

INV

Extra fine
Abcdefghijkl. Continuity ABCdefg. ABCdefg
Fine Abcdefghijklmnopqrstuvwxyz

9874156.40
0.01

1. On solving eqns as Inv. prob: Consider: $3x^2 + 7x + 3 = 0$.
To be solved w. closest fit w. ~~xxxxxx~~ resolu. .01 on x.
With a very simple p.d. (No expensive in solving), we just try all

nos. of form. $\frac{n}{100}$ in order of pc ($\approx bc \approx \log pc$). (Not nearly! - see .20)
2. When we "know" about continuity, we might try finding ~~xxx~~ ~~xxx~~
 $x_{1,2} \Rightarrow f(x_{1,2})$ are of opposite sign, then try for values between them at
.01 resolu.

3. if we know how to solve quad. eqns, we could ~~do~~ do it much faster
4. ~~xxxx~~ This seems related to "probably that 10¹⁰⁰ digit of π is 3."

In case of π , we have to believe "PI" ~~is~~ to T.M. If we define it via an
infinite series, early, (no-sophisticated) trials will involve exponents ~~and~~ finding
many digits of π via t. series. w. large const C , t . 10¹⁰⁰ digit of π can
be found exactly, via t. series.

On the Other hand. $\int_{-100}^{+100} ABCDEFG e^{-\frac{x^2}{100}} dx$ ABCDEFG abcdefg

5. On the other hand, we can solve eqns. by using t. function "solve (,)". — This seems to
be quite diffrnt. from solving t. eq. as an Inv. prob.!

Maybe not so much! — Remember that in .01, t. Inv. problem gives rise to a conditional
p.d. — t. condition being t. eq. " $3x^2 + 7x + 3 = 0$ ". — which is t. "inversion constraint" defn.

It would seem that t. "Solve" function would be easier to ~~find~~ learn/teach
than t. INV. & p.d. of .01: But presumably, a Brite I.M. would eventually
discover that they were identical!

Used 597
to program.
2) Try
COR-R first
3) P.B.C.C.
no hurry

1399 TM: 2 **CHESS**

maybe Great Break Thru! (25)

Expo: Title of Book, Peter DeMa: T. Science of Discovery, ALP2 MCT!

2 This is GREAT.

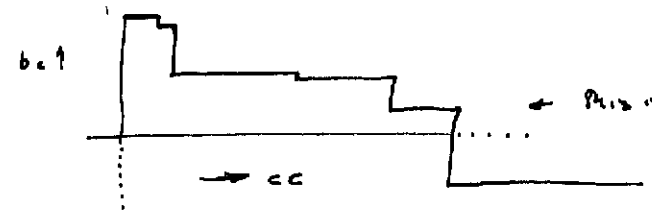
.01 Say one is spending cc on finding short codes for a corpus: One notes t_i bc of v_i corpus (thus far) was a function of cc expended. While, in general, one can't exactly extrapolate, to what extent can one, using limited CB for t_i Extrapolate?



One can note that t_1 or t_2 becomes (larger as v_i increases), who don't expect much, accuracy of cc \rightarrow extrapolate. A st. line, parabola, exponential w.

Project further into t_i future. horizontal asymptote or other forms. can all be used for Least Sq. fit.

This is colossal ABC



← This is more what it's likely to look like.

Note that ^{even} at $cc \rightarrow \infty$, bc can never be zero, but it can be close to zero!

Similar: extrapolations can be made as corpus grows w. time and cc \rightarrow time.

This discussion may be going in direction of soln. of **"Chess"** problem!

An area where we may have some idea of how bc varies w. cc. is looking for

.29 models in SM. I try a few, run on basis of results, I may have ideas as to what to try next. is expected bc? 30
see (93) 145.09 for previous work, dissn.

.25 In fact, in t_i Lech soln of t_i or Q_2 problem, one normally has pragmatic idea as to what G to expect w. a BA. cc. [In t_i present case $G = -bc$.]

So, actually, while this problem is unsolvable for $CB = \infty$, it probably is quite solvable ~~for finite CB~~ for finite CB In fact I love to solve it every time I solve an Q_2 problem via Lech!

.30 23 May be related to t_i "What to Work on Next" problem.

1.6.99 TM: Updating: Summing Machine & "Summarizing Machine"

01: (98)146.90; So it looks like I can mainly think about a sequential corpus, w. impossible
Hvr. coding "corpus increment" can be a "very many forward task";
The varieties of how this can be done are quite large. They all, hvr, have a common dimension
& so are interconvertible.

SN T. "Summarizing Machine" is but one way of expressing all or part of a P.D.
So: List of a few P.D. forms: & output of an "Updater":

- 09 1) A ^{vacant proxy} ~~sum~~ machine (under 30 ~~3~~ - no hard time): short random inputs plus d.f. on outputs.
- 2) stack operators: ~~Input~~ Input is augmentation of corpus; output is P.D. on contents of corpus. It ^{output} can be realized by as 09 or by listing (outputs in order of p.c.) or by having post. output presented, i p.c. of next output is pre.

14 3) So 1) & 2) can be varied (a) cond. or uncond. p.c. (b) output can take various forms; of Monte Carlo or usually w.r.t. random input to stack operator β given post. output, ^{string} unref. p.c. of next string.

17 γ (output, p.c.) forms in p.c. order or simply output in last order. δ ~~On~~ On (or more) control objects & an exp. fixing density distribution about these control objects. \rightarrow 9.20

Very probably .14 - .17 doesn't cover all cases ... but labor is for a while.

Next: Ways to get these P.D.'s of .14 - .17 (How to do updating):

20 First "look at" corpus: at all times we have a bunch of definitions that we have been told about or discovered to have been useful in coding. As we scan corpus, we look for instances of all of these defs. (This is a process that is readily ~~parallelizable~~ parallelizable)

Many of these defs. correlate w. methods of corpus analysis, coding. These "defs" are "obs" (observations): They somehow imply "ops" (operations on corpus)

Post yields how obs & suggest new ops, (etc). { the ob. of algebra }

One perhaps commonest op: that certain obs occur w. certain frequency that differs "significantly" from that expected in random corpus.

How does it stack up such of a SGA fitting this?

ABC

SN 20 ft. looks pretty messy! Contrast w. my ^{parent} ideas on how to (rn. practically any tsg.!) perhaps go into this simple ~~step~~ idea ... see if it works & how far it can go.

Actually, ~~the~~ stuff w. (98)88.01 & even before has a lot of nice ideas about MCT & its applications in teaching TM!

01: : 1) On "Novels": We can let T.M. read a novel ... coding it sequentially, then perhaps it can reread it & recode it again & again. We can then ask Q's about that novel. The text for the novel will be taken w. (Author, Name of Novel.). Similarly taking for Q's about that novel. After T.M. has read several novels, it will find common & bs. (s. cons.) in them, thus making future coding ("reading") of novels easier.

104 Reading novels will help T.M. answer Q's about "R.W." { R.W. = novels in which info is from either "reliable text" &/o T.M.'s inputs (sensors) in R.W.

Also, in addition to using Q's & A's for novels (learning about novels, T.M. could be asked to predict contents of text. — Hvr., this may be redundant. — T.M. normally tries to compress any input text that it is given.

2) Wolff's methods of analyzing text to discover CFB's can be very useful.

— For text, certainly — but ~~for~~ also for discovering abs. of all kinds —

by "Chunking": Start w. simple (big); small words, small grammar, simple ideas, meanings, statements. I could ask Q's about a sentence, word, sentence or paragraph.

3) At first, I was uncertain how T.M. would treat "info" from a novel ... how it would know that the "info" in the novel was specific to that novel — & not others. Hvr., if table Q's is 01-04, T.M. will learn to answer Q's about a gen. novel, using only the text of that novel.

4) Could I teach T.M. to read a "Translated to Latin" version of that book on Contract Bridges? Wilson Cohen : 8th Nxt. Conf on A.I. AAAI-90 pp 743-748

5) On Eng. Grammar: I could help T.M. learn grammar by defining nouns, verbs, ^{noun phrases} Subject, predicate. ("Doing" means how T.M. learn these defns. as functions:

e.g. equation $(2x+5=1) = 1$ "Tive": These Defns can be considered to be "HINTS".

6) An early "Grammar": a very simple sentence str. Subject verb object.

Subject & "object" are nouns & can have adjectives attached. Verbs may have adverbs attached.

There is an time sequence for verbs: The sentences tell a story sequentially: (no way for 2 sentences to be simultaneous).

Can we find a path to modify this grammar into a fuller CFG, &/o add temporal forms of verbs, & use sing, plural, male, female, it to associate

& associate nouns, verbs w. proper adjectives, & adverbs ...

Subject Verb object can be translated as "Subject, Object from various Verbs."

||6PM||

I think I want to get TM to work a bunch of disparate problems: So I can see if there is a simple, general, way to get it to work all of them

03

General Remarks: TM can use info if it is "Told" that info: Just as a human can.

But (just as a human), T.M. will get much more out of v. info if it "understands" v. info: i.e. it has compressed it - preferably if v. compression also uses cones in f. rest of f. corpus. - i.e. If TM is able to connect v. new info w. ideas of f. past corpus.

2) As TM Matures, it gets many more cones: But this does not expand to such space, because assoc. w. f. now cones are also conditional (P.D.'s that narrow down when f. cones should be used.

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3) 1 (03) is imp., because it means we can "tell" TM things - like how to solve a problem or set of problems: This is easy on f. "Teacher" TM then can will (what it has been told) just as a human) try to compress f. things it's been told "so as to fit into f. macro corpus - i.e. to compress f. macro corpus.

4) We can perhaps give TM f. set of heuristics that cannot used in AM (if we could figure out what they are! - perhaps got them from Ken Haas).

5) I need to write down just why I feel that I was much much closer to finishing TM than ever before. This will enable me to focus on remaining unsolved probs (if any!). Sol 86 & 89 have much of the outline of how TM is supposed to work; ~~before~~ At those times, I had rather narrow ideas on what kinds of T.S.Q.'s to write. This has been much expanded since then. Also, while I had this idea of "Compressing f. macro corpus" I didn't ~~know~~ really understand it in a sufficiently exact way.... ~~also~~ in particular, how to mix info from O.E.'s Inv probs, i.e. mix info from several sup. extrapoln. & finite set extrapoln. probs.... I didn't know how exactly exact level.

6) One trick was "working backwards" from a particular problem ~~to~~ to obtain a cone, not ~~starting~~ starting at f. primitive conc. level.

7) My fear is that I will begin work on a specific tsq. arena; get involved, get stuck, spend a yr. or 2 on it, then forget where I was going - i.e. forget the "Grand Preface". So I want to ^{first} make a clear, somewhat detailed deun. of f. "Grand Preface" - then get down to details. See 1 -> 7.01

(SN) Just how does TM code ^{errors} errors ("exceptions") when its doing ^{unrecorded} a corpus of finite objects?

Say "operator induction". Well, in Op.ind., we have input & we get a pd. on output string.

There is no actual "error" involved. We might, however, have a stochastic operator that

is ~~not~~ deterministic & is almost always nite. One way to do error correction:

It has 2 output classes of object: 1 (w. prob ϵ) it does its deterministic

output. 2 w. $pc = \epsilon$ it has a ~~general way~~ general way of deriving

objects. The pc of such a deriv is rather low, hvr. ϵ is multiplied by ϵ , to make it worse!

Another policy is that for ϵ of .05-.06 varies w. each output - so we can mix certain of certain responses given others. (29)

TM has to work by close simulation of a person's speech, saying certain text: It has to read the text. Then it tracks (in memory) speech to text, & can produce shift (Linguistic) or shift for analog ling ((98) 95.2)

.05
.06

.10

12: (98) 95.24: More on Analog Ling: T.M. is given ^{set of} pairs (Q_i, A_i)

The Q_i 's are English texts: words:

" A_i 's are Time varying spectrum (or a better, perhaps filter outputs of supposed human vocal tract) ^{using Markov Kalman filter for tracking.} corresponding to a particular person (α) ~~speech~~ pronouncing Q_i ."

From this, we want to induce ~~that person's~~ α 's pronouncing a new Q_j .

For some words, there is necessary ambiguity on pronunciation (like "read")

This could be resolved by context. In fact, we can have this be a separate problem: to resolve various word meanings (= pronunciation) by context of text... This is a purely "digital" problem.

T. ~~can~~ General Inverse of 12 is the problem of "Voice Recognition"

It fits in well w. TM's usual approach - i.e. given α & t , beginning of a sentence, ...

"What is t . pd. of t . next word?"

29: (10) (6.9.00) In unrecorded ^{unrecorded?} set of finite strings induction: T. code for a given finite object can be in 2 parts: 1 code for an approximate object 2 instructions on how to change approx. into exact object. If $\alpha \rightarrow \beta$ approx. & β is desired object, we can code complexity of β w.r.t. α i.e. $\frac{PC(\alpha, \beta)}{PC(\alpha)}$ This code, pc will be developed as TM matures. It will find that in certain environments, different $\alpha \rightarrow \beta$ ratios are more likely.

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1.11.99 TM: Grand Plan:

01: 5.40 : 1) So, I start by solving a simpler problem using Lurch; i.e. a very simple ~~unconditional~~ unconditional P.P. I may solve several (2 or 3 separate) problems in this way.

2) Next: Updating I now have this corpus of examples: I have to compress this Macro corpus. (It may or may not be a "Mixed corpus").

Actually, does the corpus need to consist only of examples of problems that TM has solved? Not really! Solid problems are nice because they are already compressed, parsed, "factored" but at a certain stage in TM's education, I can put unfactored, uncompressed data into the Macro corpus & have TM compress it. Now Macro corpus. TM will be able to do this well, only if it's able to "recognize" the new data, so it has ideas as to what compression methods to use on it. [See 3.20 on 6. "op, ob algebra" ideas]. Recognition can usefully occur only when TM has

accumulated an adequate lot of obs (dofas) & ops (ragy types) & correlates betw. them.

3) Superficially, it looks like the main problem is Updating.

4) An apparently diffrat problem: 2) Just how do we express various heurs as C.P.D's? How do we update these ~~new~~ ~~old~~ C.P.D's? (i.e. changes Macro P.C's) Also, small heurs expressible as CPD models? (e.g. "Quick Abort")

5) Well, no! 4) It would seem that Heurs would always be of the form: "I am in a certain situation & ~~there~~ my long term or short term goal is x" What is the CPD of my trial actions? This may include "Quick abort": since one's goal is always "fast" soln. [On the other hand, Many problem solving methods make very few trials (usually only), but it's a rather hycc trial!] hycc

6) SN (Sol 86) is not a bad way to organize my P.C's. I think I had the idea of very carefully constructed T.S.P's — "The idea of Patent T.S.P's & "cases of corruption" was still ~~there~~ (ingenuy in my mind. NOW, the idea is that Order of learning is not very critical.

Another idea was that TM₁ & TM₂ were somewhat different — that the self-improvement of TM₂ would not occur until TM₁ had worked out. Now, my impression is that TM₂ is "Updating" & is done even by the newborn TM!

7) One thing I haven't worked on ~~new~~ (branch (?)): How do we get TM to work problems in a way people do by curious deductive reasoning? — I did do work on that

30 "Planning" heuristic in Sol 86: It looks at problem, assigns probs to 4 (or more) diffrat ways of solving it. This is normally what I do now using cond. probab of problem. I put probs for various approaches: each of these approaches can call on its "plans" which is a cond. P.D. We can get potentially deep trees this way. → 8.01

1.13.98 priority "g"
about TM Grand plan.

Does "RM" mean "Real Machine Reasoning"?

01:7:40 So his begins to look like a common type of human problem solving: we have this

(Priority: AM (Low) my low level Artificial Mathematic

Very branched tree to search. If we are familiar with problem solving some nodes will have only 1 path w. much probly.

→ 8) So I'd like to make a list or tree or some kind of structure w. many kinds of problems in it → so I can see how TM would work on each type.

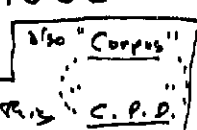
9) **RM** doesn't have to do an actual problems when it is being trained. We can give it solved problem & know to "compress" soln → it has to find how it would solve.

prob → so it uses LSrch → same as if it had been given to unsolved problem to solve → We would want to give it real probs. in its trg. to be sure that it was really learning useful stuff!

10) **frun?** with very highly branched tree: Ordering trials by PC or LC can be

a drift problem. → It's a special case of a general problem of matching

outputs of a P.A. in a (ruff PC order)



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11) The **General Plan** of RM: ① It [has] all times this "C.P.D." This CPD can take

Several forms & it may be mixed a mixture of these forms. (See 3.14-17 for a set of forms it may be.) If can (to an impl. extent) convert betw. diffrnt. forms

② It is able to use the CPD of ① to solve Inv. & OZ. probs. also to auto-polate,

interpolate, w. probs, get most likely set of ^{only} interpolations.

③ It is able to ① Improve the CPD w/ its present corpus

② When the corpus is augmented, it is able to ^{accomodate} modify its old CPD to optimally modify the old CPD to accommodate augmentation: It will do this w. whatever cc is avail. to it.

27.09 12) In general, **RM needs not have a TSCQ**: It can just have a big corpus that it

continues to work on to "compress", to find regys in it, to obtain a better & better

CPD w/ that corpus. Hvr., if we do give TM a TSCQ that is carefully prepared, TM should be able to get a v.g. CPD w. much less cc.

13) So, the history of TM is the history of its CPD: The corpus history is (to this & the corpus may be (well) regarded as a special form of CPD. (It has all of the info, but much of it is at vary by cc.)

"update" is one form of convergence betw CPD forms: limit "corpus" learn to other forms. ↑ Amusing (Nov April 2005)

...
 .01: 9.14: Logic has 3 aspects for TM: ^{This is a primary Actual Domain} ① Learning to work problems in logical calculus ^{in task domains.} ② Using Logic to solve problems of all kinds ③ learning ~~concepts~~ before ① & ②

6/9/00: Also, Logic can give a very ~~short code~~ shortcut to things that "follow logically" & very long codes to things that don't. Logic when viewed as a constraint, the more the such space much smaller. It is not ~~the~~ always of low CC, ~~but~~ if CC is too high, the ~~reduction~~ reduction of such space size may not materialize w. the available CB!

01: (98)154.40: I guess what Wallace would say: That when α arrives, we will try to find the best short code for "old corpus α ".

Robert: So "T. Best code for α " ^{is "old corpus"} does not ~~include~~ have all the statistical info that we'd like it to contain: i.e. info on less short codes would be valuable in dealing w. "unexpected situations" (which usually eventually occur).

From a practical standpt. - T. shortest code is a very incomplete desc of E. corpus. A more complete desc, would involve telling about many of T. less short codes that were found (& ignored) during T. search for T. "shortest code".

T. difference betw. T. "SCIENCE" problem & OSL, is that in "SCIENCE" we usually know what "not so good" (ideas, codes) to remember (retain). In the case of OSL, it is usually not possible: There are too many (consequences) of " " that have occurred out there, (or twice but we can't bits in them to warrant a "definition").

2.27.99

TM GENL:

→ UTILITIES ←

GREAT BREAKTHRU!!

For some time, I've been concerned that ALP didn't solve the ultimate problem of human behavior:
 i.e. "What to do next?": I assumed that one could devise a suitable "Utility function",
 i.e. that one would then try to Maximize one's expected Utility wrt that function.
 → How one obtained such a function was unclear. →

The new idea is this: That the above "Utility" Model, is merely one possible way
 to deriv. human (or living creature) behavior. As such, ALP would say "Consider
 all possibl. Utility funcs & behaviors they induce. From corpus, get pc of future behavior
 as a w/d max overall Best Utility Funcs: Wt, being a pc of past-prdn. of corpus"
 i.e. Utility funcs are just another way of derivg (coding) behavior for predn.

T. foregoing is a descr. of ^{Utility} ~~funcs~~ funcs' use to predict other people's
 (not myself) behavior. How can I use this idea (or any other method) to help
me make personal decisions for myself?

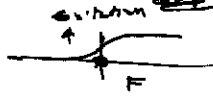
Is this Bordering on Q of asking TM. for "Whatever it is that I would like most"

i.e. asking TM to figure out just what this is. (?). — A very ill defined Question!
 Also, I probably wouldn't want TM to do that!

— That's defn. of Utility is that which, (w. pc calcn) enables one to predict a person's behavior.

