac{1}{k} \sum \mu_i$.

Try $\bar{\mu} = .24, .25, .26, .27, .28$ - look for peak.

| μ | Peak |
|-------|-------------------------|
| .265 | $1 \rightarrow 179.14$ |
| .24 | $1 \rightarrow 155.122$ |
| .23 | $1 \rightarrow 153$ |
| .22 | $1 \rightarrow 158$ |
| .2 | $1 \rightarrow 125$ |
| .1 | $1 \rightarrow 125$ |
| .26 | 165 |
| .27 | troubled at $A = .95$ |
| .28 | " " " " |
| .30 | " " " " |

troubled at $A=1$. $A = .995 \rightarrow 70.79. \leftarrow$

Just S^2 is not means it is being calculated incorrectly.

S^2 should be $\frac{1}{n} \sum (\mu_i - \bar{\mu})^2$

$SS = SS + (\bar{x} - \bar{\mu})^2$

$SS = SS/n$

In this case, 1 is clearly a pole, no matter what $\bar{\mu}$ is.

For $U = .4$ there is a pole sing at $A = 0$

" $U = .5$ Ring seems to change discontinuously, but still, \pm peak, sing at 2π .

I tried what happens if just μ . Gaussian becomes factor becomes curve.

Re: to catch of α for max pc! $(62.56 - 63.20)$ usually $\frac{A}{R}$ is slightly > 1 so $\frac{k}{a}$ is

slightly < 1 but $\gg \frac{1}{k}$, so there are no real peaks.

Looking at eq. 62.03 - it really looks like there has to be a pole at $(1-\alpha) = 0$.

perhaps look at it from pt. of view of coding: say I simply had a set μ_i to code directly. As S^2 gets small, it should become very difficult to code but distant from mean. From pt. of view of coding, I don't see how one could see how a pc $\rightarrow 0$!

Using 62.03 as a basis for coding: for each value of z , we have a code for z corpus.

Exactly how does one use 62.03 to code a corpus? - ask same q. for divergent binomial d.f. codes.

Wells: $\frac{1}{S}$ pole is a familiar function! The peak is ~~very~~ high, but also narrow. Tip product of widths $kt > 1$. \pm so μ_i is irrelevant.

In 62.03 we use an initial S , $\bar{\mu}$ is a to desc. to corpus: we then integrate over all $S, \bar{\mu}$ to get total pc.

Also, note in 62.03 1. factors $\prod e^{-\frac{1}{2} \frac{(\mu_i - \bar{\mu})^2}{S^2}}$: It has a super zero Real denominator residual singularity. any pole! While $\frac{1}{S^2}$ has a pole at $S^2 \rightarrow \frac{1}{k} \sum (\mu_i - \bar{\mu})^2$, it is a very narrow pole if $\bar{\mu}$ is corpus. S^2 is small.

Re: 62.03!

S, \bar{u} is a 2 dim indep der vars of t data set. ($\mathcal{U}[r_{ij}]$)

$M_i = \alpha \bar{u} + (1-\alpha) M_i'$

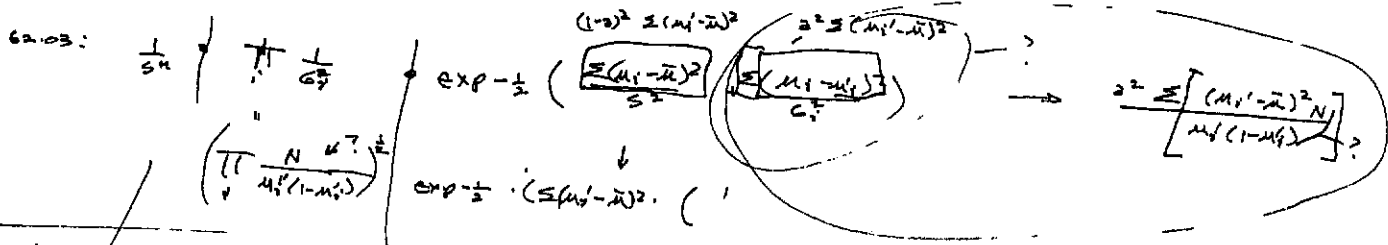
| | | |
|------------------------------|--|--|
| No. Secondary Param. This is | $S^2 = \frac{1}{N} \sum (M_i - \bar{u})^2$ | $M_i - \bar{u} = (1-\alpha)(M_i' - \bar{u})$ (62.30) |
| | $S^2 = \frac{(1-\alpha)^2}{N} \sum (M_i' - \bar{u})^2$ | |

multiply position of α in \bar{u} part.

Hvr: $\sum (M_i - \bar{u})^2 = (1-\alpha)^2 \sum (M_i' - \bar{u})^2$ (in numerator of exponent)

$M_i - M_i' = \alpha(\bar{u} - M_i')$ so $\sum (M_i - M_i')^2 = \alpha^2 \sum (M_i' - \bar{u})^2$ $\frac{1}{\sigma^2} = \frac{N}{M_i'(1-M_i')}$?

So 62.03 = $\frac{1}{S^2} \cdot \exp -\frac{1}{2} \left(\frac{\sum (M_i' - \bar{u})^2}{S^2} \right) \left(\frac{(1-\alpha)^2}{S^2} + \frac{N}{M_i'(1-M_i')} \right)$



(I think $\sigma^2 = \frac{M_i'(1-M_i')}{N}$ is o.e.! T. σ_i^2 are supposed to be "Given".)

62.03 $S^{-2} \cdot \frac{1}{N} \cdot \pi \frac{1}{M_i'(1-M_i')}$ constants. $\exp \left[-\frac{1}{2} \left(\frac{\sum (M_i' - \bar{u})^2}{S^2} (1-\alpha)^2 + \frac{N}{M_i'(1-M_i')} \right) \right]$ simple expression in terms of sum of squares of $\{M_i'\}$ & $\bar{u} - (M_i' - \bar{u})$ Similar remarks apply to this

What it will look like: $\sim S^{-N} \cdot \text{const} \cdot \exp \left[-\frac{1}{2} \left(\frac{\sum (M_i' - \bar{u})^2}{S^2} (1-\alpha)^2 + \frac{N}{M_i'(1-M_i')} \right) \right]$

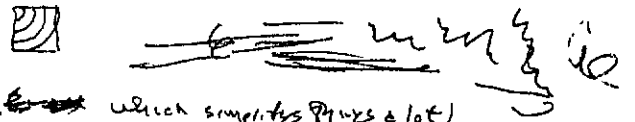
taking ln's simplifies. $-\frac{N}{2} \ln(S^2)$

It is not so sure of this structure!

for each S^2 value we can perhaps solve for \bar{u} to minimize exponential part.

so t . exponential part is a func of S^2 . Then we minimize $\frac{N}{2} \ln(S^2) + f(S)$.

can just do a 3 dim optm "by hand".



on the other hand, it's easy to max w.r.t. S^2 first which simplifies things a lot!

We then have a single function of \bar{u} & α to maximize. max is at $\alpha = 1$ (maxes)

To get actual useful output, integrate over all S, \bar{u}, α . Perhaps have range 0,1 for each - so S over t . unit cube to get total pc. of code.

One final: Pick \bar{u} around .265, Then, for each α value, integrate over all S .

Maybe there will be a peak in α .

For any value of $k=1$, these poles S seen show at $S=0$ will be removed by the $\frac{1}{S^2}$ vector.

while the β from ST&B's can't be easily modified to do this integration! I don't like ST&B.

to Rewrite this from Hoch number!

k=18, N=45

$U \equiv \bar{U} = .265 \quad (= \bar{U})$

$A \equiv \text{(set by hand)} \quad \bar{A} = z$

For A = .1 to 1, step .1 ~~(uncommented by)~~
 For S = .1 to 1 step .1

~~U = U_i~~ $U \equiv U_i ; U_i = z \bar{U} + (1-z) U_i'$

~~Z = A(J, 3)~~ $Z = U_i'$

$UU = A * U + (1-A) * Z \quad | \quad UU \equiv U_i'$

$S1 = \sum (U_i - \bar{U})^2 \quad S1 = S1 / S^2 \text{ after } J \text{ loop}$

~~For J=1 to k~~ $S1 = S1 + (UU - U)^2$

$S2 = \sum ((U_i - U_i')^2 / \sigma_i^2) = \sum (U_i - \bar{U})^2 / U_i' / (1-U_i)'$ $S2 = S2 * N$ after J loop.

Print z, S, $S^{k/2} * \exp(-\frac{1}{2}(S1+S2))$

ST 67
 Summary
 01-18

k=18, N=45
 U = .265
 A = .1

$S1 = \sum (U_i - \bar{U})^2 / S^2$
 $U_i = A \bar{U} + (1-A) U_i'$
 $S2 = \sum \left(\frac{(U_i' - \bar{U})^2 N}{U_i' (1-U_i')} \right)$

```

30 For J=1 to 20 : S = JS / 10
   S1 = 0 : S2 = 0
   For I = 1 to k
     Z = A(J, 3) / 1000
     UU = A * U + (1-A) * Z
     S1 = S1 + (UU - U)^2
     S2 = S2 + ((UU - Z)^2) / Z / (1-Z)
   Next I
   S1 = S1 / (S^2)
   S2 = S2 * N
   Print A, S, S^{k/2} * exp(-(S1+S2)/2)
 Next J
 
```

$UU \equiv U_i'$; $U \equiv \bar{U}$; $Z = U_i'$

Set for A = .1 ; sharp peak at $S = 0.09$ $e^S = 2.1$ at $S = .075$; $= 1.9 \times 10^9$ at $S = .02$

| A | S |
|-----|-------|
| .1 | .08 |
| .2 | .07 |
| .3 | .06 |
| .4 | .06 |
| .5 | .05 |
| .6 | .04 |
| .7 | .03 |
| .8 | .02 |
| .9 | .01 |
| .95 | <.005 |

The increase in e^S as $S \rightarrow 0$ is rapid, then after it gets to its peak, it drops down very rapidly.

As A increases toward 1, the wt. of S becomes closer & closer to $S = 0$.

Run on a first timer (Egauge!)

Try integrating \dots w.r.t S , ~~...~~ S_0^1 for each Δ value.

STG8.BAS

```
SO INT=0
FOR JJ=1 TO 100 : S=JJ/100
```

So it looks like almost all work is at $\Delta=1$, $S \times 0. U = .2653889$
I could try $\Delta = .25$

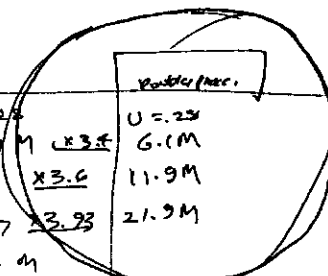
```
PRINT INT>INT+SY(-K(S)) * ...
```

Next JJ
Print INT/100.
INPUT A.

"INT" is special name! Use INTT

| INTT | U = .2653889 | U = .25 | U = .25 |
|-------------|--------------|-----------------|----------|
| 1 2.18M | 1.786M | 1.79M x3.6 | 6.1M |
| 2 4.16M | 3.43M | 3.3 x3.6 | 11.9M |
| 3 7.41M | 6.17M | 5.57 x3.93 | 21.9M |
| 4 12.77M | 10.28M | 8.86M | |
| 5 22.65M | 19.47M | 14.17M | |
| 6 45.94M | 40.3M | 25.3M | |
| 7 124.75M | 112.7M | 59.3M | |
| 8 764.20M | 724.0M | 310M x4.39 | 2.678E10 |
| 9 58458.89M | 5.845E10 | 5.8900M 5.55E10 | 1.916E10 |
| 95 | 4.98E11 | 5.67E11 grow! | 1.688E11 |

ABCd S₀₀ P₁₀₀ etc



seems to be big difference betw. Single & double precision! I wonder where it occurs!

Maybe error in computing $\exp(x)$?

I do do 100 additions, so this could lose precision too.

Anyway, the results are not encouraging! If says that U is always best estimate!

| Try | N = 200 U = .265 | try U = .265 | Add! 13.7 | N = 150 |
|-----|------------------------|--------------|-----------|---------|
| 1 | INTT x 10 ⁶ | 15.6 M | 22 | 13.7 |
| 2 | 2.06 | 5.9 | 24 | 32 |
| 3 | .43 | .7 | 17 | 32 |
| 4 | .0125 | .02 | 8 | 25 |
| 5 | 6.7E-5 | | 5.05 M | 16 |
| 6 | 2.2E-20 | | .122 | 9 |
| 7 | 1.5E-20 | | .046 | 6 |
| 8 | | | .0087 | 5 |
| 9 | | | | 38 |
| 95 | | | | 27.9 |
| 99 | | | | 9 |

STRANGE

Maybe this is correct! - i.e. for N as small as 15, all work is in $\bar{0}$.

I did get results of this by comparing piece of Bernoulli codes

Using one \bar{U} for entire code v.e. Using K \bar{U} 's for codes: $\Delta \leq N$ used \bar{U} 210

There was rapid change in betw. which method had most PC, & one would quickly demerit to other. 93.01-30 deals w. this result.

See
116.32 -
120.40
for Map
(differs) work
on arc.
63.03 ff

Some Note on previous pm. (ST 97); ^{dist from ST 67?}

- 1) Try 1000 rfs of integration w/o (EXT) extended precision.
- 2) On +. General problem of correctness of concepts used!

Initially. Say F_p is B. D.F. for ~~manus~~ each player about his ~~manus~~, M_i .
 F_u is t. D.F. for manus, M_i .
 F_F is t. D.F. for t. entire corpus, Corpus.

If we convolute F_u, F_p : $\sigma_F^2 = \sigma_u^2 + \sigma_p^2$.
 If we convolute F_u, F_p : $\frac{1}{\sigma_F} = \frac{1}{\sigma_u} + \frac{1}{\sigma_p}$.
 " " multiply F_u, F_p : $\frac{1}{\sigma_F} = \frac{1}{\sigma_u} + \frac{1}{\sigma_p}$.
 Reason easily shown for Gauss D.F.'s. (o)

.11 Using Bin D.F.s instead of Gaussian, we don't have a convolution but we have something like it.
 .12 $\int_0^1 (F_u(M_i))^{(1-M_i)N} F(M_i, M_i) d.M_i$. Normal const. should be inserted. This is an integration error

All M_i that could give rise to observed $M_i \cdot N$ data pts.

.14 To get +. final D.F. we mix all these together, ~~convolve~~ $\prod_i F(M_i)$.
 T. reason $F(\cdot)$ is not a convolution, is that for each M_i point, $F(M_i, M_i)$ has
 a somewhat different form! This makes it poss. for all of these "pseudo convolutions"
 to keep on t. interval $(0, 1)$.

I believe that I did implement .12-.14 in my last best, version of F . Bin. d.f. M_i

ie. 46.28 and ST46

In 46.28, t. prob of a hit ent. next "at bat" by t. ith player is just $\frac{X+A+1}{X+Y+N+1}$

(~~normal~~) One way to look at it: the prob of hit v.s. out is $\frac{X+A+1}{Y+B+1}$

normal prob of hit is $\frac{Y+A+1}{X+A+1+Y+B+1} = \frac{X+A+1}{X+Y+N+2}$. $X \in \mathbb{N}, Y \in \mathbb{N}$

To get a prediction, we integrate P_{hit} w. wt. of corresponding values of (X, Y) (or (\bar{X}, \bar{Y}))

To get an idea of what t. output of R, \bar{Y} looks like! One way would be to

consider many previous yrs: try to get approx induced on X, Y , induced by P_{hit} (large) data set.

.31 My guess is that for a finite data set, $\bar{Y} \rightarrow 4$ or 2 reasonable D.F. betw 0 & 1,

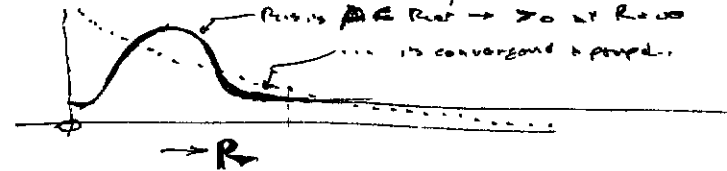
but R will have a pc > 0 for $R=0$ and (unfortunately) a pc > 0 for $R \rightarrow \infty$!

Not so bad! A.T. d.f. for large SSZ will be small (but > 0 for $R \rightarrow \infty$, it will be

very small. P_{hit} will be, here, a true approx, since $S_0^{\infty}(C) = \infty$.

.32 We have to use an auxiliary approx that does have $S_0^{\infty}(C) = 1$. Multiplying by v. D.F. of (31)

will give us a d.f. that is fairly indep of t. behavior of P_{hit} (31) approx. as ∞ .



T. product of t. 2 D.F. of course, converges.

3.2.99 SMFT STEIN c.i.? R?

I had a discussion of c.p. of α ~~46.28~~ at $R=0$ is at $R=00$; 49.07
 $a = \bar{u}$, $b = (1-\bar{u})$; for $R=00 \Rightarrow 49.07 \Rightarrow \frac{1}{2} A_i B_i$; $(\frac{M_i}{a} - \frac{1-M_i}{b})^N$
 for i. online set this becomes: $(\prod_i \frac{1}{2} \frac{M_i}{a} \frac{1-M_i}{b})^N$

(When $M_i = a$ or $b = 1-M_i$). So the value at $R=00$ will be $\leq -kN$ $\ln = \frac{kN}{1/2} = \frac{18 \cdot 45}{1/2} = \frac{810}{1/2} = -1620$

I didn't get the result at ∞ ! $G(R=00) < -1168.6$; $I B = -468.68$ on $G \frac{1}{2}$

from 49.20; T. value when $a = \bar{u}$, is $(\frac{1}{2} \frac{1-\bar{u}}{1-\bar{u}})^N = .56$ (!) $.2653899$
 $(.56) \times 510 = 465.6$

down it exactly for $U = .2653899$; $310 \times (U^U (1-U)^{1-U}) = -468.680957$
 on $G \frac{1}{2}$ $I B = 16.37$; -468.680957 very clear!

Q.4. now while $(.56)^{510}$ seems very small, in the pgm. σ STGL.B, it turns to largest value of G in the range $R=0, \infty$

I probably left out some Normal factors:

from 46.02 may be $\prod_i \left(\frac{N+1}{A_i B_i} \right)$ $\ln = \ln(N \ln N) - \sum_i (\ln A_i - B_i \ln B_i + \ln(N+1))$
 $= \frac{1}{2} \ln \left(\frac{N}{A_i B_i \cdot 2\pi} \right)$

Whether G is small at $R=00$ is unclear: depends on whether G has a peak(s) before $R=00$

T. main Q now is whether the dice of 69.31-40 is basically correct.

Get size of this in terms of M_i, N :

Try $\frac{N!}{(p^N q^N)}$ $N \ln N - pN \ln p - qN \ln q$
 $\pm \frac{1}{2} \ln \left(\frac{N}{2\pi p q} \right)$
 Multiply $N! = (p^p q^q)^N \cdot \frac{N}{2\pi p q} (1+\dots)$
 $\approx \frac{(p^p q^q)^N}{\sqrt{2\pi p q}} \cdot \frac{N}{2\pi p q} (1+\dots)$
 $\approx \frac{N!}{(p^N q^N)}$

$\frac{N+1}{A_i B_i} \approx \left(\frac{M_i}{a} \frac{1-M_i}{b} \right)^N \cdot \sqrt{\frac{N}{2\pi M_i (1-M_i)}} \cdot (1+\dots)$

For ∞ G will be $\gg 1$ if these factors cancel: because of $\left(\frac{N}{2\pi p q} \right)^{1/2}$ factor.

For ∞ 2 factors don't cancel. One is usually $>$ the other, i.e. $\ln \left(\frac{M_i}{a} \frac{1-M_i}{b} \right)$ factors, is usually $>$ to N power of $\frac{1}{2} \ln \left(\frac{N}{2\pi p q} \right)$ because of a convexity effect.

So for large N , the $\left(\frac{N}{2\pi p q} \right)^{1/2}$ factor is $\sim \left(\frac{N}{2\pi p q} \right)^{1/2}$ and the other factor is something like $(\frac{2N}{\alpha})^{1/2}$ ($\alpha < 1$)
 So it depends on whether on the size of N and α .

If the M_i are a broad dist then α is small. If M_i are close together α is closer to 1.
 Indeed we can compute an approx to α , if we know \bar{u} and the distribution of $\sum A_i^2$ above \bar{u} .

Re: Behavior for $R=00$! See 49.26! The gamma factor for $U = \bar{u}$ cancels out $\frac{1}{2}$.

Value at $R=0$ exactly: so value is exactly 1. - in contrast to value of $R=00$ which is really

α has a broad peak at $\bar{u} = \frac{1}{2}$ with mean of all M_i ; but this peak is much sharpened by the power kN (28)

For $N=95, k=18$, I'm not sure $G(R=00) < G(R=0)$; for very large N it would seem very likely to be much smaller at $R=00$. Depends on α & R .

$\approx \left(\frac{N}{2\pi \bar{u} (1-\bar{u})} \right)^{1/2} \cdot \frac{1}{\sqrt{N}} \left(\frac{M_i}{a} \frac{1-M_i}{b} \right)^N$

For $R=1$ $G \ll 2N$ for present case. (ST76)

See if this is because $\alpha^{2N} > N$. (70.28) or is G so $R=0$ much different from $R=1$?

46.28

How much different from $\frac{A!B!}{(N+1)!}$?

$\frac{1}{2!} - \frac{1}{2} \sqrt{\pi} = .28622$

$(\frac{1}{2})^2 = \frac{1}{4} \pi = .7853$

$(\frac{1}{2} \pi)^{-1} = 1.273$

$(x+\frac{1}{2})! \approx x! \cdot \sqrt{x+\frac{1}{2}}$

$= \frac{A!B! \sqrt{(A+\frac{1}{2})} \sqrt{(B+\frac{1}{2})}}{(N+1)! (N+2)}$

So it's not very much different.

This can be done better!

$(x+\frac{1}{2})! \approx x! (x+\frac{1}{2})^{\frac{1}{2}}$

is not bad approx

See 72.23 for better approx for $G(1)$

ST71

Compute $\ln \alpha$, $\alpha = \frac{\sum u_i \ln u_i + (1-u_i) \ln (1-u_i)}{N} - \bar{u} \ln \bar{u} - (1-\bar{u}) \ln (1-\bar{u})$

$\alpha = 1.741818$

$SS = \exp(\dots) = .975252717823$ - seems way too large!

$\bar{u}^N (1-\bar{u})^{N-\bar{u}} = .5606724$ (for $\bar{u} = .2653889$)

.7032421

$\frac{SS}{C} = 1.741818$

$F_1(x) = x^k (1-x)^{N-k}$

$F_1(0) = .5606724$ $F_1(.346) = .51$

error in β $\rightarrow .5672587943$

$\alpha = 1.011747218$

$\alpha = \frac{SS}{\beta}$; $\beta = F_1(\bar{u}) = \bar{u}^N (1-\bar{u})^{N-\bar{u}}$

$SS = .5672587943$

$\beta = .5606724$

$\alpha = 1.011747218$

85.12653

This looks to be much more reasonable!

Looking at 70.28

$\alpha^{2N} \approx e^{2.86076}$

So: the normal approx of $\prod \frac{N+1}{4! \beta_i!} \approx \prod \frac{N}{2\pi \sqrt{N(1-u_i)}} (1-u_i)^k e^{-k}$

$\approx \beta^k \cdot \left(\frac{N}{2\pi \sqrt{N(1-u_i)}}\right)^k \cdot e^{-k}$

$\ln \left(\frac{N}{2\pi \sqrt{N(1-u_i)}} \right)^k = 32.83027062$

$\ln \left(\frac{N}{2\pi \sqrt{N(1-u_i)}} \right) = 6.06$

$\ln \left(\frac{N}{2\pi \sqrt{N(1-u_i)}} \right) = 1.54576$

$\ln \left(\frac{N}{2\pi \sqrt{N(1-u_i)}} \right) = 6.136$

should be different base.

Running ST76: Got a low max of

-468.5718 at $R=1029$

-468.67341 " " when I took it out to 4.500000000

to 3.141592654

OH! Not's ok, on 50.20 $\ln \alpha$

-468.665 at $R=838.96$

ΔG but $R=1$ $R=2$ is only

$-482.1129 - (-468.6808) = 13.43$

$R=1$ $R=2$

Also, if the normal factor is only a function of G should be e^{-G} not e^{-482} . Woops! when I forgot a -4 exponent here

$(.5672587)^{-810}$

$= +459.221528$ in log domain. adding 32.83027062 gives $+492.0517986$: Multiple this normal by

Should give $+1$ (error in log domain, $\ln 10$)

T. approx of $\frac{N+1}{A!B!}$ of 70.23 may be many.

$N=10, A=5, B=4$

check 70.23! say $N=10, A=5, B=4$.

$\frac{11!}{5!4!} = 13860$ 2310

$(.6 \cdot .4)^{10} \cdot \frac{10}{2\pi \cdot .4 \cdot .6} \cdot (1.1)$

$937.724 \times 2.83267 = 2373$ Not far off!

$\frac{N!}{A!B!} \rightarrow \frac{N^N}{A^A B^B} = \frac{N^A \cdot N^B}{A^A B^B} = \left(\frac{N}{A}\right)^A \cdot \left(\frac{N}{B}\right)^B \rightarrow \left(\frac{N}{A}\right)^A \left(\frac{N}{B}\right)^B \cdot \sqrt{\frac{1}{\frac{A}{N} \cdot \frac{B}{N} \cdot N \cdot 2\pi}}$

$z = \frac{A}{N}, b = \frac{B}{N}$ $N+1 = N(1 + \frac{1}{N})$

$\frac{N+1!}{A!B!} = (z^A b^B)^{-N} \left(\sqrt{\frac{N}{z \cdot b \cdot 2\pi}}\right) \left(1 + \frac{1}{N}\right)$

190658 $\frac{13}{95} = \frac{2}{5} = .4$

$\prod_{i=1}^k \frac{N+1}{A_i N! (1-A_i)^N} = \prod_{i=1}^k \frac{N}{A_i (1-A_i) \cdot 2\pi} \left(1 + \frac{1}{N}\right)$

$= \beta^{-Nk} \left(\frac{N}{\bar{A}(1-\bar{A}) \cdot 2\pi}\right)^k \cdot e^{\frac{1}{N}}$

Inc: 459.23368

$\frac{N}{\bar{A}(1-\bar{A}) \cdot 2\pi} = \frac{10}{3 \cdot 7 \cdot 2\pi} = 0.24$

$3 \cdot 2.634741$

$\pm = 992.268$ in log domain: $\frac{71.38}{??}$

Lim off by 2 factor of $(3.09)^3 \sim \sqrt{\pi}^k$

well $R=1 \equiv R=0$. On 71.07 $\pm 8\%$ additional factor $\frac{N+2}{(A+\frac{1}{2})(B+\frac{1}{2})} \approx \frac{N}{N \bar{A} \bar{B} (1-\bar{A})}$

$\frac{1}{\sqrt{\bar{A}(1-\bar{A})}} = 2.24$ (putting back)

$\frac{(A+\frac{1}{2})(B+\frac{1}{2})}{N+1}$

.23

non-zero is good for $e = \frac{1}{2}$

$(x+\frac{1}{2})! \sim x! \cdot \frac{(x+\frac{1}{2})^e}{e^e}$

How bad is $x!(x+\frac{1}{2})!$ for $e=0$!

$\frac{1}{e^1} \cdot \sqrt{2\pi} = .92$

$\frac{N+2}{A! B!} \approx \frac{N+2}{N \bar{A} \bar{B} (1-\bar{A})} \approx \frac{1}{\beta} \left(1 + \frac{1}{N}\right)$

$\beta = .56720$ $\beta^{-1} = 1.7629 \approx \sqrt{\pi}$ — so that's about into size. — is it in introduction?

Also starting is at so same for $x=1$.

well, in STFC I calculated $G(R=1)$. It larger by a factor of $\approx \pi$ than $G(R=0)$

so its $G(R=0)$ should be $x - 42.11$ minus 10 or $N - 42.11$ which is what I want.

So A may be O.K. (But check again!)

Then t. Q is: Is 69.31 — 40 correct?

Another check should be a "by hand" calca. of $G(R=1)/G(R=0)$ — paper ca. I'd like an expression for it: So far, my hand calca. of $G(R=1)$ is so same O.K.

As for an expression for $G(\infty)/G(0)$ is of more interest! I think $(46.25) \approx 70.23$ area this

So I really want at least $G(0), G(\infty)$, + norm constant (so result in $G(0)=1$)

Also position, det., width of peak. — How may vary in N, k , dispersion of \bar{A}, \bar{B} & of $\bar{A} \cdot \bar{B}$.

What does $G(R)$ look like for $N=500$ and $k \rightarrow \infty$? π is 1.76 approx.

It did it for. Some dispersion of \bar{A}, \bar{B} , it would be more like t. approx of R .

So G is function of k w. $\frac{d}{dk}$ for Max value = value \bar{U} :

70.17
 $\binom{6}{2} = 15$
 $\binom{6}{5} = 6$
 $\binom{6}{4} = 15$
 $\binom{6}{3} = 20$
 $\binom{6}{2} = 15$
 $\binom{6}{1} = 6$
 $\binom{6}{0} = 1$
 $15 + 6 + 15 + 20 + 15 + 6 + 1 = 78$

1. $G(\phi) = 1$

$A_i \in N M_i$; $B_i \in N(1-M_i)$. $N = 45$, $k = 18$, $\bar{u} = .2653889$.
 $F_k(u) = x^k(1-x)^{N-k}$

03

2. Normal Const: from 602, 70.17

$A_n = \prod_{i=1}^k \frac{N+1}{A_i! B_i!}$

$\approx \prod_{i=1}^k \left[F_i(u_i)^{-N} \cdot \left(\frac{N}{2\pi A_i(1-A_i)} \right) (1+\frac{1}{N}) \right]$ (70.23)

$\approx \beta^{-Nk} \left[\prod_{i=1}^k \left(\frac{N}{A_i(1-A_i)2\pi} \right) \right] e^{\frac{k}{N}}$
 $\approx \beta^{-Nk} \left(\frac{N}{\bar{u}(1-\bar{u})2\pi} \right)^k \cdot e^{\frac{k}{N}}$; $\beta = .5672587943$ (ST 71, Bas, 71.17)
 $\bar{u} = .2653889$

$\ln(\uparrow)$
 $\ln(\)$

$\approx \left(\beta^{-N} \left(\frac{N}{\bar{u}(1-\bar{u})2\pi} \right)^{\frac{1}{N}} \cdot e^{\frac{1}{N}} \right)^k$
 $\approx (-25.51224 + 1.801879 + .0263158) \cdot N$
 $\approx -(23.6671796) \cdot N$
 $\frac{N}{\bar{u}(1-\bar{u})2\pi} = \frac{45}{1.224934977} = 36.73604$
 $\sqrt{\frac{1}{\phi}} = 6.0610267$

14

3) $G(\infty) = A_n \cdot \left(F_i(\bar{u}) \right)^{k \cdot N} = A_n \left(\bar{u}^{\bar{u}} (1-\bar{u})^{1-\bar{u}} \right)^{N \cdot k}$
 $= \left(\frac{.5606724}{\beta} \right)^{Nk} \left(\left(\frac{N}{\bar{u}(1-\bar{u})2\pi} \right)^{\frac{1}{N}} \cdot e^{\frac{1}{N}} \right)^k$
 $\left((1.01174218) \right)^N \left(\frac{N}{\bar{u}(1-\bar{u})2\pi} \right)^{\frac{1}{N}} \cdot e^{\frac{1}{N}}$

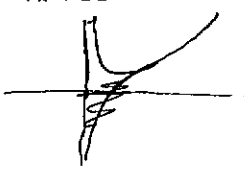
$F_i(\bar{u}) = .5606724$
 $\alpha = \frac{\beta}{F_i(\bar{u})} = 1.01174218$

So want to know how α^N compares with $\sqrt{\alpha}$ compares with
 α^N compares with $\left(\frac{N}{\bar{u}(1-\bar{u})2\pi} \right)^{\frac{1}{N}} \cdot e^{\frac{1}{N}}$; The second factor is $\sqrt{\ } = 6.0610267 \cdot e^{\frac{1}{N}}$
 $= 6.1972238$

for what N is $G(\infty) = 1$? $\alpha^N = \left(\frac{N}{\bar{u}(1-\bar{u})2\pi} \right)^{\frac{1}{N}} \cdot e^{\frac{1}{N}}$
 $(\alpha^2)^N = N / \sqrt{\bar{u}(1-\bar{u})2\pi} \cdot e^{\frac{2}{N}}$

$T^*) A^x N = N$; $e^{8 \cdot N + 2} = N$; $8N + 2 = \ln N$
 $8N \approx N'$; $N = \frac{N'}{8}$; $e^{N' + 2} = \frac{N'}{8}$; $N' + 2 = \ln N' + \ln 8$
 $N' = \ln N' + \ln 8 - 2$; $N' = \ln N' + B$; $X = \ln X + Z$; $e^X = X \cdot e^Z$

$e^Z = \frac{e^X}{X}$; so I want to inverse of $\frac{e^X}{X}$
 Surprised that it is 2 valued!



$\alpha^2 \in \mathbb{R}^D$ so $D = 2 \ln \alpha$; $e^{DN} = \frac{N \cdot D}{D \sqrt{\bar{u}(1-\bar{u})2\pi}}$; $X = DN$; $e^X = \frac{X}{D \sqrt{\bar{u}(1-\bar{u})2\pi}}$
 $e^X = X \cdot 2$ ($Z = 2 \ln 2$) ; $X = \frac{e^X}{2}$; $5, 3.335$; $0.28 ; .026578 ; .02653658$
 $X = \frac{e^X}{2}$; $X = 3.86596$

13 one soln. $N = \frac{X}{D} = 1.13$; this is not a soln. count.

$X = \ln X + \ln 2$; 5.26 ; 5.317 ; 2.014 ; 5.3249684 ; $N = \frac{X}{D} = 22.824$

$N = 22.824$ is \approx Prob N is which
 cross the crossover pt for the 2 coding methods
 64 ; 3.30 (ST 42.602)
 [Prob Σ constraint p.g. of
 $\frac{N!}{N_1! \dots N_k!} \approx \frac{N^k}{k!}$ for $k=18$ is various values.]

Look at ST42.B.3 More carefully: That $228 \approx 201$ is probably coincidence!