Some reasons that I don't want TM "finding out what I really want"

- 1) It could then use this model of me to manipulate me to further its ends.
- 2) "What I want" is based on currently limited power, intelligence; When those over increased much, "What I want" of the past, becomes not very appropriate!
- 3) I could have TM take ^{my} into account/deciding what I would want w. new power, intelligence, but I'm uncertain of the wisdom of this.

.01: (98) 181.90: This process isn't very much like ANN. One way to do it: Say we have 10 good drivers for a car, driven. $F = \sum_{i=1}^{10} a_i \cdot P_{dr_i}$, (P_{dr} is ^{price of} $\frac{1}{a_i}$ driver) we then write driver w.  so weights to "wts".

We can update to wts. in the usual ANN format, since we can get slopes from the derivatives - ~~the~~ H_v, it's not to never than is unclear. If we get to second derivatives also, we could get a very nice optimum soln!

Examine this in detail: This ~~is~~ second dim could be applicable to speed up ANN in general, by a tremendous factor. (Pro already, using standard N.L. optzm, there is an enormous speed up.)

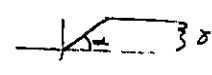
One effect is that I will probably want to use many fewer wts than normal in ANN exp.

Another possible model: Existence for drivers $\sum a_i F(x; P_{dr_i})$. Here we have 20 params, but we may be able to solve ~~the~~ for the wts. in a ~~to~~ some way as before, w. first & second driving.

Jargov's "Hessian" approach.
= Fisher Info

.01 It needs a lot of work! First I have to rework ANN - get a clear idea how back-prop. works. - Then, perhaps modify it suitably.

In estimating α & δ of various DD's + ideas in Stein's Paradox are critical; δ SS's will be small, so LIC have to pool data.



1.6.98

SMFT

Stouffer's Paradox in Statistics: Efron, Morris, Sci Am May 77 pp 119-127

Say we have k collections of data. Each w. its own mean, \bar{y}_i .

Say \bar{y} is grand mean ($= \bar{y}_i$)? $(\text{is } \bar{y} = \frac{1}{k} \sum_{i=1}^k \bar{y}_i ?)$ For k sd's, it's not easy to know. Is constant = 49 for all players?

Then Stein uses $\bar{y} + c(\bar{y}_i - \bar{y})$ as a better estimator of \bar{y}_i . $z = \bar{y}(1-c) + \bar{y}_i c$
 $= (1-c)\bar{y} + c\bar{y}_i$

$c = 1 - \frac{(k-3)\sigma^2}{\sum (\bar{y}_i - \bar{y})^2}$ (shrinking factor) Maybe σ^2 is σ^2 or what \bar{y} ? \rightarrow Problem

They eat $c = z$ for one case of k players. σ^2 most bad $\frac{\sum (\bar{y}_i - \bar{y})^2}{k-1}$ (k=95) No! \rightarrow Problem

They then divided data into 2 parts: made $c = z$ mean estimates from first $\frac{1}{2}$ of data - Problem
Then checked derivations from answers in second $\frac{1}{2}$, & it worked much better than using $c=1$ (= no shrinking factor) in this case $c < 0$ for large k

My impression is that this is a SMA problem. One reason it took to 1955 to discover it was reluctance of statisticians to use mean approx. into.

to eqs. .04-.05 would be a nice ruff & dirty estimate. SMA problem

I'd need to know exact defn of σ^2 , but. It may be that σ^2 is the mean var. of players w.r. their averages. So $\sigma^2 = \frac{1}{k} \cdot \frac{1}{k} \cdot \sum (\bar{y}_i - \bar{y})^2$: the average var. of players.

On t. other hand, in my normal SMA calc., I really know what's going on, so I have more confidence in it. In fact, $c = .04 - .05$ is not v.s. of

to data sets vary very much in size. (e.g. Efron discuss 552 = 2 for one baseball player - P124 col. III)

In general, I am rather vague, I'm not really sure what \bar{y} is - if each player has diff. no. of cases. I'm sure I know what \bar{y}_i is, but I'm uncertain about \bar{y} & σ^2 .
 \Rightarrow Is \bar{y} a weighted average of \bar{y}_i or a simple mean of \bar{y}_i ?

to eat c we want ratio of σ^2 to $\frac{\sum (\bar{y}_i - \bar{y})^2}{k-1}$

Go to Harvard: Got that issue again - see if there are references. Go to Penn! (usually there are) - very last p. of that issue Got it!
or: $\sigma^2 = \frac{1}{k} \sum (\bar{y}_i - \bar{y})^2$ No! that's like denominator of .05

.06 R is a nice defn. of σ^2 : They assume σ^2 is f. same for each i . Efron 1975 p 53 PSM-316

In other papers, they deal w. σ_i^2 varying w. i . My impression: $\sigma^2 = \frac{1}{k \cdot l} \sum \sum (\bar{y}_{ij} - \bar{y}_i)^2$: this σ^2 is weighted more in the \bar{y}_i - I think +.04 should be $\frac{1}{k \cdot l}$ not $\frac{1}{k \cdot l}$

$\frac{1}{k \cdot l} \sum \sum (\bar{y}_{ij} - \bar{y}_i)^2$ would be indep of k, l for large k, l .
Here, σ^2 is $\propto \frac{1}{k}$ for large k, l is desired.

($\propto \frac{1}{l}$ is more likely)

SMFT

1.16.99: ~~SMFT~~: Stein's Paradox: ("T. Stein Effect")

Often in statistics, the SSZ is so small that σ dominates μ ,
— So if one takes average of N observations, $\sqrt{\frac{\sigma^2}{N}} > \mu$: so one would do better

using ϕ as the mean, than using μ . "Doing better" means that using μ
as a predictor has more MSE error than using ϕ as a predictor.

I observed this, using windows for averaging & I was much confused,
disturbed. Now it seems clear!

.07 T. Way one can deal w. this effect is by pooling ~~the~~ "related" distributions.
In the "Batting average" example in Sci Amer (May 77 p. 119ff), we pool data for

.09 different players. A good model for this is to use μ used in my SOY analysis,
Say the μ_i 's of the various ^(N) players has μ mean $\bar{\mu}$ and $\sigma_i^2 = \frac{S}{N}$

Then over player i has own μ_i & σ_i^2 . So better, in our analysis, we
had those $2N$ params, μ_i & σ_i^2 . Now we have $2N + 2$ params.
Omitting μ & σ of $2N + 2$ params; the μ of the μ_i is

.20 $\prod_i \prod_j \frac{1}{\sigma_i} e^{-\frac{(x_i - \mu_i)^2}{2\sigma_i^2}} \prod_{i=1}^N e^{-\frac{(\mu_i - \mu)^2}{2\sigma^2}}$ \rightarrow 4.01

We end up w. convolutions of d.f.'s w. s.d.'s of S & σ_i^2 .

(.20 has to be worked out more carefully; it may have been in SOY work in
.24 SMFT of previous yr (or 2).) \rightarrow See 3.13 for refs

Anyway, this "Stein effect" is very imp't. I was concerned in

linear regression, that the covs in the cov. matrix could be of poor accuracy,
so the preds would be very poor. — In fact, this is so. If the SSZ isn't
large enuf, the default predn (say zero) will be better than the predn obtained
via linear regressn. In linear regressn, one can compute $\frac{(N+k)\sigma^2}{(N-k)}$ (for k params)
w. σ^2 of the raw data (about \bar{x} or about mean), so for the linear regressn helpd.

IN SM, one can effectively \uparrow SSZ by "pooling" in at least 2 ways.

- 1) As in the SOY analysis, (.09-.20) pool data from related stocks & securities.
- 2) \uparrow SSZ by using larger smoothing bins; even tho' the larger more distant past
gives data w. somewhat different characteristics.

An probably imp't application is in SMFT! The determination of the parings of P₂₀₀ (Price of driver v.s. price of driver) curve.

A possl. other applic: Could it be relevant to sh. fact that giving driver wts. didn't ↑ yield of FT?

AH! Is the Stein effect relevant to determination of whether a seq. is low dim chaotic? (2 Grassberger) fact that w.o. enormous SSZ, one ~~user~~ could get no useful info. Is this really true? — or is it an example of statisticians not wanting to make preds unless they are 95% certain?

97 SMFT
 D1797: 257.21
 Driver w. by G to maybe good drivers because they respond to "News" quickly
 looking for SOY in SMFT:
 (97) 242.23
 I bit (237.22 - 239.21): early warn.
 232.37 - 40
 is the beginning of reasonable SOY work.
 233.80 is not bad
 237.22 looks good

13:1.24 Early work on SOY: In 97 SMFT!
 231.01 - 232.32 - maybe
 232.37 - 40; ~~maybe~~
 233.30
 237.22 - 239.21
 242.23: Ref. to older work using MAPLE ①.
 251.01 - 40 is a BIG blivoo. review of SOY.
 (98) 98.01 is also a sort of review ... party on SOY.

I really have to look at this SOY stuff & write a review.
 Also there was the SMA problem!
 Maybe closer yet to Stein

Q: could Stein be relevant to the even/odd diffy of (97 SMFT 223.33)?

(99) 99.08-30 (Bibliog on aspects of SOY)
 also (arbitrarily large RMS error in preds, using various smoothing)

Also Much work on SOY in (97 TW); 141.01-40; 147.01-40
 153.01 to 168.40; 170.01-171.40; 200.01-40
~~147.40 - 147.01; 147.40 - 147.01~~
 82.40
 1997: 88... said to be final soln. to SMA problem. Also see 85.23-86.08
 we can trace backwards from 83.01: (84, 82k are Maple pm. & outputs.
 (97) 90.05: Bibliographic review of SMA/AAE problem. / Thread starts on 31.01
 Also see other roughish ideas on 90.01-40

INDEX Note: How to Get Median of a seq.
 (98) 85.01: This is for finding X kinds median filters

Re eq. 2.20: Suppose we have a Grand d.f. for th. μ_2 w. known s.d. = σ
 & known Mean = μ . We observe a bunch of data for a particular ball player:

[d] its mean is μ_2 , its s.d. = σ_2 , K cases. $\rightarrow \mu_2 = \frac{1}{K} \sum d_j$

Viewed this way a f.p. of data, $P \propto \frac{1}{S} \exp\left(-\frac{1}{2} \left(\frac{\mu_2^2}{S^2}\right)\right) \cdot \frac{1}{\sigma} \exp\left(-\frac{1}{2} \left(\frac{\sum (d_j - \mu)^2}{\sigma^2}\right)\right)$

We can view μ , now as not really a constraint, but just a variable & we want to find it

Now let us move to total of K players to $\mu+x$

$P \propto \frac{1}{S} \exp\left(-\frac{1}{2} \left(\frac{(\mu+x)^2}{S^2}\right)\right) \cdot \left(\frac{1}{\sqrt{\sigma^2+x^2}}\right)^K \exp\left(-\frac{1}{2} \left(\frac{\sum (d_j - \mu)^2 + Kx^2}{\sigma^2 + Kx^2}\right)\right)$

But! This factor may be indep of x .

$\ln P = -\ln S - \frac{1}{2} \frac{(\mu+x)^2}{S^2} - \frac{K}{2} \ln(\sigma^2+x^2) - \frac{1}{2} \frac{\sum (d_j - \mu)^2 + Kx^2}{\sigma^2 + Kx^2}$

$\frac{\partial P}{\partial x} = -\frac{1}{2} \frac{1}{S^2} \cdot 2(\mu+x) - \frac{1}{2} \frac{2xK}{\sigma^2+x^2} = \frac{1}{2} \frac{d}{dx} \left(\frac{K(\sigma^2+x^2)}{\sigma^2+Kx^2}\right)$

$-\frac{1}{2} \frac{d}{dx} \frac{K\sigma^2+x^2}{\sigma^2+x^2} = + \frac{1}{2} \frac{K\sigma^2+x^2}{(\sigma^2+x^2)^2} \cdot 2x - \frac{1}{2} \frac{2xK}{(\sigma^2+x^2)^2} \cdot 2x$
 $= \frac{Kx(\sigma^2+x^2) - Kx^2}{(\sigma^2+x^2)^2}$

$\frac{d}{dx} \frac{u}{v} = \frac{u'v - uv'}{v^2}$
 $u = K\sigma^2+x^2, v = \sigma^2+x^2$
 $u' = 2x, v' = 2x$
 $\frac{d}{dx} \frac{K\sigma^2+x^2}{\sigma^2+x^2} = \frac{2x(\sigma^2+x^2) - (K\sigma^2+x^2)2x}{(\sigma^2+x^2)^2}$

$\frac{\partial P}{\partial x} = -\frac{\mu+x}{S^2} - \frac{x}{\sigma^2+x^2} + \frac{(K-1)x^2}{(\sigma^2+x^2)^2} = -\frac{\mu+x}{S^2} + \frac{(K-2)x^2}{(\sigma^2+x^2)^2} = 0$
 $-\frac{\mu+x}{S^2} + \frac{(K-2)x^2}{(\sigma^2+x^2)^2} = 0$

for $\sigma > 1$ player $\sum \frac{-(\mu+x)^2}{S^2} + \frac{(K-2)x^2}{\sigma^2+x^2} = 0$

$(\mu+x)(\sigma^2+x^2)^2 = +S^2(K-2)(\sigma^2+x^2)x$

which means $\mu+x > 0$; ~~negative~~ Answer!

Utility! Maybe Get more to do derivative! (etc on the third d.f.) Big fish.

It might be hard to reinstall it! WOOBS! This term can be < 0 . $\frac{(K-2)x^2}{(\sigma^2+x^2)^2} > 0$.

$\frac{x}{\mu+x} > 0 ; \frac{1}{\frac{\mu}{x}+1} > 0 \quad \frac{\mu}{x}+1 > 0 \quad \text{so } \frac{\mu}{x} > -1 \quad \frac{\mu}{x}$

if $\mu = 1, x > -1$ so $\mu+x > 0$ so if $\mu > 0, \mu+x > 0$
 if $\mu = -1, x < 1$ so $\mu+x < 0$ if $\mu < 0, \mu+x < 0$
 $\frac{x}{\mu+x} > 0 \iff \mu+x > 0$ any $\mu < 0 \iff \mu+x < 0$

$\frac{x}{\mu+x} > 0 \iff \mu+x > 0 ; x > \mu+x \iff x > \mu$ \iff This is reasonable!

$(\mu+x)(\sigma^2+x^2)^2 = S^2(K-2)(\sigma^2+x^2)x$

$(\mu+x)(\sigma^2+x^2) = S^2(K-2)x$

That if S^2 & $K-2$ should both have same a flavor
 Soln. is unreasonable & unreasonable.

large K means small x , small S^2 means large x

$\left(\frac{\mu}{x}+1\right)(\sigma^2+x^2) = S^2(K-2) \quad \implies \quad S^2(K-2) \rightarrow \infty, x \rightarrow 0.$

If id \rightarrow correct $\frac{\partial P}{\partial S} = -\frac{1}{S} + \frac{1}{2} \frac{(\mu+x)^2}{S^3} + \frac{1}{2} \frac{K}{S\sigma^2} \therefore$
 $-1 = \frac{(\mu+x)^2}{2S^2} - \frac{1}{S} - \frac{K}{2S\sigma^2} \iff -\frac{1}{S} + \frac{1}{2} \frac{(\mu+x)^2}{S^2} = 0$
 $1 = \frac{1}{2} \frac{(\mu+x)^2}{S^2} \iff \frac{\mu+x}{S} = \sqrt{\frac{2}{S}}$

If given last form of 4.10 & 4.11 is indep of x:

$$\frac{\partial p}{\partial x} = -\frac{1}{s} \frac{1}{s^2} \cdot \frac{1}{2} (u+x) - \frac{1}{2} \frac{2x \cdot k}{G^2 + x^2} : \frac{\partial}{\partial x} \frac{u+x}{s^2} + \frac{x}{G^2 + x^2} = 0$$

no way need to factor "k" here:

in 4.10 $\left(\frac{1}{\sqrt{G^2+x^2}}\right)^k$

$$\frac{u+x}{s^2} + \frac{kx}{G^2+x^2} = 0 : (u+x)(G^2+x^2) = -k s^2 x$$

almost identical to 4.25!
So $\frac{u+x}{s^2} < 0$ always!
unusually!

$(u+x)(G^2+x^2) = -k s^2 x$ which is opposite in sign to 4.25!
unusually!
i.e. 4.27-4.29 looks like what I want.

$$\frac{u+x}{s^2} < 0 \quad \frac{u}{s^2} + 1 < 0 : \frac{u}{s^2} < -1 \quad \text{so if } u=1, x < -1$$

POC $\frac{1}{s} \exp -\frac{1}{2} \left(\frac{u+x}{s^2}\right) \cdot \left(\frac{1}{\sqrt{G^2+x^2}}\right)^k \cdot \exp -\frac{1}{2} \left(\frac{k(G^2+x^2)}{G^2+x^2}\right)$

ln p = $-\ln s - \frac{1}{2} \frac{(u+x)^2}{s^2} - \frac{k}{2} \ln(G^2+x^2)$ $e^{-\frac{1}{2}} = \text{const}$

$\frac{d}{dx} \ln p = -\frac{1}{s^2} (u+x) - \frac{k}{2} \frac{2x}{G^2+x^2} = 0$

$-\frac{u+x}{s^2} - \frac{kx}{G^2+x^2} = 0$ Bad! $\left(\frac{u}{s^2} + 1\right)(G^2+x^2) = -k s^2$

$\frac{e^{-\frac{(u+x)^2}{2s^2}}}{(G^2+x^2)^k} \rightarrow \left(G^2+kx\right)^k \cdot e^{\frac{(u+x)^2}{2s^2}}$ in i

as $k s^2 \rightarrow \infty$
 $x \rightarrow 0$ but then = 0 side.

$\frac{2x \cdot k}{s^2} \cdot 2x \cdot k (G^2+x^2)^{k-1} + (G^2+x^2)^k \cdot \frac{1}{s^2} \cdot e^{\frac{(u+x)^2}{2s^2}} \cdot \frac{2(u+x)}{s^2}$

$2xk + (G^2+x^2) \cdot \frac{2(u+x)}{s^2} = 0$

27

$s^2 k x + (G^2+x^2)(k+u) = 0$

all cubes w. real roots (coeff. have 1 root 1 real root).

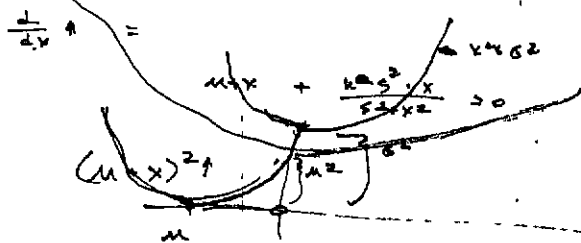
4.10 $p = x \cdot \left(\frac{1}{s} e^{-\frac{1}{2} \left(\frac{u+x}{s^2}\right)} \cdot \left(\frac{1}{\sqrt{G^2+x^2}}\right)^k \cdot e^{-\frac{1}{2} \left(\frac{2(G^2+x^2)}{k(G^2+x^2)}\right)}\right)^k$

$x = \left(\frac{1}{\sqrt{3\pi}}\right)^2$

30

ln p = $\ln u + k \ln s - \frac{1}{2} \frac{(u+x)^2}{s^2} - \frac{k}{2} \ln(G^2+x^2) = \frac{k}{2}$

$(-2 \ln p) s^2 = \beta + \frac{(u+x)^2}{s^2} + k \ln(G^2+x^2)$ $= \beta + \frac{(u+x)^2}{s^2} + k s^2 \ln(G^2+x^2)$



$2(u+x) + \frac{2k s^2}{G^2+x^2} \cdot 2x = 0$

$(u+x)(G^2+x^2) + k s^2 x = 0$

slope = 0 must be at $x < 0$, if $u > 0$.

from picture, x should be < 0 but $-x < u$

i.e. $x+u$ should be > 0 .

OH! it's ok in 27 say $u=1$

so $x+u > 0$ as it should be!

$x < 0 \quad (G^2+x^2)(x+u) = -s^2 k x > 0$ fine!

$\frac{x+u}{s^2} + \frac{kx}{G^2+x^2} = 0$

$\frac{\partial \ln p}{\partial s} = -\frac{k}{s} + \frac{1}{2} \frac{(u+x)^2}{s^3}$

$= 0 \Rightarrow -k + \frac{1}{2} \frac{(u+x)^2}{s^2} = 0$

$\frac{1}{2} \frac{(u+x)^2}{s^2} \leq \left(\frac{u+kx}{s}\right)^2$
< no "k" involved >

1.18.99

5 1/2

$$\frac{(x+6^2)(x+m)}{x} = -ks^2$$

$$\frac{x}{6} + \frac{6^2}{x} (m+x) = \frac{-ks^2}{6}$$

$$\frac{6}{6} \frac{x}{6} = y \quad x = 6y \quad \left\{ \begin{array}{l} (y+\frac{1}{y})(m+6y) = \frac{ks^2}{6} \end{array} \right.$$

5

(2000)

$$(y+\frac{1}{y})(\frac{m}{6}+y) = \frac{ks}{6^2}$$

$$(y+\frac{1}{y})(\alpha+y) = \beta$$

$$(y^2+1)(\alpha+y) = \beta y$$

$$\Rightarrow y^2 + \alpha y^2 + y + \alpha = \beta y$$

$$y^2 + \alpha y^2 + (1-\beta)y + \alpha = 0$$

$$\frac{m+x}{5} = -$$

$$\frac{ks^2 x}{6^2+x^2}$$

$$\left(\frac{m+x}{5}\right)^2 = \frac{ks^2 x^2}{(6^2+x^2)^2}$$

1) colonoscopy

2) Psych. tests

3) dermatology

4) cough

Dr. Chabany fluoride.

whole colonoscopy

Not Geard. Tested every kind of thing

u.k.

G.A.

Low fluids → dizzy

Colonoscopy: chitany

chorell.

Blood pressure.

Dr. Geardinae Sues 2 liters of fluid/di ! ?

fluid would have some Electrolytes in it.

Time was ~ 4:30 PM, none diarrhea since.

Seems very hy!

Blood press

(90

132 / 78

110

Since with Hydrate would not produce such peaks in blood pressure. (?)

But fluids wouldnt becom 70% so too less, possible (are po no fluid at nite diet?)

S.27: $-s^2 x^2 (a+x^2)(x+m)$; $\frac{x+m}{s^2 x^2} = -\frac{1}{a+x^2}$; $1 + \frac{m}{x} = -\frac{s^2 a}{a+x^2}$

$1 + \frac{m}{x} < 0$ $\frac{m}{x} < -1$ $\frac{x}{m} > -1$ $x > -m$
 $m < -x$

$x+m > 0 \leftarrow$ No! if $m < 0$

say $m = -1$

$1 + \frac{1}{x} < 0$ $-\frac{1}{x} < -1$ $\frac{1}{x} > 1$

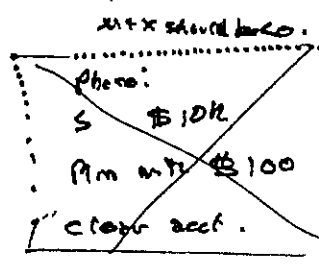
$x < 1$ so $x = 1$ ($\exists x+m$) < 0 $x+m < 0$

I find my Manip. of inequalities is faulty, (inconsi).

$1 + \frac{m}{x} < 0$

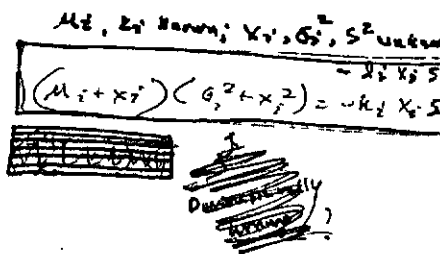
A.H. if $\frac{m}{x} < -1$ if I mult both sides by x I get $m < -x \leftarrow$ But

only if $x > 0$! So Eqns look S.O.R.!



Eq. 4, 10 using $\frac{d}{dx}$ (Do it in pencil) work out for $x=1$

This can be reconfigured as a 2 variable form, cubic eq. for x in terms of m, β, S .



work out eq. 4, 10 for many 'i' - then take $\frac{d}{dx}(\) = 0$

from (5, 30 R) we (only) get $(M_i + x_i^2)^2 = \frac{\beta_i^2}{S^2} S^2$ ($[k_i]$ are not involved) so $\frac{1}{h} \sum_{i=1}^n (M_i + x_i^2)^2 = S^2$

So we can start w. initial S value! Solve it for all $(M_i + x_i^2)$; then get new S approx for $\leq 1/2$ it. I don't know if it converges, hvr. I could just try it; if it does converge in a few cases, probably probably converges in all.

For eq. 11 perhaps use formula in Set A for first approx.

For production runs, I'll update each day, using yesterday's values for first approx.

On eq. (11 R): I set $\frac{x}{\beta} = y$; $y^3 + \alpha y^2 + \beta y + \alpha = 0$

Is this cubic particularly easy to solve? I certainly can remove 1 term from any cubic by linear substitution.

$y = z + \Delta$ maybe get rid of const term?

$z^3 + 3z^2\Delta + 3z\Delta^2 + \Delta^3$
 $\alpha z^2 + \beta z + \alpha$
 $z^3 + 3z^2\Delta + 3z\Delta^2 + \Delta^3 + \alpha z^2 + \beta z + \alpha = 0$

gotten $\Delta^2 + \Delta^2\alpha + \Delta^3 + \alpha = 0$ is same as solving original eq!
I think this true for all poly eqs!

$y = z + \frac{\Delta}{h}$

$z^3 + 3z^2\Delta + 3z\Delta^2 + \Delta^3 + \alpha z^2 + \beta z + \alpha = 0$

$z^3 + 3z^2\Delta + 3z\Delta^2 + \Delta^3 + \alpha z^2 + \beta z + \alpha = 0$

$z^3 + 3z^2\Delta + 3z\Delta^2 + \Delta^3 + \alpha z^2 + \beta z + \alpha = 0$


$\Delta^3 + 2\Delta^2 + \alpha\Delta = 0$

It may be possible to solve 11 R by

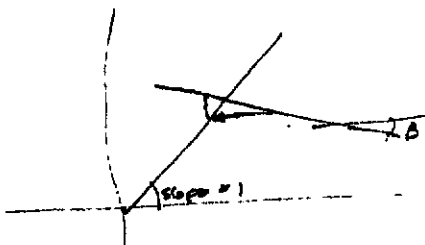
or $\frac{x^{n+1}}{1+x^n} = \frac{1}{\frac{x}{x^{n+1}} + 1} = f(x^n)$

$x_i^{n+1} = -\frac{1}{k_i S} (M_i + x_i^n)(\beta_i^2 + (x_i^n)^2)$
 $x^{n+1} = \left(\frac{1}{f(x^n)} - 1 \right)^{-1} \cdot M$

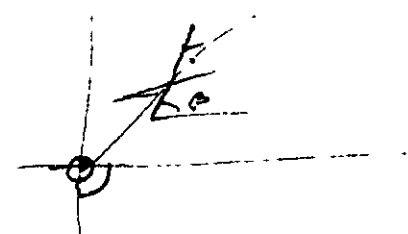
In general, if $x^{n+1} = f(x^n)$ doesn't converge, try $x^{n+1} = f^{-1}(x^n)$.

Also to speed convergence in  s.t. find

.03 try $x^{n+1} = (f(x^n) + f^{-1}(x^n)) / 2$. Averages 2 best estimates.



if $\beta = -1$ doesn't converge
 $\beta < -1$ diverges
 if $\beta > 1$ diverges



So, if $f'(x) = -1$ at the soln, the process will converge.

Since f^{-1} has slope $(f'(x))^{-1}$ if $f(x)$ doesn't converge, f^{-1} will!

If slope of $f(x)$ is ± 1 then we can do .03.

In fact, even if the system diverges somewhat with slope < -1 , .03 will get it to converge.

For slope > 1 , we can also fix it, but it's a bit harder: we look at differences betw. $f(x)$, $f(f(x))$ & $f(f(f(x)))$: from these, we extrapolate backward to expected $f^{-1}(x)$, & use it for next approx.
 Then we do .21 -> .22 from that approx. to get next step.

38x2
 Prop'd to the
 an t. center.

.24 In quite uncertain as to the definition of \bar{y} , \bar{y}_i , & σ^2 (σ^2 in particular)

In general, I'd expect σ^2 to be $> \frac{1}{2} \sum (\bar{y}_i - \bar{y})^2$ so roughly $k, < 1$

which is reasonable. See $(\frac{1}{2}, 20R)$ for a more reasonable defn. of σ^2 .

Another approach is suggested by $(\frac{1}{2}, 04R)$:

$Z = \bar{y}(1-c) + \bar{y}_i c$: which makes Z is a wtd. mean of \bar{y} .

Z averages. F & \bar{y}_i are both probab. of the next data pt. of the player i .

Say we ~~are~~ s is the s.d. of the distribn of all data (w.o. player label) &

\bar{y} is the mean: the p.s. of deriv. of the entire set is $(\frac{1}{s})^{TOT}$ using this model.

(Tot = total no. of players, tries)

The p.s. of deriv. using individual \bar{y}_i is $\sigma_i^2: \prod (\frac{1}{\sigma_i^2})$

The wtd. ratio is $\prod (\frac{\sigma_i^2}{s})^{TOT}$ — This doesn't seem reasonable

! I.e. T points σ^2 is always $>$ to mean etc. (what)

I think Big coding should use "Mixed Cases" formula

01 $(\frac{1}{2}, .05)$: $c = (-\frac{(k-3)\sigma^2}{\sum(\bar{y}_i - \bar{y})^2})$ $z = \bar{y} + c(\bar{y}_1 - \bar{y}) = (1-c)\bar{y} + c\bar{y}_1$

$z = \frac{(k-3)\sigma^2}{\sum(\bar{y}_i - \bar{y})^2} \bar{y} + (1 - \frac{(k-3)\sigma^2}{\sum(\bar{y}_i - \bar{y})^2}) \bar{y}_1$

$= \frac{(k-3)}{\sum(\bar{y}_i - \bar{y})^2} \cdot \left[\text{cancel} \sigma^2 \bar{y} + \left(\frac{\sum(\bar{y}_i - \bar{y})^2}{(k-3)} - \sigma^2 \right) \bar{y}_1 \right]$

$\equiv \sum^2$

10 $= A [\sigma^2 \bar{y} + \sum^2 \bar{y}_1] = \frac{A \sigma^2 \sum^2}{\sum^2} [\frac{\bar{y}}{\sigma^2} + \frac{\bar{y}_1}{\sigma^2}]$

$A \sigma^2 \sum^2$ really = $\frac{\sum^2 \sigma^2}{\sum^2 + \sigma^2}$: Yes! - so / σ^2 & normalizing factor.

so (0.1k) \Rightarrow 10 imply that $\bar{y} \approx \bar{y}_1$ hour w/ $\frac{1}{\sum^2} + \frac{1}{\sigma^2}$ resp:

16 Res is approx to \sum^2 area prod. = wt. but using gaussian id for w. means \bar{y}_1, \bar{y}_i

17 \sum^2 & σ^2 resp. We just take product of 2 Gaussn D.F.s w. diffnt μ 's & σ^2 .

$\rightarrow 15.01$
for mean exact
dis cov.

Some Q's: ① Why $k-3$? ($k-2$ via Akaike); but - maybe using z means \bar{y} that would be $k-4$... so No!

② The result is approx to multiplying f. 2 Gaussian beginning of 1.6 together & obtaining a new Gaussian w. f. mean, z . I don't see any way to justify Reiss, Arr.!

I really must read those papers! Try Journal of the Amer Stat Assoc. Jun 1975

Anyway: try recursion on G.11 R!

126 $X = \frac{(m+x) + (Sgs + X^2 X) / K / 95}{X=1}$

$G^2 = 2, S^2 = 4, K_1 = 10, \mu = 1$ (M13)
 $Sgs = 2, SS = 4, K = 10, m = 1$ irrelevant I find.

$X = \frac{(m+x)(G^2 + x^2)}{(K S^2)}$
 \leftarrow should be "-". (!)

20 input A:

30 Print X: Go to 10

Converged $K=1, .05, .0525, .0527, \dots, .0527089$

for $k=2, X=1, .375, .1833, .1454, \dots, .1495658$

$k=10, SS \rightarrow 3: 1, .2, .10816, \dots, .0716244$

$SS \rightarrow 2.1: 1, .285, .127, .108, \dots, .1059161$

$SS \rightarrow 4, m=1 \rightarrow 10$

$m \rightarrow 100$ converged $1, .825, .725, .677, \dots, .6715926$ converged
 $m \rightarrow 20$ $1, 7.575, 15, 1456, 1.135614, \dots$ overflows
diverges

$m \rightarrow 15$ diverges
 $m \rightarrow 12$ $.975, .957, \dots, .918$
 $m \rightarrow 13$ diverges

$m \rightarrow 125$ converged
12.25 conv
12.3 conv
12.4 conv, \downarrow
12.45 conv slower.

$m \rightarrow 12.4$ conv.
12.48 conv
12.49 conv.
12.495 conv
12.499 conv

12.9 div
12.8 div slowly
12.7 conv
12.75 conv
12.77 conv slowly

12.78 conv
12.79 conv. slowly
12.795 diverges
but slow to start.
12.8 div

Try $\sigma^2 \approx \sigma^2 = 2$ / other params of 8.26 conv

$\sigma^2 \approx 4$ conv. try $\sigma^2 \approx 100$ diverge rapidly.
 Please check \uparrow $f'(x)$.

$\sigma^2 = 2, \sigma^2 = 2, k=1, M=1$ diverges. - so using large k & σ^2 will usually converge.

$k=100; x \rightarrow .200; k=1000; x \rightarrow .02$
 $k=10$ diverges.

Woops! $M=1$, but $x > 0$! How come! o.t.! forgot "-" sign in G.11

Convergence should be same for

$\sigma^2 = 2, \sigma^2 = 2, k=10, M=10$ conv. sign > 0
 $\sigma^2 = -$ as it should be.

$x = -.542$

STEIN.BAS

$x = -(M+x)(G^2 + kx^2) / (kx^2)$

If $kx^2 < G^2$, then we have $x \approx \frac{-M+x}{2}$ (\approx large)

$x = -\frac{M}{2} - \frac{k}{2} \quad x(1+\frac{1}{2}) = -\frac{M}{2} \quad x \approx -\frac{M}{1+\frac{1}{2}}$

So $\frac{x}{M} = -\frac{1}{1+\frac{1}{2}}$: contracting out.

$\frac{z}{M} = \frac{kx^2}{G^2 + kx^2}$
 $M \frac{z}{M} = \frac{M}{1+\frac{1}{2}} \approx M(1-\frac{1}{2})$

So how did they get such a large contraction factor, w. $k=45$ (which is maybe small G^2 is large G^2 .)

Unless my eqns. are wrong! Maybe off by factor of k ?

My contraction factor is \approx

$\frac{k(G^2 + kx^2)}{kx^2}$

Pluses is

$\frac{(k-1)G^2}{k(G^2 + kx^2)}$

$\frac{(k-1)}{k} \frac{1}{1+\frac{1}{2}}$

So may have no $\frac{1}{k}$ factor here

Well, its both same, there is really $\frac{1}{k}$ (see 8.35)

It could be part of exponent in 8.10 of $(\frac{1}{\sqrt{G^2 + kx^2}})^k$ should be 1. (1)

$k=45$ rather than no. of players. This incovs notation is bad! I should use l instead of k ; $l =$ no. of games per player.

GOOD!

75:0 PM
 1:20:99
 20

Also, extending 8.10 to k players, we should get

$p \approx (\frac{1}{5})^k \approx -\frac{1}{2} \left(\frac{\sum (x_i + y_i)^2}{S^2} \right) \cdot \left(\frac{1}{\sqrt{G^2 + kx^2}} \right)^k$

Plus \uparrow affects eq. 8.7

$\ln p \approx -k \ln 5 - \frac{1}{2} \frac{\sum (x_i + y_i)^2}{S^2} - \frac{k}{2} \ln (G^2 + kx^2)$

$\frac{\partial \ln p}{\partial x} = -\frac{k}{x} + \frac{k}{2} \frac{\sum (x_i + y_i)^2}{S^2} = 0$

$S^2 = \frac{1}{k} \sum (x_i + y_i)^2$

From Carter, Ralph paper (see SA. Biol.)

X_i are mean values observed, at each of k locations $\left(\begin{matrix} k \\ i=1 \dots k \end{matrix} \right)$

At each location i d.f. is known to be Gaussian; of var $= D_i^2$. ($D_i = D = \text{constant}$ in R's example)
True means θ_i , are unknown; to be estimated. Usually $\theta_i \approx X_i$.

$\hat{\theta} = (X_1, \dots, X_k)$ is maximally likely $\in S$ known

$S = \sum (X_i - \bar{X})^2$ $\bar{X} = \frac{1}{k} \sum_{i=1}^k X_i$

$B(\bar{X}) = \text{Var}[\bar{X}] = \frac{1}{k} D^2$ usually $= \frac{k-3}{k} D^2$ $\left(\begin{matrix} \text{if } i=1 \dots k \\ \text{then } B(\bar{X}) = 0 \end{matrix} \right)$

So C is R got same as EGM, Morris, but

may be more D more closely. (and C/R discuss for awhile)

According to Tulay, γ . Scale effect is "usually very small."

Hum E & M say Tulay was criticizing Bradley's method only

My own impression: if k is large, effects small. \rightarrow depends on k, σ^2, δ^2 .

My interpretation of $1 \pm 0.07 - 0.05$ is that $k \rightarrow \infty \Rightarrow R(\bar{X}) \rightarrow 0$,

that C would be about 1/3 more as it was for, say $k=20; \delta=20$;

Hum, this is completely inappropriate! If δ (i. no. of times at bat) $(\leq 45$ m. Barry Bonds!)

\Rightarrow Then C should $= 1$; i.e. no "shrinking", since \bar{y}_i would be known for certain.

T. only passy I can think of is that my interpretation of σ^2 is incorrect — that σ^2 is $\frac{1}{R}$.

in i.e. σ^2 is, say, 1; uncertainty in \bar{y}_i : in which case $\sigma_i^2 = \frac{1}{R} \sum_{j=1}^k (y_{ij} - \bar{y}_i)^2$

Look at E & M's treatment of "Not all \bar{y}_i have same var." §3: pp 314-316

§314 \rightarrow "vars differ because of different σ^2 's" (supposing that 20 is true!)

So it looks like $(1 \pm .35)$ is the proper defn. of σ^2 . This resolves the diffy of 9.19-25!

I could analyze Major League Baseball data: from: batting average A , σ^2 var $= 2A(1-A)$ ($= 1/99$)

I could do an analysis of a system in known θ is known \Rightarrow Error σ^2 acts,

is see what E & M's formulae are, v.s. what my formula says.

Also, look at §.16-17: This is a very simple way to look at Stein! It is as if we had

2 sets of measurements for θ : One w. mean M_1 & var σ^2 ; another w. mean M_2 & var σ_2^2 .

Actually this is what occurs! We have 2 different ways to estimate M_1 , &

They each have their own means & var. §.16-17 simply combines them by multiplying

by 2 d.f.'s \rightarrow 2 print its pure Bayesian. Say $G_1(x)$ & $G_2(x)$ are 2

d.f.'s obtained. T. pc of x being f. drawn from $(200 G_1(x), G_2(x))$.

(i.e. Both measurements have to occur, & δ is product of these 2 (indip) p's is δ .)

was of that pc. "do E & M"

So δ . \Rightarrow is, how to E & M for $(k-3)$? — Akaike should be applied to

both d.f.'s. — Just exactly how is unclear.

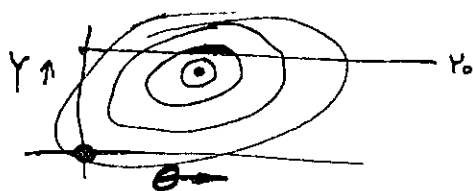
$$\frac{X}{\sigma} = \frac{\mu}{1+\delta}$$
$$X + \mu = \frac{\mu + \delta \mu - \mu}{1+\delta}$$
$$= \frac{\mu - \mu \delta}{1+\delta} = \mu \frac{1-\delta}{1+\delta}$$
$$= \frac{\mu}{1+\frac{\delta}{2}} \approx \mu \left(1 - \frac{\delta}{2}\right)$$

01. Reg Cover: When one looks at the past, one can ^{single} choose a set of params for future best.
- ② One can look at various params & choose a single ~~best~~ set that gave max yield in the past.
 - ③ One can assume some d.f. for params in the past & best equal function over (This is Cover's approach),

If may be, that w/ "Multiplicative strategies" (which is learned somewhere in the last few yrs.), Cover's strat. is really best. The major improvement may be that I now may be able to know how to best update the d.f. based on subsequent behavior.