See what ST42.6 does:

103

Basic Eq: $\frac{x!y!}{x+y!} \approx (a^2 b)^R \cdot \sqrt{2\pi a b R}$ $a = \frac{x}{R}$ $b = \frac{y}{R}$; $R \approx x+b$

check $\frac{4!5!}{10!} \approx (.4 \cdot .6)^{10} \cdot \sqrt{2\pi \cdot 4 \cdot 6} = 4.63813 E-3$
 $\frac{4!5!}{10!} = 4.762 E-3$
 $(.4 \cdot .6)^{10} = 1.1943968 E-3$
 $\sqrt{2\pi \cdot 4 \cdot 6} = 7.34$
 $1.1943968 E-3 \cdot 7.34 = 8.767 E-3$
 $\frac{8.767 E-3}{1.86} = 4.713 E-3$
 $\frac{4.713 E-3}{1.016} = 4.63813 E-3$

so $G(\bar{u}) = (F(\bar{u}))^{NR} \cdot \sqrt{2\pi \bar{u}(1-\bar{u}) \cdot N \cdot k} / (NRk)$

10

$A_N G = \prod (F(u_i))^{N_i} \sqrt{2\pi u_i(1-u_i) \cdot N} / (Nk)$ \equiv (Norman constant 73.03)⁻¹

11

How value of $G(\infty)$ is $A_N \cdot (F(\bar{u}))^{NR}$ or $\frac{F(\bar{u})^{NR}}{.10}$

In ST42.B.6 We find $N \Rightarrow \frac{F(\bar{u})^{NR}}{.10} \cdot \frac{\sqrt{2\pi \bar{u}(1-\bar{u}) \cdot N \cdot k}}{NRk} = 1$

In 73.14-40. we find $N \Rightarrow 11 = 1$

That the 2 results should be close means that value of f expressed changes rapidly w. N .

20

Anyway as $N \gg 228$, $G(\infty)$ gets smaller as $\sqrt{N} \cdot \alpha^N$ $\alpha = 1.01174218$

Each 9 of N by 65 make $G(\infty)$ smaller $\sqrt{N} \frac{1}{e^{.16}}$

23

by $v \times e^{-1}$. (since \sqrt{N} doesn't change much)

T. discuss of 20-23 are for effect of N only; Actually t. effect is $(\sqrt{N} e^{-\frac{N}{25.16}})^k$

So for $N > 238$ (say $N=300$), increase in k become $v \times e^{-1}$ in $G(R \rightarrow \infty)$.

Next you peak of $G(k)$ curve is perhaps its height at peak

27

$\left(\frac{46.28}{\text{So, unnormalized}} \right) \left(\frac{x+y+1}{x!y!} \right)^N \cdot \prod \frac{x+A_i!y+B_i!}{x+y+N+1!}$ use $x=0$ $y=f \cdot 0$

from 03:

$(R+1) \cdot F(\bar{u})^{-R} \cdot \frac{1}{\sqrt{2\pi \bar{u}(1-\bar{u})R}} \cdot \prod_{i=1}^k \frac{(R+NA_i)! R(1-u_i)+N(1-u_i)!}{R+N+1!}$

$\prod = \frac{1}{\sqrt{2\pi a b R}} \cdot \frac{1}{(R+N+1)^k}$ $a_i = \frac{R+NA_i}{R+N+1}$; $b_i = 1-a_i$

27 it doesn't look promising!

Think about A_{pipe} for R : Obtained by considering many previous year's data.

How, note that unless $N \gg 238$, $G(\infty)$ will be > 1

Try d.f. of $G(k)$ for $N \rightarrow \infty$: I did \approx this at ST46.6: See result 47.10-20

Shape of d.f. becomes indep of N as $N \rightarrow \infty$.

46.28 and 74.03: $\frac{x+y+1}{x!y!} = (F(\bar{u}))^R (2\pi \bar{u}(1-\bar{u})R)^{-1/2} \cdot (R+1)$

37

$\frac{y+NA_i!}{R+N+1!} \cdot \frac{y+u(1-A_i)!}{R+N+1!} = (F(u_i))^{R+NA_i} \cdot \sqrt{\frac{2\pi u_i(1-u_i)}{R+N+1}}$

38

So it looks like $\frac{1}{\sqrt{R+N}}$ as a function of R $\frac{\prod F(u_i)}{F(\bar{u})^R} \approx \alpha^R$ $\frac{\sqrt{R}}{(R+N)^k}$

37 is mainly controlled by the Norman constant 73.03

For any large (but finite) N , in 74.37 for $R \ll N$, we have $\prod F_i(z_i)^{R+N+1}$ or may cancel w. harmonic cons.

The $\prod F_i(z_i)$ factor is $> F_i(\bar{\mu})^k$ and causes $G(R)$ to \uparrow w. R .
 as $R \gg N$; this factor becomes $\prod F_i(\bar{\mu}) = F_i(\bar{\mu})^k$ and so $G(R)$ starts to \downarrow .

Unfortunately ~~in~~ 47.10-20, F_i 's transition didn't occur when R became $> N$, but at a fixed pt, of $R \sim 40$. for $N = 500$ roughly 200

74.37 after multiply Normal const. (73.03):

$$F_i(\mu_i)^{-N} \cdot \sqrt{N} \cdot F_i(\mu_i)^{R+N+1} \cdot \frac{1}{\sqrt{R+N}}$$

$$= \prod \left(F_i(\mu_i)^{R+N+1} \sqrt{\frac{N}{R+N}} \right) \cdot F_i(\bar{\mu})^{-R} \cdot \sqrt{R}$$

$\left(\frac{N}{R+N} \right)^{R+N+1} \left(\sqrt{\frac{R}{R+N}} \right)^k$ which $\rightarrow \infty$ as $R \rightarrow \infty$. \therefore wrong!

Look at 46.28:

$$\frac{x+y+1}{x!y!} \rightarrow F_i(\bar{\mu})^{-R} \cdot \sqrt{R}$$

$$\frac{x+y+1}{x!y!} \rightarrow F_i(\bar{\mu})^{R+N} \cdot \frac{1}{\sqrt{R+N}}$$

Product is indep of R at $R \rightarrow \infty$
 $\therefore \text{res} \rightarrow 1$.

Look at 74.38!

$$\left(\frac{\prod F_i(\mu_i)}{F_i(\bar{\mu})^k} \right)^R \cdot \left(\sqrt{\frac{R}{R+N}} \right)^k$$

T. first factor becomes close to 1 as $R \gg N$, so \uparrow slows down.

T. factor $\left(\frac{R}{R+N} \right)^k$ decreases more slowly as R gets $> N$. \therefore It could be that these

effects result in a post F_i 's indep of N for large N .

I could just write a pmf to do it! \rightarrow it's a bit more complete fur.

Instead of $R+N$ is $\frac{R+N}{\mu_i(1-\mu_i)}$ \rightarrow Post " μ_i " are really $\frac{N\mu_i + R\bar{\mu}}{N+R}$

This xfm should be about what ST 46.8 does for large N .

Study t. 47.10-20 det. Smooths w. log normal. It seems \sim log normal.

Do a simulation $2^{100} R = 20 \times 2^{(35/10)}$ $2^{10} \approx 1.07$.

Trouble is t. value of R that \uparrow and up w. will probly be much dependent

on the params I use on a \uparrow prop. — but also look! T. fact that the broad is log normal, ~~passes~~ is much on t. by R . Since also Pt. D.F. in 47.10-17 (for $N=45$) definitely passes R higher.

SN I'm mainly concerned w. how narrow the R.S.P. is \rightarrow NO!

SN The width of the x,y dist. can't be infinitely narrow since we don't have exact SSZ for $\bar{\mu}$. Guess for $\bar{\mu}$ is 800.

If we had only 1 "at bat" for each of k players, T. best est. μ would be $\bar{\mu}$
 $\mu_i \approx \bar{\mu}$ (if $\bar{\mu}$ is average for these k data pts). say SSZ $\rightarrow 2$ (2N) — what else?

\rightarrow So a possl way to get a reasonable \uparrow prop; use R (use N);

assume a log normal d.f., then get expected value of R for

with $R=45$ data j got $\in \mathbb{R}$

and t. expected value for each probly that each player will hit at next bat.

This "prop." is a way to simulate data from previous yrs.

Trouble is, it's not a real \uparrow prop.

Well, it is an approx in the sense that I more or less remember previous yrs longer pretty much like this once

A "True" ~~approx~~ approx would use more (larger no. of previous yrs, plus some approx.)

T. considers that as we have a mt. of previous yrs' data to report on this approx ↓ into notebookness (or at least it should!).

(SN) A weirdness! 47.18 - .20: Seems to be a peak at U = .255! !!

Check this at double precision, v. good value for π .

T. result of 23.14 & -40 and 74.20: That it has to be > 228 but we round } Very unreasonable
much ↓ of σ with R - No matter how large R is!
50 0278
0292
100 0227

What value of R gave best prodn for rest of year? Use MS error & pc error

See how broad this R is. Wrt. pc distribution for various R; what is

the meaning of "width": Is a factor of σ , say on pc, the width? - How is R.

"width" usable? It can have a mean use in parallel codes:

so a ↓ of pc by σ would

| |
|----------|
| 2561 |
| 300 2156 |
| 400 2192 |
| 5 |
| 36 |

(3699) How approaches:

① for conceptual debugging: write MC Carlo Pgm to produce data sets $\{U_i\}$ as a funct of \bar{u}, R, N, K . Should be easy to do: I can from use this ~~generator~~ to test various ideas I have on statistics of the set $\{U_i\}$

② Compute σ^2 theoretical of $\{U_i\}$ as funct of \bar{u}, R, N, K (I think simple)

It is $\sigma^2_{u_i} + \frac{1}{k} \sum_{i=1}^k \sigma_i^2$; T. second term is $\frac{1}{N} \int_0^1 u^x (1-u)^y \frac{u(1-u)}{N} du = \frac{x+1! y+1!}{R+3! N}$
 $= \frac{(x+1)(y+1)}{(R+2)(R+3)N} \approx \frac{U(1-U)}{N}$
 $\sigma^2_{u_i} \approx \frac{U(1-U)}{R}$

So $\sigma^2 = U(1-U) \left(\frac{1}{N} + \frac{1}{R} \right)$

So $\sigma^2_{u_i} = U(1-U) \left(\frac{1}{N} + \frac{1}{R} \right)$; $\frac{1}{R} = \frac{1}{N} + \frac{1}{R}$ \Rightarrow equiv R: $\frac{N-R}{N \cdot R} \approx R$

I may have some \approx this. $4.583899 \approx 3$; 42.53105 ; 225.183

$\frac{1}{NN} = \frac{1}{N} + \frac{1}{R}$ I got 775.183 $NN = \underline{42.53}$

ST76A.6A

It may be best by approx. $\frac{U(1-U)}{N}$ etc. for U and over transformation.

Note: transformation G of ST 2 (75) is not the best one to use!

SS for $R=200$

Strangely! when σ is $R \in WAX = 10^6$, I got ans error of .0242535322

The ST paper got .025374, see my SIG X (8) = .0225!

For $k=12$ error is same as $R=0$: Error = .024

So ST paper used $R=313$; $k=152$ is best. $R=0$ is not bad.

For $k=775$ $\sigma_{u_i} = .02273$

$\frac{\sum A_n}{R+1} \frac{1}{X! Y!}$
Sum (44.15-29)
for $u \in [0,1]$
I don't understand this
arg! - I got the
of a bin dist. later! maybe some
200 but much more complicated
derivativ.
 $\frac{N-R}{N \cdot R} \approx R$
1-p-q
SS; error
SS2; error
SS3; error

| | |
|--------------|-----------------|
| 21 | .021611 |
| 200 | .02127277 |
| 190 | .02126926 |
| 180 | .021277 |
| 175 | .021286 |
| 192 | .02126912 |
| SS (= error) | |
| SS2 | error |
| SS3 | error |
| SS + vari | $\rightarrow U$ |

In ST 76.B₂₅ (→ 76.25H), I found a R, \bar{u} → t. expected $\mu \pm \sigma^2$ of t. $[M_i]$ set produced, was most observed in $[M_i^*]$. This may make R, \bar{u} most likely generators of ΣA_i^* , but that's not usually what I'm after. I'd like more, e. d.f. of R, \bar{u} . That I got a peak in ST 76.B.

(Egness & peak) is weird! It certainly was nowhere near t. peak in ST 96!

ST 46. B finds t. D.F. of (M, R) that would produce t. observed ΣM_i^* ;

Here, I want t. D.F. of $t(M, R)$ that produces a ΣA_i^* set of t. observed σ^2 , only.

ST 46.B is more like ALP. ST 76.B is more like conventional statistics.

For (suppose) there is some continuity off. σ^2 in ST 76. So I think to do better in ST 76.B, ^{knowledge of} ~~the~~ would have to be included.

ST 77A.62

Anyway, I. next pgm is one that generates data sets for arby \bar{u}, R, N, k .

DEFPBLA=3

in A ~~...~~

```

R = 0.0
k = N.0
For J=1 to R
  X=0
  For J=1 to R
    RND
    If < u Then X=X+1
  Next J
  A( J, 1 ) = X
  Next J
  A( J, 2 ) = R/N
  Next J
  
```

this pgm. will at least check my Algebra!

ST 77 B.62

Mod. to a ST 76.B₂₅ Instead of 76.25, averaging over all possible \bar{u} entries

(75.25R) Use mean $\frac{\sum (1-u_i)}{N}$; so $\frac{\sum (1-u_i)^2}{N}$ instead of $\frac{\sum (1-u_i)}{N}$.

t. difference $\frac{(\sum (1-u_i)^2 - N \bar{u}^2)}{R}$; would seem to be quite large!

$$AA = \frac{\sum (1-u_i)^2}{R} - \frac{(\sum (1-u_i))^2}{N} = \frac{SS}{R} - \frac{U^2}{N}$$

$$R \cdot AA = \sum (1-u_i)^2 - \frac{U^2}{N} = SS - \frac{U^2}{N}$$

$$\frac{U(1-U)}{R} = AA \left(\frac{R}{N} - \frac{SS - U^2}{N} \right) ; R = \frac{U(1-U)}{AA}$$

| | | | |
|-----|------------|------------------|-------------------|
| got | R = 557.69 | (instead of 775) | Some improvement! |
| 775 | .02273 | | |
| 552 | .02357 | | |
| 192 | .02126 | Best | |
| 313 | .0216 | stem | |

Using ST 77A, I can see if this pgm or ST 76.B,
 (2) Gives me R on 1. average
 (6) which one has more var. in R,

Do I know \bar{u} const. w. sse of 775? Barley?

$$\frac{1}{R} (\sum (1-u_i)^2 - \frac{U^2}{N}) = \frac{U(1-U)}{R} + \frac{\sum (1-u_i)^2}{N} - \frac{U^2}{N} = \frac{U(1-U)}{R} + \frac{SS - U^2}{N} - \frac{U^2}{N} = \frac{U(1-U)}{R} + \frac{SS - 2U^2}{N}$$



Re: Approx of R : It's not poss. to have R com source cases; (Re In basically it seems unlikely!). Anyway, this suggests $\frac{1}{R}$ may have $\frac{1}{2}$ to be

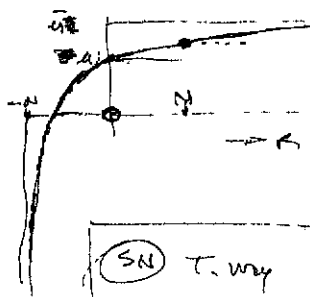
smooth ~~to~~ ~~to~~ ~~to~~ around zero. So try approx of $\frac{1}{R}$ for $R \ll \infty$

In such a case, ~~the~~ 1. first moment of f : product d.f. would be ∞ .

ABCDEFg

Es. Hrr, it's not interested in $R \ll \infty$. I want to compare ratio of 1. approx values
of f pc. for $R, \sqrt{R}, \sqrt[3]{R}, \dots, \sqrt[n]{R}$, all $[M_i]$, all $[M_i^2]$ w. $\begin{cases} N=N \\ M_i^2 = M_i^2 \end{cases}$ v.s. $\begin{cases} N=N+1 \\ M_i^2 = M_i^2 + 1 \end{cases}$

In NST 46.B, I got d.f. for R from ∞ to ∞ : (Actually, f values could be anywhere from $-\infty$ to ∞ . Large R values (like 1000) $\frac{R + M_i^2 N}{R^2} \approx \frac{M_i^2}{R}$. Actually, I don't see how this could occur. The "apparent" large R could be the result of taking difference to reciprocal of f : difference between 2 large, noisy quantities.



This suggests that solution conv. more rapidly w. $R \rightarrow \infty$, than expected

It may be possible to use $\frac{1}{R}$ as f quantity

Multiplying by $\frac{1}{R} \rightarrow \frac{1}{R^2}$ which does converge.

(SN) T. why $\frac{1}{R}$ is used as density: $\lim_{R \rightarrow \infty} \int_0^{\infty} \frac{1}{R} \cdot f(R) dR / \int_0^{\infty} \frac{1}{R} dR$

or $f(R) \rightarrow 0$

if $\lim_{R \rightarrow \infty} f(R) \rightarrow$ some constant $\neq 0$:

∞ (lim of $\cdot 20 \rightarrow \infty$)

by coaps!

doesn't work!

try $\frac{1}{R} = \frac{1}{R} \cdot \frac{1}{(1/R)^2}$

Try range $[2, \infty]$

ABCDEFGHIH
ijklmnopqrst

$$\int_2^{\infty} \frac{1}{R} \cdot \frac{1}{(1/R)^2} dR = \int_2^{\infty} \frac{1}{R} dR$$

$$\frac{d}{dR} \frac{1}{(1/R)^2} = \frac{1}{(1/R)^2} \cdot \frac{1}{R}$$

So $\ln x$ is the harmonic constant. To larger α is, f loss it is source to α ?

Anyway, try it for various α values. Standard $\alpha = 2$.

Well, O.K.: Try integration of ST 46. psm: from

α to β : first $\frac{1}{R}$ Mult by $\frac{R + M_i^2 N}{R + N}$ for $M_i^2 = \cdot 2$ say.

Also use Norman factor: $\frac{1}{R} \frac{1}{(1/R)^2} = \frac{1}{R}$

Simultaneously integrate: Norman factors to get Norman const. (from van cases, f : S is computable, so I can check)

$$\int \frac{1}{R} \frac{1}{(1/R)^2} = \frac{1}{(1/R)^2} ; \int \frac{1}{R} = \frac{1}{R}$$

If S takes too long, approximate $\frac{1}{R^2}$ by $\frac{1}{R}$ (or normal) d.f. as on 50.2.1

$e^{\alpha} \cdot \frac{1}{R^2}$ or $e^{\alpha} \frac{1}{R} \frac{1}{(1/R)^2}$ are whole factors that have

to be integrated to get e : Norman factor for

$$e^{\alpha} \int_{\alpha}^{\beta} \frac{1}{R^2} \cdot \frac{R + M_i^2 N}{R + N} dR$$

Use $\alpha = 10$ or 20 ; Use $\beta = 1000$ or 2000
But N is computable for $R \geq 200 \rightarrow 80.01$

STEIN S.D. BAS

Genus $\frac{e^{\alpha}}{R^2}$ or $G = 2.14 R$

STG1 (first slope)

at e^{α} or $(\log(\log) \text{ power})$

STG3: $f(R) = \frac{1}{R^2} \sum_{i=1}^R (M_i^2 - \bar{M})^2$
= measure of e^{α}
Get best fit

STG4: This is for $G2, 03-07$

pe of corpus as a dist of values, at \bar{M} , M_i^2 $\approx G \pm \alpha$
 $A \bar{M} + (1-A) M_i^2$

STG7 I don't see it!

STG8 Integrates STG7 for a range of S values from 0.01

ST 71 computes $(\prod_{i=1}^R M_i)$

but $\prod_{i=1}^R (1 - \frac{1}{M_i})$ is quite similar

ST 76: latest very appropriate to

Get R.

ST 76A Small Mod of ST 76 (done after ST 76)
ST 77A Numerical Data Generator
ST 77B Mod of ST 76

STEIN



Thots on APRID

1) In most cases One can choose an apripd quite easily, and the amt. of damage done by non-optimum choices is minimal.

Suggests
Suggests

-- In others, it is not so easy, & the choice can strongly influence the final apsip.

How, no matter how much data resources, its always poss. to pick an aprip so bad, that the apsip is terribly wrong!

If the aprip is Universal, how, using an old data will eventually patch things up.

-- This is not nearly true of non-universal apripds.

111

In the case of STEIN, the aprip seems very impt, critical, & non-obvious:

The aprip is for the d.f. of the μ_i . Up to now, I've been assuming that it is

of the form $\mu_i (1 - \mu_i)^{R(1-\delta)}$, w. some o.d.f. for $\delta \in R$, $\delta \geq 0$ that minimizes

the d.f. for R, δ is of the form $R(R) \cdot B(\mu)$. (i.e. $\mu \in R, \mu$ indep.)

In fact, our aprip into is (i.e. μ_i is usually sharply limited to $.1 < \mu_i < .9$).

The mean of the d.f. is more sharply limited to $.2$ to $.3$.

or.

R must be large enough so $\sigma^2 = \frac{\mu(1-\mu)}{R}$ wouldn't let μ_i get out of the $(.1, .9)$ range.

117

so $\sigma < .1$ $\sigma^2 < .01$ $\frac{.12}{R} < .01$ $\frac{.12}{R} < .01 \implies R > \frac{.12}{.01} = 12$ $R > \frac{.2}{.01} = 20$; so $R \geq 20$:

118

Also R can't be too large since μ is uncertain to $\frac{\mu(1-\mu)}{R}$

119

So probably R can't be > 810 (in the case)

$\frac{.2}{R} \leq \text{total } \sigma^2$

120

Using the limits of 20 & 810 (on R), perhaps I could do a uniform dist. on R & get reasonable results

0.1 (Spec 78.40) Hvr. $\frac{RD+M+N}{R+N} \cdot \left(\frac{1}{R^2} \text{ or } \frac{1}{R} \cdot \frac{1}{(1/R)^2}\right)$ may not be easily integrated.

Anyway, see how long it takes to do integration: I really don't know how often I'll need to do it! Also try 79.20 (using \int_{20}^{810} and a uniform d.f.)

The new encouragement, is that the thing I have to integrate, looks like $\frac{1}{R}$ for large R (i.e. $R \gg N$). This does reduce importance of aripid as by R . but see what I eat! Also, if I only need consider $R > 20$ (79.11-17) then this can also help a lot!

If it looks like its working, try some Mt. Car to generated data sets & see how well it works! (I may want to speed up function of ST46.BAS; see if double precision is needed; many places I can speed things up.)

Also, upper bound for R can be $K \cdot N$ (≈ 810 in present case) (79.18-19).

Anyway, if this works, write a long review of stuff like 79.01 & try to see how I could have shortened the long discovery process!

Also: Try to get some shorter approaches to T's optimum results.

one: $\sigma^2 - \bar{\sigma}^2 = \left(\frac{\sum M_i^2}{N}\right) - \bar{\sigma}^2 = \frac{\sum M_i^2}{N} - \bar{\sigma}^2 = -\bar{\sigma} + \frac{1}{N} \sum M_i^2$

$= 2 \frac{1}{N} \sum M_i^2 - \bar{\sigma}^2 - \bar{\sigma}$. from notation of ST 27B:

$2 - .185789$
 $\left(\frac{1}{N} \sum M_i^2 - \bar{\sigma}^2\right) - \frac{1}{N} (\sum M_i^2 (1-M_i^2))$ should be divided by N

$-\frac{1}{N} \sum M_i^2 + \frac{1}{N} \sum M_i^2 = \frac{2}{N} \sum M_i^2 - \bar{\sigma}^2 - \bar{\sigma}$

Model in ST 27B, 809

$SIG - U(1-U)/N = 4.5839E-3 = \sigma^2$ (circled) \rightarrow current SIG (4.5) \rightarrow SIG!!

$\frac{1}{6^2} = 2.78$. So I think this is "right".

From 76.37: $R = 192$ has least opt error = .0226
Stein's $R = 313$
so this is closer to minimum.

NO!
 $SIG - U(1-U)/N$
Epot $2.51512E-4 = \sigma^2$
 $\frac{1}{6^2} = 3975.9$ (4.00)

I could try this on my Mt Car to data

So I. $R = 218$ was $\frac{1}{6^2}$

$\frac{\bar{\sigma}(\bar{\sigma}-1)}{N} = 4.3323918E-3$
 $\bar{\sigma} = 2.30.81938$

$4.583904E-3$
 $SIG = \frac{\bar{\sigma}(\bar{\sigma}-1)}{R} + \frac{1}{N} \sum \frac{U_i(1-U_i)}{N}$
So $R = 311.75458 \cdot \frac{1.1949}{2.30.81938} = 60.760968$

$SIG \approx \frac{1}{N} \sum (U_i - \bar{\sigma})^2 = \text{observed var.}$ (perhaps should be divided by $(k-2)$)

"Sig" $\rightarrow \frac{1}{R-2} \rightarrow 5.1568875E-3 \rightarrow R = 2 + 2.67$

Perhaps $SIG = \frac{1}{N} \sum U_i(1-U_i) + \frac{1}{N} \sum U_i^2(1-U_i)$ $= \frac{1}{N} \sum U_i(1-U_i) \left(\frac{1}{R} + \frac{1}{N}\right)$

9003 $\frac{1}{R} = \frac{5.1568875}{\frac{1}{N} \sum U_i(1-U_i)} = \frac{1}{N} = .0517935$; $R = 19.3$ not so good.

Handy list of constants:
 $\bar{\sigma}$, σ^2 , M_i
Formulas for M_i , $1-M_i$
 α , β , opt .
STam (9.87) 79.07
2 21.13
Calculates P, Q

STam 7
 $\begin{cases} 25.14 \\ 32.03 \text{ maybe rounded} \\ 34.27 \end{cases}$
9 34.32
10 35.17
5 27.4 (monetary)
27.01
25.01

STs 1/20 convergence of approach.
2 1/21 data computer P, Q
3 1/3 opt 1/11 (P-Q) (0.
4 2/4
5 2/5
6 2/5
7 2/12
8 2/10
9 2/14
10 2/9
11 2/10
40 2/12
41 2/13
42 2/16
43 2/17
50 2/20: 2/20

.079017

3.11.99 SMART STEIN:

Some Constants of Int:

$\bar{u} = .2653889$

$\sigma(1-\bar{u}) = .1999$

$\frac{\sigma(1-\bar{u})}{N} = 4.33293918 E-3$ (recip = 230.81938)

07 $\frac{1}{k} \sum u_i^2 (1-u_i)^2 = \bar{u} - \frac{1}{k} \sum u_i^2 = \frac{.0619314}{.07501516} = (.27395547)^2$
 $\frac{1}{k} \sum u_i^2 = .07501516$
 $\frac{\bar{u} - \frac{1}{k} \sum u_i^2}{.95} = .0013762526$ (reciprocal = 726.1077)

STBIA.623: used to find values of μ and σ constants.

13 $SIG = \left(\frac{1}{k} \sum u_i^2 \right) - \bar{u}^2 = 4.583904 E-3$ (recip = 218.15485)
 $= \frac{1}{k} \sum (u_i - \bar{u})^2 = \sigma^2$

$\frac{1}{k} \sum u_i^2 = .07501516$

17 STBIA.10x: Interpolated STEIN 46 w. $\left(\frac{1}{R^2}, \frac{1}{R(1+R)}, \frac{1}{R} \right)$ Applied: $\frac{R\bar{u} + N u_i^2}{R + N}$
 Range R=10 to 800 $u_0 = .2153889$ ($= \bar{u} - .05$)

Apply: $\frac{1}{R^2}$ first. R=10 to 800

| | |
|-------|---------------------|
| I 600 | S1 = 4.58449 E-206 |
| | S2 = 2.354447 E-206 |

S2/S1 = .5135676 ! unusually P.R.S. is never near .5.

try from 700 to 800. Got S2/S1 = .307 again imposs.

S1, S2, () .31005

Print R, S1, S2

Print S1, S2, S2/S1

28 for $\frac{1}{R^2}$ $\frac{1}{R(1+R)}$ $\frac{1}{R}$: 5 got .265 $\sum U$
 .248447 = α
 .215 $\sum u_0$

$\alpha = \frac{R \cdot \bar{u} + N \cdot u_0}{R + N}$

$\alpha R - \alpha R = N \cdot u_0 - \alpha N$
 $\rightarrow \alpha R + \alpha N = R \cdot \bar{u} + N \cdot u_0$
 $(\alpha - u)R = N \cdot u_0 - \alpha N$
 $R = \frac{N \cdot u_0 - \alpha N}{\alpha - u}$
 $= N \frac{u_0 - \alpha}{\alpha - u}$

$.45 \times .215 - .248447 = .2653889$

I Got R = 89: Not so good!

Interpolate from 20 to 800: R = 93.11

20 to 2000 R = 99

R = 20 to 800, $\frac{1}{R(1+R)^2}$: R = 137.03,
 R = 20 to 2000 R = 167.7

R = 20 to 800: $\frac{1}{R}$ R = 181.9

R = 20 to 2000 $\frac{1}{R}$ R = 249.1

R = 20 to 810 $\frac{1}{R(1+R)^2}$ R = 137.47

R = 20 to 9000 R = 193

R = 20 to 10000 R = 210

R = 20 10000 " R = 252

(R = 89 is best post hoc soln: (76.37))

R = 20 to 810: $\frac{1}{R(1+R)^2}$: R = 147

| | | |
|----------|---------------|-------|
| SS error | R | |
| 137 | .02527 | |
| 192 | .02126 (best) | |
| 313 | .0216 | STEIN |

try now, $u_0 = .9$ R = 137.47
 Result unusually $u_0 = .215$ to 14 digits (precision!)
 This indicates that it's linear effect.

Since results are indep of U_0 , let $U_0 = 0$.

$R = U / (R+N)$

So final P.D. is $S_1, S_2, S_2/S_1, N + S_2/S_1 / (S_2/S_1 - 1)$

A short cut would be to find the peak of $(G - 2H R) - \text{or } G - 2H R$ then find its second derivative.
 You find it's second derivative int. No of deriv.

Actually we can simplify it further by letting $U=1$ in + update of S_2 and in to find P.O. So $S_1 = S_1 + (G-D)$; $S_2 = (G-D) * R / (R+N)$

Result $R/R = N + S_2/S_1 / (S_2/S_1 - 1)$

So we want to expect values of $R/R+N$; this ends up as $S_2/S_1 = \alpha$; and

$R/R = \frac{N\alpha}{\alpha - 1} = \frac{N\alpha}{1 - \alpha}$

Something wrong $R/R+N$ is always < 1 so $\alpha < 1$, so R/R would always be < 0 .

The getting neg. R but U is U_0 !

$\alpha = \frac{R}{R+N}$; $R + \alpha N = R$
 $\alpha R - \alpha R = \alpha N$
 $R(\alpha - 1) = \alpha N$
 $R = \frac{-\alpha N}{\alpha - 1}$

I could see if I could simulate the STEIN results using

Rec $S_{n-1} \times \text{term}$. Also look at their methods in which α 's are all to same!

Note: I really can't tell if my method is better than Stein's, from just this one case. — So Got Stein result for my M. Carlo data &

Compare w. my results.

Note on Integration in STAES:

Changing integration step from $\Delta R = 1$ to $\Delta R = 10$

$S_{10} \Delta R$ take R/R from $(37.47$ to 138.57 ; The ans. of 1 insert is multiplication.
 $\Delta R = 2$: 137.236 ; $\Delta R = 20$: 133.7 ; $\Delta R = 40$: 131.6 ; $\Delta R = 100$: 121.97
 $\Delta R = .5$: 138.600

Try \int_{20}^{100} w. $\Delta R = 10$ S_{100} using 252: still better than Stein.

Expect mean of distance. The set of mean of test set! A better test set would have same mean;

expected norm $\mu = \frac{.265(1-.265)}{.45} = \frac{.194775}{.45} = .432833$ $\sqrt{\dots} = .0155$

change Σ error 18K ans: .0043! not mean!

ST82 Try it anyway!

$A(S, 2)$ for set $A(S, 2)$ S_2 .

$S_5 = S_5 + U + V$
 $S_6 = S_6 + V$

$\mu = 26538888$
 $U = .2749888$

This is \bar{U} of test data.

$\Delta = .0091$ $\Sigma = 1$ in U of test v.s. test data.

| | | | |
|-------|--------------------------|----------------|-----------|
| ST82A | old \bar{U} : .2653889 | Σ error | $R = 192$ |
| | | .0212692 | |
| | | .0229743 | |
| | new $\bar{U} = .2653889$ | .0229743 | $R = 192$ |
| | | .0229743 | |
| | | .029144 | 225 |
| | | .024059 | 100 |
| | | .022926 | 250 |
| | | .023164 | 300 |

standard: .021611 later Σ is set by .009

": .0229178! set by .009!

Yakov, Can
Suzuki index
CAZ HV
MAENA
Fabil 1988

CAZ HV
MAENA
MAENA
21.97

ESMEX

ST82A

TRV. Grade

BONES

(FBI) x

Fabil 1988

Letters.

ISSUE IN 1987

by date

Native

can

601

9650

D. Sackel

@ Conway

So, I ↑ \bar{U} of data by .0091, so it was \bar{u} of fact set.

I also ↑ \bar{U} of stats by .0091.

This is very fine point
maximize
minimize
return

T. result was err of .021611 → .02239178 (A of error in STEIN)

BUT err2 in using $(R \cdot \bar{U} + N \cdot Z) / (R + N)$ as approx to estimate

Seems to have min error of $\approx .022869$ at $R=192$! Seems unlikely; it's \geq STEIN error!

Seems not moving to mean to b. Test mean would if this error! but it increases it.

Thus could have to do w. unequal weights in finding mean

King Shibus

What I via weighted error (as done in STEIN); error for $R=192$ is $<$ $R=192$ of STEIN.

R err2 error
182 6.10
192 6.0532 } 6.2466 : corresponds to so, $R=00$ (using \bar{U} as A_i) is better than STEIN in this case.
212 5.97798 }
225 5.9406 }
250 5.8972 }
300 5.8257 }
400 5.745122 }
450 5.74536 }
600 5.815 }
425 5.794460 } → Max p of operators for R=425 (see STEIN 4.05)

ST83A output.

18
-20
→ 00
2000 5.958
10 R 6.04458
137 6.468 worse than STEIN.
160 6.24345 - same = 6.2466
6.069885 ← U used as approx of μ_i .