It may be that the main idea here is that Cover's method gives a v.g. estimate of yield, as to others don't.

To start to apply d.f. for expected yield for each param value is needed: $P(\theta, Y)$.



It is the absolute P_0 that is selected. Say we pick $\theta_0 \Rightarrow$ Expected value of Y is θ_0 .

My impression is that Cover's method of playing may actually be best, if one uses only the info that he uses. — But I have gone over his book; one objection that I had to Cover, was that his was a method of averaging out noise; so the degree of goodness of his method, over simply picking the "best" parameter should depend on the noise level; as the system doesn't seem to deal w/ "noise level".

A big objection to Cover: As we ↑ no. of stocks in portfolio, his method ~~starts to~~ converges more & more slowly to the "best" param value, & highest yield.

It would be good if I could inject "side info" in an optimal way. Cover's last SM paper was on "side info" but ~~in~~ my impression was that it was trivial: I don't ~~remember~~ remember ~~be~~ just what kind of "side info" covered.

.01: 10.40 : Start w. α 4.10 & explain & derivation in detail for future reference.

Do it for all σ_j^2 's not v. same:

We have k players: The i^{th} player has been at bat L_i times.

~~At~~ At the j^{th} "at bat" this player got a score of r_{ij} .

$\mu_i = \frac{1}{L_i} \sum_{j=1}^{L_i} r_{ij}$ is v. "batting average" of i^{th} player.

$\sigma_i^2 = \frac{1}{L_i} \sum_{j=1}^{L_i} (r_{ij} - \mu_i)^2$ is v. the uncertainty in μ_i .

.06

.07 $\textcircled{?}$ We will assume a Gaussian distribution for r_{ij} ($j=1, \dots, L_i$) about its mean, μ_i , with a variance of $\frac{1}{L_i} \sum_{j=1}^{L_i} (r_{ij} - \mu_i)^2 = L_i \sigma_i^2$.

.09

$\textcircled{?}$ \rightarrow We will also assume a Gaussian distribution for the means, μ_i , ~~but we will~~

~~Start: The origin is at $\sum_{i=1}^k \mu_i = 0$~~

$M = \frac{1}{k} \sum_{i=1}^k \mu_i$ is the grand mean.

Its variance is $S^2 = \frac{1}{k} \sum (\mu_i - M)^2$.

Let us ~~let us assume that the r_{ij} 's were~~ ^{a priori} ~~obtained in the following way!~~ make the following assumptions about the ~~source~~ source of the data $\{r_{ij}\}$

- That the observed r_{ij} were obtained by first choosing a μ_i (to be determined) from a Gaussian distribution of mean M and variance $(S')^2$ — then

using μ_i as mean and variance $L_i (\sigma_i')^2$ (to be determined), the r_{ij} are obtained.

We will pick certain $(S')^2$ and $[(\sigma_i')^2]$ and $[\mu_i']$ and, as a function of these parameters, we will compute the probability of the observed $\{r_{ij}\}$ being generated. — Call this $\tilde{P} = \tilde{P}((S')^2, [(\sigma_i')^2], [\mu_i'])$

Then via Bayes, this \tilde{P} gives us the a posteriori probability distribution of these unknown parameters. If we pick the peak of this distribution, we will get a set of values for $(S')^2, [(\sigma_i')^2, \mu_i']$.

It turns out that these values are approximately what Stein got.

To get more accurate values, I would integrate \tilde{P} in various directions to get the expected value of each of the parameters.

Formula for \tilde{P} :

.02 $\tilde{P} = \left(\frac{1}{\sqrt{2\pi}} \frac{1}{s'} \right)^k \cdot e^{-\frac{1}{2} \left(\frac{\sum (M - \mu_i')^2}{s'^2} \right)} \cdot \prod_{i=1}^k \left(\frac{1}{\sqrt{2\pi}} \frac{1}{\sigma_i'} \right)^{R_i} e^{-\frac{1}{2} \left(\frac{\sum R_i (\mu_i' - r_{ij})^2}{\sigma_i'^2} \right)}$

.03 $\ln \tilde{P} = \frac{k}{2} \ln(2\pi) - k \ln s' - \frac{1}{2} \left(\frac{\sum (M - \mu_i')^2}{s'^2} \right) + \sum_{i=1}^k \left(\frac{R_i}{2} \ln(2\pi) - R_i \ln \sigma_i' - \frac{1}{2} \frac{\sum R_i (\mu_i' - r_{ij})^2}{\sigma_i'^2} \right)$

We will now take partial derivatives and set them to zero.

.10 $\frac{\partial \ln \tilde{P}}{\partial s'} = -\frac{k}{s'} + k \cdot \frac{\sum (M - \mu_i')^2}{s'^3} = 0$

$$(s')^2 = \frac{\sum (M - \mu_i')^2}{k} \quad \checkmark (6.17k)$$

.12 $\frac{\partial \ln \tilde{P}}{\partial \sigma_i'} = -\frac{R_i}{\sigma_i'} + R_i \frac{\sum (\mu_i' - r_{ij})^2}{\sigma_i'^3} = 0$

$$(s_i')^2 = \frac{\sum (\mu_i' - r_{ij})^2}{R_i} = 2_i \sigma_i'^2 + (\mu_i' - \mu_i)^2$$

$\frac{\partial \ln \tilde{P}}{\partial \mu_i'} =$ ~~...~~

$= + \frac{M - \mu_i'}{(s')^2} - \frac{R_i}{\sum_{j=1}^{R_i} (\mu_i' - r_{ij})} = 0$

$$\frac{M - \mu_i'}{(s')^2} = \frac{\sum_{j=1}^{R_i} (\mu_i' - r_{ij})}{\sum_{j=1}^{R_i} (\sigma_i')^2}$$

$(s')^2 = (M - \mu_i') \left(\frac{\sum (\mu_i' - r_{ij})^2}{R_i} \right) / \frac{\sum_{j=1}^{R_i} (\mu_i' - r_{ij})}{\sum_{j=1}^{R_i} (\sigma_i')^2}$
 $= (M - \mu_i') \left(\frac{\mu_i' - \mu_i}{\sigma_i'^2} \right)$

$\mu_i \approx \frac{\sum_{j=1}^{R_i} r_{ij}}{R_i}$

$(s')^2 \cdot (\mu_i' - \mu_i) = (M - \mu_i') \left(\frac{\sum (\mu_i' - r_{ij})^2}{R_i} \right) \equiv \frac{\sigma_i'^2 + (\mu_i' - \mu_i)^2}{R_i}$

.10 & .12 can be simplified, i.e. $(s')^2 \rightarrow s^2 + \frac{1}{k} \sum (M_i - \mu_i)^2 \pm \text{small}$
 $(s_i')^2 \rightarrow 2_i \sigma_i'^2 + (\mu_i' - \mu_i)^2$

$(s')^2 \cdot (\mu_i' - \mu_i) = \frac{(M - \mu_i')}{R_i} \left(2_i \sigma_i'^2 + (\mu_i' - \mu_i)^2 \right)$

So the factor of 2_i in 6.11 is not 1. There are differences in definitions betw. σ_i^2 & $(s_i')^2$. (a factor of 2_i)

Also poss. error by factor of 2_i in formula 6.11, .17.

To simplify calcus: use 12.00: $\sigma_i'^2 = \frac{1}{R_i} \sum ()^2 \stackrel{\text{not}}{=} \frac{1}{R_i^2} \sum ()^2$. We end up w. different eqs. but the difference is from stain, but the needed correction is obvious.

Better way: We have this game with k players: When the i th player played his j th game, he got a score of r_{ij} — He played a total of l_i games.

problem is to obtain good estimate of Player i 's score on next game: $r_{i,j+1}$.

$\frac{1}{l_i} \sum_{j=1}^{l_i} r_{ij}$ is one reasonable estimate. Stein has a better estimate.

Assume that $\{r_{ij}\}$ were obtained starting from a ^{Gaussian} random distribution $N(M, S^2)$ which generates $\{U_i\}$.

These $\{U_i\}$ are in turn used in indep $N(M_i, \sigma_i^2)$ which generate the r_{ij} . $M, S^2, \{M_i, \sigma_i^2\}$ are all initially unknown params. We will choose them so that the set $\{r_{ij}\}$ has max probability (density).

The probability density of $\{r_{ij}\}$ is then. (2.13.02)

~~$\tilde{P} = \dots$~~

$$\tilde{P} = \left(\frac{1}{S\sqrt{2\pi}}\right)^K e^{-\frac{1}{2} \left(\frac{M-M_i}{S}\right)^2} \cdot \prod_{i=1}^K \left(\frac{1}{\sigma_i \sqrt{2\pi}}\right)^{l_i} e^{-\frac{1}{2} \left(\frac{l_i}{\sum_{j=1}^{l_i} l_i} \frac{(M_i - r_{ij})^2}{\sigma_i^2}\right)}$$

We want $S, M, \{M_i, \sigma_i\} \rightarrow \tilde{P}$ is max.

$$\ln \tilde{P} = \frac{K}{2} \ln(2\pi) - K \ln S - \frac{1}{2} \left(\frac{M-M_i}{S}\right)^2 + \sum_{i=1}^K \left[l_i \ln(2\pi) - l_i \ln \sigma_i - \frac{1}{2} \frac{l_i}{\sum_{j=1}^{l_i} l_i} \frac{(M_i - r_{ij})^2}{\sigma_i^2} \right]$$

$$\frac{\partial \ln \tilde{P}}{\partial S} = -\frac{K}{S} + \frac{\frac{K}{S^2} (M-M_i)^2}{S^2} = 0 \quad \text{so}$$

$$\frac{\partial \ln \tilde{P}}{\partial \sigma_i} = -\frac{l_i}{\sigma_i} + \frac{\frac{l_i}{\sum_{j=1}^{l_i} l_i} (M_i - r_{ij})^2}{\sigma_i^2} = 0 \quad \text{so}$$

$$\frac{\partial \ln \tilde{P}}{\partial M_i} = \frac{M-M_i}{S^2} - \frac{\frac{l_i}{\sum_{j=1}^{l_i} l_i} (M_i - r_{ij})}{\sigma_i^2} = 0 \quad \text{so}$$

$$\frac{\partial \ln \tilde{P}}{\partial M} = \frac{\frac{K}{S^2} (M-M_i)}{S^2} = 0 \quad \text{so} \quad \sum_{i=1}^K (M-M_i) = 0 \quad \text{so}$$

$$S^2 = \frac{\sum_{i=1}^K \frac{(M-M_i)^2}{l_i}}{K}$$

$$\sigma_i^2 = \frac{\sum_{j=1}^{l_i} (M_i - r_{ij})^2}{l_i}$$

$$\frac{M-M_i}{S^2} = \frac{\frac{l_i}{\sum_{j=1}^{l_i} l_i} (M_i - r_{ij})}{\sigma_i^2}$$

$$M = \frac{1}{K} \sum_{i=1}^K M_i$$

01: ~~3.17~~: A simpler view of Stern effect: we have this data on k players:

$i = 1, \dots, k, j = 1, \dots, l_i$: r_{ij} is score of i 'th player on his j 'th game. The i 'th player played l_i games.

04 Q: What is good estimate of μ_i ? β ~~what is β~~ $\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n r_{ij}$

We can write estimates 2 ways:

06 If $\mu_i \equiv \frac{1}{l_i} \sum_{j=1}^{l_i} r_{ij}$; $M' \equiv \frac{1}{k} \sum_{i=1}^k \mu_i$ and $(S')^2 \equiv \frac{1}{k} \sum_{i=1}^k (\mu_i - M')^2$

07 ① $(\sigma_i^2)^2 \equiv \frac{1}{l_i} \sum_{j=1}^{l_i} (r_{ij} - \mu_i)^2$
 μ_i^2 is an estimator: its expected error $\frac{(\sigma_i^2)^2}{l_i - 1}$ (GA for k)
 2.20.99 should be $(S')^2$ multiplier $\frac{(\sigma_i^2)^2}{l_i - 1}$
 $(S')^2$ should be as multiplying each r_{ij} same so $(S')^2$ is multiplier
 $\frac{1}{k} \sum_{i=1}^k (\mu_i - M')^2 = \frac{1}{k} \sum_{i=1}^k \frac{1}{l_i} \sum_{j=1}^{l_i} (r_{ij} - \mu_i)^2$
 $= \frac{1}{k} \sum_{i=1}^k (\mu_i - M')^2 (\sigma_i^2)^2$

15 ② M' is also an estimator of β : its expected error is $\frac{(S')^2 \cdot k}{k-1}$

Using method ①, t. prob density of t. value β_i for i 'th player

$$P_1(\beta_i) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma_i} e^{-\frac{1}{2} \frac{(\beta_i - \mu_i)^2 (l_i - 1)}{(\sigma_i^2)^2}}$$

Using method ②, t. prob density, β

$$P_2(\beta) = \frac{1}{\sqrt{2\pi}} \frac{1}{S'} e^{-\frac{1}{2} \left(\frac{M' - \beta}{(S')^2} \right)^2 \frac{k-1}{k}}$$

25 If we assume μ_i & M' 2 methods of estimate of β_i are indep.

If we assume μ_i & M' are not indep. since both contain data r_{ij} ($j=1, \dots, l_i$) but they are not actually, this is a small part of ②'s data; we can subtract it

29 out or subtract out its effect out. final estimate.

~~Product~~ $P_1(\beta_i) \cdot P_2(\beta)$ is t. prob of having made both estimates, & this is a Bayesian d.f. for β_i .

Its close to Stern's estimator.

T. present estimate is a wtd avg of μ_i & M' : the wts are $\frac{l_i - 1}{(\sigma_i^2)^2}$ & $\frac{k-1}{k(S')^2}$ resp. Stern's results are on 7.01-17 his wts are ~~different~~ somewhat different: $\frac{1}{\sigma_i^2}$ & $\frac{k-3}{k(S')^2}$
 relevant $\sigma^2 \equiv (\sigma_i^2)^2$ is ~~large~~ $\sigma^2 \equiv \frac{(\sigma_i^2)^2}{l_i - 1}$

.01: 15.01 - 90 SN can be a rather exact analysis!
 We try to estimate β (of 15.07) in 2 ways. Both are, by themselves, legit ways.
 Estimate via 15.07 $\textcircled{1}$; or via 15.15 $\textcircled{2}$ — But in $\textcircled{2}$, to make the 2 markets
 indep., we should delete ^{direct} info about μ "i" to be predicted — this will
 give corrections to M 's S '.

SN: An annoying problem: If S and S' are to characterize the
 distribution of M , (β_i) 's (15.07 & R): Then $(S')^2$ will be grossly
 large — by the mean error in the (M_i) 's. Also, M' will have an expected
 error. So error in estimating (β_i) 's will be due to error in M 's & $(S')^2$.
 I discussed this pt. much a long time ago in my SOY problem work.

If all the σ_i^2 were the same, the resultant d.f. would be convolution of β .
 M' , S' d.f. is the M_i, σ_i^2 d.f.'s. so it $\approx \bar{\sigma}^2$ is common (σ_i^2)

Then observed $(S')^2 = \bar{\sigma}^2 + (S_{true})^2$.

If all σ_i 's were ~~equal~~ the same $\equiv \bar{\sigma}$, but $k \rightarrow \infty$; ~~error~~ error in
 M' and $(S')^2 \rightarrow 0$; error in $\bar{\sigma}^2$ is also zero, so we know S_{true}^2
 is M' . In this case, 15.07 & 15.15 ~~would be the same~~ (if we delete
 proper data) — no since $k = \infty$, it would make no difference)

can be regarded as 2 ways to estimate β , and we can then just
 take the product of 2 Normal d.f.'s. — The mean of the resultant
 d.f. is $\frac{1}{\sigma^2} \approx \frac{1}{\bar{\sigma}^2}$ wtd means $\bar{\sigma}^2$; M and M' pass

Th. Stein effect does occur if $k \rightarrow \infty$, but not if $k_i \rightarrow \infty$.

SN One of the main emph. ideas in Reg Stein discussion is that
 all prodn cases, one also watch for SS^2 & errors, to be sure they are
 not much larger than the error — one should obtain using some other method
 of pooling data — or just using zero as prodn.)

I did ~~not~~ run into this problem in the past, & I didn't realize what was
 happening! I was using k funds to smooth a P.S.; the output got, had
 larger M 's error in prediction than using zero as prediction! If the true mean
 is close to zero, then the smoothed estimate has to be quite small, or else
 it will add its value to the value of the signal to zero (larger error than
 value of the signal!)

k funds idea would seem to be very imp. in SM prediction —
 since the true yield is usually quite small.

Here, if we are trying to tell which stock or several to bet on, (maybe simple
 (arbitrary) profits may all have about the same additive error (or multiplicative error)
 - so picking the apparently best predicted stock would be best.

(SN) Another Q is put for baseball players, $\mu \in M_2 < 1$, so it can't be Gaussian!

The distribution $P(N_1, N_2)$ is more reasonable. P = prob of "hit", N_1 is no of hits,
 N_2 is no of non-hits. $N_1 + N_2 =$ no. runs at bat.

To normalize, $\frac{N_1! N_2!}{(N_1 + N_2 + 1)!} = \int_0^1 P(1-p)^{N_2} p^{N_1} dp = \frac{N_1! N_2!}{(N_1 + N_2 + 1)!}$
 is related to Beta func of N_1, N_2 .
 P. 258 Bureau of Standards

For 1. "Grand" distrib of μ_i 's! it also has to be fact. $0 < \mu_i < 1$ we could try

for 2 param. d.f. $P(T_1, T_2)$. A first approx: to T_1, T_2 :
 Say μ_i are empirical means of n years (15.06).
 UP & DOWN!

14 Then we want $T_1, T_2 \Rightarrow \prod_{i=1}^n \frac{T_1! T_2!}{(T_1 + T_2 + 1)!} \mu_i^{T_1} (1 - \mu_i)^{T_2} = \max.$

Take P as prob: $\frac{T_1! T_2!}{(T_1 + T_2 + 1)!} \prod_{i=1}^n \mu_i^{T_1} (1 - \mu_i)^{T_2} = \frac{T_1! T_2!}{(T_1 + T_2 + 1)!} \delta^{T_1} \gamma^{T_2}$
 $\delta \geq T_1, \gamma \geq T_2$

$\ln x! \approx \frac{x^x}{e^x} \cdot \sqrt{2\pi x}$
 $\ln x! \approx x \ln x - x + \frac{1}{2} \ln 2\pi + \frac{1}{2} \ln x$

20 $\ln x! + \ln y! - \ln(x+y)! - \ln(x+y+1) = x \ln x + y \ln y - x - y + \ln 2\pi + \frac{1}{2} \ln 2\pi + \frac{1}{2} \ln(x+y)$
 $- x \ln(x+y) - y \ln(x+y) + x - y - \frac{1}{2} \ln 2\pi - \frac{1}{2} \ln(x+y) - \ln(x+y+1)$

$= x \ln \frac{x}{x+y} + y \ln \frac{y}{x+y} + \frac{1}{2} \ln(2\pi) + \frac{1}{2} \ln \frac{x}{x+y} + \frac{1}{2} \ln \frac{y}{x+y} - \ln(x+y+1)$

say $u = x+y; y = u-x$
 $(x+\frac{1}{2}) \ln x = (x+\frac{1}{2}) \ln u$

$= (x+\frac{1}{2}) \ln \frac{x}{u} + (u-x+\frac{1}{2}) \ln \frac{u-x}{u} + \frac{1}{2} \ln 2\pi - \ln(u+1)$
 $\frac{\partial}{\partial u} = \frac{(x+\frac{1}{2})}{u} - \frac{(u-x+\frac{1}{2})}{u} + \frac{(u-x+\frac{1}{2})}{u-x} - u \ln u + u \ln(u-x) - \frac{1}{u+1} + \ln 5 = 0$

$\frac{\partial}{\partial x} = \frac{(x+\frac{1}{2})}{x} - \ln x - \ln u - \frac{(u-x+\frac{1}{2})}{u-x} - \ln(u-x) + \ln 5 = 0$
 $= \frac{1}{2x} - \frac{1}{2(u-x)} + \ln \frac{x}{u(u-x)} = -\ln 8$
 $\frac{1}{2} \frac{u-2x}{x(u-x)}$

Plus stuff very simple, but it's not at all correct of my algebra!

$$S_0' p^{u'}(1-p)^{v-1} dp = \frac{\Gamma(u)\Gamma(v)}{\Gamma(u+v)} \equiv \beta(u,v)$$

$$F = S_0' p^x (1-p)^y = B(x, y+1) = \frac{\Gamma(x+1)\Gamma(y+1)}{\Gamma(x+y+2)} = \frac{x!y!}{(x+y+1)!}$$

$$\frac{\partial F}{\partial x} = \left(\frac{\Gamma'(x+1)}{\Gamma(x+1)} - \frac{\Gamma'(x+y+2)}{\Gamma(x+y+2)} \right) F(x,y)$$

$$\frac{\partial F}{\partial y} = \left(\frac{\Gamma'(y+1)}{\Gamma(y+1)} - \frac{\Gamma'(x+y+2)}{\Gamma(x+y+2)} \right) F(x,y)$$

$$\frac{\partial \ln F}{\partial x} = \frac{\partial}{\partial x} \ln \Gamma(x+1) - \frac{\partial}{\partial x} \ln \Gamma(x+y+2) = \psi(x+1) - \psi(x+y+2)$$

$\psi(x)$ = digamma function = Psi func.

lots of charts on ψ Bar send. pp 258-260

so we need to solve

$$\psi(x+1) - \psi(x+y+2) = A$$

$$\psi(y+1) - \psi(x+y+2) = B$$

$$\psi(x+1) + \psi(y+1) = C$$

$$\psi(w) - \psi(w+v) = A$$

$$\psi(v) - \psi(w+v) = B$$

$$\psi(w) + \psi(v) = A - B (= C)$$

if $w = x+1, v = y+1$

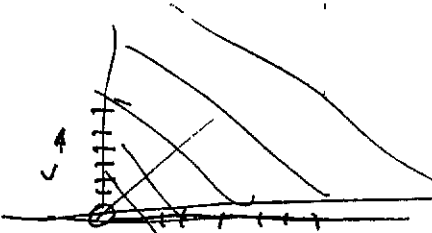
NB $\psi(2+1) = \psi(2) + \frac{1}{2}$ (!!!)

so $\psi(1.5) \approx 0$, so

$$\psi(1.5 + n) \approx 0 + \frac{1}{1.5} + \frac{1}{1.5+1} + \frac{1}{1.5+2} + \dots + \frac{1}{1.5+n}$$

$$\approx \ln n$$

$$\psi(n) \approx -\gamma + \sum_{k=1}^{n-1} \frac{1}{k}$$



Back to (7.20):

in terms of x+y:

$$x \ln x + y \ln y + \frac{1}{2} \ln x + \frac{1}{2} \ln y - x \ln(x+y) - y \ln(x+y) - \frac{1}{2} \ln(x+y) - \ln \gamma + \ln 8 \neq 0$$

$$\frac{\partial \ln F}{\partial x} = 1 + \ln x + \frac{1}{2x} - \ln(x+y) - \frac{x}{x+y} - \frac{y}{x+y} - \frac{1}{2} \frac{1}{x+y} - \frac{1}{x+y} + \ln 8 \neq 0$$

$$\ln x - \ln(x+y) + \frac{1}{2x} - \frac{1}{2(x+y)} - \frac{1}{x+y} + \ln 8 = 0$$

$$\frac{\partial \ln F}{\partial y} = \ln y - \ln(x+y) + \frac{1}{2y} - \frac{1}{2(x+y)} - \frac{1}{x+y} + \ln 8 = 0$$

$$\ln x - \ln y + \frac{1}{2x} - \frac{1}{2y} = \frac{-(\ln 8 + \ln 8)}{2}$$

$$\ln \frac{x}{y} + \frac{1}{2} \left(\frac{1}{x} - \frac{1}{y} \right) = C$$

$$\ln v - \ln u + \frac{1}{2} (u-v) = C$$

$$\frac{v}{u} + \left(\frac{u-v}{2} \right)^2 = e^{2C}$$

$$u \approx \frac{1}{2} x, v \approx \frac{1}{2} y$$

$$\frac{1}{x+y} = \frac{\frac{1}{x} - \frac{1}{y}}{\frac{1}{x} + \frac{1}{y}}$$

$$\ln(1+e) \approx e - \frac{e^2}{2}$$

$$\ln(x - \frac{1}{2})$$

$$\psi(x) \approx \Gamma'(x) / \Gamma(x) \approx \ln(x - \frac{1}{2})$$

$$\text{so } \Gamma'(x) \approx \Gamma(x) \cdot \ln(x - \frac{1}{2})$$

$\ln \Gamma(x)$	$\psi(x)$	x	$\ln(x - \frac{1}{2})$
4.200	1.60	100	4.90
3.89	3.30	50	3.90
3.178	3.198	25	3.198
2.197	2.25	10	2.25
1.386	1.506	5	1.504
.922	3	3	.916

$$\ln w - \ln(w+v) = A$$

$$\ln v - \ln(w+v) = B$$

$$\frac{w}{w+v} \approx e^A \approx \delta$$

$$\frac{v}{w+v} \approx e^B \approx \gamma$$

$$\therefore e^A + e^B \text{ must} = 1$$

$$\gamma = \left(\frac{w}{w+v} \right)^{\frac{1}{\delta}}$$

$$\delta = \left(\frac{v}{w+v} \right)^{\frac{1}{\gamma}}$$

so is $\gamma + \delta \approx 1$?
In a case I turned $\gamma \leftarrow \delta$!

-3	1-3	.2	.3	.5	→ .31
		.8	.7	.5	→ .654
					.964

Let's go thru 18.01 ft more carefully!

$\int_0^1 p^x (1-p)^y = 1$; $\int_0^1 p^{x-1} (1-p)^{y-1} = \frac{\Gamma(x)\Gamma(y)}{\Gamma(x+y)}$

$x' = x-1$; $y' = y-1$

$\frac{\partial}{\partial x} \int_0^1 p^{x-1} (1-p)^{y-1} = 0$; $\frac{\partial}{\partial y} \int_0^1 p^{x-1} (1-p)^{y-1} = 0$; $\frac{\partial}{\partial x} \frac{\Gamma(x)\Gamma(y)}{\Gamma(x+y)} = 0$; $\frac{\partial}{\partial y} \frac{\Gamma(x)\Gamma(y)}{\Gamma(x+y)} = 0$

$F = k(\ln \Gamma(x+y) - \ln \Gamma(x) - \ln \Gamma(y)) + (x-1) \sum_{i=1}^k \ln M_i + (y-1) \sum_{i=1}^k \ln(1-M_i) = (k \ln 8) \cdot k$

$\frac{\partial F}{\partial x} = \ln \Gamma(x+y) - \ln \Gamma(x) - \ln \Gamma(y) + (x-1) \frac{\sum \ln M_i}{k} + (y-1) \frac{\sum \ln(1-M_i)}{k}$

$\frac{\partial F}{\partial x} = \frac{\Gamma'(x+y)}{\Gamma(x+y)} - \frac{\Gamma'(x)}{\Gamma(x)} + \ln 8$

$\psi(x+y) - \psi(x) + \ln 8$; $\psi(z) \approx \ln z - \frac{1}{2z}$

$\ln(x+y - \frac{1}{2}) - \ln(x - \frac{1}{2}) + \ln 8 = 0$

$(x+y - \frac{1}{2}) \delta = 1$; $(x - \frac{1}{2}) \delta = x - \frac{1}{2}$

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$\frac{\partial F}{\partial y} = 0$

$(x+y - \frac{1}{2}) \delta = y - \frac{1}{2}$; $\frac{x - \frac{1}{2}}{y - \frac{1}{2}} = \frac{x}{y}$

EF
 $(x+y)\delta = x$
 $(x+y)\delta = y$
 $\therefore y = \frac{5}{8}x$

$(x + \frac{5}{8}x)\delta = x$
 $\delta x + \frac{5}{8}\delta x = x$
 $(\frac{13}{8})\delta x = x$
 $\therefore \delta = \frac{8}{13}$
 $\therefore y = \frac{5}{13}x$

From 18.01, we get "exact" values of $x \approx y$: But usually $x \approx y$ will be small $\left((x + \frac{5}{8}x)\delta = x \right)$

$\leftarrow 10$: We may know to use correction to $\psi(z) \approx \ln(z - \frac{1}{2})$

(i.e. $\psi(z) \approx \ln(z - \frac{1}{2}) + \frac{1}{2+2z}$ which is small better than $\ln(z - \frac{1}{2})$)

For $\frac{1}{2}$ term zero; 1st term $\frac{1}{2+2z}$; $\frac{1}{2+2z}$

$x + y - \frac{1}{2} = \frac{x}{\delta} - \frac{1}{2\delta}$

$\delta y - \frac{\delta}{2} = \delta x - \frac{\delta}{2}$

$x + y - \frac{1}{2} = \frac{y}{\frac{5}{8}\delta} - \frac{1}{2 \cdot \frac{5}{8}\delta}$

$y = \left(\delta x - \frac{\delta}{2} + \frac{\delta}{2} \right) / \frac{5}{8}$

$x + y(1 - \frac{1}{8}) = \frac{1}{2} - \frac{1}{2\delta} = \frac{1}{2}(1 - \frac{1}{\delta})$

$y = \frac{5}{8}x - \frac{\delta}{2} + \frac{\delta}{2} = \frac{5}{8}(x - \frac{1}{2}) + \frac{1}{2}$

$(x - \frac{1}{2}) + y = \frac{y}{\frac{5}{8}} - \frac{1}{2\delta}$
 $y = \frac{5}{8}(y - \frac{1}{2}) + \frac{1}{2}$

$x - \frac{1}{2} = (y - \frac{1}{2}) \frac{5}{8}$ from (2)

$x - \frac{1}{2} + y = \frac{5}{8}(y - \frac{1}{2}) + \frac{1}{2}$ from (2)

$(y - \frac{1}{2}) \frac{5}{8} + y = \frac{5}{8}(y - \frac{1}{2}) + \frac{1}{2}$

$y \left(\frac{5}{8} + 1 - \frac{1}{8} \right) = \frac{5}{8} - \frac{1}{2\delta}$

$y = \frac{\frac{5}{8} - \frac{1}{2\delta}}{1 + \frac{5}{8} - \frac{1}{8}}$

$= \frac{1}{2} \frac{1}{1 + \frac{5}{8} - \frac{1}{8}}$

$= \frac{1}{2} \frac{1}{1 + \frac{4}{8}}$

$x = \frac{1}{2} \frac{1}{1 + \frac{5}{8} - \frac{1}{8}}$
 $= \frac{1}{2} \frac{1}{1 + \frac{4}{8}}$

So $\frac{x}{s-1}$ and $\frac{y}{s-1}$ are critical params.

$$\delta \equiv \left(\frac{\mu}{\sigma^2} M_1 \right)^2 \quad S \equiv \left(\frac{\mu}{\sigma^2} (-M_0) \right)^2$$

s & x are both below a δ so these are co.

$x = \frac{1}{2} \frac{1}{1-\frac{x}{s}}$ so if $x \approx 1-s$ $x \approx y$ in (65).

if $x = 1-s$ $x \approx y \approx \infty$ (so they should)

This result is reasonable, — but only if x & y are > 2 , say.

Try EAM's baseball data.

$$\frac{x}{s-1} - \frac{y}{s-1} = \frac{x^2 - y^2 - s^2 + s}{(s-1)(x-1)} \quad \left| \quad \frac{x}{s-1} \cdot \frac{s-1}{s} = \frac{x^2-1}{s^2-1}$$

$$1 - \frac{x}{s-1} = \frac{s}{1-s} ; \frac{s}{1-s} \quad \begin{matrix} 1-s > x \\ 1 > x+s \end{matrix}$$

$$1 - \frac{x}{1-s} = \frac{1-s-x}{1-s} \quad x = \frac{1}{2} \frac{1}{1-\frac{x}{s}} = \frac{1}{2} \frac{1}{\frac{1-s-x}{1-s}} = \frac{1}{2} \frac{1-s}{1-s-x}$$

$$x+y-2 = \frac{1}{2} \frac{1}{1-s-x} - \frac{1}{2} \quad y = \frac{1}{2} \frac{1-s}{1-s-x} ; \quad x+y = \frac{1}{2} \left(\frac{1-s-x+1}{1-s-x} \right) = \frac{1}{2} \left(1 + \frac{1}{1-s-x} \right)$$

is like a SSZ for Grand d.f.

data 1, 346, 400, 290

26 δ, s, x, y do same 19.19.20

out $.2569572$ $.721332$ for δ, s using 18 ball players, 15 times at bat each.

$$1 - \frac{x}{s-1} = \frac{s}{1-s} = 85.76739 \quad x-y-2 = \left(\frac{1}{2} \cdot 85.76 \right) - 1.5 = 41.383625 \text{ not!}$$

checks,

$$x = \frac{1}{2} \frac{1-s}{1-s-x} = 11.51927663 \quad x-y-\frac{1}{2} = 42.883625$$

27 $y = \frac{1}{2} \frac{1-s}{1-s-x} = 31.86442$

mean $= \frac{x-1}{x+y-2} = .2941889$

28 $y = \frac{1}{2} \left(\frac{s+(1-s-x)}{1-s-x} \right) = \frac{1}{2} \left(1 + \frac{1}{1-s-x} \right)$

$95 \cdot .12 + 41.3836 \cdot .2541889 = 86.383695$

$.95093 \text{ Mit } .12177$

$1 \rightarrow .342$
 $9 \rightarrow .2695 \cdot .256$
 $10 \rightarrow .256$
 $18 \rightarrow .207$

My method gets σ^2 error of .032 v.s. .0216 for Stein's .07537 for raw means!

34 Maybe check on my arithmetic) — The \bar{V} (variance) was .265 not

Also, One's measure of "true" means,

One Q is to "s" I used for Grand d.f. — it really should be sharper —

I measured its variance from samples directly: I should subtract out f. var of f. individual players: One way to deal w. Q is: Add number mean wt. of players to grand d.f.

So wt. of Grand d.f. is 86.383695

35 $42.883625 \cdot .2569572 = 11.01927663$ ① ✓

$(x+y-\frac{1}{2}) \cdot s = 4.5 = y$ ✓ ② ✓

30.7673

13099 SMART STEIN.

A worrysome guy: t. man of 20.25 & t. 2.1% man of 20.34 : (I check & calcns: room etc.)

05 try $\frac{45 \cdot \mu_1 + (41.7 \cdot 20.25 + 45)}{x+y=2+45+45} + (.65749 \cdot E) = .167127103$
 $\frac{.17499 \cdot \mu_1}{.26939}$

But $.52093164 \mu_1 + .167127103$ gave $E_{arr} = .05958$ ($>$ border)

Using E & t. man of .26539: got even worse $E_{arr} = .0712$
 (most of bad as uncorrected data)

09 $.342508 \mu_1 + 120000 \cdot .167127$ Got E_{arr} of .02407

03 Slightly $>$ Stein. (This is for extent on grand mean | v.s. .0216 for Stein)

19 Try $\bar{\mu} = .26939$: so $E = .16713 + .17499$ slightly less error: .02918
 Still $>$ over than Stein!

13 STEIN 2.60 Got "Basic" to do calcns of costs, etc.

P	Q	$1/(1-p)$
.2569572	.7313833	85.76739

Using logs instead of Mult. E_{arr} PQ same as decimal accuracy and $1/(1-p)$ to 5 decimals.

SN \rightarrow ~~not~~ possibly sample errors:

1) If S_1 & S_2 are SSZ 's of 2 d.f.s. t. SSZ of P & Q is $S_1 + S_2$, but $\left(\frac{1}{S_1} + \frac{1}{S_2}\right)^{-1} = \frac{S_1 S_2}{S_1 + S_2}$

26 For differences $S_3 = \frac{S_1 S_2}{S_1 - S_2}$: Since S_1 & S_2 are large, and close to each other, it's noisy; this is a big source of error!

2) P & Q gave ~~arr~~ should not be Σ error but

max arr : $\log \frac{\mu_c}{\mu_{arr}} + \log \frac{(1-\mu_c)^{1-u}}{(1-\mu_{arr})^{1-u}}$

S_1	increase	Z	-3969.881
S_2	Stein	W	-3909.799
S_3	my arr		-3912.350
S_4	Actual russel fraction	V	-3892.172

using .09 \pm got -3915.202 even worse! $\mu_{arr} = .64$

x to 1	n	Final Ave	Final
$\sqrt{2}$		Initial Ave (Value)	
$\sqrt{3}$		Stein Ave	
$\sqrt{4}$			
$\sqrt{5}$			

Time at both ends of season

13199 SDFT Stein

$S_2 = \frac{1}{n-2} \sum (y_i - \hat{y}_i)^2 = 41.383695$ (20.01)

Try $\hat{\mu}$ in with by formula $\frac{S_1 S_2}{S_1 - S_2} = 514.9638$

$.03 \frac{45 \cdot \mu_i + 514.9638 \cdot .26539}{45 + 514.9638} = .08026 \mu_i + .24905$

This gets ~~3908.012~~ 3908.012
 Basis for (variance stab) for (II type Gove.)
 Try using $\hat{\mu}$ alone. as estimate $- 3908.837$

(1.7 worse than Stein) So, it was Better!
 (3.4 worse than Stein)

Using Σ error as criterion, $\hat{\mu}$ got $.02495$; v.s. $.02318$
 v.s. $.021611$ for Stein

my best for Σ error using $.03$ $\hat{\mu}$ got for $.08026 \mu_i + .24905$ (Σ error = $.02265$) Better than
 Try $\hat{\mu}$ of 20.25 : $.2541889 \rightarrow .23376$ Still slightly worse than Stein, previous
 $.08026 \mu_i + .23376$ Σ error = $.024052$ so $>$ my best

NR What to rep. suggests is that it is very impt to get a true value of to "Grand D.F.". Since it involves rather small differences but large, noisy numbers; it is often of much uncertainty! — Hrr, one can always integrate over all possible in doing to predict. — But can be very impt in such a noisy situation.

T. ~~best~~ problem was my ~~to~~ Grand $\hat{\mu}$ using $\hat{\mu}$ of 20.25 dis from worse than $\hat{\mu}$ simple with mean.

→ In fact, the difference can be < 0 ("var" < 0) which is meaningless if taken by itself. — but if we integrate over all legal posses — then it's OK. if it's "most likely var" was < 0 (!).
 Actually, it's difference is positive but small, we'd probably just use $wt = 0$ for $\hat{\mu}$ — or if difference is < 0 , If we "integrate", I suspect best results (for large wt) will not be much different than for $wt = 0$.

For the product Gove, we wish key to move this Gove, then we report again, it would be good for prediction: $(20.252, .2541889)$
 T. **BIG Q** is why $\hat{\mu}$ Σ got via $\hat{\mu}$ (product Gove) differs ~~from~~ so much from $\hat{\mu}$ (usual mean) (using $\hat{\mu}$ Σ sp. Gove), $(.2541889, .205)$ 4% diff.

We could compare Σ error given in Product Gove, by considering error per data pt. For product, consider amount above perfect score: $3908.12 - 3892.17 = 15.95 = \Delta \mu$. $\rightarrow 17.62$ for Stein v.s. $.021611$ for Σ error for Stein. (13 predictions for Σ error) $+ 1.67$
 Many more for product Gove. $\sim 300 \times 18 \times 6 \text{ k}$: $\frac{16}{300} = .053$, so within factor of 2?

Some random notes: 1) Look at some mean of "rect of. convol." data: How does it compare w. mean of "first 1/2"?

0.03 2) Note: $\frac{1}{2}$ of the $\Gamma(1-p)$ distribn is not exactly $u+v$. ~~is~~ - it depends on u (also).
 ∴ the stuff about var. of convolution being sum of var's of convoluted d.f.'s doesn't hold.

0.05 Also they don't "convolute" anyway! T. range of z ~~is~~ d.f.'s convoluted $[0, 1]$ each of range $\rightarrow [1, +3]$!