ST83 Modify ST 81A so $\bar{U} = U + DEL$, $Z = Z + del$ (Del = .0091)

~~Whoops! ST83A looks very messy! forgot to divide by 1000~~

$R = 20$ to 840 using $\frac{1}{R(N+2)}$ for approx of R !
I got $R = 1468$ instead of 137.47

ST83A Modif. of ST83: uses (of likelihood func: $VU \times (p_i \ln p_i' + p_i' \ln p_i)$)
This is (E Risk) more stringent than \bar{u} error.

err: should use for mid. of ST83; But Modif. of ST 82A.05,
Func for STEIN2 - 3907.959 - so $\% R=160$

| RR | Cost | RR | Cost |
|---------------|-----------|-------|-----------|
| 160 | -3907.977 | 137 | -3908.563 |
| 192 | -3907.478 | 181.9 | 7.607 |
| 150 | -3908.200 | 106 | -3907.373 |
| 225 | 07.579 | | |
| 300 | 6.875 | | |
| 450 | 6.778 | | |
| 500 | 6.778 | | |
| 250 | 6.872 | | |
| 1000 | 6.762 | | |
| 424 | 6.771 | | |
| 400 | 6.774 | | |
| 475 | 6.773 | | |
| → 437.5 - 390 | 6.770 max | | |

01 I've been doing correction in last data backwards! correction should be -.0091 not +.0091 /
Not Quite! But ST82A; W, i. last data, should not be modified,
It is .0091 too by. We only ↑ the data by .0091. (also u),

ST84

So! fixed! ST82

Strange Error for RR = 425, is 5.794468 | w.o. t. .0091 correction error is 5.794460 (Not much difference!)

try RR=212 : 5.977882 same as 83.10,
LR=60 : 6.069885 " " 83.20!

$(.0091)^2 * 18 = \sim 10^{-4} * 18 = .0018$ (it should show up!) No!
Not 'is': ~ 200 times (g.) — much more savings.

Trying Del = .009 → 6.07 RR=0 → $\sigma^2 = 61.0925$ 10 times as large!
= .01 6.07
.00 6.620495 | woops! , = 83.20

0.4. 83.10 & .20 very w. t. .0091 correction; but I also increased test data: which I shouldn't have done!

Try double prec. ^{original} for integration! See if it makes any difference.

I was double prec. ^{in 81A.05.} for R=20 to 810 $\frac{1}{R \ln R}$; it gave R = 137.476836055008
for single prec. I got "division by 0", it may be that 10^{-206} is too small for
single prec. $10^{-206} = e = \frac{206 \ln 10}{1000} = 1410 \approx 2.3 \cdot 460$

I did G = G + 460: T from then worked ok, I got R = 137.4819,
which is quite close precision! I got it in the (G = G + 460) instruction it does no harm,
Results are same for single ~~prec.~~ prec.

Using stop of for integration, increased R by 137.4768 → 137.695 (double prec.)
← ← (sec. on single prec.)

31499 SMART!

This is a replacement
for 2 (lost or non-exist, but see
Page 85) 85

I noticed 81.38 R that the result was indep of u . Also, (82.04) its indep of " u " as happens
in the integrand.

Since $S = \int_{-\infty}^{\infty} e^{aR} \frac{M_1 M + \bar{D} R}{N + R} dR$: The integrand is a linear function of M_1 & \bar{D} . = $A' M_1 + B' \bar{D}$

also let $A u_1 + B \bar{D}$ be normal result. = α (81.28) = $\frac{N u_1 + R \bar{D}}{R + N}$ ($A + B = 1$)

~~the~~ ~~the~~ $\frac{N}{R+N} = A$ so $R = \frac{N}{A} - N = \frac{N - NA}{A} = N \left(\frac{1-A}{A} \right) = N \left(\frac{1}{A} - 1 \right)$

so $\int e^{aR} \frac{1}{N+R} dR$ has an integral in computer R .

On e^G : using an integration step of 1, we can express e^G exactly as a product
and quotient of factors: There are just N factors but out cancel is up to R involves
maybe $3N$ factors. ~~There are N factors~~ — but I should check all this!

[did use this about form to get e^G for $R = \infty$ (maybe for $R = 0$).

.01 Well, I have some understanding of the Bayesian approach! T. approach of EM using does appear to extract the result a lot - i.e. the R value I get depends much on the approach of R: Here the estimator of μ doesn't depend so much on the approach.

My impression is that if $k > \sim 200$, $\uparrow k$ will give a sharp approx, relatively independent of the approach.

.06 Here are some Q's: ① For a given initial R and parameters (M, Car/O) data, how accurate is my R estimate & how accurate is my μ estimate? —

.08 A rough estimate of variance > What is actual uncertainty in μ , μ ?

.10 How do the answers to .06-.08 compare w. those for the various "STEIN".

.11 Solns?

88.01

.12 Going back to $1 \pm .01 \approx -2.45 \pm 10.01$ off:

Reading the Efron - Morris ~~JASA~~ ~~1975~~ paper:

They give us Stein's estimator: $\mu_i^s + \left(1 - \frac{(k-2)}{S}\right) (X_i - \mu_i) = \frac{k-2}{S} \mu_i + \left(1 - \frac{k-2}{S}\right) X_i$

where μ_i are my initial guesses of μ_i .

What is $S = \sum (X_i - \mu_i)^2$ on p 318 eq. (1.4) is unclear: The X_i are of unity variance.

$S = \sum (X_i - \mu_i)^2$

Temporarily set $\mu_i = \bar{\mu} = \frac{1}{k} \sum X_i$

So ~~variance~~ $S = \sum (X_i - \bar{\mu})^2$ is the variance of X_i about their mean.

on p 312 eqs. 1.7, 1.8: They put estimator

$(\mu_i \cdot \frac{1}{k} + X_i) / (\frac{1}{k} + 1)$: i.e. wts of $\frac{1}{k}$ & 1 for

for 2 estimators μ_i & X_i : T. estimator μ_i has

var. $\frac{1}{k}$ (i.e. it wts) if estimator X_i has var. 1; (i.e. wts.)

From eq 1.3 $S \approx (1 + \tau^2) \frac{1}{k}$ = chi sq. df k & deg. freedom.

$\frac{k-2}{S} \approx \frac{1}{1 + \tau^2} \Rightarrow \frac{S}{k-2} \approx 1 + \tau^2 \therefore S = (1 + \tau^2)(k-2) \approx \frac{1}{k} (1 + \tau^2) k \approx k + \tau^2 k$

$E\left(\frac{1}{S}\right) = \frac{1}{k-2}$? $E\left(\frac{k-2}{S}\right) = \frac{1}{1 + \tau^2}$ so $E\left(\frac{1}{S}\right) = \frac{k-2}{1 + \tau^2 k}$

$\frac{1}{S} = \frac{1}{k-2} (X_i - \mu_i)^{-1}$ $E\left(\frac{1}{S}\right) = ?$

$1 + \tau^2 = \frac{S}{k-2}$ τ^2 will be usually $\ll 1 \Rightarrow \tau^2 \approx \frac{S}{k-2} - 1$ will be

every way estimator of τ^2 : so Ray propose using $\tau^2 = 0$ if $\frac{S}{k-2} > 1$.

Could show (161 (12.24)) give $k_n = 2^{n-1} (n-1)! k$

as the nB results out. To first n second cumulant are μ & σ of t. d. v.

\pm need t. ~~more~~ more (first moment) so $\mu = 2^0 \neq 0$; $k = k$, not $k-2$.

Here I think we need to ~~be~~ at $\frac{1}{S}$ not $E(S)$: $E\left(\frac{1}{S}\right)$ (i.e.

Here: $\frac{1}{1 + \tau^2} \approx \frac{1}{S} \cdot X_i^2$ E of both sides gives $\frac{1}{1 + \tau^2} = \frac{1}{S} (k)$ as before: (not $(k-2)$).

$$\begin{aligned} k - \frac{(k-2)S}{(k-2) + \frac{S}{k}} &= \frac{k(k-2)^2}{2k-2+1} = \frac{k(k-2)^2}{2k-1} \\ k - \left(\frac{k-2}{1 + \frac{1}{k-2}} \right) &\approx (k-2) \left(1 + \frac{1}{k-2} \right) \\ &\approx k-2+1 = k-1 \\ k - (k-1) &= 1 \end{aligned}$$

1399 $\sin^{-1} \sin^{-1}$
 But should we use $E\left(\frac{1}{X^2}\right)$? This is confusing!

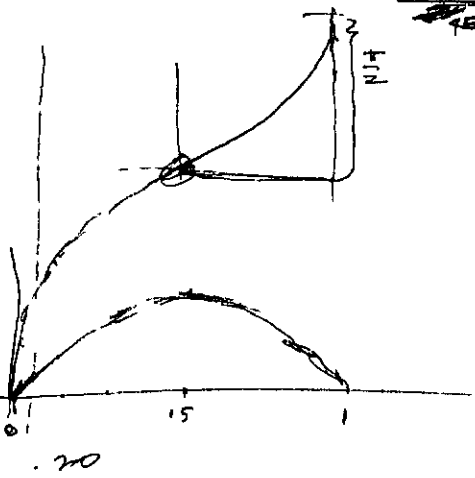
~~So the way~~

Anyway; $\sigma^2 = 1.791$; $\tau^2 = .26422$; $\frac{1}{\tau} = 3.7896$

$\frac{E\{X^2\}}{\tau^2} = 170.31$ / $(\mu(1-\mu)) = .19477$; $= 874.4$. $\frac{E\{X^2\}}{\tau^2} = 225 \approx \frac{1}{\sigma^2}$

They do $\mu_i \rightarrow .45 \pm . \sin^{-1}(2\mu_i - 1)$ to get all values ≈ 1 .

\rightarrow opposed to $\frac{\mu_i'(1-\mu_i)}{45}$ $\sin^{-1}(2\mu_i - 1)$ v.s. $\sin^{-1}(\dots)$



$$\int_0^1 x(1-x) = \int_0^1 (x-x^2) = \frac{x^2}{2} - \frac{x^3}{3}$$

$\frac{\mu N}{x} \frac{(1-\mu)N}{(1-x)} \cdot \sin^{-1}(2x-1)$ we could just drop μ to $\mu=0.5$ for \approx constant of μ i.e. independent of μ .

perhaps instead of \sin^{-1} , use $\frac{1}{x(1-x)}$.

value of $x^{\mu N-1} (1-x)^{(1-\mu)N-1}$ is

$$\approx \frac{(\mu N-1)(1-\mu)N-1}{(N-2)^2}$$

if N is large, this is much dependent on μ .

01: 8.6.11; Some points that I'd like to work on;

1) Got to R d.f. for the epsil data: It should be much better have a Poisson form; then ~~variance~~ Asym R d.f. would be better. D.f. obtained from previous year (9).

We would have to include a f. (remote) kernel factor like $\frac{1}{R(\ln R)^2}$ or $\frac{1}{R^2}$

2) Using Φ , E & M method, Gauss exactly, see how well it does on f. averaged for M f. Carlo data, using several R values. Compare w. results for 81A. Bas.

Use both M.S. error & ~~epsil~~ epsil of data. as criteria.

3) I think the E & M method is \hat{M}_i estimate = $\bar{v} \cdot \frac{n-3}{\sum (M_i - \bar{M})^2} + (1 - \bar{v}) M_i$.

This assumes the M_i all have unity variance. If they all have ^{same} variance σ^2 ,

We use $\frac{\sigma^2(n-3)}{\sum (M_i - \bar{M})^2}$ rather than $\frac{n-3}{\sum (M_i - \bar{M})^2}$

The x.f.a. $X_i = n^{\frac{1}{2}} \cdot \sin^{-1}(2Y_i - 1)$ is used, so the data points are close to 1.

§ 30 ft. E & M paper deals w. cases in which σ_i^2 are not all the same.

I really need a good approx. soln. to this case. Perhaps compare it to the pure Bayesian

case. They use Gauss d.f.s, but the appropriate d.f. is the Binomial dist.

Unfortunately, the data they give is not raw parameter frequencies, so it looks like a Gaussian analysis

My Mit is best

22 (3A) Try 81A. Bas w. various α, β \int_{α}^{β}

| $\frac{1}{R(\ln R)^2}$ | β | α | R |
|------------------------|---------|----------|--------|
| | 810 | 20 | 137.48 |

So it looks like

α is not critical.

| α | R |
|----------|------------------------------|
| 10 | 134.34 |
| 5 | 134.055 |
| 2 | 134.057 |
| 1 | impossi. because $\ln R > 0$ |

something wrong!

| | |
|------|-------------------------------|
| (1) | 133.85% (stop 1 in integrand) |
| (10) | 132.605 stop 01 in integrand. |

Asym $\frac{1}{R^2}$
 $\frac{1}{R(\ln R)^2}$

$\ln(1+\epsilon)^2 \sim \epsilon^2$
 $\frac{1}{\epsilon^2}$

| $\frac{1}{R(\ln R)^2}$ | R | stop |
|------------------------|---|--------------------|
| 100k | 2 | 14.07 |
| 200k | 2 | 246.3191 (stop 1) |
| 10k | 2 | 235.6 |
| 300k | 2 | 204.9425 (stop 10) |
| ... | 2 | 287.7 |
| 750k | 2 | 141.3101 |
| 100k | 2 | 41.446 |
| 850k | 2 | 1328.7 (stop 10) |
| ... | 2 | 998.8 |

is not necessary use R=1!
use R=1
use R=1

30

$\frac{1}{R^2}$ stop 1 810 2 58.6

all, stop 10

| | | |
|------|---|-------|
| 10k | 2 | 97.23 |
| 100k | 2 | 97.96 |

$\frac{1}{R}$

| | | |
|------|---|---------|
| 100k | 2 | 567.619 |
| 100k | 1 | 567.611 |

all stop 10

$\frac{1}{R^2}$

| | | |
|------|----|---------|
| 100k | 10 | 567.65 |
| 810 | 10 | 181.56 |
| 810 | 20 | 182.027 |

| A | B |
|---------------------|------------------------------|
| $\frac{1}{\ln 100}$ | $\frac{1}{\ln 1000}$ |
| A | A |
| $\frac{1}{\ln 100}$ | $\frac{1}{\ln 100 + \ln 10}$ |

$\frac{1}{R(\ln R)^2}$ from 1.1 to 2 stop .1
 $\rightarrow 1.2$
1.01 to 2 stop .01
 $\rightarrow 1.027$
1.001 to 2 stop .001
1.0097

There ~~does~~ seem to be something wrong in $\int_{1+\epsilon}^2 \frac{1}{R(\ln R)^2}$: it should 1 as $\epsilon \downarrow$ but

in fact, it $\rightarrow 1$ from above! ~~WRONG!~~

No! What's interesting is not \int but \int rate of

as $\epsilon \rightarrow 0$ this rate approaches value of the integrand for $R=1$ - which may be ≈ 1 .

Should make ~~term~~ dit for $\int_{1+\epsilon}^2$

$$\frac{\int_{1+\epsilon}^2 \frac{1}{R(\ln R)^2}}{\int_{1+\epsilon}^2 \frac{1}{R(\ln R)^2}}$$

| $\int_{1+\epsilon}^2 \frac{1}{R(\ln R)^2} dx$ | ϵ | K | S | $\frac{1}{\ln \epsilon}$ | A | S | A | $S1$ |
|---|------------|------|--------|--------------------------|-------|-----------|-------|------|
| | 63.9 | 10k | 141.07 | .1447 | | .2012109 | | |
| | 48.4 | 10k | 20496 | .096 | .0361 | -2.175785 | .0163 | |
| | 108 | 2.4k | 2463 | .0866 | .0220 | 12243677 | | |
| | | 10k | 13287 | .0724 | .0142 | 2566954 | | |

O.H. ! R is not to S at all!

Also, int. convergence divergence of

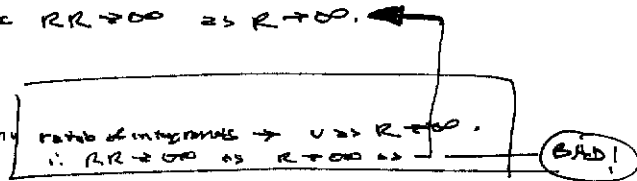
$\frac{1}{R(\ln R)^2}$ near $R=1$ ($(.98, .99, \dots, 1.0)$). The integrals are $S1 \approx S2 \approx$ R ratios are $S1/S2$

Also, it appears that \int integrand, e^G approaches 0 as $R \rightarrow \infty$: for

$R = 10^6$ its ~~value~~ .265377 ; in such case $RR \rightarrow \infty \Rightarrow R \rightarrow \infty$.

~~WRONG!~~ $S1 = S e^G / (R(\ln R)^2)$

$S2 = S e^G / (R(\ln R)^2) \cdot \frac{R}{R+N}$



It was $S1$ ~~ratio~~ e^G that ~~is~~ R .

So $S1$ will be closely related to $\frac{1}{\ln R}$ for large R - But it ~~is~~ doesn't seem to!

For $M = M+10$ $S1 = 1.94345 \cdot 11$ ~~is~~ M - ~~ratio~~ R ~~is~~ $\frac{1}{R(\ln R)^2}$.
 104 1044 $S1 = 2.14 E-9$

At ~~double~~ ~~step~~ $R=1000$ but $RR = 246.52$ (246.13 single prec)
 $R=M$ " $RR = 272.866$ (1325.7 single prec.)

Well, if I have to add 106 items, single prec. is ~~not~~ only 6 or 7 decimals, so we could run into trouble. But for $R=10^6$; ~~at~~ ~~step~~ only 105 items! Still, it was \int difference betw to close quantities, I'm not sure I really understand what went wrong! - Also from 24, $RR \rightarrow \infty$ as $\beta \rightarrow \infty$.

~~Think this out more carefully!~~

\int_2^{10M} step 100 $\Rightarrow RR = 394!$

try more precision

\int_2^{1000} step 1000 $\Rightarrow RR = 1082$. (maybe $\rightarrow \infty$?)
 as $\beta \rightarrow \infty$.

e^G is constant for all values of $R > 2$.

$$\int_{100}^{\beta} \frac{1}{R(\ln R)^2} \cdot \frac{R}{R+N} \int_{100}^{\beta} \frac{1}{R(\ln R)^2}$$

I think it should be $\rightarrow 0$ as $\beta \rightarrow \infty$.
 it should differ by like $\int \frac{1}{R(\ln R)^2} \cdot \frac{N}{R+N}$ $\approx \int \frac{1}{R(\ln R)^2}$

So! Computer RR for $\beta = \infty$ ~~is~~ exactly, ~~is~~ computer $(\frac{1}{R+N}) \int \frac{1}{R(\ln R)^2} dr$

from 78 **INDEX** → 165
 Also from 80

ST90: This obtains ratios:

$$A = \int_2^k ; B = \int_2^{10k} ; C = \int_2^{100k} ; D = \int_2^M$$

This is a check integration of ST81A - it checks.

$$BA = B - A ; CB = C - B ; DC = D - C$$

$$\frac{CB}{BA} \text{ should } = .6 ; \frac{DC}{CB} \text{ should } = .9 \text{ (if } G \text{ is constant for } R \geq 1000)$$

I got 1595 & .396 resp., using Double prec. in all calcs. So, D.K.

A worrysome defect: 89.24, $\frac{S_2}{S_1}$ seems empirically to $\rightarrow U$ as $R \rightarrow \infty$!

My integrations for large β may be way off!

Step 100 is o.k. for most much of the integrand is constant but for

then $\frac{1}{R \ln(R)}$ it is not.

I'd like $\int_x^{\beta} \frac{1}{R(\ln R)^2} \cdot \frac{1}{R+N} dR$

$$R = e^x ; dR = e^x dx$$

$$\int \frac{e^{-x}}{x^2} \cdot \frac{1}{e^x + N} dx$$

$$\int \frac{dx}{x^2(e^x + N)} \quad \frac{ds}{(s-N) \ln^2(s-N)} \cdot \frac{1}{s}$$

$$d \frac{1}{\ln x} = \frac{1}{\ln x} \cdot \frac{1}{x} \therefore \text{int by parts:}$$

$$\int \frac{1}{x \ln x} dx = \int u \cdot v' = u v - \int v du$$

$$u \cdot v = \int u dv + \int v du \therefore \int u dv = u \cdot v - \int v du$$

$$u = \frac{1}{\ln R} ; v = \frac{1}{e^R + N} \quad \int v du \text{ desired: } u \cdot v - \int \frac{1}{\ln R} d \left(\frac{1}{e^R + N} \right)$$

$$d \frac{1}{e^R + N} = - \frac{1}{(e^R + N)^2} \cdot e^R dR \quad \text{so } \int \frac{1}{\ln R \cdot (e^R + N)^2} = \int \frac{dx}{(x+N)^2 \ln x}$$

$$\int \frac{dx}{x^2 \ln(x+N)} \quad G \& R \text{ P552 } \& 2.91.2$$

$$\int \frac{dx}{x^2 \ln(x+A)} = \frac{1}{p} \text{li}(p)$$

$$\int \frac{dx}{x^2 \ln(x+A)}$$

$$\int \frac{dx}{(x+N)^2 \ln x}$$

$$x+A = e^y ; dx = e^y dy ; x = e^y ; dx = e^y dy ; x = e^y$$

$$\frac{1}{R+N} = \frac{1}{R} \left(1 - \frac{N}{R} + \frac{N^2}{R^2} - \frac{N^3}{R^3} + \dots \right) \quad \frac{1}{R} \left(1 + \frac{N}{R} \right) = \frac{1}{R} \left(1 - \frac{N}{R} + \frac{N^2}{R^2} - \frac{N^3}{R^3} + \dots \right)$$

$$\int \frac{1}{R^2 \ln^2 R} \left(1 + \frac{N}{R} \right) \quad \text{so } \int \frac{1}{R^2 \ln^2 R} = G \& R \text{ tables}$$

$$\int \frac{dx}{R^2 \ln R} \quad \text{ibid } 2.724.2 \quad \int \frac{x^y}{\ln x} = \text{li}(x^{y+1})$$

so that may solve it! I'd have to find a formula for $\int (x)$.

Meple. Actually, probably best to get Meple to do it. S.!

ST81 (from ST81A)
 Uses Monte Carlo generation of data

ST81A. Main program for integrating e^x w. $(2 \ln R)^y$ & $\frac{0.0001}{R+N}$.

ST82 (from ST76)
 Is used to find wtd mean of $\psi(1) \psi(2)$

ST82A (from ST76)
 Used to calculate R based on Gaussian D.F. (to STEIN)

ST83 (from ST81A)
 Uses Moves \bar{u} by .0091 using data.

ST83A (from ST81A)
 from ST76 to ST82A
 uses $U \rightarrow U + .0091$
 Also uses P cost done for 2 ways to do prod.

ST84 (from ST82A)
 Correction of ST82A
 Score 84.01

ST90: Checks on integration of ST81A

Actually, the soln. isn't so difficult! $\frac{1}{R+N} = \frac{1}{R} \left(\frac{1}{1+\frac{N}{R}} \right) = \frac{1}{R} \left(1 - \frac{N}{R} + \frac{N^2}{R^2} - \frac{N^3}{R^3} \dots \right)$

no mult $\int \frac{1}{R(\ln R)^2} \frac{dR}{R+N} = \int \frac{1}{(\ln R)^2} \frac{1}{R} \left(1 - \frac{N}{R} + \frac{N^2}{R^2} \dots \right)$

$\frac{1}{R} \int \frac{R^n}{(\ln R)^2}$ reduces to $\int \frac{R^n}{\ln R}$ by m+by parts. (P204 GGR)

$\int \frac{R^n}{\ln R} = li(R^{n+1})$; $li(x) = \text{from B.S. P510: } \int_0^x \frac{1}{\ln t} dt = O(1, 1, -\ln R^{n+1})$

$U(1, 1, z) = \frac{\pi}{\sin \pi \cdot b} \left(\frac{e^{-z}}{\Gamma(1+b) \Gamma(b)} - \frac{e^{-z}}{\Gamma(a) \Gamma(2-b)} \right) M(1, z) = e^{-z}$

$a \rightarrow 1, b \rightarrow 1 = \frac{\pi}{\sin(\pi \cdot 1)} e^{-z}$ This is not clear!

$li(x) = E_1(\ln x) = E_2(N+1, \ln R)$; $E_2(x) = \gamma + \ln x + \sum_{n=2}^{\infty} \frac{x^n}{n!}$ so this converges really.

$E_2(x) = \sum_{n=2}^{\infty} \frac{x^n}{n!} = 1 - \sum_{n=1}^{\infty} \frac{x^{n-1}}{n!} \quad \left| \quad \frac{d}{dx} E_2(x) = \frac{1}{x} + \sum_{n=2}^{\infty} \frac{x^{n-1}}{n!} \right.$

$\frac{e^x - 1}{x} = \sum_{n=1}^{\infty} \frac{x^{n-1}}{n!} \quad \Rightarrow \quad \int \left(\frac{e^x}{x} - \frac{1}{x} \right) = \sum_{n=1}^{\infty} \frac{x^n}{n!} = E_2(x) - \frac{1}{x} - \gamma$

Does $\int_0^x E_1(x)$ power series converge really for large neg x?
 If like some other power converges faster. $E_1(x)$ may be $\approx \frac{1}{x}$ for $x > 6!$
 From P 242-243 $x e^{-x} E_1(x) \rightarrow 1$ as $x \rightarrow \infty$ for $x \gg$ smaller z , this

expression is only 1.34 from fig 5.1 P 228 $E_1(x)$ really looks linear for $x > .81$,

so $E_1(x) \approx \frac{e^x}{x}$

1.65 1.46
1.90
3.55

Also $E_1(x) x e^x + x e^x E_1(x) \approx 2.1$ which is good, because there are more formulae for $E_1(x)$ not so good approx!

But also $E_1(x) \approx \int_0^x \frac{e^t}{t} dt$; $li(x) = \int_0^x \frac{dt}{\ln t}$; $\int \frac{x^t dx}{\ln x} = li(x^{x+1})$

Actually, what I used is $\frac{s_2}{1 - \frac{s_2}{s_1}} = \frac{s_2}{s_1 - s_2}$

$s_1 - s_2 \Rightarrow \sum_{R=N}^{\infty} \frac{1}{R+N}$; by using $\frac{1}{R+N} \approx \frac{1}{R} - \frac{1}{R+N}$

so $\int \frac{1}{R^2(\ln R)} = \frac{1}{R} \int \frac{1}{\ln R} = \frac{1}{R} li(R) = \frac{1}{R} \left(\frac{1}{\ln R} - \int \frac{1}{2 \ln R} \right)$

$n=2, m=2 \quad \frac{x^{-1}}{(1-\ln x)^2} + \frac{-1}{1} \int \frac{x^{-2}}{(1-\ln x)} = \frac{1}{2 \ln R} - \int \frac{1}{2 \ln R}$

$\int \frac{x^{-2}}{\ln x} = li(x^{-1})$ so I need $li(x^{-1})$ for large x; say $x = 1000$

$li(x) = E_1(\ln x)$ for $x > 1$; $li(x^{-1}) = E_1(-\ln x) = E_2(-\ln R)$

For $R = 1000$ $li(-?)$
 $\sim \frac{1}{1000} \left(\sum \frac{1}{7} + \frac{2}{7^2} + \frac{6}{7^3} + \frac{6}{7^3} \cdot \frac{7}{7} \right)$
 .0175
 .2001
 (.8) $\frac{1}{e-4}$

From complex vars by Spradell:
 P275 $E_1(z) = \int_0^{\infty} \frac{e^{-t}}{t} dt$ actually use Euler's approx.
 $\approx e^{-z} \sum_{k=0}^{\infty} \frac{(-1)^k k!}{z^{k+1}}$
 is asymptotic expansion. Sometimes a more \Rightarrow first term Δ is needed.

What I need is $\int_p^{\infty} \left(\frac{1}{R \ln R} \cdot \frac{1}{R+N} \right) dR$.

with $\beta = e^7$. $E_i(x) = -E_1(x)$: from Bureau Standards.

$E_1(7) = 1.1548 E^{-4}$ ($e^7 = 1096.63 \approx 1000$).

$\frac{e^7}{4.5} = 24.36 \left(\frac{1}{7}\right) = .0410$

use $\int_p^{\infty} \frac{1}{R^2 \ln R} dR$: for $\beta = e^7$; verification near 4.1% by.

$\int \frac{1}{R^2 \ln R} dR = \int \frac{1}{R \ln R} \cdot \frac{1}{R} dR = -\int \frac{1}{R \ln R} d(\ln R)$

$\int \frac{1}{R \ln R} d(\ln R) = \ln\left(\frac{1}{R}\right) = E_1(-\ln R) = -E_1(\ln R)$

$\int \frac{1}{R^2 \ln R} dR = \frac{1}{R \ln R} + E_1(\ln R)$

Trouble is, $\int_p^{\infty} \frac{1}{R^2 \ln R} dR$ is > 0 for $\beta > 1$

Actually, I can estimate $\int_p^{\infty} \frac{1}{R(R+N) \ln R} dR$ w. known accuracy!

$\sum_{i=0}^{\infty} f(i) < \int_0^{\infty} f(x) dx < \sum_{i=1}^{\infty} f(i)$

Make step size so integrated \downarrow 1% in each \downarrow step.

So each time R doubles, step size is $\times 4$.

w. $R = 1000$; \int & E integrated to $R = 10000$

max remaining sum will be $< 1\%$. $\int \frac{1}{R^2} = -\frac{1}{R}$

for $R = 1000$ E converges to 0.

.67 26
4.4 15
2.6 10

I use steps of **ST83**:

$S1 = S1 + \text{EGD} / R / LL$

$S1 = S1 + \text{EGD}$

$S2 = S2 + \text{EGD} \cdot R / (R+N)$

print

$N * S2 / S1 / (1 - S2 / S1)$

This is same as

$\frac{N * S2}{S1 - S2}$

w. can just compute $S3 = S1 - S2$ w. $S3 = S3 + N / (R+N)$.

so initialize $S3 = 0$;

print $N * S2 / S3$.

Integrate from 1000 to 100k steps. First 60% for ST83, 40%:

T. message pay is the \uparrow from $\beta = 1000$ to $\beta = 10000$! I would expect $< 10\%$ change in $S1 - S2$!

From ST83

| | |
|------|---------------|
| 1k | 148.5437 |
| 10k | 217.6987 |
| 100k | 262.1534 ~16" |
| M | 292.0644 |

What has happened! $S3$ converged at $R = 1000$! But $S2$ continued to grow. ($S2 = S1 + S3$)

$S1$ is pure norm. So easily integrated to ∞

$\int \frac{1}{R \ln R} dR = -\frac{1}{\ln R}$

Should be minus

so value of $S1$ at $R = 100000$ is $3.0296488 E - 208$ (did I use step = 1000?)

$S1$ did go down as $\frac{1}{\ln R}$.

so $S1$ for $R = 1000$ is as for from ST83: $R = M$

$\Rightarrow S1, R = M$ is from $E1; R = K$ $\left| \frac{1}{\ln K} \right|$ $\left(\frac{1}{\ln 1000} \right)$

$E_1(x) = \int_x^{\infty} \frac{e^{-t}}{t} dt$

$E_1(z) = \int_1^{\infty} \frac{e^{-zt}}{t} dt = \int_1^{\infty} \frac{e^{-x}}{x} dx$

$z dt = dx$

$z dt = \frac{dx}{z} \quad dt = \frac{dx}{z}$

so $E_1(x) = E_1(z)$

$E_1(x) = - \int_x^{\infty} \frac{e^{-t}}{t} dt$

$\Rightarrow E_1(-x) = -E_1(x)$

$E_1(x) = -E_1(-x)$

$\frac{1}{e^{10}} \left(\frac{1}{10} + \frac{2}{1000} + \frac{6}{10k} + \frac{24}{1000k} \right)$
 $= \frac{1}{7} + \frac{2}{7^2} + \frac{6}{7^3} + \frac{24}{7^4}$
 $E_1(10) = 1.1548 E^{-4}$

3.16.99 SMART STEIN

So: T. result appears to be $R = 532.097$ for integration from $R=20$ to ∞ .
 for $\int \frac{1}{R} dR$ Integral from 20 to 1k, 10k, 100k, M, & S followed the $\frac{1}{\ln R}$ law,

So extrapolating to ∞ , I got S_{100} for S_{20} .
 I had $S_{300} (= S_1 - S_2)$ for S_{20} ; $S_2 = (S_1 + S_3)$ - should be $S_2 = S_1 - S_3$

I needed $A = N * \frac{S_2/S_1}{1 - S_2/S_1}$ (using $u=1$ in d. last 3 insts of ~~ST83~~ ST83/ST93)
 $= N \frac{S_2}{S_1 - S_2} = N * \frac{S_1 + S_3}{S_3} = N (\frac{S_1}{S_3} + 1)$

S_{100} was $4.378191 E-208$
 S_{300} was $.4104475 E-208$ } $N=95$ so R_{int} gave 532.097 for $R_{extrapolated}$ \int_{20}^{∞}

For other colors: Get S_3 for, say S_{10k} or $100k$.
 Get S_1 for $R = 100k$ and $100k$: for this calculate value for $R = \infty$.

$S_{10k} + 4(S_{100k} - S_{10k})$
 $S_{100} = S_{10k} + 4S_{100k} - 4S_{10k} = 4S_{100k} - 3S_{10k} = 4.382679 E-208$
 $2S_{1M} - S_{1K} = 4.37191 E-208$

2 D - A
 1k 10k 100k M
 $\frac{1}{3}$ $\frac{1}{4}$ $\frac{1}{5}$ $\frac{1}{6}$
 A \rightarrow C D

to get \int_{10k}^{∞} it would be constant to get $\frac{1}{R}$, $\frac{1}{R^2}$ constant, then use $\int_{20}^{\infty} \frac{1}{R} dR = \frac{1}{\ln R}$

So 4 results are cons:

Some Moves:

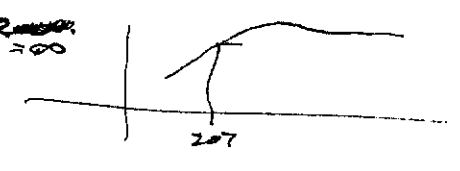
1) Computing error in S_1 & designing to calcn. so that $S_2 - S_1 (= S_3)$ was calculated, was not difficult to do, but it took a long time to realize this!

2) But only S C had to do analytically was $\int \frac{dR}{R(R)^2} = \frac{1}{\ln R}$

Next Project: Get apsid of R . using ~~the~~ suitable wtd data.
 Use total data (i.e. include first ~~5~~ "at data".
 Start w. new total data!

ST93 from Stein 50 A(, 2) is total data $A(, 5) \approx 552$ U changed to $U \approx .0091$

Probing result: $\lambda N \approx 2$ before: Wanted: Down $\frac{1}{2}$ from λ max at a slight peak at $R \approx 700$ Down maybe e^{-2} from $R_{max} = 100$
 Down $\frac{1}{2}$ at "form" peak at $R \approx 207$
 I think copy to λ by $\frac{1}{R^2}$ or $\frac{1}{R(\ln R)^2}$.



vs $\frac{1}{R^2}$; a slight peak at $R \approx 207$ $G = -3918.36$ down $\frac{1}{2}$ at $\lambda R \approx 88, 586$
 "Peak is not quite symmetric in log domain."