T. reason to get fairly good results, is that per hypothesis effects $\cdot 0.03$ is "cancel" (d')

Anyway, the correct way to do this (like w. the Gamma d.f.s):

0.10 $\exp(G) = \prod_i (u_i^x (1-u_i)^y)$. $u_i: u_i' = .45$ $(1-u_i)' = (.55 - u_i' \cdot .45)$ $\frac{\Gamma(x+y+2)}{\Gamma(x+1)\Gamma(y+1)}$

$G = \sum_i (x \ln u_i + y \ln(1-u_i) + (.55 \cdot u_i') \ln u_i + (.55 u_i' \cdot .45) \ln(1-u_i) + \ln \Gamma(x+y+2) - \ln \Gamma(x+1) - \ln \Gamma(y+1))$

0.18 $\frac{\partial G}{\partial x} = \left(\sum_i \ln u_i' + \ln(x+y+\frac{1}{2}) - \ln(x+\frac{1}{2}) \right) = 0 \Rightarrow \left(\prod_i u_i' \right)^{\frac{1}{2}} \cdot \left(\frac{x+y+\frac{1}{2}}{x+\frac{1}{2}} \right)^{\frac{1}{2}} = 1$

0.19 $\frac{\partial G}{\partial y} = \left(\sum_i \ln(1-u_i) + \ln(x+y+\frac{1}{2}) - \ln(y+\frac{1}{2}) \right) = 0 \Rightarrow \left(\prod_i (1-u_i) \right)^{\frac{1}{2}} \cdot \left(\frac{x+y+\frac{1}{2}}{y+\frac{1}{2}} \right)^{\frac{1}{2}} = 1$

Def: A_i, B_i

0.20 $\frac{\partial G}{\partial u_i} = \frac{x + .45 u_i'}{u_i'} - \frac{y + (.55 - .45 u_i')}{(1-u_i')} = 0$

$\frac{x + A_i}{u_i} = \frac{y + B_i}{(1-u_i)}$ $\Rightarrow \beta_i = .45 - A_i$
 $\frac{x + A_i}{u_i} = \frac{y + B_i}{(1-u_i)}$
 $\frac{x + A_i}{u_i} = \frac{y + B_i}{(1-u_i)}$

0.21 $\frac{\prod_i (x + A_i)}{\prod u_i} = \frac{\prod_i (y + B_i)}{\prod (1-u_i)}$ $\Rightarrow \prod u_i = \left(\frac{x + \frac{1}{2}}{x + y + \frac{1}{2}} \right)^k$ $\Rightarrow \prod (1-u_i) = \left(\frac{y + \frac{1}{2}}{x + y + \frac{1}{2}} \right)^k$

0.21 $\Rightarrow \frac{\prod (x + A_i)}{(x + \frac{1}{2})^k} = \frac{\prod (y + B_i)}{(y + \frac{1}{2})^k}$ $\Rightarrow \prod \left(\frac{x + A_i}{x + \frac{1}{2}} \right) = \prod \left(\frac{y + B_i}{y + \frac{1}{2}} \right)$

0.22 $x_i: x + \frac{1}{2} \quad A_i: A_i - \frac{1}{2}$ (w. y) $\Rightarrow \prod \left(1 + \frac{A_i}{x + \frac{1}{2}} \right) = \prod \left(1 + \frac{B_i}{y + \frac{1}{2}} \right)$

so $y = f(x)$ then $(.28A)$

$\frac{x + A_i}{u_i} = \frac{y + B_i}{1-u_i}$

so if we know x & y , all u_i 's can be obtained from this linear eq.

0.20 $\frac{x + A_i}{u_i} = \frac{y + B_i}{1-u_i} \Rightarrow u_i(y + B_i) = x + A_i - u_i(x + A_i)$
 $u_i(y + B_i + x + A_i) = x + A_i \Rightarrow u_i = \frac{y + B_i + x + A_i}{x + A_i}$

0.25 $u_i = \frac{y + B_i + x + A_i}{x + A_i}$

$1 = \frac{(x+y+\frac{1}{2}) \prod (x+A_i)(y+B_i)}{(x+\frac{1}{2})^k (y+\frac{1}{2})^k}$

so $(x + A_i)(y + B_i) = 1$ (unlikely) x, y, A_i, B_i are usually > 1 .

$1-u_i = \frac{x+y+\frac{1}{2}}{x+A_i} = \frac{y+B_i}{x+y+\frac{1}{2}}$

$u_i = \frac{x + \frac{1}{2}}{x + A_i} + \frac{A_i}{x + A_i}$

$1 - \frac{.45}{x+y+\frac{1}{2}} = \frac{x+y}{x+y+\frac{1}{2}}$

$\frac{x + A_i}{x+y + \frac{1}{2}}$

$\frac{x + .45 A_i}{x+y + \frac{1}{2}}$

$\frac{x + y}{x+y + \frac{1}{2}} + 1$

.01 $\mu_i = \frac{X + A_i}{X + Y + 45} = \frac{X + 95\mu_i}{X + Y + 45}$ is quite reasonable! $X \neq Y$ are actual "F32's"
 .02 $(1 - \mu_i) = \frac{Y + B_i}{X + Y + 45}$ not $\frac{55z + 1 + 55z - 1}{z}$
 $\Rightarrow \frac{X}{X+Y} = \frac{A_i}{A_i + B_i} = \frac{A_i}{k}$ (i.e. $\frac{A_i}{k} = \frac{X}{X+Y} = 0$?)

I don't know, but out of fact here (20.18): $\prod \left(\mu_i = \frac{X + A_i}{X + Y + 45} \right) = 1$, also $\left(\frac{\mu_i}{\frac{X + A_i}{X + Y + 45}} \right) = 1$
 * $\mu_i \left(\frac{\frac{X}{45} + \frac{Y}{45} + 1}{\frac{X}{45} + \frac{Y}{45} + 1} \right)$ So maybe "normalize" X & Y to $\frac{X}{45}, \frac{Y}{45}$?

.04 α Given X, Y trial; $\frac{X + \frac{1}{2}}{X + Y + \frac{1}{2}} = C$ & $\frac{Y + \frac{1}{2}}{X + Y + \frac{1}{2}} = D$ from 20.18, 19. from these, we get X & Y a loop to α (.04)
 why $\frac{X + \frac{1}{2}}{X + Y + \frac{1}{2}} = C$ $\frac{Y + \frac{1}{2}}{X + Y + \frac{1}{2}} = D$ $\frac{X + Y + \frac{1}{2} - \frac{1}{2}}{X + Y + \frac{1}{2}} = (C + D)$ $(X+Y) \left(\frac{1}{X+Y+\frac{1}{2}} \right) = \frac{1}{2} + \frac{1}{2}(C+D)$
 $Z = X + Y + \frac{1}{2}$ $\frac{Z - \frac{1}{2}}{Z} = C + D$ $1 - \frac{1}{2Z} = C + D$ $\frac{1}{2Z} = 1 - C - D$ $Z = \frac{\frac{1}{2}}{2(1-C-D)}$
 $Z = X + Y + \frac{1}{2} = \frac{1}{1-C-D}$ $X = C \cdot Z - \frac{1}{2}$ $Y = D \cdot Z - \frac{1}{2}$

.20 $C = \left(\prod \mu_i \right)^{\frac{1}{k}} = \left(\prod \frac{X + A_i}{X + Y + 45} \right)^{\frac{1}{k}} = \frac{\left(\prod (X + A_i) \right)^{\frac{1}{k}}}{X + Y + 45}$ $X + Y = \frac{C + D}{1 - (C + D)}$
 .21 $D = \left(\prod (-\mu_i) \right)^{\frac{1}{k}} = \left(\prod \frac{Y + B_i}{X + Y + 45} \right)^{\frac{1}{k}} = \frac{\left(\prod (Y + B_i) \right)^{\frac{1}{k}}}{X + Y + 45}$ $X + Y = \frac{1}{1 - C - D}$

.24 Initial $\mu_i = \bar{\mu}_i$; $\frac{X}{X+Y} = \bar{\mu}_i$ $X + Y = 500$ (Guess).
 .25 or this \rightarrow So $X = 500 \bar{\mu}_i$; $Y = 500(1 - \bar{\mu}_i)$; $\bar{\mu}_i = \bar{\mu}_i = .26539$
 .25 is easier to start with. (Starting w. .24 $C = \bar{\mu}_i$ since $X+Y=500$.)
 $D = 1 - \bar{\mu}_i$

.30 α $\frac{X}{X+Y} = \bar{\mu}_i$ from .01, .02 $\mu_i, 1 - \mu_i$; from 20, 21, get C, D . $\frac{1}{2} \left(\frac{C}{1-C-D} - 1 \right)$
 Prod $X = \frac{1}{2} \left(\frac{C}{1-C-D} - 1 \right)$ $Y = \frac{1}{2} \left(\frac{D}{1-C-D} - 1 \right)$ $X + Y = \frac{1}{2} \left(\frac{C+D}{1-C-D} - 2 \right) = \frac{3C+3D-2}{2(1-C-D)}$ $\frac{A \cdot C + D - 1}{1 - C - D}$
 $X + Y + \frac{1}{2} = \frac{3C+3D-2}{2(1-C-D)} + \frac{1}{2} \left(\frac{3-3C-3D}{2(1-C-D)} \right) = \frac{1}{2(1-C-D)}$ so it should!
 $\frac{1}{2} \frac{C+D}{1-C-D} + \frac{1}{2} = \frac{1}{2} \left(\frac{C+D}{1-C-D} + 1 \right) = \frac{1}{2(1-C-D)}$

$x+y=1$ corresponds to what I had before - w.o. subtracting out recurrence,

So look at formula for e^G (2.9.10): I think it's essentially correct, w. a constant factor omitted

$$e^G = \prod_{i=1}^k \left[\frac{\Gamma(x+y+2)}{\Gamma(x+1)\Gamma(y+1)} M_i^{x+1} (1-M_i)^y \cdot \left(\frac{\Gamma(45+2)}{\Gamma(45+M_i+1)\Gamma(45-45M_i+1)} M_i^{45} (1-M_i)^{45-45M_i} \right) \right]$$

These are constant factors A_i don't influence maximum of x, y [45].

Good function w/ integer values.

.10 $G = \sum_{i=1}^k \left[\ln \Gamma(x+y+2) - \ln \Gamma(x+1) - \ln \Gamma(y+1) + (x+45M_i) \ln M_i + (y+45-45M_i) \ln(1-M_i) \right]$

.12 $\frac{\partial G}{\partial M_i} = \frac{x+45M_i}{M_i} - \frac{y+45-45M_i}{1-M_i} = 0$

.16 $\frac{\partial G}{\partial x} = \sum_{i=1}^k \left(\frac{2 \ln \Gamma(x+y+2)}{\partial x} - \frac{\partial \ln \Gamma(x+1)}{\partial x} + \ln M_i \right) = 0$

.17 $\frac{\partial G}{\partial y} = \sum_{i=1}^k \left(\frac{2 \ln \Gamma(x+y+2)}{\partial y} - \frac{\partial \ln \Gamma(y+1)}{\partial y} + \ln(1-M_i) \right) = 0$

$\frac{d \ln \Gamma(z)}{dz} \equiv \psi(z) \approx \ln(z - \frac{1}{2})$

Aside: $\psi(z) = \ln z - \frac{1}{2z} + \frac{1}{20z^3} + \dots$
 No $\frac{1}{z}$ term.

.21 from .16 $k \left(\ln(x+y+\frac{1}{2}) - \ln(x+\frac{1}{2}) \right) + \sum_{i=1}^k \ln M_i = 0$

.22 from .17 $k \left(\ln(x+y+\frac{1}{2}) - \ln(y+\frac{1}{2}) \right) + \sum_{i=1}^k \ln(1-M_i) = 0$

.23 from .21 $\left(\prod_{i=1}^k M_i \right)^{\frac{1}{k}} = \frac{x+\frac{1}{2}}{x+y+\frac{1}{2}}$ call this "C"

.25 from .22 $\left(\prod_{i=1}^k (1-M_i) \right)^{\frac{1}{k}} = \frac{y+\frac{1}{2}}{x+y+\frac{1}{2}}$ call this "D"

$\ln(z - \frac{1}{2}) = \ln z + \ln(1 - \frac{1}{2z}) = \ln z - \frac{1}{2z} + \frac{1}{8z^3} \dots$

$\ln(z - \frac{1}{2}) \approx \psi(z)$

1	-.093	-.5772
2	.405	.922
3	.916	.922
5	1.504	1.504
10	2.2573	2.257
25	3.19867	3.19874

We want to solve the system .12, .16, .17. This is equivalent to .12, .23, .25

Plan: Pick initial x, y : Use .12 to solve for all M_i and $(1-M_i)$
 From these, use .23 and .25 to generate C and D. From C and D solve for x and y
 This x and y is for the next recursion.

Re: Eq. .12: Let $45M_i = A_i$; $45-45M_i = B_i$; so $A_i + B_i = 45$

.34 from .12 is $\frac{x+A_i}{M_i} = \frac{y+B_i}{(1-M_i)} \Rightarrow$ Given x and y : $M_i = \frac{x+A_i}{x+y+45}$ } from .12
 $(1-M_i) = \frac{y+B_i}{x+y+45}$

So; Program: start with x and y :

from .23 $C = \left(\prod_{i=1}^k M_i \right)^{\frac{1}{k}} = \left(\prod_{i=1}^k \left(\frac{x+A_i}{x+y+45} \right) \right)^{\frac{1}{k}} = \frac{x+\frac{1}{2}}{x+y+\frac{1}{2}}$

$D = \left(\prod_{i=1}^k (1-M_i) \right)^{\frac{1}{k}} = \left(\prod_{i=1}^k \left(\frac{y+B_i}{x+y+45} \right) \right)^{\frac{1}{k}} = \frac{y+\frac{1}{2}}{x+y+\frac{1}{2}}$

$C = \left(\prod_{i=1}^k \left(\frac{y+B_i}{x+y+45} \right) \right)^{\frac{1}{k}}$; $D = \left(\prod_{i=1}^k \left(\frac{x+A_i}{x+y+45} \right) \right)^{\frac{1}{k}}$; since $\frac{x+\frac{1}{2}}{x+y+\frac{1}{2}} = C$ and $\frac{y+\frac{1}{2}}{x+y+\frac{1}{2}} = D$:

Given C and D we can solve for x and y for the next recursion: $x = \frac{1}{2} \left(\frac{C}{1-C-D} - 1 \right)$; $y = \frac{1}{2} \left(\frac{D}{1-C-D} - 1 \right)$

$x+y=1$ corresponds to what I had before - w.o. subtracting overrange.

So look at formula for E^G (23.10): I think it's essentially correct, w. a constant factor omitted

$$E^G = \prod_{i=1}^k \left[\frac{\Gamma(x+y+2)}{\Gamma(x+1)\Gamma(y+1)} M_i^{x+1} (1-M_i)^y \cdot \left(\frac{\Gamma(45+2)}{\Gamma(45M_i+2)\Gamma(45-45M_i+2)} M_i^{45} (1-M_i)^{45-45M_i} \right) \right]$$

These are constant factors that don't influence the maxim of $x, y, \{M_i\}$.

$A_i = B_i = 45 - A_i$
 $45M_i$
 M_i
 $(1-M_i)$

.10 $G = \sum_{i=1}^k \left[\ln \Gamma(x+y+2) - \ln \Gamma(x+1) - \ln \Gamma(y+1) + (x+45M_i) \ln M_i + (y+45-45M_i) \ln(1-M_i) \right]$

load
run
w/ more
code.

.12 $\frac{\partial G}{\partial M_i} = \frac{x+45M_i}{M_i} - \frac{y+45-45M_i}{1-M_i} = 0$

.16 $\frac{\partial G}{\partial x} = \sum_{i=1}^k \left(\frac{2 \ln \Gamma(x+y+2)}{\partial x} - \frac{\partial \ln \Gamma(x+1)}{\partial x} + \ln M_i \right) = 0$

.17 $\frac{\partial G}{\partial y} = \sum_{i=1}^k \left(\frac{2 \ln \Gamma(x+y+2)}{\partial y} - \frac{\partial \ln \Gamma(y+1)}{\partial y} + \ln(1-M_i) \right) = 0$

$\frac{d \ln \Gamma(z)}{dz} \equiv \psi(z) \approx \ln(z - \frac{1}{2})$

.21 from .16 $k \left(\ln(x+y+\frac{1}{2}) - \ln(x+\frac{1}{2}) \right) + \sum_{i=1}^k \ln M_i = 0$

.22 from .17 $k \left(\ln(x+y+\frac{1}{2}) - \ln(y+\frac{1}{2}) \right) + \sum_{i=1}^k \ln(1-M_i) = 0$

.23 from .21 $\left(\prod_{i=1}^k M_i \right)^k = \frac{x+\frac{1}{2}}{x+y+\frac{1}{2}}$ call this "C"

.25 from .22 $\left(\prod_{i=1}^k (1-M_i) \right)^k = \frac{y+\frac{1}{2}}{x+y+\frac{1}{2}}$ call this "D"

Aside: $\psi(z) = \ln z - \frac{1}{2z} + \frac{1}{12z^3} - \dots$
 No $\frac{1}{2z}$ term.

z	$\ln(z - \frac{1}{2})$	$\psi(z)$
1	-.693	-.5772
2	.405	.422
3	.916	.922
5	1.504	1.506
10	2.2513	2.2517
25	3.19867	3.19874

We want to solve the system .12, .16, .17. This is equivalent to .12, .23, .25

Plan: Pick initial x, y : Use .12 to solve for all M_i and $(1-M_i)$
 from these, use .23 and .25 to generate C and D. From C and D solve for x and y
 This x and y is for the next recursion.

Re: Eq. .12: Let $45M_i = A_i$; $45-45M_i = B_i$; so $A_i + B_i = 45$

Then .12 is $\frac{x+A_i}{M_i} = \frac{y+B_i}{(1-M_i)}$: Given x and y : $M_i = \frac{x+A_i}{x+y+45}$
 $1-M_i = \frac{y+B_i}{x+y+45}$ } from .12

So: Program: start with x and y :

from .23 $C = \left(\prod_{i=1}^k M_i \right)^k = \left(\prod_{i=1}^k \frac{x+A_i}{x+y+45} \right)^k = \frac{x+\frac{1}{2}}{x+y+\frac{1}{2}}$

$D = \left(\prod_{i=1}^k (1-M_i) \right)^k = \left(\prod_{i=1}^k \frac{y+B_i}{x+y+45} \right)^k = \frac{y+\frac{1}{2}}{x+y+\frac{1}{2}}$

$C = \left(\prod_{i=1}^k \frac{x+A_i}{x+y+45} \right)^k$; $D = \left(\prod_{i=1}^k \frac{y+B_i}{x+y+45} \right)^k$; since $\frac{x+\frac{1}{2}}{x+y+\frac{1}{2}} = C$ and $\frac{y+\frac{1}{2}}{x+y+\frac{1}{2}} = D$:

Given C and D we can solve for x and y for the next recursion: $x = \frac{1}{2} \left(\frac{C}{1-C-D} - 1 \right)$; $y = \frac{1}{2} \left(\frac{D}{1-C-D} - 1 \right)$

2.499 sm Ar.

Step 5: starting w $R = 500$; $X = R \cdot 0.265$; $Y = R \cdot X$

$500 \rightarrow$	$V, Y = 135, 42$	$459, 239$		
$R = 1000 \rightarrow$		$6073, 16845$	$X+Y =$	$X/(X+Y)$
$100 \rightarrow$		$177, 327$	22918	0.2645
$50 \rightarrow$		$50, 140$		
$25 \rightarrow$		$26, 76$		
$15 \rightarrow$		$19, 50$		
$12 \rightarrow$		$17, 50$		
$10 \rightarrow$		$16, 46$		
$8 \rightarrow$		$14, 43$	$\frac{X}{X+Y} = 0.245$	$500:101$

$R = 10,946$; $\bar{u} = 0.2165$; 6000 $X = 13.77$, $Y = 7.2$; $X+Y = 20.97$, $\bar{u} = 0.24822$!

C & D were not properly initialized after each loop!!