01 Running ST33 but omitting $N = A(J, 5)$ [so $N = 45$]: keeping $U = U + .0091$.
 peak in $\frac{1}{R^2}$ output at $\sim R = 103$
 In G output; down $\Delta G = 1$ from $R = 1658$, at $\sim R = 207$

36
24
30

Comparing 6: 2 D. f.'s: ① Both are down $\Delta G = 1$ for $R = 207$; with $R = 1658$
 & $R = 00$.

② In $N = 45$; from $R = .8$ to $R = 1658$; $\Delta G = 20$
 $N = A(J, 5)$ " " " $\Delta G = 25$

③ In $N = 45$: $\frac{1}{R^2}$ peak is at $\sim R = 103$ down from peak by 1 at $R = 36, 586$
 $N = A(J, 5)$ " " " $\sim R = 207$ $R = 80, 586$

Well, $\Delta G = .01$ ff isn't just noise! It uses $A(J, 2)$ data. w. $N = 45$.

which is not realistic. - But anyway, using $A(J, 2)$ data w. $N = 450$ for all players

39.90
36.20
3.70

did error a peak (w. $\frac{1}{R^2}$) at $R = 207$; $\Delta G = 6$ at $R = 1658$
 $N = 450$ $R = 207$ up $\Delta G = .6$ then $R = 1658$

Try $N = 369$: peak at $R = 293$ only $\Delta G = 2$ up from $R = 1658$
 $N = 300$: peak at $R = 293$ only $\Delta G = 2$ up from $R = 1658$

$N = 250$ " " $R = 293$ " $\Delta G = 1$ " " $R = 1658$
 $N = 200$ " " $R = 300$ " $\Delta G = .2$ " " $R = 1658$

7.25
6.71
.94

Turns out $N = A(J, 5)$ has 2 peaks at (658, it's down only $\Delta G = .35$ at $R = 6635$)

Mean Value $A(J, 5) = 369.38$ Surprisingly low N : so I'd expect a peak! See 47.10 for work on Larger N

Well, ΔG a peak in G with using $A(J, 5)$ at $R = 586$; ΔG down $\Delta G = .25$ at $R = 1658$
 But $\Delta G = 1$ at $R = 6635$; using $N = 369$ for all players Got a much sharper peak

It may be that large N_i ($\geq A(J, 5)$) is very empty for peaks & small N_i is of no
 effect at all. So if we have a distribution of N_i about $N = 369$,
 This is wrong. $N = A(J, 5)$ has peak at 586; down only $\Delta G = .2$ at $R = 1658$, i.e. line

for $A(J, 5)$ value of G at $R = 6747$ (assumed) was -3907.43580 ; down $\sim .7$ only, from
 peak at $R = 572$

Try multiply $A(J, 5)$ by 10! Max at $R = 128$, nearby about $\Delta G = 15$ from $R = 00$
 peak was down by $\Delta G = 1$ w. $R = 64, 572$. (Sharper peak)

Well After multiply by $\frac{1}{R^2}$, peak was at about same position. (maybe R max $\div 1.4$ for 2)

74.35
69.48

Contrast in old Stein 30! ($N = 45$, $Z = A(J, 3)/1000$... (Try. data)

Peak at $R \sim 1200$; About $\Delta G = 100$ above $R = 00$ } very broad "peak"
 Down $\Delta G = -1$ from peak at $R \sim 64$ } very broad ΔG to ∞ .

.845
.849
82.3
-468.8485
13.5

ΔG below peak ($\Delta R = 00$) & $R = 00$: 13.5
 for $A(J, 5)$ (ΔG data) ΔG below $R = .8$ to $\Delta R = 00$ was 25 (About wide vs sharp)

It's down $\Delta G = 1$ from peak at $R = 64$, at $R = 6747$ for data on $N = A(J, 5)$

Unit var. of $\frac{1}{R^2}$ from 0.61 would mean $P \propto \frac{1}{R^2}$ from 1 to ∞ . Did I ever do $\sum_{i=1}^{\infty} \frac{1}{i^2}$?

What I've forgotten: In ST 4, I found best PC score predns. using wts of .105 & .890
 probably not wts of 1 & 0 → 95, 905 so R = 405.

But: $R = 425$ from min error² on 83, 18

I think STEIN was equal to R = 109.

Using $\sum_{i=1}^n \frac{e_i^2}{R(N_i)^2}$ I got R = 532,097 | probably $\sum_{i=1}^n \frac{e_i^2}{R(N_i)^2}$ would be the same.

$\int_0^{\infty} \frac{e^2}{R(N_i)^2}$ has little info. Using closest to $\ln R$ would probably not affect result much, but I'm not sure.

So R_2 & R_3 would seem like an O.K. set.

Re: Using "test data" as T_{19} data. (f. N_i are not constant). In ST 81A, the final result " \bar{R} ": $\bar{R} = \frac{N_1 S_2}{S_1 - S_2} = N_1 \frac{S_1 + S_2}{S_3} = N_1 (1 + \frac{S_1}{S_3})$. error 500 96.20

$S_3 = \int (A) \frac{dR}{R+N_i}$; $S_1 = \int (A) dR$

If \bar{R} was better for all i (which is desirable). $\bar{R} = N_1 \frac{S_1 + S_2}{S_3}$; $S_3 = \frac{S_1}{\frac{\bar{R}}{N_1} - 1}$

Subst. $\bar{R} = N_1 + \frac{2(N_1)^2}{S_3}$; $\bar{R} = N_1 + \frac{2(N_1)^2}{S_3}$; $S_3 = \frac{S_1}{\frac{\bar{R}}{N_1} - 1}$

so \bar{R} must be a function of N_i . S_3 is a function of N_i which should be -1 so 96.20

$\frac{\bar{R}}{N_1} \downarrow$; $\frac{\bar{R}}{N_1} - 1 \downarrow$; $\frac{S_1}{S_3} \downarrow$ (if $\frac{N_2}{N_1} > 1$) ; $\frac{S_1}{N_1} \uparrow$; S_3

So N_1 & S_3 must move in same direction. \bar{R} is indep of N_1 . Hvr. from (TR) S_3 is a function of N_1 .

Well: If $\frac{\bar{R}}{N_1} > 1$ then N_1 & S_3 move in same direction. If $\frac{\bar{R}}{N_1} < 1$ then N_1 & S_3 move in opposite directions.

Actually, $\frac{N_1}{N_2}$ is the same as $\frac{S_2}{S_3}$ so $\frac{\bar{R}}{N_1} = 1 + \frac{S_1}{S_2} = \frac{S_1 + S_2}{S_2} = \frac{S_2}{S_2}$

So to reduce wts, $\frac{\bar{R}}{N_1}$ is $1 + \frac{S_2}{S_3}$ which is always > 1 ! even when N_1 is large!

N_0 $\frac{S_2}{S_3}$ can't be < 1 because $\frac{S_1}{S_2}$ is always > 1

(this is the same unreasonable result that I got before, but with a simpler calcn. (couldn't find that calcn. hvr.) $S_1 = 210$ $S_2 = 6-8$ near N_{19} .)

It was: something like getting wts. of 2 methods of predicting whether player would get out at next bat ball. Hvr, in that analysis,

Edwards always N_i that got $> \frac{1}{2}$ of wt. Then I considered $\frac{1}{N} \sum_{i=1}^N \frac{N_i^2}{N_i} = \frac{1}{N} \sum_{i=1}^N N_i$

$\frac{1}{N} \sum_{i=1}^N \frac{N_i^2}{N_i} = \frac{1}{N} \sum_{i=1}^N N_i$ Permanent var. using each N_i for predn.

$\frac{1}{N} \sum_{i=1}^N (N_i - \bar{N})^2$ mean var using \bar{N} for predn. $= \frac{1}{N} \sum_{i=1}^N N_i^2 - \frac{1}{N} \bar{N}^2$

While I did try this, that's not how I'm thinking of it.

0.1: on the other hand, ~~20~~ ^{95.200} ~~is not~~ so reasonable. $(\frac{R}{N} = 1 + \frac{S_1}{S_2})$
 It should be poss. to get ~~any~~ $\frac{R}{N}$ into w. suitable data, ~~at~~ (95.200) means this impress.

S_1 is normal const. S_2 is $\int \frac{f(R)}{N+R} dR$ (interest)

w. suitable spread of F , ($S F dR \geq 1$) ~~can~~ ^{$\frac{S_2}{S_1}$} can have any value betw. $\frac{1}{N}$ & 0.

0.4. if ~~we~~ so it ~~is~~ $(\frac{S_2}{S_1})^{-1} \rightarrow 1+N \rightarrow \infty$. so it can't even get near 1!

This is still ~~some~~ wrong!

$$\int f\left(\frac{R\bar{U} + N\bar{U}d}{R+N}\right) dR \text{ over } R_0 \bar{U} + N_0 \quad \text{say } f(R) = S(R-R_0)$$

say: $\bar{U} = 1; N_0 = 0$ using $f(S(R-R_0))$ $S = \frac{R}{R+N}$: can't even get from $\frac{1}{N}$ to 0. ; if $\bar{U} = 1, R_0 = 0$; if $\bar{U} = 0, R_0 = 0$.

I think it was a matter of $\bar{U} = 1, N_0 = 0$ that caused the trouble.

$$S_1 = \int f dR; \quad S_2 = \int f \cdot \frac{R\bar{U} + N\bar{U}d}{R+N}; \quad \text{in STEIN: } S_1 = S f; \quad S_2 = S f \frac{R}{R+N}$$

It could be that to simplify I introduced in f. instead of $(0 \leq u \leq 1)$ will not work when we have ~~different~~ N_0 values.

$$\frac{R}{R+N} = \frac{S_2}{S_1} = \frac{S_1}{S_2} = 1 + \frac{N}{R}; \quad \frac{S_1 + S_2}{S_2} = \frac{N}{R}; \quad S_1 - S_2 = S_3; \quad S_1 = S_2 + S_3$$

in 95.10 ; $S_2 = S_1 + S_3$ this is wrong!

$$S_2 = S_1 - S_3; \quad S_3 \text{ is betw } 0 \text{ \& } S_1 \text{ so } \frac{S_1}{S_3} \text{ is betw } 1 \text{ \& } \infty; \quad \frac{S_1}{S_3} \text{ is betw } 0 \text{ \& } \infty; \text{ it's divided.}$$

$$S_3 = \int f \frac{N}{R+N} dR; \quad S_3 \text{ is an \& } \text{function of } N; \quad \frac{S_1}{S_3} \text{ is a \& } \text{function of } N.$$

$\frac{R}{N}$ is a function of N_0 - so it may be O.K.

ST96

First ~~find~~ ~~modify~~ ~~ST93~~ so it can compute $S_1^{(0)} \left(\frac{1}{(R \ln R)^2} \right)$

First I find out how far out to go before ~~it~~ G is constant $\Rightarrow RR$ say $RR \sim 1000$.

Get ~~exact~~ value of $e^G(RR)$. $\equiv A_0$

Compute $\int_{RR}^{1000RR} \left(\frac{1}{(R \ln R)^2} \cdot \frac{N}{R+N} \right) = S_3$ using simpl.

Compute $S_1^{(0)}(RR) = S_1$ ST93

$S_1 = S_1 + \text{...} \cdot A_0 / \ln RR$

then compute R as before

34

To find RR : ~~find~~ $G(R=1000)$: then $R=2000, 3000$ act until $G(R) \sim G(R-1000) + 0.1$

Use large SRTN to find $G(R)$. ~~First~~ find $G(R)$.

Have to print RR and e^G ~~from~~ from do need 14 digits.

$RR=1$

Do until $G < G + 0.1$ ~~until~~

Go sub 100

Go sub 100

Loop

Print RR : END

$\Rightarrow 97.11$

$G = -100000$

$RR=1, G_1 = -100000$

10 Go sub 100

If $G < G + 0.1$ then print RR

$RR = RR + 1000$

$G = 0$

$R=241000$

3 20 99 SMAT: STEIN:

Q1 → Well, I think there is it wrt to optimum soln. via Bayes:

Getting an optimum R value is not really a nitpicky, (fall N's are not the same).

At any rate, the theoretically correct way to do Bayes is to get the total prior (integrating R wrt R) using uniform D.F.'s for \bar{D} & U_i 's.

We then get the relative priors for $a = 0$ or $a = 1$ being the next data pt. for the player.

So, say we have $[N_i, U_i]$ for i corpus. We want the rel. priors ($\equiv \frac{e^G}{e^G + 1}$)

for ① $\frac{e^{G_1}}{e^{G_1} + 1}$ corpus, but ~~for~~ for one of the players, $N_j \rightarrow N_j + 1, U_j \rightarrow \frac{U_j \cdot N_j + 1}{N_j + 1}$ — making a hit

② " " " " " " $N_j \rightarrow N_j + 1, U_j \rightarrow \frac{U_j \cdot N_j}{N_j + 1}$ — making an out

This is also the ideal method to use if all of the N 's are $\frac{1}{2}$ known,

So : 1) Make a table of e^G & sum:

2) Get RR viz ~~26.34~~ 96.34

.10

.11 : 96.40 ~~SWER~~ ST96 (Cont) ~~is~~ after use ~~RR~~ RR, $G \approx G_1 = G$.

After ~~the~~ integration

Actually, in STEIN, we integrate $S_2 = \int e^G \frac{1}{R(N+1)^2} \cdot \frac{R}{R+U}$

$S_3 = \int e^G \frac{1}{R(N+1)^2} \cdot \frac{U}{R+U}$

In the context of varying N 's; the "N" is missing (ccs).

All we really need is $S_1 = \int e^G \cdot \frac{1}{R(N+1)^2}$

- .001 : 2001
- .0001 : 2001
- .00001 : 2001

Another point in RR do formula, $G \downarrow$ as $N \uparrow$ becomes constant.



- 101 G
- 10097 G1 ← larger.
- 10003 G

I got RR (cc = 2000) from the following pm.

Then $S_1 = \int_2^{2000} = 1.94168 \times 10^{-208}$

$\frac{e^{cc}}{1/R} = 2.451589 \times 10^{-208}$

So must get S for S1 occurs for $R > 2000$!

If $J = \frac{cc}{max}$ BAT = 0 or 1; $N = 46$; $A(J, 3) = (A(J, 3) + 45 + \frac{BAT}{46}) / 46$

$CC = (1 + kR)$; $BAT = 0$ or 1 .

| | | | | |
|----|-----|-----|-----|-----|
| cc | | | | |
| 17 | 316 | 178 | 244 | 408 |
| | | AG | | |

| | |
|----------|-------|
| cc = 10 | 273 |
| hit | 11919 |
| | 31688 |
| 16 | 273 |
| cc = 210 | |

Putting the "FR" line changes RR from 24 to 235K if $(hit = 20)$ not reasonable. " " 236K " $(hit = 1)$

For $hit = 0$ cc = 1; $R = 237200$ Now $hit = 288$

$\frac{400 \times 95 + 1}{46}$ should be > 900 .

hit 1.2565
3.1008

So for player #1 I got 288 batter.

.28836

Stein got 290 seems unreasonable; $\bar{D} = 265$!

Try cc = 18, 265

$0 \rightarrow 32,004$ A
 $1000 \rightarrow 11530$ B
 $\frac{B}{A+B} = \left(\frac{A}{B} + 1\right)^{-1}$

32199 SMART Stern:

| CC | Rew Ave | My value | 5 Team | 197 coins | Any w. $D=0$ |
|---------|---------|----------|--------|-----------|--------------|
| 265 135 | 1 | 400 | 288 | 290 | 280 367 265 |
| | 10 | 244 | 273 | 259 | 263 200 265 |
| | 11 | 222 | 254 | 234 | 262 125 |
| | 18 | 156 | 265 | 239 | 253 70 265 |
| 265 104 | | | 254 | | 262 |

using $D=0$

413.04) So v. modified Bar avgs. check, 391.3

50470
18030
263!

248 → 11 : $\frac{12}{46}, \frac{11}{45}$

For CC=10 result seems nutty

Check from w. $CC=0$; $D=0$ against ST 83 (92.28)

Check C1 Also check bar integral against process when $D=0$ bar! 93.14

Examine $\frac{R}{S}$

93.14: runny ST 93 for $D=0.0091$! $R=12 \rightarrow S1 = 1.681106 E-208 = \times 3 = ? \rightarrow 4.3825108 E-208$

10k $S1 = 2.35645 \times 4 = 4.3825108 E-208 = C_{10}$

Pr. agrees w. 93.14 Now go to ST 96 $C=0 D=0.0091$

$R=5000$

- x3 $S1 = 3.502295 E-205$; $S1 = 6.85996 E-205$

+ x4 $S1_{tot} = 4.2151056 E-205$

Try S_{100} using different D limit.

Using $(G-6) < 0.001$ $R=10000$, $S_{100} = 6.85996 E-205$

Using $(G-6) < 0.01$ $R=2000$, $S_{100} = 6.8771 E-205$

The disparity is appreciable! Inexact Arithmetic.

6.85 v.s. 6.85 7.7% error

- x3 $S1 = 15k$ $S_{15k} = 3.885284 E-205$

+ x4 $S1 = 170$ $S_{170} = 4.45776 E-205$

$\rightarrow C_{10} = 6.17520$

1 5k to 50k. No! I have to do 1k & 10k. See (93.14 R) AF

1/15k 1/170k.

-4x $C_{10k} = 3.7546 E-205$

+5x $C_{100k} = 4.373 E-205$

$\rightarrow 6.848 E-205$ or should be $E-205$

So it checks out fine! C_{100} may be off.

Wax thru. on 92.28, I got $C1 = 3.029 \dots E-208$ A factor of 100 smaller.

Maybe I did step 100! No! running ST 83. Bas! $R=20$ to 10k total $S1 = 2.356 E-208$

ST 83: $\int_{100}^{1000} S1 = 4.28091 E-211$ $D=0.0091$

ST 96 $\int_{100}^{1000} S1 = 6.6119 E-208$ $D=0$

Differences Defn. ST96 & ST83.

1) ST96 doesn't do Del in Re so Sub(loop)

Still, it should not use the same difference!

| ST96 | R | $e^{\frac{R}{R(NR)^2}$ | d |
|------|------|------------------------|---|
| | 1000 | | |
| | 1010 | | |
| | 2000 | | |
| | 5000 | | |

$$6.046958 - 209 = 5.837$$

$$5.9723049 - 209 = 5.763$$

$$2.787 - 209 = 2.578$$

$$7.8344 - 210 = 7.624$$

| ST83 | 1000 | 6.046958 - 209 | Del = 0 |
|------|------|----------------|---------|
|------|------|----------------|---------|

So Del = .0091 means by difference! \int_{1000}^{1010} are smaller ST83, ST96; \int_{200}^{210} R Del = 20 m bpl.

$$H = R\bar{u} + z \quad L = R(1-\bar{u}) + N - z \quad F = R + N$$

$$G = G + H \ln H + L \ln L - R \ln R - N \ln N$$

$$(H+1) \ln(H+1) + (L-1) \ln(L-1)$$

$$H \ln(H+1) + L \ln(L-1) + \ln(H+1) - \ln(L-1)$$

$$2\pi \sqrt{\frac{(H+1)(L-1)}{E-1}} \rightarrow \sqrt{\frac{(H+1)^2}{E-1}} \cdot (H+1)^H \cdot (L-1)^L$$

$$\left(\frac{H+1}{E-1}\right)^{\frac{E-1}{2}} \cdot \left(\frac{H+1}{E-1}\right)^H \cdot \left(\frac{L-1}{E-1}\right)^L$$

$$\sqrt{\frac{H+1}{E-1}} \cdot \left(\frac{H+1}{E-1}\right)^{\frac{H-1}{2}} \cdot \left(\frac{L-1}{E-1}\right)^{\frac{L-1}{2}}$$

$$\frac{(H+1)^{H+1/2}}{(H-1)^{H+1/2}} \cdot \frac{(L-1)^{-L+1/2}}{(L-1)^{-L+1/2}} = \frac{H^2}{L^2} \cdot e^{\frac{1}{E} - \frac{1}{L}}$$

$$\frac{1+\frac{1}{H}}{1-\frac{1}{H}} = 1 + \frac{1}{H} + \frac{1}{H^2} + \frac{1}{H^3} + \dots$$

$$\frac{L-1}{L+1} = 1 - \frac{1}{L} + \frac{1}{L^2} - \frac{1}{L^3} + \dots$$

$$= 1 - \frac{2}{L} + \frac{2}{L^3} - \frac{2}{L^5} + \dots$$

So $H \rightarrow H+1$ v.s. $H \rightarrow H-1$ produces ratios of the same order of

$$\frac{H^2}{L^2} \cdot e^{\frac{1}{E} - \frac{1}{L}} \approx \text{larger } R. \quad \text{Hvr } \frac{H^2}{L^2} \rightarrow \text{larger } R$$

So the change in E occurs at small values of R - say $R \sim N$.

$$\frac{450}{1500} = \frac{267}{5} = \frac{267}{26} = \frac{239}{26}$$

12.8 I find ST83 on CC=1; got 279,589 - same as before.

| CC=11 | → 262.125 | row 222 |
|-------|-------------|---------|
| =12 | → same | |
| 16 | → 260 | 200 |
| 17 | → 257.75 | 178 |
| 18 | → 255 | 156 |
| 8 | → 266.54158 | 267 |
| 7 | → 268.756 | 289 |
| 5 | → 270.9706 | 311 |
| 10 | → 275.3548 | 356 |

| ΔStam. | Y ¹⁰⁰⁰ | A-U | A | 265 | B | B-U | ratio |
|--------|-------------------|------|-----|-----|----------|---------|--------|
| 35 | (3.8) | 1376 | 400 | 280 | 279.504 | 1.41 | 9.54 |
| | | 906 | 349 | 281 | 275.3548 | 9.96 | 9.09 |
| | | 456 | 311 | 273 | 270.97 | 5.61 | 8.128 |
| | | 236 | 268 | 268 | 268.756 | 3.367 | 7.012 |
| | | 161 | 267 | 264 | 266.54 | 1.111 | (1.45) |
| | | 100 | 244 | 259 | 263 | -2.3889 | 8.9 |
| | | | 222 | 254 | 262.125 | -3.2639 | (13.9) |
| | | | 16 | 200 | 260 | -5.3889 | 12.11 |
| | | | 178 | 244 | 257.75 | -7.64 | 11.44 |
| | | | 109 | 156 | 255 | -10.4 | 10.52 |

It is conceivable that it is like: write program to calculate values exactly automatically!
Then put ~~me~~ error.

I could put values into the Data table. I only need to calculate 2 more values.

But $R_2 \rightarrow$ hand calc. is not very accurate!

A correction! When we have $CC > 0$, $U \rightarrow (U * 810 + HIT/1000) / 811$

| Δ to my pred. | okigridly. | Δ to exp date | now 10%u |
|----------------------|------------|----------------------|----------|
| 1: 278.7560 | 279.504 | 13,367 | 10.06957 |
| 3 | | | |
| 5 | | | |
| 7 | | | |
| .575112 | 265.964 | 267.264 | 2.8011 |

This makes some difference.

Recover N17 18 59

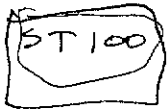
Process, ans wd with \approx dec/s.

inval
w/val
w/



In 4. case of $CC > 1$ (May 04) my pred of 279.504 \rightarrow 278.756 drop \approx .75

So maybe "optimal R" \downarrow for small $U_i - \bar{U}$ + effect was perhaps more reasonable?



Same as ST96 but modify to do both Hit = P \approx 1000.

$A * 45/46$; $(A * 46 + 1000) / 46 = A + 1000/46$

For $CC = 8$, seems to get same answer, but when $C \uparrow$ $A(8, 3)$ why does $C \downarrow$? well, because the Hit is less likely than 24 out.

$A / ((H_0 / H_1) + 1) = H_1 / (H_0 + H_1)$

$A \rightarrow \frac{A * 45}{46}$

$A = (A - 1000/46) * 46/45$

$= A * 46/45 - 1000/45$

BA = final result. ; so I want

$R_2 = (BA - \text{sum}(1000/46)) / (A(8, 3) - 1000/45)$

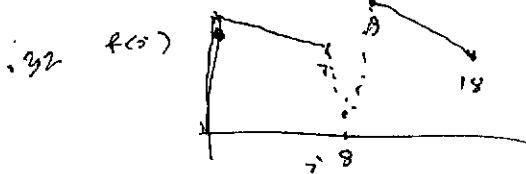
- 261.195
- 282.934
- ~~267~~
- 267
- 1.06079
- 1.0835
- 1.1258

Well: T. out put of ST100 is Disturbing!

$f(z) = \frac{A * \mu_i - \bar{U}}{\mu_i - \bar{U}}$ z_i is problem.

$R(z) \approx 4.5$ for $z=1$ then \rightarrow ≈ 8 at $z=7$; drops to 2.7 at $z=8$

Then up to 11.4 at $z=9$; drops ~~to~~ monotonically down to 9.8 at $z=18$.



Also, \approx EPS \approx (G-0) \approx EPS determines RR

EPS from .001 to .01 for $f(z)$ values close by $\times 1.06$ to $\times 1.125$

for EPS = .0001 values are (relatively) close to Prices for EPS = .001

32299 SMART STEIN.

This "ruffness" of $f(z)$ (at 100.32) is very disturbing!

Poss. causes:

- 1) I should also consider width of the def. in the \bar{A} direction and multiply to S by it.
- 2) Hardware bug(s)
- 3) S.W. Bug(s)
- 4) Some other thing.

(NB) \rightarrow (14, 12A, EST14, BA tests ST values ~~are~~ points on a smooth "ruffness".

\rightarrow At any rate, what I could do is get GARC for A and B — both. My stuff's ST values — R u A P R. it may be, it may have good GARC. Actually, it looks like against R is very large, so it probably does have good data.

Modifn. of ST100:

A from BA is computed.

Use ~~BA/1000~~ $BA = BA/1000$; $S2 = -3907.92876$ $A5 = A2/1000$ $(-BA) A5 - A5 = A2/1000$

$S3 = -3909.7935$ $A5 - A5 = A2/1000$

Also do it for $S3$ A (stored) instead of BA

probably would be good idea to divide all data by 1000.

(NS) $S2$
(A) Test data.

$S2 = BA$ (max. probn) } log likelihood: $S2 = -3907.92876$ ST

$S3 = S$ term: $S3 = -3909.7935$

So BA is better than $S3$ by 2 log likelihood \log likelihood of

$1.85479 \rightarrow$
 $0.185479 = 1.85479$

Try $S4 =$ using $x = 0.9 + 0.1 * A(CC, 3)/1000$

$S4$ got -3907.95274

is only .014 better in log likelihood = $x 1.014$ \odot

I can speed up the point of $S3 = S2$ by running R from 2 to 2

Woops! I got 2 GARC for BA of -3911.47 ! Must of G. account \rightarrow values were > 10

(except $CC = 1, 2, 3$, which is $n = 12$!)

Using 0.9 as constant, was -3908.837 , better than S term, but worse than BA.

I think I seem, that this log likelihood is not very sensitive!

for above results were for $EPS = .01$; for $EPS = .001$,

$S2 = -3907.8531$: slightly better than $EPS = .01$

$S3 =$

$S2 = -3907.84029$ very slight further improvement,

using $EPS = .01$ and $0.9 = 0.9 + 0.001$, I got -3907.86

(Not surprising, hrr, no R u BA values it obtained were a bit weird!

compp. — when better than $EPS = .01$ value for $0.9 = .268282$

ST101 : This is an attempt to clean up ST100 by dividing all data by 1000! It hangs up around (56 line of **ERTIV 100**!)

with $EPS = .01$ and $0.9 = 0.9 + 0.001$

I got $S2 = -3907.86$ BA

$S3 = -3909.7935$ ST

$S4 = -3906.765$ (Best) because of $+0.001$

Wall! its effort answers!

3 23 99 SMART STEIN

well, I don't quite know what to ~~make~~ make of it! The log likelihood score seems inconsistent.

try Σ error Ganc.

BA $S_2 = .0219944$ worst
 ST $S_3 = .021611$ best
 G, 1M, S, 4 = .02194 worst

- almost identical. So ST did best
 \Rightarrow Σ error Ganc!

BA
 ST
 .9, .1 mix.

The differences are so small! — Not enough to distinguish between methods!

I don't know if it's true or f. In likelihood Ganc, perhaps also true!

I could easily set up 50 points of all 6 Gancs. I need to initialize S_1, S_2, S_3 .

I inserted 2 wt. of $A(C, S)$ fort. ~~the~~ Σ error Ganc!

BA 6.2505
 Best 6.915

Stream 6.915

198, 1 WT 6.2570

5.8306 $\downarrow \Delta = .93$ 6.246

\downarrow Best
 5.7948
 should be if it made a better fit!

I + I changed data by $A(C, 2) \rightarrow A(C, 2) - .009$
 so weights at test of true data were same.

using U_2 as estimate. S_2 w. wts. $\Delta \rightarrow .0091$

Σ error = 29.98 (w 30) for

assumed Ganc:

No: s BA -3846.65
 ST -3847.816
 .9 + .1 -3846.959 ← Best
 μ_2 -3849.68 - very bad
 \bar{U} -3847.23 better than ST!

— Better is using correct \bar{U} .

Log like Ganc: -3909.6096 better than ST?
 -3909.6096

Stun Bats -3847.8 under these circumstances

BA Gancs -3876.6

~~the~~
 .9 + .1 μ_1 Ganc -3846.559 Best

S_2 S_3
 S_4 .9 + .1

O.k. Re-creating for STEIN algorithm

$$X_i = (N)^{\frac{1}{2}} \sin^{-1} (2A_i - 1) ; \quad \mu_i = \bar{x} \frac{k-3}{v} + (1 - \frac{k-3}{v}) \cdot X_i ; \quad \Sigma = (X_i - \bar{x})^2 = \Sigma X_i^2 - \frac{(\sum X_i)^2}{N}$$

ST 103

$s_2 = 0, s_3 = 0$
 for $J = 1$ to K : $X = 2A(J, 3) - 1$
 ~~$A(J, 3) = N \cdot 1.5 + \text{random ATN} (X * (1 - X^2))^{1.5}$~~
 $Y = A(J, 6) = Y$
 $S \pm S + Y$
 $SS = SS + Y * Y$
 $(X * (1 - X^2)^{1.5})$ $\left. \begin{array}{l} \sin^{-1} X = \tan^{-1} \frac{X}{\sqrt{1-X^2}} \\ \text{ATN} \end{array} \right\}$

Next J
 for $J = 1$ to K : $S = S / 3, W = SS - SS / K, W = \frac{k-3}{v}$
 ~~$A(J, 7) = S * (1 - W) / v + (1 - (1 - W) / v) * A(J, 3)$~~
 Next J. $S * W + (1 - W) * A(J, 3)$

Print W, S
 $\frac{1}{L} \tan^{-1} = .204124 = -.20135$

$u_i = \left(S * \left(\frac{X_i}{N^{\frac{1}{2}}} + 1 \right) / 2 \right)$
 $\tan^{-1} = .2013 = \text{smaller}$
 $-.1987 \quad - .2013$

$\sin \theta = .22, \cos \theta = \sqrt{1 - .22^2}$
 $\tan \theta = \frac{\sin \theta}{\cos \theta} = \frac{.22}{\sqrt{1 - .22^2}} = .204124 ; \theta = .20135$

Find M use integer values for no. of bits per player. This is counter to $k=1$ or $k=2$ — using simple 3 significant digits for Y_i doesn't give them X_i on the other hand, taking the decimal base values gets $.3165$! V, W, S
 Play goal (-3.275) \leftarrow probably typo

So far, about $W = \frac{k-3}{v}$ ratio = .791
 — just has with base values of X_i .

For k value equal to $W = .791 \Rightarrow$
 $\frac{W * 95}{1 - W} = 170.3$
 $\frac{W}{1 - W} = .45 \quad R = 95$
 $\frac{R}{95} = \frac{W}{1 - W}$

for factor $(k=3)$ "R" = 170.3

| | | |
|-------|---------------|--------|
| $k=2$ | \rightarrow | 243.0 |
| $k=1$ | \rightarrow | 389.76 |
| $k=0$ | \rightarrow | 841.36 |

So this integer does seem to be important. — well, for small k .

[Handwritten flourish]

So to work on \bar{u} is $\frac{1}{R} \frac{d^2}{dt^2}$

$\frac{1}{R^2}$ is the variance of total d.f., $\frac{1}{R^2}$ is the mean of 200 d.f.

If R is large, then \bar{u} value is close to \bar{u} , and noise w is on \bar{u} .

14 96d
28
32
35 d 10997
1.6 pp/d.
 $\frac{2}{3} = \frac{10}{15}$
 $\frac{1}{45} = 2.22$

(Try $\frac{1}{R^2}$ to "sprinkle")

I have these two first 200 d.f. values - 9 to 1 f. whole values - 39 07.9667

| | | | | |
|-----|-------------|-----------------------|-------------------------------|---------|
| 103 | 5.2 | 5.3 | 5.4 | Stern |
| | BA | | | |
| | -7.9387 | -9.7937 | -7.9527 | LL Gore |
| 07 | -10.3587 | | | |
| | -6.834 | using $\frac{1}{R^2}$ | ! by function $\frac{1}{R^2}$ | |
| | -6.6344 | using $\frac{1}{R^2}$ | | |
| | -39 06.63 | | | |
| | -39 06.615 | using $\frac{1}{R^2}$ | approx Best | |
| | -39 07.9667 | | | |

But note that these are all not what they seem because they use \bar{u} $\frac{d^2}{dt^2}$ addition to S , which is not appropriate.

These are ~~not~~ All using $\epsilon_{PS} = .01$

$RPS = 100$

I think I did a little of this because of the way, but don't know.

It might be based on χ^2 d.f., which is d.f. for squares of vars.

this χ^2 is easily found to non-equal vars, here - EAM may not know about it.

I think Ray would try to estimate to $\frac{1}{R^2}$ of the \bar{u} generator. (Loren?)

They got a ~~data~~ d.f. (perhaps) for σ^2 of $\bar{u} = \frac{1}{R}$ so, R^2 is like using $\frac{1}{R^2}$ to "sprinkle". - Actually I don't know what produces $\frac{1}{R^2}$ would give **.07** is

doesn't integrate from R^2 to ∞ properly - it would be easy to do, here.

~~Just~~ $\int \frac{1}{R^2} dR = \frac{1}{R}$ just use $\frac{1}{R}$ for S instead of $\frac{1}{R^2}$.

I got -3910.905 even worse than .07! - but \approx Stern!

If σ has a uniform d.f. what is d.f. of σ^2 ? $\sigma^2 = \frac{1}{R^2}$?

(SN) Perhaps the "irregularity" of the BA results has to do with the ~~SP~~ SP any of the \bar{u} ; that is, estimates of \bar{u} depends much on \bar{u}_{i-1} & \bar{u}_{i+1} as well as \bar{u}_i (ultimately!)

| | |
|----|----|
| 0 | 18 |
| 1 | 17 |
| 2 | 16 |
| 3 | 15 |
| 4 | 14 |
| 5 | 13 |
| 6 | 12 |
| 7 | 11 |
| 8 | 10 |
| 9 | 10 |
| 10 | 10 |
| 11 | 10 |
| 12 | 10 |
| 13 | 10 |
| 14 | 10 |
| 15 | 10 |
| 16 | 10 |
| 17 | 10 |
| 18 | 10 |

These are ways to get more values of $A(t, \beta)$. - These were used by EAM

More Reason My "BA" soln (perhaps $CC=8$) got unusual results because it's RR values are differently distributed from CC 's: All right, against this - that effect should be less prominent as EP s becomes smaller
 (E RR) - This doesn't occur.

24 (2) ESM: My answer is Gauss for t_i 's w. unknown mean & var: from t_i observed u_i are of 2 "known" vars.

My (old) analysis of the X^2 situation: That if a very ^{big} Gauss, a best zero, one knows t_i d.f. for X^2 .
 One also knows t_i d.f. for X^2 . If one has a bunch of Gauss. vars. of various σ^2 , the

d.f.'s of t_i Sum of their squares is the convolution of the individual X^2 d.f.'s.
 Also, the variances of these d.f.'s add.

If the d.f.'s are all about zero, one knows the d.f. of the sum.

Now, if one chooses means of these random vars, as in EP (using a Gauss d.f.) & the vars of t_i random vars over all t_i same, then the final d.f. of the vars is a χ^2 conv. ~~of~~

Say the d.f. of u_i is $N(\bar{u}, \sigma^2)$ if individual vars are all $N(0, \sigma^2)$

Then final d.f. is $N(\bar{u}, \sigma^2/k)$. Now given a sample D.F. and known σ^2 , to find \bar{u} is $\frac{1}{k} \sum u_i$. This mean of the sample D.F. can be used for \bar{u} .

I should think that a best estimator for $S^2 + \sigma^2$ would be $\frac{1}{k-1} \sum (u_i - \bar{u})^2$ if σ^2 is known.
 " $(\sigma^2 + \sigma^2)$ " $\approx V$ as k by ESM. I should think that $V - \sigma^2$ would be a good estimate of τ^2 .

(E ESM) $\sigma^2 = \tau^2$ so $\frac{1}{k-1} \sum u_i^2$ would be a ~~best~~ estimator! Instead they use $\frac{k-3}{V}$

The in eq. 1.105 = $\sum (X_j - u_j)^2$ is "approx" $\tau^2 + 1$. Only use $\frac{S}{k-2}$ to estimate $\tau^2 + 1$

estimate of u_j in 1.8 is $u_j + (X_j - u_j) = \frac{X_j - u_j}{1 + \tau^2} = X_j \frac{1}{1 + \tau^2} + u_j \frac{\tau^2}{1 + \tau^2}$
 $= X_j \left(\frac{1}{1 + \tau^2} \right) + \frac{u_j}{1 + \tau^2} = X_j \frac{1}{1 + \frac{1}{\tau^2}} + \frac{u_j \cdot \frac{1}{\tau^2}}{1 + \frac{1}{\tau^2}}$

We use (2.1 R) because $\frac{1}{\tau^2} \approx 1$ are relative wts.

Analogously, in the binomial case, τ^2 is $\frac{u_j(1-u_j)}{N}$

$\tau^2 = \frac{\sum (u_j - \bar{u})^2}{k-3} = \frac{\sum u_j^2 (1-u_j^2)}{k-3} \left(\sigma_j^2 = \frac{u_j(1-u_j)}{N} \right)$
 with u_j estimate = $\left(\frac{\bar{u}}{\tau^2} + \frac{u_j^2 N}{u_j^2(1-u_j^2)} \right) / \frac{1}{\tau^2} + \frac{N}{u_j^2(1-u_j^2)} \rightarrow 106.01$

26 A POSSL tree: I'd like to integrate to get the D.F. wrt \bar{u} : It may be possible to do this analytically - Plan do Num. integ. wrt R . See 96.23 for eq.

$\prod_r \left(\frac{R+1}{\bar{u}^R (1-\bar{u})^R} \cdot \frac{(\bar{u}^R + u_j^R) ((1-\bar{u})^R + u_j^R)}{R+N+1} \right) = \frac{R+1}{R+N+1} \prod_{j=1}^{R+1} \frac{\bar{u}^R + u_j^R}{\bar{u}^R} \frac{((1-\bar{u})^R + u_j^R)}{(1-\bar{u})^R}$

No obvious way to do it so ~~use~~ it with \bar{u} in \bar{u} direction varies much in R .

Q: check again by whether this ~~is~~ partially ~~displays~~ \bar{u}^k weights! - I probably does - is


6. σ^2 of R (σ^2) Plan go outside Plan \prod_r sign.


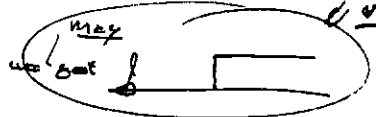
Getting back to the original Q: In general, as $n \rightarrow \infty$ of data t , the i.i.d. $\rightarrow (P_i(x))^{SS}$.

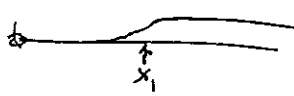
$P_0(x)$ = approx is, indep of SS . If $P_i(x)$ has a peak \gg all other peaks, peak at $x = x_0$

$(P_i(x))^{SS} \approx \delta(x-x_0) \int P_i(x) dx$. $P_0(x)$ is essentially indep of $P_i(x)$.

it is $P_0(x_0)$ which cancels out after normal.

If $P_i(x)$ is like  Then SS must be very large
 before we get a δ function approx.

If $P_i(x)$ is  then for $SS \rightarrow \infty$ we get  *may be*

or, concisely \approx  function which x_1 is f. width of δ -step } *may vary common.*
 depends on SS .

We're, now, interested in the ratio of $\int P_i(x) P_0(x) dx$ & $\int P_0(x) P_0(x) dx$

01 On the earlier, simpler approach to STERN: Assume that each M_i^2 is of known var, σ_i^2 but unknown mean, μ_i .

~~Each~~ $[M_i^2]$ is assumed to be a norm d.f., of outcome $D, \in \mathbb{Z}$.

Each datum, M_i has its own d.f., of mean $\mu + \mu_i$; $\text{var} = \Sigma^2 + \sigma_i^2$.

~~Then~~ Each $(M_i^2)^k$ also has a d.f. of. norm & var, that is constant

$\mu, \Sigma^2, \mu_i, \sigma_i^2$. (Is its mean $\Sigma^2 + \sigma_i^2 + (\mu + \mu_i)^2$? - or is $\Sigma^2 = (\mu + \mu_i)^2$? - If $\Sigma^2 + \sigma_i^2$ is non-constant) \rightarrow See 02

Anyway, if we know $\mu, \mu_i \in \mathbb{Z}$ of a norm d.f. we know: μ is of its square, Σ^2 .

Assume a norm of sq. of (a "Norm" about zero, w. var Σ^2) is say $\Sigma \in \mathbb{Z}$.

Then convolute σ_i^2 : Woops! Actually, I'd have to find d.f. directly: -

But Anyway, given the mean & var of k squares of the M_i 's, the d.f. for sum of k squares

\rightarrow is known. From: observed mean & var of k d.f. of M_i given, once with

the σ_i^2 to find estimate $\mu \in \mathbb{Z}$ (The μ is pretty best estimated as \bar{M}_i) \neq -

So we only need k data to find $\Sigma \in \mathbb{Z}$.

In observing k var. Σ we can do $k \rightarrow k-1$ or $\rightarrow k-2$ - i.e. find its rationality

I do want to see what kind of answers I get using Monte Carlo & various D.F.'s for k . - for BA & ST.

WRT a single datum M_i^2 : Its expected square is:

$\mu^2 + \Sigma^2 + \sigma_i^2$: We must find $\Sigma(M_i^2)$ w. a factor of $\Sigma^2 (\mu^2 + \Sigma^2 + \sigma_i^2)$

$\Sigma M_i^2 = k (\mu^2 + \Sigma^2) + \Sigma \sigma_i^2$. So $\Sigma^2 = \frac{\Sigma M_i^2 - \Sigma \sigma_i^2}{k} = \bar{M}^2$

25 $\Sigma^2 = \frac{\Sigma M_i^2 - \frac{\Sigma M_i^2 (1 - M_i^2)}{N}}{k} - \bar{M}^2 = \frac{\Sigma M_i^2}{k} - \bar{M}^2 - \left(\frac{\Sigma M_i^2 (1 - M_i^2)}{k \cdot N} \right)$

$= \frac{\Sigma M_i^2}{k} - \left(\frac{\Sigma M_i^2}{k \cdot N} + \frac{\Sigma M_i^2}{k \cdot N} \right) - \bar{M}^2$

$= \frac{\Sigma M_i^2}{k} (1 + N) - \frac{\Sigma M_i^2}{k \cdot N} - \bar{M}^2$

$= \frac{\Sigma M_i^2}{k} - \bar{M}^2 + \frac{\Sigma M_i^2}{N} - \bar{M}^2$

$= \frac{\Sigma M_i^2}{k} \cdot \frac{1}{N} - \left(\frac{\Sigma M_i^2}{k} \right) \cdot \frac{1}{N} = \left(\frac{\Sigma M_i^2}{k} - \bar{M} \right) \cdot \frac{1}{N}$

30 $4.583904E-3$ (91.13) $\alpha = \dots$

32 Norm $\sigma_i^2 = \frac{1}{2} \Sigma (M_i^2 (1 - M_i^2)) = 0619314$ (81.07) $\beta = \dots$

33 $\Sigma^2 = \alpha - \frac{\beta}{N}$ from (24) $\beta = 4.2305271E$

$\alpha = .003207650$; $\frac{1}{2} = 311.7546$ (if $\Sigma^2 = \alpha - \frac{\beta}{N}$; $\frac{1}{2} = 287.58$ for $\alpha + \frac{\beta}{N}$; $\frac{1}{2} = 263$)

So $\Sigma^2 = (\text{Var of total corpus}) - \text{mean } \sigma_i^2 \text{ of } [M_i^2] \text{ sum}$

We also need corrections relative to k when k is small. So var of k squares will be at least $\frac{k}{1-k}$ times as big as α . $\Sigma^2 \approx M^2 \text{ var } \sigma_i^2 \approx 1$, so $\Sigma^2 \approx \alpha - \frac{1}{N}$ etc. $(1 + \frac{1}{N}) = \alpha$

I could test it w. Mt. Carlo data.

estimator $\mu_i = \left(\frac{\mu_i' - \bar{\mu}}{N\tau^2} + \frac{\bar{\mu}}{\tau^2} \right) \left(\frac{N}{\mu_i'(1-\mu_i')} + \frac{1}{\tau^2} \right) = \left(\tau^2 \mu_i' + \frac{\mu_i'(1-\mu_i') \cdot \bar{\mu}}{N} \right) / \left(\tau^2 + \frac{\mu_i'(1-\mu_i')}{N} \right)$

$\frac{\mu_i'}{1 + \frac{\mu_i'(1-\mu_i')}{N\tau^2}} + \frac{\bar{\mu}}{1 + \frac{N\tau^2}{\mu_i'(1-\mu_i')}} = \frac{1}{1+\tau} + \frac{1}{1+\frac{1}{\tau}} = 1$

So calculate $\frac{\mu_i'(1-\mu_i')}{N\tau^2}$ for each μ_i' scenario.

So how much does $\mu_i' - \bar{\mu}$ shrink estimator μ_i' ?



$\alpha = 0.2$
So $B = 1.2 = 1$

$\mu_i = A \mu_i' + B \bar{\mu}$; $\mu_i - \bar{\mu} = A(\mu_i' - \bar{\mu})$

$\frac{\mu_i - \bar{\mu}}{\mu_i' - \bar{\mu}} = A = \frac{1}{1 + \frac{\mu_i'(1-\mu_i')}{N\tau^2}}$ Which is a smooth function of μ_i' .

$\frac{\mu_i'(1-\mu_i')}{N\tau^2} \sim 10$

So get $\frac{1}{\tau^2} = 311.7$ (for 297 to $\alpha = \frac{k}{k-1}$ (for 292 to $\alpha = \frac{k}{k-3}$ ($k \geq 10$),

for $\mu_i' = .2$ to $.4$

$\mu_i'(1-\mu_i') = .2 \cdot .8$ to $.3 \cdot .6$
 $16 \rightarrow 24 \rightarrow 36 \rightarrow 45$

$\frac{311.7}{45} = 6.926$; $\left(\frac{.13166}{.24} + 1 \right) = 2.66$

$.156 \rightarrow \left(\frac{.13166}{.24} + 1 \right) = .24$
So factor of ~ 2

So rather than $\alpha = 1$ from 297 to 292 ; It is monotonic from $.156$ to $.90$

My results are not monotonic in that region ; I got 2 dip at $\mu_i = .267$

I should compare this simple result w. STEIN (using Pro Stein stuff).

These results do show α is a lot different from α STEIN from β & τ .

$\frac{.95}{.12} = 22.5$ so τ^2 is even larger as β doesn't give $\bar{\mu}$ as much wt. as greater β .
I found a post hoc ratio of ~ 1 to 9 (or 10 ?) to be optimum.

Perhaps it would be good to check on α & β values!

$\Sigma^2 = \alpha - \frac{\beta}{N} = \alpha - \frac{\beta}{45}$

error: $\alpha = 4.582564E-3$ etc.

ST109
(from ST81
see 108.30.32k)
for α, β

$\frac{\beta}{15} = 4.23052716$

so, multiply $\frac{\mu_i'(1-\mu_i')}{N}$ to get a relative ratio

$(\alpha - \frac{\beta}{45})^{-1} = 2829.83$

$\rightarrow 12.5 \rightarrow \frac{.2}{45} = \frac{1}{225}$

Since we want $\sim 1 + \frac{\mu_i'(1-\mu_i')}{N\tau^2} \approx 9$
 $\alpha \rightarrow \alpha \frac{19}{17}$ is needed.

$(\alpha - \frac{\beta}{45})^{-1} = 1605.03$

$\rightarrow 7.13 \rightarrow 3.13$

$(\alpha - \frac{\beta}{45})^{-1} = 1079.48$

$\rightarrow 4.79 \rightarrow 5.79$

$(\alpha - \frac{\beta}{45})^{-1} = 787.30$

$\rightarrow 3.5 \rightarrow 4.5$

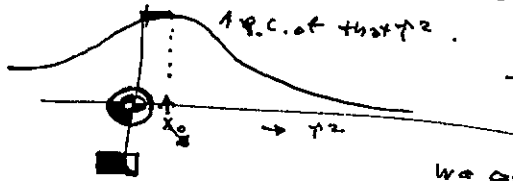
Whoops! This is all wrong: ST81 makes random data! R was set at 100

So true $\frac{1}{\tau^2}$ was $\frac{100}{\sigma^2(1-\sigma)} = 512.93$ so $\alpha \rightarrow \frac{\alpha \cdot 18}{15}$ would have been closest.

Whoops on second plot, T p.m. reads of Baseball data, for β only. (Pro random part is not used unless we "comment out" the "READ" statement)

Even if random you ~ 8 times! Got $\frac{1}{\tau^2} = 467, 529, 1274, 337, 363, 376, -16080, 622$. ; not unreasonable.
These were all for $\alpha \rightarrow \alpha \frac{18}{15}$ chosen ($\alpha \rightarrow \alpha$ would have more negative ratios)

ball: The ~~value of τ^2~~ $\frac{0.18}{(15, 16 \text{ or } 17)} - \frac{E}{\tau^2}$ is only ~~2000~~ ~~of τ^2~~ .
 It does, hrs, give us a d.f. for τ^2 . If $x_0 < 0$, t. d.f. for τ^2 is close to β .



— we have to multiply d.f. by τ ~~prop~~ of τ^2 , which cuts off the neg. part. — t. d.f. is given, ~~(τ^2)~~!

We can use a normal approx. for $\tau^2 > 0$, but we may want to cut off τ at

say .2 (since t. Bartley Aves are like .2 to .9. : we may want ~~to~~ $E(\tau^2)$.)

T. above analysis ~~can be done~~ is of uncertain value, unless we τ^2 is close to 0 or τ^2 has a narrow and peak ~~to~~ for that peak to be used as an estimate of τ^2 .



A more exact method would be much less "cl." — ~~is~~ ~~we~~ we would use ~~all~~ ~~values~~ of τ^2 .

Probably the best way would be closer to the "BA" method, in which

I compute total prop. for ~~the~~ corpus w. a w.o. a "normal".
 ~~$E(\tau^2)$~~ Most likely τ^2 is most cl.
 $E \tau^2$ is most.

$$E(x_i) = 10^2, 0) : \text{total form } E\left(\frac{\tau^2 x_i + A_i}{\tau^2 + B_i}\right)$$

i.e. $M_i^2 E\left(\frac{\tau^2 + A_i}{\tau^2 + B_i}\right)$ A_i, B_i are constants \approx slightly $E\left(\frac{1 + \frac{A_i}{\tau^2}}{1 + \frac{B_i}{\tau^2}}\right)$

~~total~~ ~~and~~ ~~compute~~ ~~from~~ $E\left(\frac{1}{\tau^2 + B_i}\right)$ and $E\left(\frac{\tau^2 B_i}{\tau^2 + B_i}\right) = E(1)$

so we just shift $\frac{1}{\tau^2}$ in the ~~direction~~ direction by B_i .

$$\int_0^\infty e^{-\frac{(x-x_0)^2}{2\tau^2}} \cdot \tau^2 \cdot \frac{1}{\tau^2 + B_i} d\tau \text{ which } \tau > .21 \text{ amounts to } \int_0^\infty \frac{e^{-\frac{(x-x_0)^2}{2\tau^2}}}{e^{-\frac{x^2}{2\tau^2}}} \cdot \frac{1}{\tau^2 + B_i}$$

amount to $\int_{x_0}^\infty \frac{e^{-\frac{x^2}{2\tau^2}}}{e^{-\frac{x^2}{2\tau^2}}} \frac{dx}{x+C_i}$ x_0 & C_i are ~~2~~ \geq params. C_i perhaps $\frac{y_0}{s} \approx \frac{C_i}{s}$

3.30.99 AH! Consider M. Corp data: As $N \rightarrow \infty$, the d.f. for R should become quite sharp! Essentially we have these "exact" values for t. $[M_i]$ set and we want their cov. If t. eqs do not (analytically or "experimentally" $\left(\approx$ M. Carlo simulation) show this, then there is something wrong w. t. eqs.

Note also, that while I have broad largish N for the Biscuit data sets I've not heard large k for the M. Carlo set. Larger k can have a somewhat different effect on t. R d.f. than large N (?).

So; do a Poisson analysis of $N \rightarrow \infty$: see what t. d.f. looks like for liberal R, \bar{u} .
 T. d.f. will have 2 params: Then for finite N , try to match to R, \bar{u} for that D.f. (usually), $x \cdot \bar{u}$ will have a narrow d.f. ~~to~~ so as its more like 1 param desc by t. d.f.

T. factor of most interest is 46.28 is $\prod_{i=1}^k \frac{(x+A_i)(y+B_i)}{(x+y+N+1)}$
 The factor $\left(\frac{x+y+1}{x!y!}\right)^k$ is relatively simple, in terms of \bar{u} & R .

$$\frac{A!B!}{(A+B)!} \approx \int_0^1 u^A (1-u)^B du \quad ; \quad N \approx A+B; \quad u = \frac{A}{N} = \frac{A}{A+B}$$

63
+PC

(SN) Consider $u=1$ for finite N to expect $R \rightarrow \infty$ to be mainly at ∞ .

Then x falls: $\approx \frac{x!y!}{x!y!}$ so for $R \rightarrow \infty$: $(u^A (1-u)^B)^R \cdot (u^A (1-u)^B)^N$

which \rightarrow exp exponentially as $(u^A (1-u)^B)^{R+N}$ \rightarrow Reservoir < 1 .

Here, x exponent is $R-u$: for $R < N$, the value is small.

Or just try fitting R, R , out. data set $\{u_i\}$ - assuming all the u_i were exactly

Correct (i.e. $N \rightarrow \infty$)

$$PC = \prod_{i=1}^N u_i^R (1-u_i)^R = \prod_{i=1}^N u_i^R (1-u_i)^R \quad A \equiv \prod u_i; \quad B \equiv \prod (1-u_i) \quad \left| \begin{array}{l} A < 1 \\ B < 1 \end{array} \right.$$

$$PC \approx (A^R B^R) / (A^R B^R) \quad \text{Partners with Normalized constants for } X, Y! \quad \left| \begin{array}{l} A' \equiv A^{\frac{1}{2}} \\ B' \equiv B^{\frac{1}{2}} \end{array} \right. \quad \text{if } R \neq 1$$

$$\frac{x!y!}{x!y!} \approx \frac{1}{2} \cdot (u^A (1-u)^B)^R \quad u > A \quad \frac{A+B}{2} \quad (A+B)^2$$

$$\approx \sqrt{\frac{R}{R \cdot u \cdot R(1-u)}} \quad (1-u) > B$$

$$\approx \sqrt{R} \cdot (u+B)^{-R}$$

Reservoir u

So $\frac{1}{R} \leq \ln A \leq \frac{1}{R}$
 $\frac{1}{R} \leq \ln B \leq \frac{1}{R}$

log of norm n
> mean log.

so, so $A' \equiv A^{\frac{1}{2}}, B' \equiv B^{\frac{1}{2}}; \quad PC \approx \left(\frac{A'}{u} \right)^u \left(\frac{B'}{1-u} \right)^{1-u}$ Partners wrong! Score (2.13)

PC of $(1-u)^R \cdot R^{\pm}$

so ϵ determines peak width of $d.f.$

PC $\sim e^{-\epsilon R} R^{\pm}; \quad \ln PC \approx -\epsilon R + \frac{1}{2} \ln R$

So $R = \frac{1}{2\epsilon}$ $\frac{d}{dR} = -\epsilon + \frac{1}{2R} = 0$

we can probably estimate ϵ from the variance of the data set $\{u_i\}$.

We could see if it is close to R that we'd get from known σ^2 of $\{u_i\}$.

Probably easiest: just check by finding $(e^{-\epsilon})^{\frac{1}{2}}$ of a binomial data

then compares it w. σ^2 of $\{u_i\}$ data set.

$$\int_0^{\infty} t^2 e^{-t} dt = 2!$$

32 correct σ^2 of data set should be $\frac{u(1-u)}{R} = u(1-u) \cdot 2\epsilon$

33 t peak is very broad, here: $e^{-R} \cdot \sqrt{R}$; what is width?

For first 3 moments are $\frac{1}{2}!, \frac{1}{2}!, 2 \frac{1}{2}!$
 $\mu = \frac{m_1}{m_0} = \frac{1}{2}$ $\Gamma(\frac{1}{2}) = \sqrt{\pi}$ $\frac{1}{2} \sqrt{\pi}$
 $\sigma^2 = \frac{m_2}{m_0} - \left(\frac{m_1}{m_0}\right)^2 = \frac{3}{2} - \left(\frac{1}{2}\right)^2 = \frac{3}{2} - \frac{1}{4} = \frac{5}{4}$
 $\mu = \frac{3}{2}$; but peak is $\frac{1}{2}$!

$\frac{1}{2}! = m_0 = \frac{1}{2} \sqrt{\pi}$
 $\frac{1}{2}! = m_1 = \frac{1}{2} \sqrt{\pi} \cdot \frac{1}{2}$
 $2 \frac{1}{2}! = m_2 = \frac{1}{2} \sqrt{\pi} \cdot \frac{3}{2}$

Handwritten notes on the left margin, including "Correct" and "1/2!"

Wrong!
11.33 is correct

Since $\int_0^\infty x^n e^{-x} dx = n!$

$m_0 = 1!$
 $m_1 = \frac{1}{2}! = (-\frac{1}{2}!) \times \frac{1}{2}$
 $m_2 = \frac{1}{2}! \times \frac{1}{2} \times \frac{3}{2}$

$\mu = \frac{m_1}{m_0} = \frac{1}{2}$
 $\sigma^2 = \frac{m_2}{m_0} - \mu^2 = \frac{1}{2} \cdot \frac{3}{2} - (\frac{1}{2})^2 = \frac{3}{4} - \frac{1}{4} = \frac{1}{2}$

Yes, $\int_0^\infty x^n e^{-x} dx = n!$ but
 No! 11.33 is correct:
 f. funct is $e^{-R} \cdot R^{\frac{1}{2}}$
 $m_0 = \frac{1}{2}!$
 $m_1 = \frac{1}{2}! = m_0 \cdot \frac{3}{2}$
 $m_2 = 2 \frac{1}{2}! = m_0 \cdot \frac{3}{2} \cdot \frac{5}{2}$
 $\mu = \frac{m_1}{m_0} = \frac{3}{2}$
 $\sigma^2 = \frac{m_2}{m_0} - \mu^2 = \frac{3 \cdot 5}{2 \cdot 2} - \frac{3 \cdot 3}{2 \cdot 2} = \frac{15}{4} - \frac{9}{4} = \frac{6}{4} = \frac{3}{2}$

So $\mu = \frac{3}{2}$; $\sigma^2 = \frac{3}{2}$, \Rightarrow 11.33: kvr, peak is $\frac{1}{2}$!
 The peak of $x^{\frac{1}{2}} e^{-x} =$ peak of $\frac{1}{2} \ln x - x$: $\frac{1}{2} x = 1 \Rightarrow x = \frac{1}{2}$

So, no matter how large k is we don't have μ certainly in σ^2 !! This sounds crazy!

Contrast with Gaussian fitting

13. O.H. I may see it! 11.20 is wrong. $1 - \epsilon = \left(\frac{A}{U}\right)^k \cdot \left(\frac{B}{U}\right)^k \left(= \frac{A}{U^k} \cdot \frac{B}{(U-u)^k} \right)$
 So in 11.20: $p(x) = (1 - \epsilon)^{kx} \cdot R^{\frac{1}{2}} = e^{-\epsilon k x} R^{\frac{1}{2}}$: ϵ depends on var of $[u_i]$ dat.

~~part~~ $\ln p(x) = -\epsilon k \cdot x + \frac{1}{2} \ln R$: $\epsilon k = \frac{1}{2R}$: $R_0 = \frac{1}{2\epsilon k}$ peak.

18. $\mu = 3R_0$ ~~XXXXXXXXXXXXXXXXXXXX~~ $\sigma^2 = 3R_0$ also.

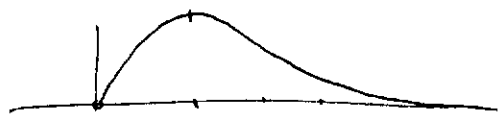
$p(x) = \left(\frac{A}{U} \cdot \frac{B}{1-u}\right)^k R \cdot \sqrt{R}$

$\left(\frac{A}{U} \cdot \frac{B}{1-u}\right)$ is expected to be close to 1
 \Rightarrow not ind. of u .

18 is unremarkable! $\Rightarrow 3R_0$ becomes large,
 Its var $\frac{\sigma}{\mu}$ is $\frac{\sqrt{3R_0}}{3R_0} = \frac{1}{\sqrt{3R_0}}$ becomes small
 - in which case we expect μ & peak to be close.
 They are not!

So $\hookrightarrow 1 - \epsilon$ from 32 wrong we expect.
 var of $[u_i] = \frac{U(1-u)}{R}$ But do we use
 peak or 3rd mom.
 peak, for R ?

This is also wrong! $p(x) = (1 - \epsilon)^{kx} R^{\frac{1}{2}}$



ST 112: $s_0 = 0, s_1 = 0, s_2 = 20$
 for $x = 1$ to ∞ step .001
 $\sum_{i=0}^{\infty} \exp(-x) \cdot \text{sqrt}(x)$
 $s_0 = s_0 + y$
 $s_1 = s_1 + y \cdot x$
 $s_2 = s_2 + y \cdot x \cdot x$
 Next $U = \sqrt{s_2}$
 Print $U, s_2/s_0 = U \cdot U$
 1.5 1.5

Cost
~~2.22475~~
~~2.22679~~
~~2.22785~~
 $\int_0^\infty e^{-x} \cdot \sqrt{x}$
 $U = 1.5$
 $\sigma^2 = 1.5$ as calculator. $(e^{-x} x^{\frac{1}{2}})$ has peak at $x = 1.5 = \frac{3}{2}$
 $(e^{-x} x^{\frac{3}{2}})$ has peak at $\frac{5}{2}$.
 $\cdot -x^{\frac{1}{2}} + \frac{1}{2}x^{-\frac{1}{2}} = 0$
 $\pi = \frac{1}{x} \cdot x = 1$

peak is $1.5 = \frac{3}{2}$ calculated

| | | | | | | | | | | |
|---|-----|-----|-----|------|-----|-----|-----|------|------|------|
| x | 0.5 | 1 | 1.5 | 2 | 2.5 | 3 | 4 | 5 | 6 | 7 |
| y | .4 | .42 | .41 | .367 | .27 | .19 | .13 | .096 | .076 | .062 |

Going over 11.10 off more carefully

$$P_C = \prod_{i=1}^k \frac{x+y+1}{x!y!} u_i^x (1-u_i)^y$$

$$(R+1) \sqrt{\frac{R}{R \cdot u \cdot R(1-u)}} \left(\frac{u}{1-u} \right)^{-R} \cdot u_i^x (1-u_i)^y \Rightarrow \propto \left(\frac{u}{1-u} \right)^{-R} \cdot \left(\frac{u}{1-u} \right)^x \cdot (1-u)^{-y} R$$

for $k \gg 1$. ~~$P_C \propto R^{\frac{k}{2}}$~~

So I forgot to put $k^{\frac{k}{2}}$ inside $\prod_{i=1}^k \frac{1}{R}$ so $\rightarrow R^{\frac{k}{2}} \cdot \left(\frac{A!}{U} \right)^U \cdot \left(\frac{B!}{U} \right)^{1-U} k R$.

I.e. $(R^{\frac{k}{2}} (1-u)^k)^k \approx R^{\frac{k}{2}} e^{-kR}$ $(-E) \approx \left(\frac{A!}{U} \right)^U \cdot \left(\frac{B!}{U} \right)^{1-U}$

Looks more reasonable:

$R^{\frac{k}{2}} e^{-kR}$ has a peak at $R_0 = \frac{1}{2E}$; first moment $\approx \frac{3}{2} R_0 = \mu$
for $k=1$ μ width \approx standard deviation $\sigma =$ about μ is $\sqrt{\frac{3}{2}} \cdot R_0$

However, as $k \uparrow$, P_C peak stays at $R_0 = \frac{1}{2E}$, but the d.f. gets narrower and narrower so $P_C \mu$ moves forward for peak is or gets smaller. ▣

This is the kind of behavior ~~is expected~~!

$$\int_0^{\infty} R^k e^{-\alpha R} dR = \frac{1}{\alpha^{k+1}} \int_0^{\infty} x^k e^{-x} dx = \frac{k!}{\alpha^{k+1}}$$

$\alpha R = x \quad R = \frac{x}{\alpha} \quad dR = \frac{dx}{\alpha}$

$R^{\frac{k}{2}} e^{-kR}$; $k = \frac{k}{2} \cdot \frac{k}{2} + 1, \frac{k}{2} + 2$; $\alpha = k$

AH: k is an implicit param. Indip of N , \uparrow peak is at $R_0 = \frac{1}{2E}$

$$M_0 = \frac{k!}{k^{\frac{k}{2}+1}} \quad M_1 = \frac{\frac{k}{2}! \cdot \frac{k}{2} + 1}{k^{\frac{k}{2}+1}} \quad M_2 = \frac{M_0 \cdot \frac{k}{2} + 1 \cdot \frac{k}{2} + 2}{(k^{\frac{k}{2}})^2}$$

$\frac{1}{2R} = kE$
 $R_0 = \frac{1}{2E}$

$$\mu = \frac{\frac{k}{2} + 1}{kE} \quad \text{for } k \gg 1; \mu \approx \frac{1}{2E}$$

$$\frac{M_2}{M_0} = \frac{(\frac{k}{2} + 1)(\frac{k}{2} + 2)}{k^2 E^2} \approx \frac{1}{(2E)^2} \quad \text{for } k \gg 1.$$

but $\frac{M_2}{M_0} = \mu^2$ (skewness due to non-normality)

$\mu = \frac{k!}{k^{\frac{k}{2}}}$ $\frac{M_2}{M_0} = \frac{k! \cdot k!}{k^2 E^2}$ $\sigma^2 = \frac{M_2}{M_0} - \mu^2 = \frac{1}{k^2 E^2} \left((k! + 1)(k! + 2) - k!^2 \right)$

$$\frac{3k! + 2}{k^2 E^2} = \frac{3k + 2}{k^2 E^2} \approx \frac{3}{2kE^2} \quad \text{for } k \gg 1$$

$\approx \frac{3 \cdot 2}{k} + \frac{1}{(kE)^2} \approx 6 \approx \sqrt{\frac{6}{k}} \cdot \frac{1}{2E} = R_0$

so \leftarrow with opt. peak is $\sqrt{\frac{6}{k}}$ times \leftarrow R_0 value of \uparrow peak.

Final! — But k has to \uparrow faster w/ opt narrow peak. (even if $N \rightarrow \infty$), we need larger k for narrow peak.

32

Now consider $k \rightarrow \infty$, but N is finite; T. simple approach 108.01 — 110.25 would probably give quick results, but not nearly easy to apply to P_C Model of 46.28

The main q is — why 46.28 doesn't have a peak at all.

→ But I can easily check my old pems to see what happens w. $k \uparrow$ is $\approx N \rightarrow \infty$. on 47.10 — 22 I got N up to 1200. The peak stabilized at $R = 40$, but the width of the peak stayed constant as $N \uparrow$ — as expected. I'd need to $\uparrow k$ in order to narrow the peak.