Same Bug in \sum form! Fixed:

starting w $X = 132$, $Y = 368$; it diverges; \bar{u} reads perm. w. no limitation of C, D; \bar{u} did converge - maybe (\bar{u}, \bar{u}) - apparently not, because the values converged to, but system did not give those values in repeat.

I haven't been able to find a soln for $R = \bar{u}$ "by hand" \bar{u} initially $0.2165 > 0.265$ for \bar{u} & returns R values.

Try to do a max of 26.10 "by hand".

$\ln \Gamma(x) = (x - \frac{1}{2}) \ln x - x + \frac{1}{2} \ln(2\pi)$ concats. $\frac{x^x \cdot x^x}{x^x}$

$\ln \Gamma(x+y+2) + \ln \Gamma(x+1) - \ln \Gamma(y+1) = (x+y+2) \ln(x+y+2) - (x+1) \ln(x+1) - (y+1) \ln(y+1) - \frac{1}{2} (\ln(x+y+2) + \ln(x+1) + \ln(y+1)) + 2 \cdot \frac{1}{2} \ln(2\pi)$

$A = x+1, B = y+1, C = x+y+2, F = x+y+e$ $(x+z) \cdot (y+e-z)$

$\alpha = A \ln A + B \ln B + C \ln C - \frac{1}{2} (\ln(A) + \ln(B) + \ln(C)) - \ln(A \cdot B / C)$ $k=14; l=45$

$G(26.10) = k \cdot \alpha + \sum_{i=1}^k ((x+z_i) \cdot \ln a_i + (y+e-z_i) \ln(1-u_i))$ $z_i = 45 \cdot A_i$
 $= k \cdot \alpha + \sum_{i=1}^k ((x+z_i) \cdot \ln((x+z_i)/F) + (y+e-z_i) \cdot \ln((y+e-z_i)/F))$ 26.34
 $= k \cdot \alpha + \sum_{i=1}^k ((x+z_i) \ln(x+z_i) + (y+e-z_i) \ln(y+e-z_i)) - F \ln F$ $(-\ln F) \cdot (x+z_i + y+e-z_i) = -F \ln F$

$A = x+1; B = y+1; C = A+B;$

For $s = 1014$; $H = x+z; L = y+e-z; F = x+y+e$

$G = -A \ln A + B \ln B + C \ln C - \frac{1}{2} \ln(A \cdot B / C)$

$G \rightarrow G + H \ln H + L \ln L - F \ln F$
Next.

Check the $\ln(\beta(x,y))$ formula w. calc outputs.

$A = X+1, B = Y+1; E = A+B$
 $G = \dots + \frac{1}{2} \ln(E/A/B/2/\pi)$

$\ln \frac{\Gamma(x+1)\Gamma(y+1)}{\Gamma(x+y+1)} = \ln \left(\frac{x!y!}{(x+y)!} \right)$
 say $x=3, y=4$
 $x+y=7$
 $\frac{3!4!}{7!} = \frac{6 \cdot 24}{5040} = \frac{144}{5040} = \frac{1}{35}$
 $\ln \frac{1}{35} = -3.555348$

$E = 3+4 = 7$ for $A=3, B=4, E=7$
 $\ln \Gamma(3.55192) = 3.5.23$. | Well 3! and 4! can be
 odd via simpler starting!

try $A=10, B=11, E=21$
 pen cut 2
 $\rightarrow G = 12.78535$ etc.

$\ln \frac{2!}{10!11!} = \frac{2!}{10!11!}$ or calculator.
 (2.7734)

$\ln x! = (x+\frac{1}{2}) \ln x + \frac{1}{2} \ln(2\pi) - x$
 $= x \ln x + \frac{1}{2} \ln(2\pi) - x$
 check for $x=10$

for $V=1$ to 18: $Z = .005 \times A \binom{3}{2,1}$; $H = X+2; L = Y+45-Z$; $R = H+L$

$G = G + H \log H + L \log L - R \log R$
 part.

using $R = 450$	$U = 265$	$E = 600$	$G = -425.2578$
500	"	"	-496.2154
400	"	"	-494.1
300	"	"	-499.2
100	"	"	-479.9

$R = 10, 265$	$G = -457.2595$
$2, 265$	$G = -448.57$
$.001, 265$	$G = -444.5771$
$-10, 265$	negative R is illegal.
$.001, 200$	$G = -444.5718$
$.001, .001$	$G = -444.5681$
$.001, -1$	$G = -444.5661$

looks uninteresting!

find: $E = A+B+1$ m

for $U = 265$	$R = 400$	G
.2	365	-7.98
.3	366	-3.67
1000	360.457	-3.66
.24	60.19	-3.60
max. $\rightarrow .25$	359.9	-3.58
.24	360.00	-3.48
.23	360.5	3.42
	1000	-3.9345
2000, .25		-3.6784

doubling $R \rightarrow G \rightarrow G+6 \approx$

So peaks at $\bar{U} = .25$ 360 1000
 N. $R = \infty$. (!)
 So vary pretty big.

$F(x+y+z)$ $U = .253$ doubling w. 2 corrections "+1" back to "0"
 doubling R still $\downarrow G$ by about 6! So it must be in the order of the second order gears.

$\sum A_i \ln(x+A_i) - A_i \ln(x+y+z) + B_i \ln(y+B_i) - B_i \ln(x+y+z)$
 $\sum A_i \ln(x+A_i) + B_i \ln(y+B_i) - (A_i+B_i) \ln(x+y+z)$
 $\sum (x+A_i) \ln(x+A_i) - (x+y+z) \ln(x+y+z) + x+B_i \ln(x+B_i) - (x+B_i) \ln(x+y+z)$
 $\sum (x+y+z) \ln(x+y+z)$

$E = 20.10$; for first part of G: want $\ln \Gamma(x+y+2) - \ln \Gamma(x+1) - \ln \Gamma(y+1)$
 since $A = x+1, B = y+1, E = A+B = x+y+2$: want $\ln \Gamma(E) - \ln \Gamma(A) - \ln \Gamma(B)$
 $\ln \Gamma(E) = E \ln E - \frac{1}{2} \ln E + \text{const}$ $\ln x! = x \ln x + \frac{1}{2} \ln x$
smoothly + also in (E)

so $G_{\text{initial}} = [E \ln E - A \ln A - B \ln B - \frac{1}{2} \ln(E/(A \cdot B \cdot 2\pi))] \cdot 18$ is correct: I checked. $A=10, B=11, E=21$.

Also for J to 18: $Z = 0.05ACJ, H = X^2, L = Y^2, R = 1 + H + L$
 $G = E \ln H + L \ln L - R \ln R$ seems to be correct

I may have gotten Γ & ! mixed up! See 28.05! Γ "G" of 28.04 is for

$\frac{\Gamma(E)}{\Gamma(x) \cdot \Gamma(y)}$, but I tested it for $\frac{E!}{x!y!}$: that's o.k.: off only

need to change the size of $\frac{1}{x} \left(\frac{E}{x \cdot y} \right)$ to get from $x!$ to $\Gamma(x)$,
 "+" to $x!$ "-" to $\Gamma(x)$.

strange! for $U, 2.5$
 $A = 10$ double R , usually
 got $G \rightarrow G + 26$
 $1000 \rightarrow -360$
 but $R = 2000 \rightarrow -354$
 $R = 4000 \rightarrow -362$!!!
 $R = 8000 \rightarrow -356$
 $R = 16000 \rightarrow -350$
 $R = 32000 \rightarrow -344$

1.6.99 Random notes: Maybe spaced, simplify STEIN, Bas

1) By getting $E \ln R$ (with a code of Z) in a computer
 definition of G .

2) Perhaps use MAPLE to run R in C++ Beta function

So see first $(\text{Beta}(k+1, y+1)) \int_0^1 x^k (1-x)^y dx = 1$.

Then check that

```

or just
for z=0 to 1 step .01
  s = s + z^x * (1-z)^y
next z
print s/100
  
```

Print initial (\int_0^1) = 8.5 E+7

and $G = 20.1$: 5.391 E 8

using step 10000 .001 ; 8.9877 → 8.98857

$E = x+y-1$ gives close 7.6 E 7

$\frac{x!y!}{x+y+1!} = \frac{10!15!}{26!} = 8.43577$ close to
 So S is o.k. = $\frac{x!y!}{x+y+1!}$

According to 28.04 + formula for G is $E \ln E - A \ln A - B \ln B$ for $A=10, B=11, E=21$

= $\frac{1}{2} \ln \left(\frac{E}{A \cdot B} \right)$ in line 28 E mes $\frac{(A+B)!}{A!B!}$ x 22

I did $A=x, B=y, E=x+y+1$

$G = \dots B \ln B - 1 + \frac{1}{2} \ln(E/A/B) \dots$

(No! It was 8498. v.s 8590) only ~1.2% off

~~Get close to G within 1 of of computer~~

using $A=x, B=y, E=x+y$
 $G = B \ln B + \frac{1}{2} \ln(E/A) + \ln(E+1)$ G do very close to (summarized by x same "i")

~~A=10, B=11, E=21~~
 toward "+" formula. 2000;

3303435, 15.00047
 $268762, 14.99992139$ very close
 so: $A=x, B=y, E=A+B, G = \dots + \log(E+1) + \frac{1}{2} \ln(E)$

2.5.99 \rightarrow STAIR STEIN:

So I find G! Still for $u = .265$. Correct by G for each doubling of R! — like before.

So the correct G is:

$$A=x, B=y, E=x+y.$$

$$G = (E \ln E - A \ln A - B \ln B + \ln(E+1) + \frac{1}{2} (\ln E / A / B / 2 / \pi))$$

Algorithm:

$$G = E \ln E - A \ln A - B \ln B - 1 + \frac{1}{2} \ln \left(\frac{E}{A \cdot B \cdot 2 \cdot \pi} \right)$$

I think $\frac{1}{2}$ I think

$$\begin{aligned} & \log(E+1) \\ & \log E + \log(1 + \frac{1}{E}) \\ & \sim \ln E + \frac{1}{E} \\ & \frac{(E+1) \log(E+1)}{E \log E + \log(E+1)} \\ & = E \log(E+1) + \log(E+1) \\ & = E (\ln E + \frac{1}{E}) \\ & = E \ln E + 1 \\ & + 1 \\ & \frac{1}{2} \ln(E+1) = \\ & \frac{1}{2} (\ln E + \frac{1}{E}) \end{aligned}$$

R = U = 1.5 (or .265)
A = U * R, B = 1 - U * R

$$\ln \left(\frac{x+y}{x!y!} \right) = \ln(x+y) - \ln(x!) - \ln(y!) + \frac{1}{2} \ln \left(\frac{E}{A \cdot B \cdot 2 \cdot \pi} \right)$$

$\frac{A+B+1}{A!B!}$ seems when R is doubled, since α^R from max. or $e^{\alpha A}$...

For $U = .5$

$$\frac{2x!}{x! \cdot x!} \rightarrow \frac{4x!}{2x! \cdot 2x!}$$

$$\frac{2x!}{2^x} \rightarrow 2^{2x} = (2^x)^2$$

$2x! \approx (x!)^2 \cdot 2^x$

$$\frac{U}{\alpha(1-\alpha)} \Big|_{R \rightarrow 2R}$$

X + 45U; y
Using $R=1, A=1/2$

Doubling R gives
 $\Delta \approx .3$ for $u=1$
 $\Delta \approx 1.2$ " $u=4$
 $\Delta \approx 6$ " $R=18$ ($u=5A$)

300/Point.
Bride
Leaving Program

So say G OK

Since present sum converges to how fast as $R \rightarrow \infty$ (maybe $u = .265$), look at behavior of each

$$\prod_{i=1}^k \frac{1}{(B(x_i, y_i))^{x_i}} \approx \prod_{i=1}^k \frac{1}{(1-u_i)^{x_i}} \approx \prod_{i=1}^k \frac{1}{(1-u_i)^{x_i}}$$

$$z_i = \frac{x_i}{x+y}$$

$$z_i = u_i \quad z_i' = 1 - z_i$$

$$z_i = \frac{x_i}{x+y} \quad u_i = \frac{x_i}{x+y}$$

$A_i = 2 \cdot A_i'$
This result is independent of the constant for x, y .

neg(x)/x, y. \rightarrow yes, but as $x, y \rightarrow \infty, M_i \rightarrow \frac{x}{x+y} (!)$.

E change 45 to "100" $\Delta \approx .6$ of .01 + $G \approx 4.5$
" " "200" $\Delta \rightarrow .7, .28, 5.5, 3.9$ (for $k=200$ approx. $\Delta R \approx 200 \cdot G \approx 5.7$)

For $N=900$, $u = .265$; f. plot of G u. \rightarrow f is peaked

R	25	50	100	200	400	800	3600	7200
G + 1000	61	59	57	59	64	71	73	85
								83

so maybe for both largest R's
beginning to decrease & begins to
↑ again.

2099 SHAT: STEIN

So A review: The problem is Baseball Batting Averages. See Effron, Morris, Sci Amer, May 1977, pp 109-111.

The model I used: Each ~~one~~ of k players has 2 true batting averages μ_i ($i=1 \dots k$).

Each time at bat the prob of μ_i of making a "hit"; $(1-\mu_i)$ is prob of failure.

I assume for μ_i over from a monomial distribu. from 0 to 1.

Call this Distribution $P_i(\mu_i)$.

After μ_i is chosen, each player's performance is a Bernoulli sequence with parameter μ_i ; so for N times at bat, the probability of the apparent average of μ_i is just $\mu_i^{x_i} (1-\mu_i)^{y_i}$.

Say we have k values of μ_i for N times at bat for each player.

11 The probability of this data is then $\prod_{i=1}^k P_i(\mu_i) \cdot \mu_i^{x_i} (1-\mu_i)^{y_i}$.

12 A reasonable form for $P(\mu_i)$ is $B(x+1, y+1)^{-1} \mu_i^x (1-\mu_i)^y$.

The $B(\cdot, \cdot)$ is the beta function; this is a normalization factor to the integral.

$B(x+1, y+1) = \frac{x!y!}{(x+y+1)!}$. [for info on Beta func, see Biometrika's Math Tables p 258]

mean of the P distribution is $\frac{x}{x+y}$; The width of the distribution is $\approx \sqrt{\frac{x+y}{x \cdot y}}$ if it's standard deviation maybe $(\frac{x+y}{x \cdot y})^{\frac{1}{2}}$ on whether each player

maybe $\sigma^2 = \frac{x+y}{x \cdot y}$

The P form of 12 is also very favorable mathematically

~~It takes a Beta distribution and we have k, y and N~~

Consider the cost of coding the $k \cdot N$ bits of data had a hit or no on his N times at bat.

Given X only we code the data in 2 parts: First we describe the μ_i values.

22 The probability cost is $\prod_{i=1}^k P(\mu_i) = \frac{(x+y+1)^k}{k!y!} \prod_{i=1}^k \mu_i^x (1-\mu_i)^y$

22 Given the μ_i , the probability of the observed data is $\prod_{i=1}^k \mu_i^{x_i} (1-\mu_i)^{y_i}$

Given X only; The total probability of the data is (2.2) times (2.4) or

27 $\left(\frac{(x+y+1)^k}{x!y!} \right) \prod_{i=1}^k \mu_i^x (1-\mu_i)^y \cdot \mu_i^{x_i} (1-\mu_i)^{y_i}$

30 let $G = \ln(2.27) = k \ln \left(\frac{x+y+1}{x!y!} \right) + \sum_{i=1}^k \left[(x + \mu_i^i N) \ln \mu_i + (y + N(1-\mu_i)) \ln(1-\mu_i) \right]$

If we try to find the μ_i so that this expression is MAX

$\frac{\partial G}{\partial \mu_i} = \frac{x + \mu_i^i N}{\mu_i} - \frac{y + N(1-\mu_i)}{1-\mu_i} = 0$: solving for μ_i and $1-\mu_i$ in terms of x, y .

35 $\mu_i = \frac{x + \mu_i^i N}{x + y + N} (1-\mu_i) = \frac{y + N(1-\mu_i^i)}{x + y + N}$

Noting that $\ln(x!) \approx x \ln x - x + \frac{1}{2} \ln(2\pi x)$; 30 becomes

37 $k \cdot \left[(x+y) \ln(x+y) - x \ln x - y \ln y + \ln(x+y) + \frac{1}{2} \ln \left(\frac{2\pi(x+y)}{x \cdot y} \right) \right]$

38 $+ \sum_{i=1}^k \left[\frac{(x + \mu_i^i N)}{x + y + N} \ln \frac{x + \mu_i^i N}{x + y + N} + y + N(1-\mu_i^i) \ln \frac{y + N(1-\mu_i^i)}{x + y + N} \right]$

2.7.99 SMT STEIN

We want to find x, y such that t -expression of $\sum 1.27, .38$ is Max.

Let $E \equiv x+y$. and let $z_i \equiv M_i \cdot N$; $H_i \equiv x+z_i$; $L_i \equiv y+N-z_i$; $F = H_i + L_i = x+y+N$
for 3.37 we get

.04 $k \cdot [E \ln E - x \ln x - y \ln y + \ln(E+N) - \frac{1}{2} \ln \left(\frac{E \cdot 2\pi}{x \cdot y} \right)]$ and 3.38 becomes

.05 $+\sum_{i=1}^k (H_i \ln H_i + L_i \ln L_i - F \ln F)$

So we want to find x and y to Maximize (.04 + .05).

.09 The program STEIN 7. Bas would enable us to do this: The data is for $N=45; k=18$

From ~~the~~ a posteriori data, The values of x and y that maximize the probability of this data are $(x+y) = 450$; $x = .275 \cdot 450$; $y = .725 \cdot 450$.

However, if we investigate the behavior of .04 + .05 in STEIN 7. Bas, we

find that there is no maximum for that expression: If we let $x = .25R$

then .04 + .05 seems to approach ∞ as $R \rightarrow \infty$. $y = .75R$,

Doubling R increases (.04 + .05) by about 6. So $\exp(.04 + .05)$ is proportional to about R^{10} .

For fixed large R , and $x = U \cdot R$, $y = (1-U)R$: There seems to be a peak for U about .267.

What this means is that M_i is $\approx .25$; independently of z_i .

For the present data, this gives much not bad results. (much better than using $M_i = M_i'$), but still not very correct.

2 899 SMAT

STEIN

35.17-40

(also try $\frac{(x)!}{(x)!(1-x)!}$)

any way: from 32.04: $E \approx R = 2x$

$k \cdot \left(\frac{4R}{\sqrt{\pi R}} (R+1) \cdot \frac{2R^2}{2\pi R} \right)$

say $R \approx 2x$

$\frac{2x! (2x+1)}{x! x!} = \frac{2 \cdot 2 \cdot \dots \cdot 2}{x \cdot x \cdot \dots \cdot x} = 2^{2x}$
 $\approx \frac{2^{2x} (2x)}{\sqrt{\pi} \cdot \sqrt{x}} = 2^{2x} \cdot \sqrt{\frac{2}{\pi}}$

109 in 31.27 $\prod_{i=1}^k (m_i^{x+M_i} (1-m_i)^{y+N-M_i})$ from 31.05: $\rightarrow \left(\frac{x+M_i}{x+y+N} \right)^{x+M_i}$
 $= \left(\frac{x}{x+y+N} + \frac{M_i}{x+y+N} \right)^{x+M_i} \left[\left(\frac{x}{x+y+N} \right)^x \left(1 + \frac{M_i}{x} \right)^x \right] = \left(\frac{x}{x+y+N} \right)^x \cdot e^{\frac{M_i(x+M_i)}{x}}$

$\frac{A(x+N)}{x} = A + \frac{A \cdot N}{x}$

116 product of y's factors: $\left(\frac{y}{x+y+N} \right)^{y+N-M_i} = \left(\frac{y}{x+y+N} \right)^{y+N-M_i} \cdot e^{-M_i \frac{y}{x+y+N}}$

117 In R. case $x=y=R$ mult. by $\frac{4^x \sqrt{2}}{\sqrt{\pi}}$
 $\left(\frac{1}{2} \right)^{2R+N} \cdot e^N$

for each factor: so use best fit power of R

for entire expression for function of R

119 This is for $U = \frac{1}{2}$; Actually I used $U = .25$ or $.265$.
 NOTE by using $x=R, y=R$, $\frac{2}{\sqrt{\pi}}$ which is of order 1 since $k \geq 10$.
 Actually it's $\frac{2}{\sqrt{\pi}}$ or $\frac{1}{\sqrt{\pi}}$ depending on the definition of R .
 Approx holds: $\frac{2}{\sqrt{\pi}} \approx 1.128$

120 so any convergent (to avoid non-convergent!) assignment of x and y to R will give a limit of $\frac{2}{\sqrt{\pi}}$.
 for $e^R \gg R \rightarrow \infty$. They approach R of $\frac{1}{2}$ near $\frac{1}{2}$! see it result is much different. lim. a tiny bit annoying; I found to take a U of .25 rather than .265. for the peak! Check this out!