40

I'd probably need Monte Carlo help to verify it empirically. → 116.09 spec

A discrepancy thing about $47.13 - .20$; t paid was at $u = .255$ rather than $.25$.
 The difference in G was quite small, but: $\Delta G = .16$ betw $u = .255$ & $.25$; $\approx 16\%$.
 Some deriv of this \downarrow on 75.20 ft

$N=300$ for $e^G = 0$ at $R=0$ & ∞ . (E Risk) $\rightarrow e^G = (R \pm e - eR)^L$
 so maybe its finite N derivatives $e^G > 0$ & $\frac{R_0}{R_0} = \frac{1}{1000}$.

The IT doesn't seem very reasonable!

I could write up a clear summary for Alex (i myself!)
 See if he can find any bugs in Reasoning.

101
 103 ST
 186
 109
 Final Post 55
 2 3 4 5
 1 x 1001

ST114

I was concerned w. t. (ed of smoothness) ST/100 output!

I.e. $A(c,c,3) - 1000 \times u$
~~BA~~
~~1000 x u~~
~~1000 x u~~
~~1000 x u~~
 T. results were a smooth function
 of $A(c,c,3) - 1000 \times u$.
 Which I found disturbing.
 See $100 \frac{1}{2}, 3$: last column.

I ran ST100. Bas is modified.
 $A(c,c,3) - 1000 \times u$
 $A(c,c,4) - 1000 \times u$
 $R = ST$
 See 114 1/2 output. last column: It looks as
 bad as, maybe worse! This is surprising, because
 the ST pfm is fairly simple, & one would expect
 smooth output

This is still a bit
 for output to be

On the other hand, the ST pfm, ~~shrinks~~ multiplies R_i u_i 's by shrinking their terms ($N^2 \sin^2(2k-1)$)
 toward to mean of R_i terms. — Then inverts f. known mass
 "shrink" R_i 's. In general, t. ~~mean~~ mean of R_i 's,
 if not same as R_i of t means — so this could give
 much error near to mean, ($A(c,c,3) \approx 1000 \times u$).

Woff 112 relaxes some of my anxiety about my "BA" pfm!

T. other: discrepancy is cu how results seem to be much dependent on
 just what applied one uses. I could see how t^2 gave t (say MS or Log, etc)

for error for produs, change of w. change of t^2 :
 → Did I do this already? $104.03 - .18$ looks like that → But they have to be done more carefully!
 $\frac{e^G}{1+R}$ correction term was in appropriate.

A poss. reason why I've been having trouble: $t^2 + \overline{G_i^2} = \sum^2$
 ↓ $\frac{1}{N}$ var of total $\{u_i\}$

since N is "small", $\sum^2 \approx \overline{G_i^2}$ see lots of error in t^2 : $\sum^2 - \overline{G_i^2}$ could < 0

In such a case perhaps split into is very impr. [R_i in present case, when
 we are uncertain about t^2 & we know its > 0 , then, error in t^2 isn't so small.

in assigning wts to \bar{u} & u_i (in estimating u). In the present case $\sum^2 - \overline{G_i^2} < 0$
 here let t^2 be ϕ w. much trouble.

(NB) final result! Once t^2 is known, it's easy to get t . D.f. for each u_i . — This is done in a Bayesian way.
 If u_i is observed, it is the result of a choice of u_i (w. probab. $N(\bar{u}, \sigma^2)$), followed by a choice
 of u_i w. probab. $u_i: N(u_i, \sigma_i^2)$. T. product of these \geq causes it to d.f. of u_i . Its mean is t w. d.
 mean of \bar{u} & u_i ; wts are $\frac{1}{\sigma_i^2}$ & $\frac{1}{\sigma^2}$, resp.

Notes for a Review: Things to include

45
126, 138, 143
78, 80, 90, 115, 124

Inclusion of 78
90 - Monte Carlo
90 - ST 90

- 1) Previous reviews, 52.01 (Mainly empty shell)
- 2) List of papers - (from "history") - & what they do: Which ones have h.c. output.
(Note from the Generation of Mt Carlo Corpus [STB] ST 109)
- 3) List of various approaches to ST: Bibliog. of each & which papers dealt with each - for both Generation & Testing. (see 3)
- 4) What are main conclusions? Best ways to Approximate → 6
- 5) What are main unsolved ("open") problems? - Uncertainties.
- 6) (Related to 4): Describe in a clear way, the main approaches used: e.g. t. Marquet (1) 08.01-11.40, (2) 46.02; 46.28ff (3) 12.12-12.40

The "ruthlessness" of estimating sequences.
The "k=3" effect
Wasserman's $\frac{1}{2} \sin^{-1}(2x-1)$ form
Was legit.
How to spread sources to minimize results excessively.

7) GENESIS of STEIN: (EAM had a version that is more verbose); A Big Genesis is to Monte Carlo Another (More culture) is to MIXD Games Theory.
8) Compare Empirically, using Mt. Carlo data, to various Approaches [STB to Mt. Carlo factor]

107 main disc rd
Support of exp's correct
is affected by sample, also 26.01
47.10-22 Support d.t. for large R see 94.14
D.P. of R30, 80!
49.20: R=0
50.20 different from 66 in that (20) for R=22 constant.

My impression of ~~the~~ main implications:

- 1) 46.02 - 46.28 The Binomial d.f. w. ~~from~~ STB A.D.S. (then finally, integration over R) then used integrals to estimate $E[M_i X]$ (ST 101).
- 2) Extension of Reproduction of EAM's work of computing ST using $\sqrt{N} \sin^{-1}(2X-1)$ form.
- 3) Criticism of D1: Most Serious: That results depended ~~on~~ Approach for R

116.32 - 120.40: ON
Gauss D.F. Results
Seem ~ to predictor
ST100, ST101

99.28: -100.40: final results using proper ~~approach~~ to calc v_i 's: Results are "ragged"

ST100 & implements ~~subsets~~ "ragged" results.
ST101 (cleaner form of ST100)

ST103: Computation of "STEIN" values using $M_i \sin^{-1}(2X-1)$

104.03: Working of $[M_i]$ using direct spreads for R! (Hvr, serious error in calc) do this again (IAPT!).

10x.04: 27 More on EAM STEIN
106.01-40

105.28: Paper ST 101. ~~much~~ improved \int integrated w.r.t. R also

107.01: Revised effect of σ^2 on sharpness of D.F. Best Approx is applied.

108.01 - 114.46: Earlier approach using Gaussian d.f. Very reasonable, very simple: for varying σ^2 : Here, I don't know why G is used (k=3) rather than (k=2) or why (k=2) was used

Approach can be used w. Binomial d.f. - also effect of spread of R can be studied.

62.01 - 69.10: Gaussian Model
69.11... Back to Binomial D.F.
74.03: Good approx $\frac{x!y!}{(x+y)!} = \left(\frac{x}{x+y}\right)^x \left(\frac{y}{x+y}\right)^y$

76.25: Comparison of $\frac{1}{2} \sin^{-1}$ of Bin. d.f.'s
something done this better elsewhere
STB A.D.S. Integration of RC w.r.t. R with spread $\frac{1}{2\sigma}$, $\frac{1}{R_2}$, $\frac{1}{R_1}$

STEIN Approach given 86.12 - 87.20

89.22 \int_0^1 : lower bound α

Found not critical. \Rightarrow is impl. hvr.

94.14: Use of test data set Common (large) N for all players see 4.10

95.01 ft working of wrong integrals!

97.01 - 10 EAM "final" v.g. spac
was based on estimates.

→ 12.40!

I want to write down the d.f. of the square of $V = \sum_{i=1}^k V_i$; what happens to

$$\sum_{i=1}^k V_i^2 \text{ v.s. } \left\{ \begin{aligned} \sum (V_i - c)^2 &= \sum V_i^2 - 2c \sum V_i + kc^2. \quad | \text{ say we let } c = \frac{1}{k} \sum V_i \\ &= \left(\sum V_i^2 \right) - \frac{1}{k} \left(\sum V_i \right)^2 \end{aligned} \right.$$

That's 2 formulas, one correct/valid, - giving trouble!

107

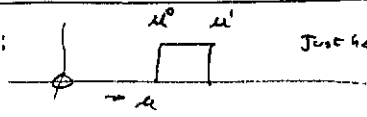


find d.f. of V^2 as a function of d.f. of V .
 Para: " " $(V - \alpha)^2$ " " " " " $V - \alpha$.

Also, I think b.

Each d.f. has a mean, & the mean of sum is sum of means.

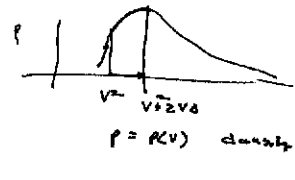
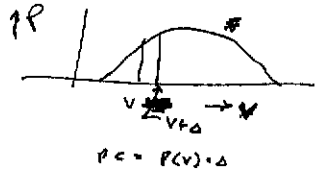
09:18.40 (SN) 19.40: One way to do $k \rightarrow \infty$: Just have a bunch of uniformly dense values of V_i from μ^0 to μ^1 .



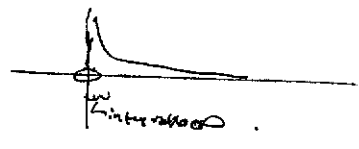
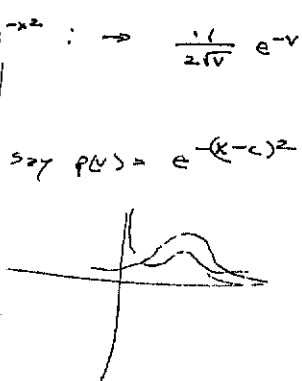
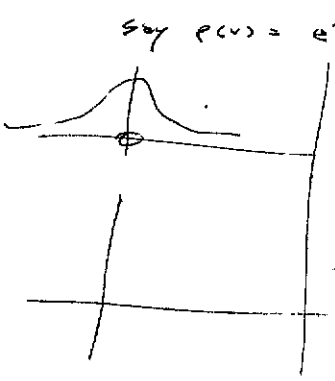
Then the density of data pts in that range; This would be in $N = \infty$, hrr. Easy to analyze, hrr. \rightarrow

Now, by each of the (dense) data pts has a 'column' of z . (or a $\pm \sigma$), (Still unclear)

$$(V - c)^2 = V^2 - 2cV + c^2.$$



Say $V = \sqrt{U}$ density = $\frac{P(\sqrt{U})}{2\sqrt{U}}$



Say $P(V) = e^{-x^2} : \rightarrow \frac{1}{2\sqrt{V}} e^{-V}$

Say $P(V) = e^{-(V-c)^2}$

$$\rightarrow \frac{1}{2\sqrt{V}} e^{-(\sqrt{V}-c)^2} = \frac{1}{2\sqrt{V}} e^{-V + 2\sqrt{V} \cdot c - c^2}$$

This may be convertible to the normal moment of $e^{-(V-c)^2}$.
 So maybe some function of $\frac{c}{\sqrt{V}}$.

So, if one has a bunch of V_i , their squares will be independent, $(V_i - c)^2$'s will be independent.
 Getting μ & σ^2 of $(V_i - c)^2$ may not be easy hrr. but one might know the μ & σ^2 of V sum, & easy.

32: **Normal PE 62-68**: This really looks like fitting unless we use the "2" eq.

$k+2$ params to k data pts!

But more of 62-68: A basic idea: we start w. unknown μ, σ^2 ; [41] w. known [45, 65, c].
 It seems to be linear params, the pc of the corpus is:

37: $\prod_{i=1}^k \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(V_i - \mu)^2}{2\sigma^2}} = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(V_i - \mu)^2}{2\sigma^2}}$ Next, we integrate each factor & $\int_{-\infty}^{\infty} dV_i$.

38: $\int_{-\infty}^{\infty} e^{-Ax^2 + Bx + C} dx = \int_{-\infty}^{\infty} e^{-A(x - \frac{B}{2A})^2 + \frac{B^2}{4A} + C} dx = \sqrt{\frac{\pi}{A}} e^{\frac{B^2}{4A} + C} \approx \frac{1}{\sqrt{2A}}$
 $b = 2\sqrt{A} \cdot V \Rightarrow V = \frac{b}{2\sqrt{A}}$
NO! $\int_{-\infty}^{\infty} e^{-\frac{x^2}{2\sigma^2}} dx = \sqrt{2\pi}\sigma$

On to (Binomial) d.f. version: If we decide on an R, N value, this is equiv. to an opt. | $A \leq R$
 $M^A (1-M)^B$ & Using Stirling's "Rule" determine its equiv. from, for M , $B \leq N-R$

of $M^A N + A$ bits and $(1-M)^B N + B$ bits so, $B \leq \frac{M^A N + A}{M + R}$: This is obtainable by setting
 prodns from $M^A (1-M)^B \cdot M^{M^A N} (1-M)^{(1-M)^B N} = M^{A+M^A N} (1-M)^{B+(1-M)^B N}$.

which, using Lap's rule gives $M_2 = \frac{A+M^A N+1}{R+N+2}$ (E.P.M.A), (So ≈ 48.01)

.08 This suggests, that if $P(R)$ is the d.f. for R - obtained via STG, say.

.09 then M_2 should be $\int_0^\infty P(R) \frac{A+M^A N+1}{R+N+2} dR$. - which is ≈ 81.17 ft, 85.03,

hence ST96 then finally ST100 & ST101 I switched over to a very general (correct) way of doing Precision Probs. - However, I think the results should be to same as .09 - it may be possible to show that these 2 methods are mathematically equivalent.

I had been using .09 because it was in literature reasonable - but probably it's exactly right. (It may only be a v.f. approx, but... this would have to be worked out in detail.)

on the Gaussian Approach of 108.01-114.40: Attempts at a clear, exact discuss.

Suppose the data set $\{u_i\}$ was generated from by first choosing μ_i , from $P_i(\mu_i)$, z d.f. of known mean, μ , but unknown var, τ^2 . μ_i is then generated using a (say Gaussian) d.f. of mean μ_i & known var, σ_i^2 .

We want to make measurements on the data set, that will enable us to estimate τ^2 .

First say we know τ^2 & and $P_i(\mu_i)$, but we don't know the $\{u_i\}$

What would be the expected var of the $\{u_i\}$ set?

.13 SN Actually, ~~in the~~ in the baseball case, if we know μ and τ^2 (or more exactly, expected if we know $P_i(\mu_i)$, the final d.f. of the set $\{u_i\}$ is completely determined:

Monte Carlo wise: Get $P_i(\mu_i)$ to pick a μ_i : Then using N trials, w. probly u_i for a hit, generate a Monte Carlo u_i . We sample n times to obtain a sample. Each time, we can measure the var. of the final d.f.

(μ_i determined from its mean). For each value of τ^2 we will get a d.f. of var

See 12.2, 3.2 for sample exact way!

↓

Not really, 12.2, 3.2 get d.f. of obtaining individual $\{u_i\}$ set just observed. var about 0.

We then look at the var of the two sample $\{u_i\}$, from .20, using Bayes, we

.23 can set the d.f. of τ^2 .

From τ^2 , we can know $P_i(\mu_i)$ and for each i , τ^2 is invariant d.f. of $u_i = P_i(\mu_i) \cdot u_i^{u_i \cdot R} (1-u_i)^{(1-u_i) \cdot R}$.

Since we don't know τ^2 exactly, but only know a d.f. for it, the d.f. for u_i

.24 becomes $\int d\tau^2 \left(D(\tau^2) \cdot P_i(\tau^2, u_i) \cdot u_i^{u_i \cdot R} (1-u_i)^{(1-u_i) \cdot R} \right)$

Here $D(\tau^2)$ is the density of τ^2 : obtained from .20 & .23

Actually, what we want is the probly of a hit at player i 's next "at bat"

& expected value of u_i in .27 may be about it. (put ~~the~~ u_i under

the \int sign & ~~integrate~~ integrate w.r.t u_i as well as τ^2 . I f. $P_i(\tau^2, u_i)$ is

of the form $u_i^A (1-u_i)^B$ (which is reasonable to do) then f. \int w.r.t u_i is easy $\frac{1}{R+1}$.

we have $\int d\tau^2 \left(\frac{(x + u_i \cdot R)! (y + (1-u_i) \cdot R)!}{(R + N + 1)!} \right)$
 $\tau^2 = \frac{u(1-u)}{R}$: $x \in [0, R]$, $y \in [0, R]$. so $R = \frac{u(1-u)}{\tau^2}$

Is there any way to do .20-.23 analytically? (not M.C. or B.)

Even if it. Ideas as .13 if could be practically implemented by M.C. or analytical calcs, I think the script for τ^2 would still be very imp.

So, our (tentative, tho strong) conclusion: That for data sets in which τ^2 is small, the script of τ^2 will be very imp. — This will be true whether one uses Gaussian,

4.33 S.M.P.T.

Binomial dist. or any other d.f. If one uses E.M.'s method, one ends up taking a difference between 2/ noisy values. The uncertainty of this difference is very large.

Which to people seems critical in determining τ^2 when τ^2 is small, what is not clear is how much MS error or log-likelihood are affected by ~~error~~ error & a definition of spread of τ^2 (or of R).

If R is uniform between 0 & 1, $\frac{1}{R}$ has density $\frac{1}{R^2}$; $R \sim \frac{1}{R}$ so density $\propto \frac{1}{R^2}$
 If R^2 is uniform between 0 & 1,

σ uniform between 0, 1 $G \rightarrow G + \sigma$
 $\frac{1}{G} \rightarrow \frac{1}{G + \sigma} \rightarrow \frac{2\sigma}{G^2}$; $\frac{1}{G} \rightarrow 1 + \frac{\sigma}{G}$

12

A quick method E.M.'s method: by using $X \rightarrow N^{\frac{1}{2}} \sin^{-1}(2X-1)$

Presumably σ_i^2 constant (indep of i): for k trials known \bar{u} is τ^2 , the d.f. of expected u_i^2 known is to calculate of 2 d.f.s: i.e. the d.f. $P_i(u_i)$ and the d.f. of center u_i is var = $\sigma_i^2 (\approx \sigma_i^2)$. So to have of u_i conv. is just $\tau^2 + \sigma_i^2$. We then measure var of $\{u_i^2\}$ & subtract out σ_i^2 , to get τ^2 .

If the σ_i^2 are not all the same, then each x_i has its own d.f.:

Its mean is \bar{u} its var is $\tau^2 + \sigma_i^2$. ~~variance~~ ~~to~~ to expected value (mean) of $(u_i^2 - \bar{u}^2)^2$ is $\tau^2 + \sigma_i^2$. (w. a certain second moment).

The expected value of $\sum_{i=1}^k (u_i^2 - \bar{u}^2)^2$ is $\sum (\tau^2 + \sigma_i^2) = k\tau^2 + \sum \sigma_i^2$.
 so we can easily solve for τ^2 , since $\sum (u_i^2 - \bar{u}^2)^2 \approx \sum \sigma_i^2$ is known

24

Then is, how to $k-1$, $k-2$ or $k-3$ correction for $\sum (u_i^2 - \bar{u}^2)^2$.

12-24 seems like a very quick and dirty way to understand the Stem Approx.

One could determine whether $k-1$, $k-2$, or $k-3$ is best, by Monte Carlo simulation

— Her, an apparent imp error in 12-24! That σ_i^2 & u_i^2 are functionally related (i.e. "highly correlated"). 12.1, 13.4 deals very explicitly with this concern.

32: 12.20

Given \bar{u} , R & N , the exact dist. is $M_i X + N u_i (1-u_i)^Y + N(1-u_i)$ ← More likely
 or is it $u_i^{X+N} (1-u_i)^{Y+N(1-u_i)} = \left(u_i^{\bar{u}} (1-u_i)^{(1-\bar{u})} \right)^{R+N}$

34: 32

$M_i^Y (1-M_i)^Y \cdot M_i^{u_i N} (1-u_i)^{(1-u_i)N} = \left(u_i^{\bar{u}} (1-u_i)^{(1-\bar{u})} \right)^R \cdot \left(u_i^{u_i} (1-u_i)^{(1-u_i)} \right)^N$

I don't know if it's easy to find first or second moments of 32 (34)

The 33 can one do $\int_0^1 du \left(u^{\bar{u}} (1-u)^{(1-\bar{u})} \right)^R \cdot u^x (1-u)^y$? for any fixed N , x , y

well, it's easy to do Numerically. So that solves 12.20 = 12.24

01 → Well, I'm beginning to understand the whole mess! - How to diffract approaches relate to one another.

(SW) fine excursion: if u_i is the prob of hit, what is the prob of A_i hits in N times at t ? Is it $P = C_i^N (u_i)^i (1-u_i)^{N-i}$ or P mult by $N!$ no. of diff. orders? i.e. $\frac{A_i! (N-A_i)!}{N!} = \frac{A_i!}{N(N-1)\dots(N-A_i+1)}$ (T. expression has to be invariant $A_i \rightarrow N-A_i$)

A good way to think about it is Monte Carlo simulation.

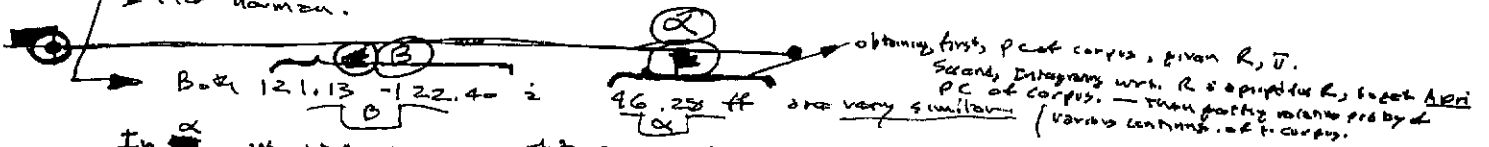
Note $(u_i + (1-u_i))^N = \sum_{j=0}^N \binom{N}{j} u_i^j (1-u_i)^{N-j} = 1$

So sum of all probs = 1. This amounts to a subtle correction in α, β

i.e. $\frac{A_i! B_i!}{N!}$, but since it's indep of x, y ($R=0$) it's not imp. in those contexts.

Hence, if at least cancels out to a factor $\frac{N+1}{A_i! B_i!}$; so we end up w. $(N+1)^k$.

→ after normal.



In α , we start w. given τ^2, \bar{u} or R, \bar{u} , or x, y ; and we find the prob that

the set $\{u_i\}$ was generated.

In β we look at $Z = \sum (u_i - \bar{u})^2$; starting w. the same τ^2, \bar{u} (at all)

of α , we ask, what is the prob of generating in k trials,

a data set $\{v_i\}$ with $Z = \sum (v_i - \bar{u})^2 = Z$. (we don't use it as a prob, but a density).

In $122=121+1$, we pick the "most likely" value of τ^2 ; for small "true" τ^2 , R 's

we can often be ≤ 0 . So, as in β , if we want a more precise answer,

we consider not the most likely value of τ^2 , but the d.f. of τ^2 .

If it were a narrow d.f. "most likely" would be fine, but it is not a narrow d.f.,

so we do have to consider the d.f., i.e. a prior, i.e. a prior does seem

to be imp.



I'm not really ^{sure} about T. a prior is imp the "exact" values of R ,

say, but in the large R case, that I was washing w , large

changes in R produce very small changes in G_{ave} (MS. ^{enough likelyhood} ~~log likelihood~~)

So it may be that T. a prior really is of much imp. w.r.t. G_{ave} .

115.40 Outline of Review: See 115.01 for many Impl ideas. Also see 15.01 for early review outline.

111.03 - 113.32
on N=00.

1) Derb. STEIN problems its parameters. (115.11)

2) Derb. various solns $\textcircled{E \approx M}$ (08.01 - ~~110.20~~ 110.20; This is ok.

E.g. $\uparrow z = \Sigma z = \frac{\Sigma x_i^2}{n} - \bar{x}^2 = \frac{1}{n} \cdot \frac{1}{n} \sum_{i=1}^n x_i^2 (1 - x_i^2) : \uparrow z = \frac{R}{N}$

But 121.13 - 122.40 gives a better understanding of the process.

(SN) on Smallest D.F. Define $B(A, B, X) \equiv X^A (1-X)^B$. $B_0(A, B) = \frac{A! B!}{(A+B)!} = \text{constant of } B(A, B, X)$
 B_1, B_2 are first, second moments $\mu = \frac{B_1}{B_0}$; $\sigma^2 = \frac{B_2}{B_0} - \mu^2$

Here, we can probably get moments of x^2 !

Step 1 $P(x)$ is only that x is betw. x_0 & x_1 .

Try x is betw x_0 & x_1 ; x^2 is betw. x^2 & $x^2 + 2x_1 x$. So Prob x is betw x^2 & $x^2 + 2x_1 x$ is $\frac{P(x)}{2x}$

So $P_1(x) = \frac{P(x)}{2x}$ Say $V \in x^2$; Then $P_1(V) = \text{prob } V \text{ is betw } V & V + 2x_1 \text{ is } \frac{P(x)}{2x} = \frac{P(\sqrt{V})}{2\sqrt{V}}$.

Which is density func for x^2 .

• 10
 • say $P(x) = B(A, B, X) := X^A (1-X)^B$; $P_1(V) = \frac{\sqrt{V}^A (1-\sqrt{V})^B}{2\sqrt{V}}$
 $= \frac{1}{2} V^{A-\frac{1}{2}} (1-\sqrt{V})^B$; to get moments, we want $\int_0^1 V^n \cdot \frac{1}{2} V^{A-\frac{1}{2}} (1-\sqrt{V})^B dV$.

can $\int_0^1 V^n (1-\sqrt{V})^B dV$. let $V = x^2$ $dV = 2x dx$; $\int_0^1 x^{2n} \frac{x^A (1-x)^B}{2x} 2x dx = B_{2n}(A, B)$ (!)

⚠ This seems too simple! This if $P(x)$ were some other D.F. say, from $0 < x < \infty$ or from $0 < x < \infty$, the eq. would be as simple!

On second flat, it seems reasonable. When we want 1. first moment of x^2 , we want to expect values of x^2 .

Try it out numerically to test the idea.

If true, it would make it easy to get E. μ & σ^2 of x^2 for $P(x) = B(A, B, X)$.

To check, use lower A, B ; i. first moment, should be for x^2 should be E. square of μ .

$$\int_0^1 x(1-x) = \int_0^1 x - x^2 = \left[\frac{x^2}{2} - \frac{x^3}{3} \right]_0^1 = \frac{1}{2} - \frac{1}{3} = \frac{1}{6} = \frac{1! \cdot 1!}{3!} = \frac{1}{6} \quad \text{checks.}$$

$$\frac{\int_0^1 x^2 x^A (1-x)^B dx}{\int_0^1 x^A (1-x)^B dx} = \frac{\frac{(A+2)! B!}{(A+B+2)!}}{\frac{A! B!}{(A+B)!}} = \text{first moment} = \frac{(A+2)(A+1)}{(A+B)(A+B+1)} \approx \left(\frac{A}{A+B} \right)^2 \approx \mu^2 \text{ as expected.}$$

Second moment w/ $x^2 = \mu^2$

$$\sigma^2 = \frac{A+1}{A+B+2} \frac{A+2}{A+B+1} - \left(\frac{A+1}{A+B+1} \right)^2 = \frac{(A+1)(A+2)(A+B+1) - (A+1)^2(A+B+2)}{(A+B+2)(A+B+1)^2}$$

$$= \frac{(A+3)(A+2)(C+3)(C+5) - (A+1)(A+2)(C+4)(C+5)}{(C+2)(C+3)(C+4)(C+5)}$$

So 144.15 - .29 for simpler derivation & result & direction of result.

$\sigma^2 = \frac{x+1}{R+2} \cdot \frac{y+1}{R+2} \cdot \frac{1}{R+3}$ for $x > -1$ $y > -1$ works for $R > 0$ (I checked it too).
 $x = \mu R$; $y = (-\mu)R$; $x+y = R$
 This is ok, but I off am working on a different problem: i.e. second moment of σ^2 .

01.12.90 A General deriv. of the problem! In Sci Am May 77, pp 119 ff: ^{error} Efron & Morris's adverb. problem:
 k(=18) baseball players have ~~not~~ all been at bat only N(=45) times per year. Player i has
 batting average μ_i . We want probly that player i will have a hit next time at bat.
 If $N \gg 1$, then μ_i is a very good estimate. If N=1 or some small no., then
 $\bar{\mu} \equiv \frac{1}{k} \sum \mu_i$ is ^{is} ~~is~~ a much better estimate. The problem, then, is how much wt. do $\bar{\mu}$ & μ_i
 for various values of N.

In .01 we were using data from "related sources" to estimate each player's worth.
 In this case it seems clear that Stein's is legit. - but more generally, we can
 have other sources of data (e.g. football players, or data on monthly precipitation) -
 how now should we decide how much wt. to use?

Generalizing of Stein problem: (1) Meta-Analysis: How to use data from "related"
 studies (2) "T. Mixed Corpus Perm" also is a (somewhat) general ~~formulation~~ formulation
 and solution of the problem. T. bibliography in Sci Am art. gives a ref. to a
 paper by Efron & Morris on "Conzeus of Stein".

I will discuss a few ^{with} Conzeus of STEIN!

The "true" u_i were created by some ^{unknown} P.D. $P_0(u_i)$. Then from each
 u_i , ~~we~~ u_i' was obtained by a ^{$P(u_i')$} known P.D. (e.g. $N(u_i, \frac{u_i(1-u_i)}{N})$)

In the ^{most} ~~most~~ ^{problem of 0,1,} $P_0(u_i) = C \cdot u_i^x \cdot (1-u_i)^y$ is a reasonable form for P_0 .
 $0 < u_i < 1$; Using a Gaussian $P_0(u)$ ^{is not} ~~is not~~ ^{reasonable} because Gauss is born $\pm \infty$.

Have set $X = \bar{U} R$; $Y = (-\bar{U}) R$; \bar{U} is the mean of $P(u)$ and R is like $u_i' - u_i$.

The σ^2 of a d.f. is $\frac{\bar{u}(1-\bar{u})}{R}$.
 In the baseball problem, $P(u_i) = C \cdot u_i^{x_i} \cdot (1-u_i)^{y_i}$

Given \bar{u} , R and the data set $[u_i']$, the probability of the "true" averages being $[u_i]$ is

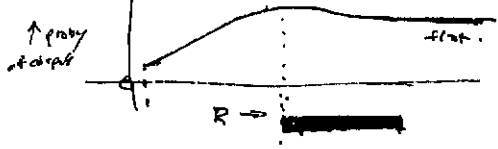
23
$$\prod_{i=1}^k \left(C \cdot u_i^x \cdot (1-u_i)^y \cdot u_i^{u_i' N} \cdot (1-u_i)^{(1-u_i') N} \right)$$

If we integrate over each u_i from 0 to 1, we obtain the probability that the set $[u_i']$ was obtained
 from the D.R. \bar{u} , R . - and from a Bayesian view. The resultant D.R. is a D.R.

for \bar{u} and R .! See 46.28 for the resultant integrated form of ⁽²³⁾

It ^{was} ~~is~~ easy to integrate over u_i , since $\int_0^1 x^D (1-x)^E dx = \frac{D! E!}{(D+E+1)!}$.

We have written ST46 to ^{compute} ~~the~~ ^{approx. 46.28} ~~integrate~~ ^{integrate} this. The D.R. is rather sharp in \bar{u} , but
 not at all sharp in R , so the data given by E.S.M. for $\bar{u} = \frac{1}{k} \sum \mu_i$, which is ~~the~~ ^{the} ~~only~~ ^{only}



The peak is very slightly $> R=200$
 The peak is at $R=30$ (perhaps)

4.999 SNAFU, STEIN.

.01 If the R d.f. were ≥ 5 sharp narrow peaks, we could use it to get good U_i values:

The d.f. for U_i would be (2.5.29): It has the form $U_i^k (1-U_i)^E$; so we can easily

.03 find its means (or peak) and variances (see 12.5.01-40 for how to do this)

For 4. data of ESM, since there is no peak, we may want to use the expected value of R. Since R ranges to $+\infty$, we need an approx for R. — such

as $\frac{1}{R^2}$ or $\frac{1}{R(\ln R)^2}$. Using such approxs, we can get $E(R)$, but this is not

a rigorous argument — (we would, presumably, use that R is m .01 - .03, to make products of U_i^k).

A better way: For each R we (assume we know \bar{U}), we can find an expected

.12 value of U_i : it will be $\frac{R \cdot \bar{U} + N U_i^k}{R + N}$: ~~roughly~~

~~to~~ to get $E U_i$ over all R, we integrate say $\int_0^{\infty} (4.9.28) \cdot .12 \cdot \left(\frac{1}{R^2} \text{ or } \frac{1}{R(\ln R)^2} \right) dR$

.15 This can be done numerically.

A better way (perhaps equivalent), is to use the general (but "exact" Bayesian approach. Given any data set $\{U_i\}$ we can assume the \bar{U} , R model at P_0 ,

and, by integrating over all U_i & R, we obtain the approx. of that $\{U_i\}$ set.

What is the relative probab that the j^{th} player will have a hit rather than an out on his next trial? Say $P(\{U_i\})$ is the probab we obtain in .17 for the data set $\{U_i\}$

Let S_j^0 be the "data set $\{U_i\}$ " but with $N \rightarrow N+1$ for player j and $U_j \rightarrow \frac{U_j \cdot N}{N+1}$ ("an out")

" S_j^1 " " " " " " " " " " " $U_j \rightarrow \frac{U_j \cdot (N+1)}{N+1}$ ("a hit")

.23 Then the rel probab of hit vs. out on next trial are $\frac{P(S_j^1)}{P(S_j^0)}$ from this ratio, we can

.24 readily determine U_j . I suspect this result will be about the same as that obtained in ~~the~~ .17

The results of .23 - .24 are obtained in ST100.BNS and ST 101.BNS.

The foregoing analysis is not the way ESM do it.

The "Exact" idea of ESM is $P_0(S_j)$

We have $P_0(U_j)$ — It is of known mean $\bar{U} = \frac{1}{N} \sum_{i=1}^N U_i^k$ but unknown variance, τ^2 .

.32 From if we know τ^2 & \bar{U} , and N, we could, ~~obtain the expected variance of the resultant data set $\{U_i^k\}$ if we knew τ^2 & \bar{U}~~ obtain the expected variance of the resultant data set $\{U_i^k\}$. Then, by

looking at the actual varc. of $\{U_i^k\}$, we can solve for τ^2 (since we know N & assume \bar{U})

Approximately: $\text{Varc of } [U_i^k] = \tau^2 + \frac{1}{N} \sum U_i^{2k} - \left(\frac{1}{N} \sum U_i^k \right)^2$. (Actually, exact for any d.f.s for " τ^2 " is G^2)

.37 so $\tau^2 = \left[\frac{1}{N} \sum (U_i^k)^2 - \left(\frac{1}{N} \sum U_i^k \right)^2 \right] - \frac{1}{N} \sum \frac{U_i^k (1-U_i^k)}{N}$
 (Note: $\frac{U_i^k (1-U_i^k)}{N}$ is the variance of the binomial distribution for a given U_i)

[5N] There would seem to be a systematic error in using $\frac{U_i^k (1-U_i^k)}{N}$ instead of $\frac{U_i^k (1-U_i^k)}{N}$ — since all U_i^k must be ≤ 1

4-9-99 SMAT STEIN

.01: A more exact treatment of 127.32: Given X, y (equiv. to R, \bar{U} or \bar{r}, \bar{U}).
The d.f. of any particular U_i is $\frac{1}{46.28}$

.03
$$\frac{x+y+1}{x!y!} = \frac{x+N \cdot U_i!}{x+y+N+1!} \frac{y+N(1-U_i)!}{y+N(1-U_i)!}$$

We want the d.f. of .03 about \bar{U} - is more precisely the second moment of the .03 d.f. about \bar{U} .

.07 SW perhaps express .03 as a Gaussian or better as a Binomial d.f. in U_i - to make it easier to get a moment → 130.01

Discn. w. Alex: 1) He didn't know what to do w. a Bernoulli (log odds) when freq. of 0's spiked out zero.

I told him about Laplace's rule: Radix r : same as using st rule, but "pre-assign" $a_1, a_2, a_3, \dots, a_r$

• 03. About it was derived from uniform prior: $x_1^{N_1} x_2^{N_2} \dots x_r^{N_r} = P(x)$. $\sum_{i=1}^r x_i = 1$

This gives p.c. of x_1, \dots, x_r in terms of data N_1, N_2, \dots, N_r . The expected value of x_i is $\frac{N_i}{\sum N_i + r}$

is obtained by usual comparison of exponents. $\frac{N_1! N_2! \dots N_r!}{((\sum N_i) + r)!}$

How to get SSS (0.3) w. r constraints, was ~~some~~ something I solved long ago - I don't remember how.

I think it involves ~~the~~ multiple S 's in which upper ~~part~~ integration in each is a linear funct of some of the x_i . — That γ formula is obtained recursively.

He was

concerned w. string problems in which one wanted to "pool" data, but didn't know how "pooled" γ potential "pooling" were — & just how to adapt & use it. "Clustering".

• Perhaps Get more info on just what his problem is (in spoken recognition), & perhaps work on it. This seems like a very general problem probably quite impt.

317 $\rightarrow \downarrow$

128.07

01! 127.40 A more elementary to do it than 127.37!

Given \bar{u}, R, N , The d.f. for U_i (if U_i ~~was not known~~) would be (from 96.28)

03

$$\frac{x!y!}{x!y!} \frac{(x+u_iN)!(y+(1-u_i)N)!}{x!y+N!} : \text{ want only 1 red part varies w. } U_i :$$

So we want its d.f. We can probably get its mean & var & approximate it as a Gauss or Binomial d.f.

We then want to d.f. of $U_i - \bar{u}$, and its second moment (σ^2) about that \bar{u} .

So we want to say this second moment is $F(R, \bar{u}, N)$.

It is 1. Expected value of $(U_i - \bar{u})^2$.

If we make the choices of U_i is add them then $(U_i - \bar{u})^2$ is we expect to get

11 $k = F(R, \bar{u}, N)$. We then ~~write~~ write

03 $\sum (U_i - \bar{u})^2 = k F(R, \bar{u}, N)$ and solve for R in terms of $\bar{u}, N, \{U_i\}$.

13 Often, this eq. will have no number soln. Cx. ~~But~~ $R < 0, (\frac{1}{T^2} < 0, T^2 < 0)$

In such a case, $T^2 > 0$ ($R = \infty$) is not a bad approx.

To do it ~~more~~ correctly, in 03 ~~of~~ we get the var of the second moment.

of σ . red approx. This gives ~~us~~ $\sigma^2(R, \bar{u}, N)$, so we have a

d.f. for R . When ~~we~~ $\sum (U_i - \bar{u})^2$ is known, this gives (by Bayes)

a d.f. for R (i.e. of T^2), ~~we~~ This deals w. t. "R < 0" diffy of 13

In General! for expressions like 03 we want to mean = (first moment / zeroth moment)

Also σ^2 = second moment / zeroth moment - (mean)².

If we get the d.f. for $(U')^2$, then if we find its mean is this σ^2 (I'm not sure).

Say $H(V)$ is the d.f. for $V = (U')^2$, its mean is M_V

Then if we take K samples $(U_i - \bar{u})^2$, we expect their d.f. to be $H(\frac{V}{K})$ & its mean to be $\frac{1}{K} M_V$. We also ~~may~~ may be able to compute the var of M_V .

01 On + Variance of Variance

Consider $e^{-\frac{x^2}{2}}$: Its mean is 0, var = 1.

say $X^2 = V$ i.e. d.f. is $\propto \frac{1}{2X} e^{-\frac{X^2}{2}} \propto \frac{1}{\sqrt{V}} e^{-\frac{\sqrt{V}}{2}}$: $\boxed{f(V)}$

∴ $f(V)$: Mo is $\int_0^\infty \frac{1}{\sqrt{V}} e^{-\frac{\sqrt{V}}{2}} dV = \frac{1}{\sqrt{2}} \int_0^\infty \frac{1}{\sqrt{u}} e^{-\frac{u}{2}} du = \frac{1}{\sqrt{2}} \left(\frac{1}{2}\right)!$

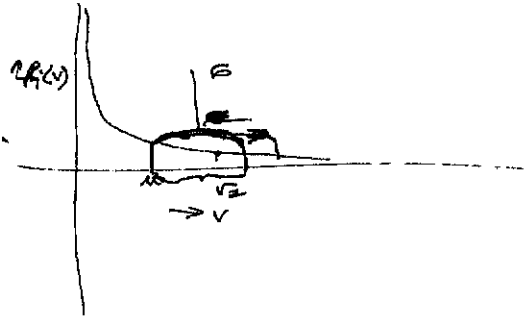
$M_1 = \int_0^\infty \sqrt{V} e^{-\frac{\sqrt{V}}{2}} dV = \sqrt{2} \int_0^\infty \sqrt{u} e^{-\frac{u}{2}} du = 2\sqrt{2} \left(\frac{1}{2}\right)! = 2\sqrt{2} \left(\frac{1}{2}\right) \cdot \frac{1}{2}$

$M_2 = \int_0^\infty \sqrt{V}^2 e^{-\frac{\sqrt{V}}{2}} dV = \left(\frac{1}{\sqrt{2}}\right)^2 \int_0^\infty u^2 e^{-\frac{u}{2}} du = 2 \cdot 2 \cdot \sqrt{2} \cdot \left(\frac{1}{2}\right)! \cdot \frac{1}{2}$

$\frac{M_1}{M_0} = \frac{2\sqrt{2} \cdot \frac{1}{2}}{\frac{1}{\sqrt{2}}} = \frac{2 \cdot \sqrt{2} \cdot \sqrt{2}}{2 \cdot 2} = 1$

$\frac{M_2}{M_0} = \frac{2 \cdot 2 \cdot \sqrt{2} \cdot \frac{1}{2}}{\frac{1}{\sqrt{2}}} = 3$

So Var of $f(V)$ is $3 - 1^2 = 2$: $\sigma = \sqrt{2}$.
Mean of $f(V)$ is 1



This is a very simple idea! Whenever we have a var. μ is obtained as the sum of a bunch of random variables, we know μ : mean is sum of means & var is sum of vars:

This gives us the d.f. for the var. of the sum variable — how uncertain of it we are.

20: on Approx exact analysis of the Gaussian case: $P_0(u) \propto e^{-\frac{u^2}{2\sigma^2}}$; mean 0.

As u obtained is then subject to a d.f. $e^{-\frac{(u-\mu)^2}{2\sigma^2}}$

∴ resultant d.f. is $\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(u-\mu)^2}{2(\sigma^2 + \tau^2)}}$: ∴ var is $\tau^2 + \sigma^2$ because now d.f. is the convolution of V , a d.f. of var. τ^2 & u , var. σ^2 .

Consider σ^2 rather than σ as constant

the d.f. of $V_i \equiv u_i^2$ is $\frac{1}{2\sigma^2} e^{-\frac{u_i^2}{2\sigma^2}} = \frac{1}{2\sqrt{V_i}} e^{-\frac{\sqrt{V_i}}{2\sigma^2}}$

To study this, let all $\sigma^2 = a^2 =$ same constant:

d.f. $\propto \frac{1}{\sqrt{V}} e^{-\frac{\sqrt{V}}{2a}} \equiv f_1(V)$

But small first term $\frac{1}{\sqrt{V}} \approx \frac{1}{2a} (2a - \sqrt{V})^2 \equiv \frac{1}{2a} \tau^2$

If we take K th convolution of $f_1(V)$, we will get the d.f. for the sum of K values of K , u_i^2 .

The mean will be $K \times (\text{mean of } f_1(V))$ (which is prob $\sigma^2 + \tau^2$). This convolution will

be much narrower (like $f_1(V)$ (2.26 R), but the peak will be narrower relative to the mean (width $\propto \frac{1}{\sqrt{K}}$ mean)

Isn't that slow about how rapidly this convolution $\rightarrow 0$ at $\tau^2 = 2\sigma^2$, here.

Consider the convoln of $\frac{1}{2a} e^{-\frac{\sqrt{V}}{2a}}$ w. itself. : $\frac{1}{2a}$



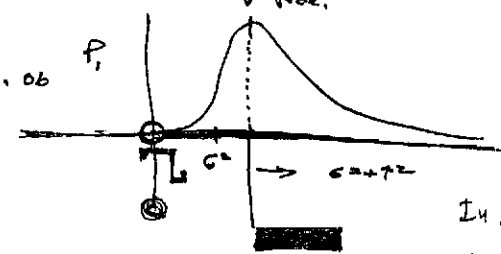
In the graph, for large x , we may can approximate the convoln by integrating $\frac{1}{2a} e^{-\frac{\sqrt{V}}{2a}}$

$\int_{x/2}^{x/2} \frac{1}{2a} e^{-\frac{\sqrt{V}}{2a}} dV = \frac{1}{2a} \ln \left(\frac{x/2}{x/2} \right) \approx \frac{1}{2a} \left(1 + \frac{2a}{x} \right) \approx \frac{1}{2a} = \frac{1}{2a}$

So for that kind of func, convolving seems to behave by x values invariant

Anyway, I also assume that we can write $F_1(v)$ d.f. is at 131.27 R:

The peak gets narrower (relative to mean), but its behaviour at τ^2 remains as $\frac{1}{\sigma^2 + \tau^2}$.



If κ is small, the peak can be at $< \sigma^2$ but for larger κ , it's very likely that peak is $> \sigma^2$ (Unless τ^2 is, in fact, very small).

In general, the peak will tend to be at $\sigma^2 + \tau^2$, but if κ is small and τ^2 is small, it can occur at $< \sigma^2$

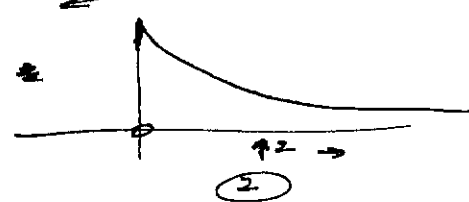
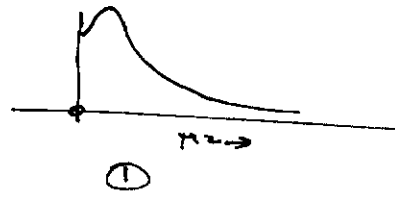
See also: NN! 4.12.99
www.zark.com

The general formula of χ^2 distribution $\chi^2 \equiv \sum_{i=1}^n (M_i - \bar{M})^2 \approx V$

131.27 $f_1(v) \approx \frac{1}{\sqrt{V} \sqrt{\sigma^2 + \tau^2}} \cdot e^{-\frac{v}{\sigma^2 + \tau^2}}$

We know $V \approx \chi^2$, so this gives us a d.f. for $\sigma^2 + \tau^2$. (by Bayes).

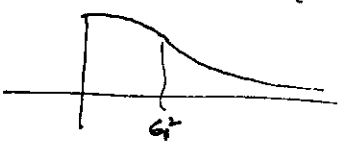
If $\sigma^2 <$ the peak of the curve (see 0.06) we get 1 if $\sigma^2 >$ the peak we get 2



Using Bayes. The d.f. for τ^2 is $M_i = \frac{\frac{\tau^2}{\tau^2} + \frac{M_i}{\sigma^2}}{\frac{1}{\tau^2} + \frac{1}{\sigma^2}}$

We can integrate τ^2 from 0 to ∞ to produce $[0.10]$ to get the probability $[0.21]$

(Maybe \approx ~~the integral~~ $\int \frac{1}{(\tau^2 + \sigma^2)(\tau^2 + \sigma^2)} d\tau^2$)



or $\frac{1}{(\tau^2 + \sigma^2 + c)} \frac{1}{\ln(\tau^2 + c)}$ moves the gradient by c .

This integral would give us the correct value of M_i - considering all poss.

128 Values of τ^2 .

129 This evaln. would be $\approx T$. same as ST100 Bas, ST101 Bas if χ^2 statistics χ^2 (.09) has as much info as $[M_i]$ w.r.t. to estimation of M_i .

The other method ~~of ST100 Bas~~ ST101 Bas finds the d.f. for R ($\approx \frac{1}{\tau^2}$) by comparing to probly put each τ^2 produced known $[M_i]$.

The other method 131.20 - 132.28 finds the d.f. of τ^2 by comparing to probly put each τ^2 produced to observed $-\sum_{i=1}^n (M_i - \bar{M})^2 \approx \chi^2$.

Both methods could use (MCMC) .21 - .26 to compute M_i .

Here, in ST101 Bas what we actually do is marginal: we assign a probly to the data set $[M_i]$ or any conceivable data set. We then put the vari. probly of various poss. realizations of f . compare (data set) by comparing the vari. probly of the assoc. compl.

01 This latter method is more general, it works for all problems.

Both methods ~~seem~~ seem to point out the imp. of ϵ approx — of by values:
 In one case by $R (= \frac{1}{\epsilon})$ in the other case by τ^2 . In both cases no problem for
 small R or τ^2 : — which seems crazy! It may be that in both cases, ϵ .
 dependence on behaviour for by R or by τ^2 produces ~~small~~ negligible changes
 in t . Govc. ~~ALWAYS~~ ^{nat.} ~~usom~~ This would mean τ / wts near 0 or near 1,
 t exact values are not very imp.

But, in General, I'm not easy w. to state of affairs.

Another thing I'm uneasy about is G. & M's using ~~the~~

$\frac{\sum^2}{n-3}$ instead of $\frac{\sum^2}{n-1}$ to estimate V . I could use the M.C. data

data generator to find, empirically, which gives best person

Write ^{details} / out line of talk on STEIN for Oxbridge:

Then ~~fill~~ fill in outline, w. Actual text; also refs to these notes

Att! 1) Re: the $\sin^{-1}(2x-1)$ form! While t G^2 is correlated w x_i ,
 that's not imp. : t only thing of imp. is whether to defeat M_i 's are
 correlated or whether their G_i^2 are correlated. — They are not
 — which is all we need to know.

2) In $S(100)$ Bas, we integrate 46.25 in R , w. constant
 \bar{U} . Actually, the \bar{U} for each \bar{u} or \bar{U} , the width may vary
 w. R is t . width may vary w. t . comp — (so to compare ~~widths~~)
~~the~~ t approx (\equiv integral) of 2 modulus of t . corpls, one must
 see if t . widths in t . \bar{U} directions are different).

To get R 's width as a function of R may not be so diff / t!

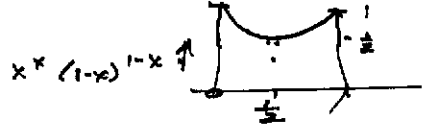
I may have come close to doing this calculation in 49.07 — .30; [10.01 — 76.40]

It may involve something like $\frac{\prod_{i=1}^N (M_i^2 (1-M_i^2)^{1-M_i^2})}{(\prod_{i=1}^N (1-\theta)(1-\theta)^{1-\theta})^N}$

70.07 — 40 is particularly relevant
 f. concavity argt. at 70.34

The num. numerator is always $>$ (or $<$?) t . denominator — by some simple convexity argt.

whether t want



or it's reciprocal, is unclear!
 at any rate, just varying \bar{U} would make t . peak at $\bar{U} = 1/2$!
 — so look into this more carefully!

- 3) must require
- 1) M.C. data
- 2) 100 Bas
- 3) points to do $\sin^{-1}(2x-1)$ form & get Ed M results exactly.
- 4) points to do ~~Gaussian~~ case: but for $p_0(x)$. $Gauss(G^2)$ to $p_0(x)$.
- $\sum_{i=1}^N \frac{(G_i^2(1-G_i^2))}{N}$
- Did I compare this w. Ed M & BA?

17

36.09

01 One application of STEIN effect: Choosing Mutual funds. →
 Say we list all Rib. funds, but we might consider getting into.

Not in Stein filter but S.M.F.T. 1999
 Wm, Soc (99) 3.10 vary in μ (id)

Or, use large list of No load funds to which we use an on-line broker & switch over monthly or every 6 months.

Say we examine recent gains of funds: μ and σ , μ set to zero;
 Expected yield is $\frac{\mu_1}{1 + \frac{\sigma_1^2}{T_1}} + \frac{\mu_2}{1 + \frac{\sigma_2^2}{T_2}} = \frac{\mu_1}{1 + \frac{\sigma_1^2}{T_1}} = \mu_1 \cdot \frac{1}{1 + \frac{\sigma_1^2}{T_1}} = \frac{\mu_1}{1 + \frac{\sigma_1^2}{T_1}}$

Say we use μ_i & σ_i^2 for exponential, last 5 yrs; 6 month data pts.

Each 6 mo. we pick a fund w. best $\frac{\mu_i}{1 + \frac{\sigma_i^2}{T_i}}$ fund. "Best 5 yrs".

μ_1 is 6 mo. yield.

For a "FT" type scheme: ① For each driver, find driver that correlates best with
 — for prodn. Using Stein idea, compare for each driver α_i ⇒

13 $\mu_i + \alpha_i \cdot \sigma_i^2 \cdot P_i^2$ ⇒ best poss. predictor of P_i^2 :
 μ_i is Δ price of driver. (w/it returns, μ_i).
 σ_i^2 " " " " driver. (w/it its mean)
 α_i is coeff of corr betw. P_i^2 & P_i^2 .
 α_i is obtained from Stein analysis.

What is μ_i ? — how down goes?
 Maximum over many (driver, down) pairs.

Compare w. normal linear regression:

we want $\beta \Rightarrow \beta(x - \bar{x}) \approx (y - \bar{y})$
 $S \equiv \sum (y - \bar{y} - \beta(x - \bar{x}))^2 = \min$; $\frac{\partial S}{\partial \beta} = 2 \sum (x - \bar{x})(y - \bar{y} - \beta(x - \bar{x})) = 0$.
 $\sum (x - \bar{x})(y - \bar{y}) = \beta \sum (x - \bar{x})(x - \bar{x})$ so $\beta = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sum (x - \bar{x})^2} \equiv$ correln. coeff.
 Say $\bar{x} = \bar{y} = 0$; to simplify.

From linear regression it would appear that α_i (in 13) = 1.
 Hw, if σ_i^2 (or σ_i) is small, α_i is more important as knowledge of σ_i (mean) (β) . The $\frac{\sigma_i^2}{T_i}$ effect is of some help here —
 — but is it the whole story? This effect talks us expected corner in future,

32 but it doesn't tell us to multiply estimate by α_i w. $\alpha_i \sigma_i^2$!!

→ 136.01
 136.01

Say the corr coeff β is β_T was obtained in T window. If T is small (say 2),
 the error due to small T is quite large. Consider R windows: divide composite
 sections of length T ; β_T for each section. We can then use Stein Capitalization
 for estimating β_T . Since we are mixing data, this amounts to very large T .

36 Perhaps more relevant: Due to fact that seq. is slowly changing its
 params, we are limited in how large T can be. Say T can be as large
 as T_0 , but no larger. Then each section of T corpus, of length T_0 ,
 corresponds to a different Baseball player (in the STEIN analysis).

01 In SMPPT To get a 200/day ^{MKT} — P2's was due to ^{ending} lot of ~~debt~~ & pairs worked.
— Gov., each dd could have its own ~~to~~ to.

628 9792
3:00 P

In ~~trying to~~ trying to evaluate corr. coeffs: Say we use ~~the~~ windows, τ .
Each day we get a new value of β . — so we get from P2's a σ_p^2 (σ_p^2) per day,
which will be about expected over β . [τ corr. coeff. is closely analogous to Betting
Average: ^{Beta} gives τ p.d. for τ next data pt.] In Baseball, its probly of ~~out~~ out v. s. hit.
in τ , its probly distribn of ~~the~~ Δp_i^2 .

11 In 134.36 ff: we could assume a Gaussian D.f. for τ corr coeffs of each
 τ sized set (sub corpus). In J form, these corr coeffs would be statistically
indip. In most time series, they would be sequentially correlated.
Using X windows into be one way of doing it.

Long ago, I was devised by the following analysis: I had a random var, X_t , w.
mean value ϵ (ϵ small, but $\neq 0$). If I used X window to smooth X_t to obtain estimate
 $X_{t+\tau}$, the ^{s.d.} error of my estimate was $> \epsilon$, so I'd do better by choosing zero every
time. (I didn't know what ϵ was). So zero estimate of zero, had less
mgs. error than τ windows X_t . I was really puzzled by this!

→ Actually in 134.36 is τ (135.11), one could deal w. this linearly
by assuming τ signal had a slowly & a rapidly changing component.
So perhaps a "Wiener filter" would be the best way to deal w. this.

Or, in the spirit of neural nets, think 2 or 3 τ windows τ , so assoc.
wts. τ make predn. a sum of them. τ reason its like ANN is
that 1. predn is τ sum of 3 filter outputs, a "each filter has 2 prams —
one is size in τ direction & other is amplitude in τ direction.
This can be much better than simply adjusting amplitudes of several
"pre-processed" wfreq functions. This is ~~an~~ an impl. idea from
A. Barron's 1993 paper

Looks
Good!

How it is a N.L. curve fitting problem, & probly best to solve using some
Standard N.L. curve fitting prog. (Optim).

4-1999 As I see it, a more idea is to get good preds for all stocks (funds).
we then pick the best one, & we can estimate yield using the ideas of "SOY"
analysis.

- .01: ^(Spec) (134.32): Another way to look at this! Consider f. situation of 134.13 - .32; (mean=0)
- .02 Say we do linear regression for some T window: we observe $\sigma_{ob}^2 \rightarrow \sigma_{amp}^2 = \sigma_{ob}^2 \cdot \frac{T+1}{T-1}$.
If σ_{ob}^2 is comparable to $\frac{1}{T}$ window, then we have 2 ~~ideas~~ ideas for f. data that are of comparable length. The pc/symbol of the 2 codes are $\frac{1}{\sigma_{amp}}$ & $\frac{1}{\sqrt{kE}}$.
- .08 ~~It's~~ initial pc's of f. codes are different. The "biton zero ($\hat{\mu}$)" code has by ~~approx.~~ \rightarrow

.09: 133.17 **SN** R_e : $E \hat{\mu}$ M's $\frac{S}{k-3}$ My ^{strong} impression is that R_{e12} should be $\frac{S}{k-1}$.
Say we have a Gaussian process w. var. T^2+1 , & mean μ . We do MLE Carlo runs & observe in T run, mean $\hat{\mu}$, & its deviation from true mean of σ_{ob}^2 .
An unbiased estimator of T^2+1 , is then $\sigma_{ob}^2 \cdot \frac{k}{k-1}$, not $\sigma_{ob}^2 \cdot \frac{k}{k-3}$.

A new, simple way of getting d.f. for Sum of squares of Gaussian variables!
Consider first known mean so. We have a k dimensional ~~linear~~ spherical Gaussian d.f.; say f. d.f. is $e^{-\frac{x^2}{2}} \rightarrow e^{-\frac{\sum x_i^2}{2}}$.
Then the k th moment of f. d.f. is $(R \approx \sqrt{\frac{\sum x_i^2}{2}})$ $\int_0^\infty R^k e^{-\frac{R^2}{2}} \cdot f(R) dR$
 $f(R)$ is the area of a k dimensional hypersphere of radius R . it is $\propto R^{k-1}$ and so $\int R^k f(R) dR$ - so we end up w. integrals of form $\int_0^\infty R^k e^{-\frac{R^2}{2}} dR$ which are known well known.

.28 If f. mean is ~~known~~ zero ^{But} & is unknown; we can get f. d.f. of $\sum x_i^2 - (\frac{\sum x_i}{k})^2$ which is d.f. of $\sum x_i^2$ minus $\frac{1}{k}$ x d.f. of $(\sum x_i)^2$.
d.f. of $(\sum x_i)^2$ is not so easy; first get d.f. of $\sum x_i$.
or, we know f. d.f. of X ; it's a Gaussian d.f. about μ with var $\frac{1}{k}$ + var of X_0 . Thus, given f. d.f. of X , we can get f. d.f. of $(\sum x_i)^2$! it is $\frac{1}{2\pi} P(X) = \frac{1}{2\pi k} P(\sqrt{\sum x_i^2})$

.29 So .28 - .29 would seem to be messy soln. to f. problem of whether to use $\frac{S}{k-1}$ or $\frac{S}{k-3}$ or whatever. We could then confirm our soln. by M.C. simulation.

also note 139.20

So R_{e12} may more or less, settle STEIN for now.
Applying to ~~same~~ ^{same} ideas to ~~SM~~ SM in an optimum manner is another question, hvr.

.30 ⁽⁰²⁾ A nice way to study β_{e1} : say $Y_i = \beta X_i + N_i$ N_i = Noise of $\sigma^2 = N_0$ & mean of N_i is ϕ .
Using finite T , ~~comp~~ ^{estimator} $\hat{\beta}$ from Y corpus. We can use .01-.08 to get wts. of 2 probn. methods: ① using ϕ as probn. ② using $\sum x_i^2$ as probn. We know expected errors for each. It would seem that as N gets larger f. probn ① gets narrower - it should get all wts as $N \rightarrow \infty$. From R_{e12} model, I should be able to \rightarrow (38.01)

01 **NB** A very imp. aspect of the EIM approach to Stein: We have a model for the corpus (or, more exactly, a model for an ensemble). We make a "What is the d.f. of the params of the model, in view of the corpus?" Then we integrate over those params to get the output of the corpus.

Another way (the one EIM uses). We make a certain measurement of the corpus. What is the d.f. of one (or more) params of the model ~~in view of this measurement~~ in view of this measurement? — EIM narrows further by asking ("as 'statistics'")

"What single value of the params fits the measurement best?"

This last is often ~~much~~ much easier to ~~compute~~ than. Answer Q's of .01-.02;

— The often it doesn't give exactly the answers, it sweeps out Q's a bit & gives "under the rug".

Anyway, EIM's method is one kind of "ruff & dirty" soln. to an inductive problem.

→ In general, how do we go about inventing ~~approximations~~ approximations of this sort?

Some Common heuristic tricks: Instead of a d.f. for a bunch of params, use the mean, or if the peak is too broad expected values.

[These all assume that the underlying spread is a "uniform"]

The idea of picking a ^{or star} (single) measurement of the corpus is getting the "best fit" or d.f. of model params ~~in view of this~~ ^(set of) measurements (s). Is perhaps a common trick — the statisticians probably do it w.o. ~~realizing~~ realizing they are doing this heuristic approach.

There is also idea of "sufficient statistic".

How to discover such measurements? Well, consider a single param of the

model: To get its pd. or "best value": Consider extreme values of that param.

How would they affect the way the corpus looked? From this one ~~we~~ could

get ideas of what measurements (s) to make on the corpus, that would be most sensitive to this param. (or sensitive at all!)

Another trick: to find how to measured param is a funct of τ^2 (say),

first: Consider extreme values of τ^2 (say 0 & ∞): This ^{may} give ideas on ~~how~~ form of functional relation (we may use some intermediate values)

Anyway, using Monte Carlo simulation, for various τ^2 values get the values of the

measured param. Do a curve fit on this data. Or, for various τ^2 , get the

Monte Carlo d.f. of the values of the measured param. by curve fitting on this last data, one could (by Bayes) find d.f. of τ^2 as a funct of the measured param.

This can be useful in A.I., if one doesn't have a good intuitive model of the data.

- 01: 136.90 : Estimate ms error of my proposed "a" & any "mix" of methods (1 & 2)
- My such mix is optimal to reduce "a" by a certain factor — so I can find ~~the~~ error, if I know error assoc w. any "a".

REVIEW

see 115 for list of reviews, also 1 & 3

GA

I will actually write a "paper" on this for my own remembrance, since it's an impr. idea: Outlines:

- 1) What's Stein Problem is as in f. EdM Sci Amer Art. (1977).
 Descr in terms of Baseball: Give intuitive picture of \$3201 vs. \$3200.
- 2) Generalizations of f. ~~the~~ Problem (why it's an impr. problem) (2) Paper by EdM on Germans.
- 3) General to Bin. & Gauss d.f.'s (2) Various kinds of auxiliary facts: (C1) Meta-analysis, (C2) The Milk & Corpus Firm.
- 3) ~~2~~ 4 versions of f. Problem: (a) Gaussian v.s. Binomial d.f.'s; (C) Exact v.s. approximate solns. ("Exact" means ~~the~~ complete Bayesian Soln. including priors. — Approx: no money viny $\Sigma^2 = \Sigma (u_i^2 - v_i^2)^2$ as a "sufficient statistic")
- 4) Various Mathematical methods, identities, inequalities, equations, formulas helpful in this area. formulas for moments & in a GR of Bin. D.f. (144.15 ff)
 How to get d.f. ~~for~~ X^2 from d.f. for X . 125.01 ff is one track on this
 Derivative of ~~the~~ $\ln \Gamma(z)$ is $\psi(z)$ p 258 (B of Stand):
 $\psi(z)$ is very close to $\ln(x - \frac{1}{2})$ for $x \geq 2$.
 $\int_0^1 x^A y^B dy = \frac{x! y!}{(x+y)!} \left(p 258 : B. of Stand \right)$
 $\frac{x! y!}{(x+y)!} \approx \left(\frac{2}{\pi} \right)^{1/2} \sqrt{\frac{x! y!}{(x+y)!}} \approx \frac{1}{\sqrt{2\pi xy}}$ 79.03, $a = \frac{x}{R}$; $b = \frac{y}{R}$; $R = x+y$.
 $\ln \left(\frac{x! y!}{(x+y)!} \right) \approx x \ln x + y \ln y - R \ln R + \frac{1}{2} \ln \left(\frac{2\pi xy}{R} \right)$
 $x! \approx \left(\frac{x}{e} \right)^x \sqrt{2\pi x} \cdot e^{\frac{1}{12x}}$ is very good bin. out. See my Approx
 for $x=2$ it gets $2! \approx 2.0005$. It gets much better as $x \uparrow$.
 Variance of Variance: 131.01.
 Vari of Binomial d.f. 76.25 (approx); 144.15 - .25 (exact)

4.30.99 SIFT STEIN:

There is a (KALP) model of the (Gaussian) problem, say μ is known to be ϕ .

We have 2 methods of prediction, predict ϕ , which has error σ^2 .

We have M_i as predn, which has error σ_i^2 : ~~potentially variable~~

To get a pd. of ϕ , we're reading, we mult. 2 d.f.'s together, to get a Gaussian d.f.

of mean $(\frac{\phi}{\sigma^2} + \frac{M_i}{\sigma_i^2}) / (\frac{1}{\sigma^2} + \frac{1}{\sigma_i^2})$.

Hvr, we can't find σ^2 so easily! say we're using linear predn,

so $y_i \approx \alpha x_i$. (mean) we can't ~~use~~ ^{use} ~~term~~ ^{term} in predn $\sum (y_i - \alpha x_i)^2$ w.

$B \equiv \sum y_i^2$. A is always $\leq B$.

Hvr, say we've \approx wide w. T as smoothing time; we compute α on basis of (not T data pts) \approx make predn. It has $\frac{1}{T}$ error of A : R_{11} can be $>$ us value of y .

By Algebra methods, we can find expected value of A by looking at past only.

use $\approx \frac{T+1}{T-1}$ factor. R_{11} is may be $\approx k$.



"proof" My ~~proof~~ of σ . Akiba correction factor doesn't give reasonable

answers for $k \geq 1$ (no. of params). — BUT Go from R_{11} is N dimensional

Gaussian d.f. predn. — It doesn't seem to be "singular" when

$N \leq k$. I just got to check $\frac{N+1}{N-1}$... but check that out!

Consider just error in $\mu = \sum_{i=1}^k \sigma_i^2$. I.e. expected value of free variance. \leftarrow

R_{11} should simplify it a lot!

This is \approx to problem of 136.24-29 which I think is rather simple, & it's one only word means (or unbiased estimates)

The expected error in mean (of all dimensions have error σ^2) is ≈ 2 ans $n \cdot k \cdot \sigma^2$ — so maybe it washes out \approx small.

its $n k \sigma^2$ because it's equal to taking $n \cdot k$ samples ^{each} of var. σ^2

Well, Turns out I was doing this wrong! The method I used to get Akiba factor for $k=1$ doesn't work (directly) for $k \geq 1$. So we have k variables X_{ij} of $\sigma_i^2 = \sigma^2$ (constant) T means over all ϕ , but we don't know that. The avg. error in y_i mean var, is ϕ mean of ϕ means: which is essentially a single param, — so we act \approx like " $k=1$ " So we don't get factor of $\frac{N+1}{N-k}$: ~~($\frac{N+1}{N-k}$)~~ $\frac{N+1}{N-k-1}$

Close to correct: $\left[\begin{matrix} y_i \\ x_{ij} \end{matrix} \right]_{j=1}^k$ are temp of mean ϕ is Gaussian. $\left[\begin{matrix} y_i \\ x_{ij} \end{matrix} \right]_{j=1}^k$
 we want to predict y by $y_i = \sum_{j=1}^k X_{ij} \beta_j$
 we predict $\hat{y} = \hat{\beta}$ that gives min MSE error. The observed error = $\sum_{i=1}^N (y_i - \hat{y}_i)^2 = \sum_{i=1}^N$

4.30.99 SMART STEIN

Here, $\hat{\Sigma}^2$ is true Σ^2 is larger, since $\hat{\Sigma}^2$ is incorrect.

If $\hat{\Sigma}^2$ is true value, then $(\hat{\Sigma}_0^2 - \hat{\Sigma}^2)$ falls (proportionally) how much must be added to Σ_0^2 to get Σ^2 : $(\hat{\Sigma}_0^2 - \hat{\Sigma}^2)$ can be found by looking at 1. Second derivative of t . Σ_0^2 total squared error in probn.

05 One implication is that STEIN can be considered to be a special case of "the mean of various coding Methods". One method I did try was perhaps ST42.6a1. What I'm thinking of:

Value of Bin. P.f. 3628

Method 1: Deriv. the sequence of N hits & n 's as a simple Bernsq.

11 Its p.c. is $\frac{n! m!}{(n+m)!} = e^{-G} \frac{m^m}{m!} \frac{n^n}{n!}$ no total no. of obs $m+n=N$; $m = \sum_{i=1}^k M_i \cdot N$
 $m = \sum_{i=1}^k M_i \cdot N$ hits.

Another way to deriv. the data set (MaxComp form) is

15 $\prod_{i=1}^k \frac{n_i! m_i!}{(n_i+m_i)!} = e^{-G}$ $m_i = M_i \cdot N =$ no. of hits by player i
 $n_i = n_i$ no. of obs by player i
 $n = N - m$

To do proofs, we use wtd. mean of 2 deriv. methods. (wts $\propto e^{G_1, G_2}$)

43.09-30 are some values of $G_1 - G_2$ (in. of ratio of wts) for various values of N .

~~$G_1 = G_2$~~ at $N \approx 200$, but I'm not sure of how much deviation from 200

N would need to get $G_1 - G_2 = 1$ or 2 or 3 : 43.28 says Nitrogen factor of 5 betw wts.

$N \rightarrow N+10$ give $G_1 + G_2 + e^{0.67}$; so $\Delta N = 10 \times 1.67$. $1 \approx \frac{1}{e^5}$ v.s. e^5 .

So this method would seem to use the method of t. obs; except for a narrow range of N values about $N \approx 100$.

22 $\ln \left(\frac{n! m!}{(n+m)!} \right) = n \ln \frac{n}{n+m} + m \ln \frac{m}{n+m} - (n+m) \ln (n+m) + \frac{1}{2} \ln \left(\frac{2\pi n \cdot m}{n+m} \right) + \frac{1}{2} \ln \left(\frac{2\pi \cdot \frac{n}{m+n} \cdot \frac{m}{m+n} \cdot m+n}{m+n} \right) + \frac{1}{2} \ln (2\pi n \cdot (1-n) \cdot N)$
 $= N \ln n + (1-n) N \ln (1-n)$
 $= N (\ln n + (1-n) \ln (1-n))$

So it looks like the formula of 43.28 is correct.

32 At any Rate, this result seems to be much different from results obtained using the "Cascaded" method.

33 The 2nd diff's w. τ^2 & $\{G_i^2\}$ (using either Binomial &/o Gauss diff's).

34 WHY IS THIS? Well, 33 assumes some knowledge in times of t. players - not nearly $\tau^2 = 0$ but not $\tau^2 = \infty$ either.

32 assumes there are only 2 ways of Generation: $\tau^2 = 0$ or $\tau^2 = \infty$.

37 $\tau^2 = 0$ corresponds to .11; $\tau^2 = \infty$ corresponds to .15

33 assumes a continuum of poss. τ^2 values.

See 45.33 Probability

(NB) 43.32 doesn't actually assume $\tau^2 \geq 200$, but it does give (perhaps) equal likely hood to all M_i values: More exactly, if we were considering

40

5.4.99 SMART STEIN

Bin d.f.s: .32 could assume a uniform ^(uniform) spread of μ_i .
 .02 This is equiv to $\mu(1-\mu) = 1$; (i.e. $R=0$, in eq. 46.28, $x = \bar{\mu} \cdot \phi = 0$; $y = (1-\bar{\mu}) \cdot \theta = 0$)
 Guess it's justified!

Hvr. ~~for~~ for eq. 140.11 I have no immediate way of getting it out of 46.28.

As $R \rightarrow \infty$; $x = \mu R$, $y = (1-\mu)R$ both $\rightarrow \infty$ & proportional μ_i (i_1, \dots)
 become unimp. — but not ~~the~~ converge strictly to a PCOO as $R \rightarrow \infty$.

The only way to get it from 46.28 would be Let $\mu \rightarrow \phi$, but

Let R be original N . so we get $\frac{x! y!}{(x+y+1)!} = \frac{N \cdot \mu! N(1-\mu)!}{N+1!}$

Then $N \rightarrow \phi$ of .02 is of unclear interpretation.

Anyway, The discussion of 140.05 — 141.10 does explain away an imp.

ditty in the whole analysis: i.e. why ~~the~~ 140.32 & 140.33 so different?
 140.34 is a reasonable explain. Those 2 methods ~~are~~ really
 assume different things about the corpus! The model of 140.33 seems to
 incorporate more reasonable assumptions about the data source.

i.e. that the μ_i are bunched together some where: 140.32 has only
2 models: No bunching (uniform spread of μ_i betw. 0 & 1) & all μ_i over the same $\bar{\mu}$,
 w. $\bar{\mu}$ having uniform spread betw. ϕ & 1.

140.33 is a more general model, & ^{considers} ~~incorporates~~ a large no. of poss. models

but 141.32 does not consider. (40.33 does, hvr, consider one of models of 140.32 (i.e. $R=0$)
 I'm not sure about the other model, 09-11 suggests two the former $N=R$ | 02

Model ~~is~~ not accessible to 140.33. I'm not so sure! If we include
 the proper normen. constant in 141.33, we may be able to get the desired d.f.

It's probly hard to put in all of the normen. constants. — & we may get

2 140.32 is 140.33 w. $R=0$ & $R=\infty$. (i.e. 140.32 considers only 2
 of the models of 140.33.)

As such, it is certainly a quick, rather dirty way to solve the system
 problem: It usually gives wts $\neq 0$, or 1 to the 2 models. i.e. use the
either the ensemble average or the individual averages. A narrow range of
 N values where the wts are not very close to ϕ & 1.

→ So essentially, it tells us whether to use μ_i or $\bar{\mu}$ as an estimate of μ_i

More generally, ^{through} we can assign wts to μ_i & $\bar{\mu}$. Say the wt. on $\bar{\mu}$ is β
 or μ_i is $(1-\beta)$: β is uniform spread from 0 to 1. We consider all these models as
 parallel codes for the corpus.

There is some ditty in doing these "0" codes: A first attempt!

36

- .01 codes k bits of all k players at same time: T. cost of i is j bits of i . 2nd player is obtained by looking at all data bits for i is j bit, using wt. $(1-\alpha)$ for interim i 's previous bits, & wt. α for previous bits of all other players. (we can have a 0,1 process for each player)

An easy (no ~~more~~ exact) way is to compare $\prod_{i=1}^k (u_i^{u_i} (1-u_i)^{1-u_i})^N$ w. $(\prod_{i=1}^k (1-\alpha)^{\alpha})^{kN}$.

.07 value = $\left(\prod_{i=1}^k \frac{u_i^{u_i}}{\alpha^\alpha} \cdot \frac{(1-u_i)^{1-u_i}}{(1-\alpha)^{1-\alpha}} \right)^N$. ~~Whether~~ whether this ratio is

$>$ or $<$ 1 is indep of N . — which is quite direct from 140.52!

T. max difference is $\frac{1}{2} \ln(\dots)$ terms in 140.32-30.

.07 only considers the N (multiplication) part as 140.30.

.18 T. difference is $\sum_{i=1}^k \frac{1}{2} \ln(2\pi u_i(1-u_i)^N) - \frac{1}{2} \ln(2\pi \alpha(1-\alpha) \cdot kN)$

.19 = $\frac{1}{2} \sum_{i=1}^k \ln \left(\frac{u_i^{u_i} (1-u_i)^{1-u_i}}{\alpha^\alpha (1-\alpha)^{1-\alpha}} \right) \Rightarrow \sum_{i=1}^k \sqrt{\frac{u_i (1-u_i)}{\alpha (1-\alpha)}}$

which ~~changes~~ changes .07 by $N \rightarrow N \pm$ (or $N \pm$?)

At any rate, ~~to~~ whether the result is $>$ 1 or $<$ 1 is indep of N !

So there is an error somewhere!

well .18 is ok, but .19 doesn't follow from it!

subtract & add: ~~add~~ $\left(\frac{1}{2} \ln 2\pi \alpha(1-\alpha) \cdot kN \right)$ from .19.

\rightarrow .01-.03 sounds reasonable! it is a truly sequential code (in fact the j bits of all k players are not usually simultaneous).

Anyway, I have to put STEIN to Bed!

Actually, I should be able to get ~~the~~ proper (relative) pe's for codes w. various α values.

.32: IDEA! One of Dittys w. Bin d.f. approach (i.e. Gaussian) was Apparent ~~and~~ critical dependence of soln. on a prop of R . HVR, instead of R , use τ^2 , w. value between 0 & 1 (?) is perhaps in form d.f. : Since τ^2 is for a Gaussian d.f. is not exactly appropriate, its ok for small τ^2 (i.e. large R), but has to be fixed up for

some large τ^2 — i.e. small R . My impression was that τ^2 is a prop of R for small R was not simple, so maybe letting prop of R to be $\frac{1}{R^2}$ (since since $R \propto \frac{1}{\tau^2}$)

\rightarrow using under d.f. for τ^2 at $\tau^2=0$ for large R ;

$\tau^2 = \left(\frac{u_i(1-u_i)}{\alpha(1-\alpha)} \right)^R$ for small R . I think we get uniform d.f. for u_i , when $R \rightarrow 0$. $\int \frac{dR}{R^2}$ diverges. \rightarrow at $R=0$ — so we are in trouble again! We could just retreat to $R=0$ spec

always $\frac{1}{R^2} < 1$ will not affect things much, since $N \gg 1$ (i.e. $N \gg R$ in most regions) so maybe $\frac{1}{R^2}$ is a prop of R at $R=0$ would be ok. — Tho it doesn't give fractional results! $R(N, \alpha)^2$ was much much better

Review of Reviews: 115.01 has a list of reviews! This will tell what each is about!

45: Outline of what a Review should contain (this was before ep. 46.28 which was then (immediately after that))

52.01 My early work on Stein: pp 1, 2, 3, 9, 10: I was just beginning to get some ideas as to what to put down.

79: Index to Ppms: ST50 thru ST77B: Gives brief dem. of each psm.

80: Index of ST thru ST90: Dates that ~~was~~ ^{was} written for ST 7, 9, 10; gives page ~~number~~ ^{number} & a brief on references & items

90: ST 81 ^{ST90} through ST90 Brief dems of each psm.

115: Brief reviews of Work from ~~46.01~~ 46.01 thru ~~120~~ ¹²⁰

Also 115 Gives outline of a Review, some imp. things it should contain.

124 Outline of Review.

126 - 128.07: Actual writing of review.

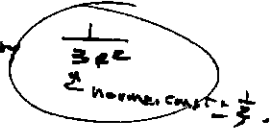
139.04: another Outline of Review! (I seem to have forgotten that I had written 126-128.07!)

ST 90
93
96
100
101
103

76.25
Vanc. of
Bridg.
at at

5.10.99 SMFT STEIN

01: (Spac 42.90) Actually \uparrow^2 can't be as large as 1, so $\frac{1}{R}$ can't be > 1 , so R can't be < 1 . — So $\frac{1}{R}$ ($R < \infty$) is ok, w. applied $\frac{1}{R^2}$



If not sure that I did it right when I tried $\frac{1}{R^2}$: I didn't properly integrate from RR to ∞ . — So I'd have to do it again.

Also σ results I got were w.o. integrality over \bar{U} , as \bar{U} should — it was a point to measuring σ diff. w.r.t. \bar{U} was indep of R is of $\sum U_i$!

Actually since $z^2 = \bar{U}(1-\bar{U})$, \bar{U} max value z^2 can have is $\frac{1}{4}$. — Well, this assumes $\sigma = 1$.

15 for downward case $\frac{1}{R} \left(U^{\bar{U}} (1-U)^{1-\bar{U}} \right)^R$ There is an easy way to get it as a function of R, \bar{U} using σ^2 , first is second moment of

$$\sigma^2 = \frac{x^2 y^2}{x+y+1} ; m_1 = \frac{x+1 y^2}{x+y+1} ; m_2 = \frac{x+2 y^2}{x+y+3}$$

$$\sigma^2 = \frac{m_2}{m_0} - \left(\frac{m_1}{m_0} \right)^2 = \frac{x+2 y^2}{x+y+3} - \left(\frac{x+1 y^2}{x+y+1} \right)^2$$

$$\frac{m_1}{m_0} = \frac{x+1}{x+y+2} ; \frac{m_2}{m_0} = \frac{(x+1)(x+2)}{(x+y+2)(x+y+3)} = \frac{m_1}{m_0} \cdot \frac{x+2}{x+y+3}$$

$$\sigma^2 = \frac{x+1}{x+y+2} \left(\frac{x+2}{x+y+3} - \frac{x+1}{x+y+2} \right) = \frac{x+1}{R+2} \left(\frac{(x+2)(R+2) - (x+1)(R+3)}{(R+2)(R+3)} \right)$$

Actually $\frac{x+1}{R+2}$ Lap's rule for x ; $\frac{y+1}{R+2}$ Lap's rule for y . — I don't know how to integrate $\frac{1}{(R+2)^2}$.

29 $\sigma^2 = \frac{x+1}{R+2} \cdot \frac{y+1}{R+2} \cdot \frac{1}{R+3}$ If a df. has to be below 0.5, perhaps σ must increase can have it

w. σ function σ^2 of σ at 1; so σ^2

So max value of σ^2 is $\frac{1}{4}$.

32 w. $R < 0$: standard $\bar{U} = 0, R = -\infty$.

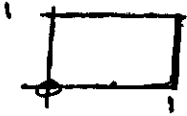
Let $X' = X+1$; $Y' = Y+1$; $R' = X+Y+1$; so $\sigma^2 = \frac{X'}{R'} \cdot \frac{Y'}{R'} \cdot \frac{1}{R'+1}$

$$\sigma^2 = \frac{X'+1}{R'+2} \cdot \frac{(Y'+1)}{R'+2} \cdot \frac{1}{R'+3}$$

woops! $R < 0$, $\sigma^2 < 0$! See 14.20 for explain! R can't be < -2 ; U^x would diverge as $U \rightarrow 0$ at $U=0$. The derivation of σ^2 seems to work for negative R . — Maybe not; the function is weird for negative integer values, — but say $R = -5/2$.

for $A=0$ we expect $\sigma^2 \rightarrow \frac{1}{4}$ as $R \rightarrow -\infty$ as (14.32 R):

For $R=0$, i.e. forward bias $\frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{3}$, seems reasonable!



$m_0 = 1$
 $m_1 = \frac{1}{2}$
 $m_2 = \frac{1}{3}$

$\frac{1}{3} - (\frac{1}{2})^2 = \frac{1}{12}$ which is

So what happens as $R = -2$, or $R = -3$. — Wagon $\sigma^2 = \infty$!

say $U = \frac{1}{2}$ $R = -2, X = Y = -1$
 $U^{-1} (1-U)^{-1}$: $M_0 = \frac{-1! -1!}{0!} = -1! = \infty$

$R = -2 + \epsilon$
 $X = Y = -1 + \frac{\epsilon}{2}$

So how do we get $\sigma^2 > \frac{1}{4}$? from 14.20 $\frac{m_1}{m_0} = \frac{X+1}{X+Y+2} = \frac{\epsilon}{\epsilon}$
 but say R is just close to -2 , $R = -2 + \epsilon$ $\frac{m_1}{m_0} = \frac{\epsilon}{-1-1+2+\epsilon+\frac{\epsilon}{2}} = \frac{\epsilon}{\frac{\epsilon}{2}}$
 $X = \frac{R}{2} = -1 + \frac{\epsilon}{2}$

so $\frac{m_2}{m_0} = \frac{1}{3}$ $\frac{m_2}{m_0} = \frac{m_1}{m_0} \cdot \frac{X+2}{R+3} = \frac{1}{2} \cdot \frac{1+\frac{\epsilon}{2}}{1+\epsilon} \rightarrow \frac{1}{2}$; $\frac{m_2}{m_0} - (\frac{m_1}{m_0})^2 = \frac{1}{2} - \frac{1}{4} = \frac{1}{4}$.

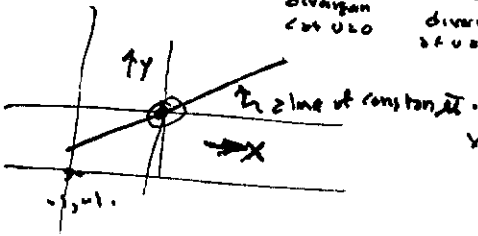
which is reasonable, since $\frac{1}{4}$ is the largest possible σ^2

Maybe not so unreasonable! $U^{-1} (1-U)^{-1}$ is not a proper d.f. since $\int_0^1 U^{-1} (1-U)^{-1} dU = \infty$.
 and the normal constant could effectively get all wts. $\delta = 0 \neq 1$.

for $R < -2$, P_{10} divergence is even worse

i.e. U^{-10} diverges very badly at $U=0$.

In general $X > -1, Y > -1$ so $X+Y > -2$:
 divergence at $U=0$ divergence at $U=1$.



Y can be -10 , Y can be $+10$.

The only constraints are $X > -1$
 $Y > -1$
 say plot in X, Y plane satisfying these constraints is ok.

33: 140.38 5/12/99 On second Prof, it is not clear why considering all $M_0^2 \bar{U} + (n-2)M_1^2$ models is much different from assuming wtd mean of s. 2 models, $M_0^2 \bar{U}$ & $M_1^2 M_1^2$.

01 How do we get expected/Var, ^{observed} Σ^2 in terms of Σ^2 & $\Sigma \sigma_i^2$?

(Not so complicated!) Say we had this d.f. w. var Σ^2 (d.f. need not be Gaussian or Empirical)

We select a ~~part~~ (M.C. Carlo) pt. from Σ^2 d.f., then we corrupt it by σ_i^2 .

(The σ_i^2 d.f. need not be any d.f. w. finite, var.) T. resultant d.f. has var $\Sigma^2 + \sigma_i^2$.

We start over w. t. Σ^2 & we do a new σ_j^2 & get " " " " $\Sigma^2 + \sigma_j^2$

We do this for many σ_i^2 's & we get many "fresh" d.f.'s!

If we average over all these "fresh" d.f.s we get $\text{Var} = \Sigma^2 + \frac{1}{k} \Sigma \sigma_i^2$.

10 Note: σ_i^2 that we use will be $\frac{N_i \sigma_i^2}{N-1}$ (N is size for part σ_i^2).

Applications of ST to O.K. & variance

- 1) 139.01 A application to FT acct. (Also see 132 20th accounts (34.113 - .32) & uncertainty to how to do it, it's just correlation (coeff. dist) & correlation units direction!) beer.
- 2) Get more detail from Alex on other his problems
- 3) T. idea of using last yrs' data to decide if certain params are "related" in a useful way

| Σ sq. error | units | "rest of yrs' data" | rms. |
|--------------------|---------|---------------------|--------|
| 1) μ_i^2 | .07534 | 3.8055 | .06468 |
| 2) $\bar{\mu}$ | .024259 | 1.122 | .0367 |
| 3) Stan | .021611 | 3.486 | .0346 |

$$\text{var } \frac{1}{k} \Sigma (\mu_i - \bar{\mu})^2$$

$$\frac{1}{k} \Sigma \frac{\mu_i^2 (1 - \mu_i^2)}{N}$$

I don't do it.

Do: Give details on just how well "Baseball" analysis did:

- 1) $(U_i - U_j)^2$
- 2) $(U_i - U_j)^2$
- 3) $(\bar{U} - U_{\text{stems}})^2$

Give p.o. w. some O.S. & Roots.

Define $\mu_i, \bar{\mu}, \Sigma^2$
 $\mu_i, \sigma_i^2, \Sigma^2$.

See ST 109

$\mu_i \rightarrow \Sigma \mu_i^2 \leq \mu_i^2$

if very large

$$\Sigma^2 = \frac{\Sigma \mu_i^2 (1 - \mu_i^2)}{N}$$

$$\frac{1}{k} \Sigma \mu_i^2 - \left(\frac{\Sigma \mu_i}{N} \right)^2$$

$$= \Sigma^2$$

$$\frac{1}{k} \Sigma \sigma_i^2 = \frac{1}{k} \Sigma \frac{\mu_i^2 (1 - \mu_i^2)}{N}$$

$$= \frac{1}{k} \frac{1}{N} \Sigma \mu_i^2 - \frac{1}{N} \frac{\Sigma \mu_i^2}{k}$$

$$= \frac{1}{N} \beta - \frac{1}{N} \alpha$$

v.s. $\alpha - \beta^2$

7/17/99 STEIN

146±

Some time ago, I compared a simplified ALP model w. only 2 d.crn!

② using $\bar{\mu}$ as estimate of μ_i ① using μ_i^2 as estimate of μ_i . From fr. relative pct's, I got relative wts. Th. value of R^2 was plotted as a func of N fr. no. of times "At Bet".

T. wts changed from 0 to 1 over a narrow range of N values, so I got it was not

Such a good idea: Now, how. It may be that fr. RMS Difference better if,

∴ conventional Stein are quite small. Look at this in more detail!

4305-.30 The transition betw. fr. 2 methods was very sharp in N

for N = ~~211.4~~ ^{211.4} wts were about = but change factor of $(0^2 + 1.68 \times 5.4 \text{ or } \frac{1}{5.4})$ for N = ~~211.4~~ ^{211.4 ± 10}.

See if Regular Stein does this also.

~~Not really, since regular Stein only has N=35~~

| ST103: | N | w |
|--------|-----|---------|
| | 150 | .2373 |
| | 210 | .167 |
| | 270 | .1318 |
| | 100 | .356 |
| | 95 | .791 |
| | 20 | 1.779 ! |
| | 30 | 1.118 |
| | 35 | 1.017 |

strangely used! as N goes thru 35 w/ changes sign, but general direction of μ_i products about the same. at N=35, $w \approx 1$ ∴ all products of μ_i are $\approx \bar{\mu}$ (expected) Hvr, that $w = 1$ for N as large as 35 seems inappropriate.

(1-w) > 0!

Using "k-1" instead of "k-3" in calcns.

k-3 → k-1

| N | w |
|----|-------|
| 35 | 1.15 |
| 40 | 1.008 |
| 45 | .85 |

So, $w \approx 0$ fr. goes from $N=35$ to $N=40$! So $k-1$ is perhaps worse! we would like $w \rightarrow 1$ as $N \rightarrow 0$.

So: via ST42, & ST103 to get fr. 2 estimates of μ_i and their rms difference!

compare w. rms errors of 1. p8ms — say simple rms of prod by "just a yr" estimator)

Easiest to do: Get rms error of both methods ∴ func of N.

I am a bit ^(suppressed) ~~dismayed~~ at ST42: But to think, Stein was so sharp!

Suggesting error impem:

7799 GXR

- 1) Storn Effect: relationship Evaluating bunch of strats.
- 2) try: 1984 → 1994 to get less correlated.
- 3) Try other cats (time of day, cross commodities, zero Mkt)

$$f(f(x)) = x$$

$$= f(x)$$

$$f(-x) = -f(x)$$

$$f(x) = -f(-x)$$

$$f(f(x)) = f(x)$$

$$f(x) = f^{-1}(-x)$$

$$f(-x) = f(x)$$

Probn from "Self" is highly mixed.

Bugs in "Trading Pgm"

\$5 - US\$/yr.


20 trades/day

\$100/d → 25% / yr

Proj 15/trade is due to big losses. (Small size may be statistically undetectable!) say $\sigma^2 = 250$

1) Portm product strats to have RETS, MKTs

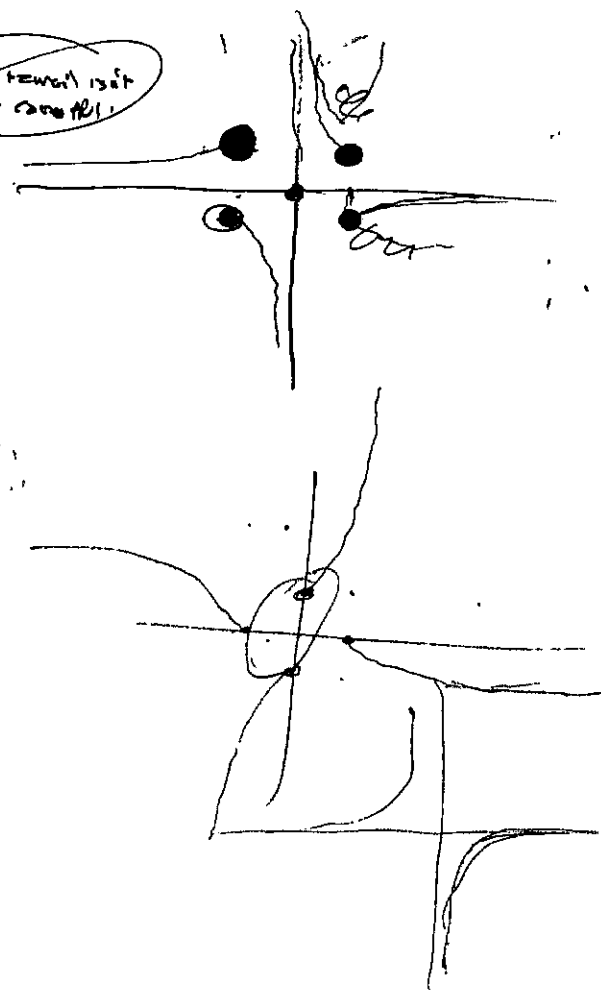
→ Tweaking current strats w. originally desired (More complex)

3) Really new strats → 

Kurzweil says 5% of MKB is Geometric Means.

Margin put up can be imp.

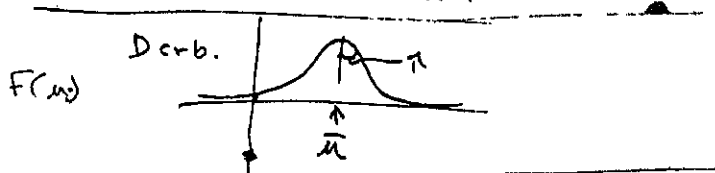
Probn will not keep constant!




7/15/99 STEIN Paradox:


Dirb. Baseball situation : k players = 18; n times at bat = 95.
 "Kifer not hit".

Diracbe $N = 500$ cases
 $n = 1$ case.



Start with all $\sigma_i^2 = 1$ / later option $\sigma_i^2 \neq 1$.

Explain about final D.f. $f_i(\mu_i)$ 
 $f_i(\mu_i) \cdot F(\mu_i)$. Prob of observation =

Prob of μ_i being chosen times prob of observed μ_i given μ_i
 which is given by  (BAYES Rule.)

Using d.f. with τ and $e^{-\frac{\tau}{\pi}}$ for smoothing

Say Σ of sources exponential $M(s)$ way to ~~...~~
 useful.

Mixing of ... Baseball, basketball.

Given:

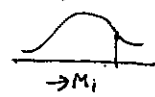
Basket Ball: Mix 1, 2:

Binomial d.f.?

look at previous yr (E) for
 a difference, - re. 24
 means closer?

7/15/99

STEIN PARADOX

μ_i - batting average
 true mean for i^{th} player 

μ_i' - apparent mean for i^{th} player based on batting average. $\mu_i' - \mu_i$ deviation from observed batting average

σ_i^2 - Variance of data for i^{th} player.

$\bar{\mu}$ - average of all μ_i' : $\bar{\mu} = \frac{1}{k} \sum \mu_i'$



\uparrow^2 - variance of distribution generating $[\mu_i']$

Σ^2 - Variance of observed distribution of $[\mu_i']$:

$$\Sigma^2 = \frac{1}{k-1} \sum (\mu_i' - \bar{\mu})^2$$

$\overline{\sigma_i^2}$ - mean of σ_i^2 : $\overline{\sigma_i^2} = \frac{1}{k} \sum \sigma_i^2$

k - number of players : ($k=18$ in this example)

n - number of times at bat (same for each player : $n=45$ in this example)

$$\sigma_i^2 = \frac{\mu_i' (1 - \mu_i')}{n}$$

$$\uparrow^2 \approx \Sigma^2 - \overline{\sigma_i^2}$$

Stein's estimate of μ_i : $\left(\frac{\bar{\mu}}{\uparrow^2} + \frac{\mu_i'}{\sigma_i^2} \right) / \left(\frac{1}{\uparrow^2} + \frac{1}{\sigma_i^2} \right)$

Empirical rms errors: (error with respect to data on about 400 more "at bat's" for rest of year (1970))

μ_i' as estimate of μ_i : .06468

$\bar{\mu}$ " " " " : .0367

Stein " " " " : .0346

STEIN'S Paradox : ~~EMMA~~ Efron, Morris, Sci Amer, May 1977 P 119-127
 More refs in 2nd last page of issue

Data Analysis Using Stein's Estimator and Its Generalizations: Efron, Morris
 Journ. Am. Stat. Assoc Jun 1995 P 311

Empirical Bayes Methods Applied to Estimating Fire Alarm Probabilities
 Carter, Rolph; Journ Amer. Stat. Assoc, Dec 1974

7/15/99

STEIN PARADOX

original.

μ_i true mean for i^{th} player

μ'_i apparent mean for i^{th} player

σ_i^2 variance of data for i^{th} player.

$\bar{\mu}$ average of all μ'_i : $\bar{\mu} = \frac{1}{k} \sum \mu'_i$

τ^2 variance of distribution generating $[\mu'_i]$

Σ^2 variance of observed distribution of $[\mu'_i]$:

$$\Sigma^2 = \frac{1}{k-1} \sum (\mu'_i - \bar{\mu})^2$$

$\bar{\sigma}_i^2$ mean of σ_i^2 : $\bar{\sigma}_i^2 = \frac{1}{k} \sum \sigma_i^2$

k number of players : ($k=18$ in this example)

n number of times at bat (same for each player : $n=15$ in this example)

$$\sigma_i^2 = \frac{\mu'_i (1 - \mu'_i)}{n}$$

$$\tau^2 \approx \Sigma^2 - \bar{\sigma}_i^2$$

Stein's estimate of μ_i : $\left(\frac{\bar{\mu}}{\tau^2} + \frac{\mu'_i}{\sigma_i^2} \right) / \left(\frac{1}{\tau^2} + \frac{1}{\sigma_i^2} \right)$

Empirical rms errors: (error with respect to data on about 400 more "at bats" for rest of year (1970))

μ'_i as estimate of μ_i : .06468

$\bar{\mu}$ " " " " : .0367

Stein " " " " : .0346

Stein's Paradox : ~~Wikipedia~~ Efron, Morris, Sci Amer, May 1977 p119-127
More refs in \approx last page of issue

Data Analysis Using Stein's Estimator and Its Generalizations: Efron, Morris
Journ. Am. Stat. Assoc Jun 1995 p311

Empirical Bayes Methods Applied to Estimating Fire Alarm Probabilities
Carter, Ralph; Journ. Am. Stat. Assoc, Dec 1974

This is fine, except for the fact that the observed variance τ' is subject to random variations and could potentially be much smaller than it is supposed to be. In that case, $\tau'^2 - 1$ could potentially be negative. Even if it is positive, if it were tiny, because of random variations, the estimate of τ would be very much in error.

A more careful way of estimating τ from τ' would be an improvement.

we could use prior d.f. for τ^2 .
cutoff for $\tau^2 < 0$.

1.2 Fixing up to remove the unit variances

1.3 Bayes formulation

1.4 Tree version of the problem

This is a variation on the original setting which is relevant to clustering.

We have a large set of random variables, some of which are very similar to each other, and others are more different. We have observations of each of them, and we want to estimate the mean of each random variable. The problem is that we only have a few observations of each RV, not enough to do a good job of estimating its mean. So we would like to also use observations from other RV. The observations from very similar RVs would have a large weight, and observations from less similar RVs would have a smaller weight. We want to use some Stein-like formulation to decide how the different observations should be weighted.

We will assume that the similarity of the RVs has been already determined somehow, and expressed in a tree. Two random variables that are very similar will have a near common ancestor, perhaps even the same parent or grandparent. Two RVs that are less similar will have a more distant common ancestor.

To go along with the tree of random variables (and their observations) we will imagine another parallel tree of random variables, related to the Stein estimation setting. At the root of the tree will be a random variable U_0 , with mean u_0 and variance τ_0 . It will have several children U_{0i} and their means u_{0i} will be samples taken from their parent. I don't know where their variance will come from. They will in turn have children U_{0ij} , whose means u_{0ij} and (variances τ_{0ij} ?) will be samples from their parents U_{0i} . This will be repeated all the way down to the leaves, which will correspond to the actual random variables whose means we want to estimate.

Since the means (and variances?) of each node in the tree are themselves random variables, the RVs can be thought of as several different random variables, each will different means and variances, depending on how many times we compose it with its ancestors.

For example, a RV at the bottom of the tree can be thought of as having mean $u_{0ij\dots yz}$ and variance $\tau_{0ij\dots yz}^2$ or mean $u_{0ij\dots y}$ and variance $\tau_{0ij\dots yz}^2 + \tau_{0ij\dots y}^2$ or ... mean u_0 and variance $\tau_0^2 + \tau_{0i}^2 + \dots + \tau_{0ij\dots yz}^2$.

2 Conclusions

References

[1] A.U.Thor, Ph.D., "Big Hairy Equations", Faceless Corporate Press, 1988

7/14/99 Alex: Voice Recogn.

They use "Triphones" (a phoneme in "before" context).

Every 10ms they get a spectrum: which is spectrum of log of spectrum?
Perhaps they should take spectrum w. log in w. dimension - better spectrum of power
- anyway, the spectrum is supposed to give a picture of the acoustic response of
the filter that "buzz" is subject to... leaving out all pitch information.
Each spectrum is represented by 45 params. So they get 1,45 vector every
10 ms.

They have a HMM w. 5 states that model a triphone. The 5 states are
connected, so they have to go L \rightarrow R, but may skip 1 or more.

The p.d.f.'s in 45 space are modeled as "Gaussian Mixtures"
9. Gaussian are MV d.f.'s w. only diagonal cov. They sum up to
256 of these Gaussian. together form "mixture" d.f.

Guess that the triphones are each a sequence of 5 (or less) states
in each state is a p.d. on this mix of 256 Gaussians. (\equiv Multivariate d.f.)

Also they have a "Language model" using "digrams" (word pairs)
"trigrams" & "ngrams". SSZ is far away from uni-dim: so how can
we pool data in the whole sort of Stern Model can we use?
One way to pool words is parts of speech. "Parts of speech" can be
"defined" by: (1) what comes after "The"

They have a corpus of ~150 hrs of speech (over telephones):
at 1 sec./word this is ~ 1.5M ~~words~~ words - so SSZ for
digrams & trigrams would be rather small.