Anyway, inserting a factor of R^{-1} or R^{-2} (or $R^{-1.5}$) is better!

122 So: try to output STEIN 7

Since e has a $E+1$ ($E \approx R+1$) factor, getting rid of it is equal to adding $\frac{1}{R}$, $R > 1$.

So Stein 9 is still a 7, but e has no $\log(E+1)$ term.

123 I want to prove: ~~it's~~ its max (for $R \geq 0$) is $\sim R^{-2}$!

124 Stein 9: $.265^R \cdot 450 \cdot 5246$
 for $R = 450$ best U was $.259$
 for $R = 10$ best U was $.285$

instead of $\ln \left(\frac{R+1}{R} \right)$ use $\ln \left(\frac{E+1}{\sqrt{R^2+10^2}} \right)$

This is 20% with change!
 $\ln \left(\frac{E+1}{R} \right) \approx -\frac{1}{2} \ln \left(R^2 + 10^2 \right)$

This gives a peak for R near 10 using 100^2 here
 peak was ≈ 8 around $R = 80$

.25	2970
.255	4.98
.260	4.5717
.265	4.617
.258	4.5513
.257	4.5777
.259	4.5919

(lim R not independent of ϵ , say because $\frac{1}{R}$ diverges as $R \rightarrow \infty$)
 $R=1$

.22	.0087	.0187
.23	.0052	.005
.24		.0651
.205		2.9997

This is disturbing! Peak depends critically on shape of approx for R!

try $\frac{1}{R} \left(\log_2 R + 2 \log_2 \log_2 R \right) = \frac{1}{R (\log_2 R)^2} \approx \frac{2^{\log_2 \log_2 R}}{(\log_2 R)^2}$

This causes convergence w/ by R values,

But that's not a problem! (Note how the factor $\frac{1}{(\log_2 R)^2}$ only occurs when $\log_2 R$ is > 0 , i.e. $R > 1$). — So r. trouble around $R=0$ would persist.

Approx of $\left(\frac{1}{\sqrt{R^2 + A^2}} \right)$ seems to ~~be~~ a peak at $\sim A$, \therefore critically dependent on A —

Using $A = 15$ gave peak at in R at \sim 30 to 35 \Rightarrow 33 is v.g. of $3E8 - 3E7$

.18 Stein (0, 800)
 In $\frac{1}{R} \log_2 R$ try $\log + \ln(E+1) \rightarrow + \frac{1}{2} (\ln(E+1))/2$. This fraction drops out.
 Even if it worked, it would be spent on approx at $\sim \frac{1}{\sqrt{R}}$: Expect trouble at low R

.19 Mybo ~~was~~ by Stein: which has a loop for incrementing R .
 .17 didn't seem to work: ~~simple~~ $\in \mathbb{Q}$ \vdash as $R \uparrow$, rapidly at first $\frac{2.3}{\text{doubling of } R}$ at $R=1$.

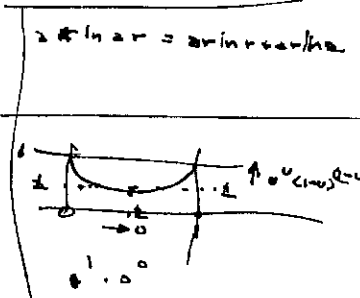
Then loss of precision — only if $\log R = 500 \rightarrow 1000$. Using $v = 255$ gave 2 results. — π result \approx $\frac{1}{2} \ln \frac{1}{2}$

Even if in some sense there was a peak, clearly, we need an approx for R that δ increases at least as rapidly as $\frac{1}{R}$ for $\log R$. This simply cuts out by R

.22 $R = r$, $k = \frac{a}{r}$, $y = (r \cdot u) R$: $\ln \left(\frac{R!}{x! y!} \right) \approx \frac{1}{2} \ln \pi + \frac{1}{2} \ln r - \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r$
 $- \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r$
 $- \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r$

$r \ln r - (a+b) \ln r - a \ln a - b \ln b$
 $- \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r$
 $- \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r$

$-\frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r$
 $-\frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r$
 $-\frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r - \frac{1}{2} \ln \pi r$



.30 If $x = y = \frac{1}{2} R$ \uparrow $\rightarrow \left(\frac{1}{2} \frac{1}{2} \frac{1}{2} \right) = \frac{1}{2}$ This factor cancels ~~that~~

wants factor occurring, ≈ 4.16 : $\left(\frac{x}{x+y+n} \right)^{x+y+n} \approx \frac{2 \cdot r}{2} = (2)^r$
 $(b)^r$

So for large R: ($R \gg 45$) we put $E+1 = r \approx r$ so
 $\left(\frac{r \cdot 2 \cdot b \cdot 2 \pi}{2 \cdot b \cdot 2 \pi} \right)^{\frac{1}{2} \cdot r} = \left(\frac{r}{2 \cdot b \cdot 2 \pi} \right)^{\frac{1}{2} \cdot r}$ which is most $\in \mathbb{Q}$ for "large R ".
 $\frac{1}{2} \approx 0$; $b \approx (1-0)$

2.16.99 SMAT. STEIN:

Going back to the original Argument! Say $\bar{\mu}$ is the "mean of means" &



$\{A_i\}$ are the true means. Say σ_i^2 is the variance of the A_i d.f.

& σ_i 's all have var σ^2 .

If the d.f.s were Gaussian, then it is cheaper to describe a set of A_i that cluster closely about $\bar{\mu}$.

a. & say $\bar{\mu} = 0$; the set A_i described about ϕ has $p.c. = \prod_{i=1}^n \frac{1}{\sigma_i} e^{-\frac{A_i^2}{2\sigma_i^2}} = (\prod \sigma_i)^{-n} \cdot e^{-\frac{\sum A_i^2}{2\sigma_i^2}}$

$$\frac{1}{\sqrt{2\pi}\sigma} \cdot e^{-\frac{x^2}{2\sigma^2}}$$

we neglect σ_i , so effect of σ is $-\frac{n}{2} \ln \sigma^2$ so $p.c. = (\prod \sigma_i)^{-n} \cdot e^{-\frac{\sum A_i^2}{2\sigma_i^2}}$. So $p.c.$ is σ^{-n} .

So smaller σ, σ^2 is better (more likely).

On the other hand, if $\{A_i\}$ are σ ^{unrelated} ~~independent~~ ^{overlapping}, we have to pay extra

to move the A_i away from the A_i^0 , toward $\bar{\mu}$.

using Bernoulli: Given $\sum A_i$ we want $\prod p(U, R, A_i) \rightarrow \max$

Whoops! Am I using the right normal constant for the Bernoulli d.f.? I think so: $\int_{-\infty}^{\infty} \dots = 1$.

17 $(B(x, y)^{-1})^n \prod_{i=1}^n u_i^x (1-u_i)^y \rightarrow \max$

18 $n \ln \left(\frac{(x+y)!}{x!y!} \right) + \sum_{i=1}^n x \ln u_i + y \ln (1-u_i) \rightarrow \max$

$$\prod_{i=1}^n u_i \equiv A : \prod_{i=1}^n (1-u_i) \equiv B$$

$A' = nA$ $B' = nB$

19 $n \ln \left(\frac{(x+y)!}{x!y!} \right) + \sum_{i=1}^n x \ln u_i + y \ln (1-u_i) \rightarrow \max$

looks like there is an optimum x, y !

20 $n \left(-\ln(2^x b^y) \cdot (x+y) + \frac{1}{2} \ln(x+y) + x \ln A + y \ln B \right) \rightarrow \max$

Wrong!

21 $n \left(\frac{1}{2} \ln(2^x b^y) \right) + x \ln A + y \ln B \rightarrow \max$

No prob! \rightarrow (if $b=1/2$) can be found. (the inequality holds if $A' = \frac{nA}{2}$, $B' = \frac{nB}{2}$ = some means of A_i 's.)

So this says that the ^{optimum} mean of the d.f. can be found, but there is no best σ 's.

22 $\ln(2^x b^y) = x \ln 2 + y \ln b = x \ln A' + y \ln B' + \frac{1}{2}$

$2^x b^y = (A')^x \cdot (B')^y \cdot e^{\frac{1}{2}}$ | $e^{\frac{1}{2}} \approx 1.65$

23 $\frac{(x+y)!}{x!y!} \cdot \frac{x+1}{x+1} \cdot \frac{y+1}{y+1} = \frac{(x+1)(y+1)}{(x+y+2)!} = \frac{x+1}{x+y+2}$

24 $\frac{(x+1)(x+2)}{(x+y+2)(x+y+3)} - \frac{(x+1)(x+1)}{(x+y+2)(x+y+2)} = \frac{x+1}{x+y+2} \left(\frac{x+2}{x+y+3} - \frac{x+1}{x+y+2} \right)$

25 $\frac{x+1}{x+y+2} \left(\frac{(x+2)(x+y+2) - (x+1)(x+y+3)}{(x+y+3)(x+y+2)} \right)$

26 $\frac{x+1}{(x+y+2)^2 (x+y+3)} \cdot \frac{x+1}{x+y+3}$

2-10-99 SMART STEIN.

01 If $x' = k+1, y' = y+1$ then $\frac{x'}{x'+y'} = \frac{y'}{x'+y'} = \frac{1}{x'+y'+1}$

02 or $\frac{U \cdot (1-U)}{r}$ which vaguely suggests that 36.20 is 35.30 maybe wrong — or perhaps 2b should be in numerator. 35.30 should be easy to check, numerically.



The normal constant should ↑ as x' ↑ because $e^{-(x')^2}$ will ↓.

Normal const. $\int_{-\infty}^{\infty} P(x) dx = 1$.

$$\frac{E}{x' y'} = \left(\frac{x'}{E}\right)^x \left(\frac{y'}{E}\right)^y = \frac{x'^x \cdot y'^y}{E^{x+y}} = (U \cdot (1-U))^{x+y} \cdot E^{-1} \cdot \left(\frac{E}{AB} \cdot \pi\right)^{-1}$$

$$\text{Normal const.} = (U \cdot (1-U))^{-R} \cdot \left(\frac{E \cdot \pi}{\sqrt{E}}\right) \sqrt{\frac{1}{U(1-U) \cdot 2\pi}}$$

$$\approx (U \cdot (1-U))^{-R} \cdot \sqrt{\frac{1}{U(1-U)}} \cdot \sqrt{\frac{1}{2\pi}} \cdot (R + \frac{1}{2})$$

$$\left(U^{U+R} (1-U)^{1-U+R} \right)^{-R} \cdot \left(\sqrt{U} \cdot \frac{1}{\sqrt{1-U}} \right) \cdot \frac{1}{\sqrt{2\pi}} \cdot \text{so the normal const. } \uparrow \text{ w. } R.$$

20' 36.23 $36.23 \approx \frac{2 \ln R}{R} - \ln(2^a b^b) \cdot R + \frac{1}{2} \ln R + R(\ln A' + b \ln B') = \text{max.}$

21 $R \cdot (2 \ln A' + b \ln B' - \ln(2^a b^b)) = \frac{1}{2} \ln R = \text{max}$

$2 \ln A' + b \ln B' - \ln(2^a b^b) = \alpha$ $R \cdot \alpha + \frac{1}{2} \ln R = \text{max}$ $\alpha + \frac{1}{2} = 0$ $R = -\frac{1}{2\alpha}$

$\frac{1}{2} \ln R = \text{max}$ $R = -\frac{1}{2\alpha}$

26 $R_{\text{max}} = \frac{1}{2} \frac{1}{2 \ln A' + b \ln B' - \ln(2^a b^b)} = \frac{1}{2} \frac{1}{2 \ln \frac{A'}{2} + b \ln \frac{B'}{2}} = \frac{1}{2} \left(2 \ln \frac{A'}{2} + b \ln \frac{B'}{2} \right)^{-1}$

Not too relevant. $A' = \left(\frac{K}{\pi} \cdot \alpha_i\right)^{\frac{1}{2}}$, $B' = \left(\frac{K}{\pi} \cdot (1-\alpha_i)\right)^{\frac{1}{2}}$

So if 36.17 has a peak for $R(\alpha, x, y)$

What about 26.03? $B(x, y) = \frac{K}{\pi} \int_{-1}^1 u_i^x (1-u_i)^y \cdot u_i^{x-1} (1-u_i)^{y-1} du_i$

$\frac{K}{\pi} \int_{-1}^1 u_i^{x+u_i N} (1-u_i)^{y+(1-u_i) N} du_i$

Say we decide on a value of U ($x = U \cdot R, y = (1-U) \cdot R$): U will be some sort of mean of the data $\{u_i\}$.

Then we consider various α values ($0 < \alpha < 1$): $\Rightarrow u_i = \alpha U + (1-\alpha) u_i'$.

23 for each α compute (1) the pc of the set of u_i 's (as a function of α), ~~the~~ w.r.t. the optimality of (20-26).

(2) Compute the total pc of the empirical data using these u_i 's & u_i' 's. This, too, will be a function of α .

- (1) should ↓ w. α ; it's max when $\alpha = 0$. (corresponds to $R = 0$)
- (2) should ↑ w. α ; it's max when $\alpha = 1$. (corresponds to $R = 0$)

Then presumably, the product of (1) & (2) should have a max value between 0 & 1. — unless one or the other dominates completely! —

2.12.99

INDEX

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Random Notes: ① γ - exponent should be only odd once in a problem! It is R_{max} modified in subsequent problems. I seem to be using the same exponent k times!
② γ result to get us to optimal smooth - But at one pt I found to have gotten a local max in R (see 29.12R).

STEIN PGM:

Semi. Bas (9.17) Examines rate of convergence of certain successive approx systems relating to PZ or Gaussian λ const.

$$X_{n+1} = -(M + X_n)(G_{2n} X_n) / k S^2.$$

STEIN PGM
Semi. Bas
2.1.13

computes $\prod_{i=1}^n A_i$; $\prod_{i=1}^n (1-A_i)$ and $\frac{1}{1-P} = 85.7639$
Also computes $\sum_{i=1}^n A_i$ for various prob. models; $\frac{.7313933}{.2569572} = 42.8819$

is using $\lambda_i = \mu_i$; using "is fast" ; (using ~~APPROX~~ some other why method)

(10B) = 19.05 - 1.40 complex base as for $x+y$ to date; This is done approx on
36.07 - 2.23, 37.20 - 3.85 ; The results are almost the same, but $x+y$ differs by $\frac{1}{2}$ (addition)

is quite v. similar to each other here exact since it is based on approx.
 $\ln(x) \approx \ln(x+\frac{1}{2})$ which is a v. b. approx. \therefore unimodal result is broken down
 $x \approx x^x \cdot e^{-x} \cdot \sqrt{2\pi x}$, which is v. close.

of how close?
 $\ln x = \ln(x-1) - \frac{(x-1)^2}{2} \dots$

for real 34.27
Sum 7 = 6 72.05
S for 10 (at 35.17)
S for 9 = 6 35.19
See (35.01 - 20 R)
for more notes
on PZ calculation

01:38.40: 35.22 / 35.40 and up w. an express. for $\frac{(k+y)!}{x!y!}$: $k \geq 0, y \geq 0, x \geq 1, n \geq 1$

02 $\frac{x+y}{x!y!} \sim (a^2 b^2)^{-n} \frac{1}{\sqrt{r \cdot a \cdot b \cdot 2\pi}}$: we mult by $(r+1)$ to get a norman const

04 $\frac{r(r+1)}{(a^2 b^2)^{-n}} \sim \frac{\sqrt{r}}{\sqrt{2\pi ab}}$

10 we mult. by $\left(\prod_{i=1}^k \frac{x}{U_i} \prod_{i=1}^y \frac{y}{(-U_i)} \prod_{i=1}^n \frac{n}{U_i} \right) \left(\prod_{i=1}^k \frac{1}{(1-U_i)} \prod_{i=1}^y \frac{1}{(1-U_i)} \right)$ (the $\frac{1}{(1-U_i)}$'s are a row of 325)

In 35.33 the $-\frac{1}{2}$'s into change \bar{A} a bit, but wouldn't affect R ($\neq x+y$) at all.

15 $\prod_{i=1}^k \frac{x}{U_i} \prod_{i=1}^y \frac{y}{(-U_i)} \prod_{i=1}^n \frac{n}{U_i} \sim \frac{(x+45n)^{x-1/2} (y+45n)^{y-1/2}}{(x+y+45n)^{x+y-1/2}}$; so $U_i = \frac{x+45n_i}{x+y+45n}$

STEIN 40.60s

(site modification STEIN 40.60s) 35.10

Double R change ΔG by \dots
 from $R(x+y) = 1.4$ to 1224 , G was monotonic \uparrow .
 for Doubling R $\Delta G = 1.9$ for $R = 1224$
 " " " " 5.8 " $R = 512 \rightarrow 2026$
 " " " " 7 " $R = 524258 \rightarrow 648576$

For $\epsilon = 1.9$, doubling R gives $\Delta G = 1.9$

for larger R, ϵ \rightarrow more oscillations, oscillates!

R is easy! trouble. Q basic (interpretation)?

Or for "Basic" Mult. (R is R interpreted @ Basic that come w. DOS 6.22 or good on calculator.)

It would seem possible to show that $\exp(\epsilon)$ is like R^k w. $\alpha \approx \frac{1}{2}$ or $-\log > 0$.

If so, then ψ is clearly wrong because $\exp(\epsilon) > 0$ - all ψ are R .

Now, the norman fact 0.2 (is always $1 - \text{uh loss}$) 2.0 is very close to 1

The factor 0.15 can't be > 1 - its product of factors, $U_i, (-U_i)$ - all < 1 .

So how did ϵ get $\in \mathbb{C}$ or $R^{\frac{1}{2}}$? - 34.19 - the water 0.2, but

33

35.22 - 30 In 35.30 we get Norman fact

$$\frac{(a^2 b^2)^{-n} \sqrt{R(n)}}{\sqrt{2\pi ab}}$$

for R. fact of ϵ $\in \mathbb{C}$: 34.16 gets $\left(\frac{x}{x+y+n} \right)^{x+n} \cdot \left(\frac{y}{x+y+n} \right)^{y+n} \cdot e^N$

So 34.16 looks like $a^2 R \cdot b^2 R \cdot e^N = (a^2 b^2) R \cdot e^N$.

Multiplying by a factor: Monotonicity: $a^2 R \cdot b^2 R \cdot a^2 R^2$

Well 34.16 looks clean up!

Start w. 34.09! Just one factor: $\prod_i \left(\frac{x + u_i N}{x + y + N} \right)^{x + u_i N} \rightarrow \prod_i \left(\frac{x}{x + y + N} \right) \left(1 + \frac{u_i N}{x} \right)^{x + u_i N}$

$= \prod_i \left(\frac{x}{x + y + N} \right)^x \left(1 + \frac{u_i N}{x} \right)^x \left(\frac{y}{x + y + N} \right)^{u_i N} \left(1 + \frac{u_i N}{x} \right)^{u_i N}$

dividing by $\prod_i M_i^{x + u_i N}$

convergence "y" products

$\prod_i \frac{1}{x} \rightarrow \frac{1}{x^R}$
 $\prod_i e^{u_i N} \rightarrow e^{(u_i N)R}$
 $\prod_i \frac{1}{x + y + N} \rightarrow \frac{1}{(x + y + N)^R}$
 $\prod_i e^{(u_i N)^2} \rightarrow e^{(u_i^2 N^2)R}$

Sub product $(a^2 b^2)^{R \cdot R}$

which totally dominates the $(a^2 b^2)^{-R}$ of 40.33 (i.e. 35:30)

No! The Normal factor is taken to the R^2 power!
 M_i^x for $u_i > 2$; becomes $\binom{x}{u_i}^R \cdot \binom{x}{u_i}^{R^2}$ - so $1.08 \approx 1.1$!

so $(a^2 b^2)^{R^2} \cdot e^{kN} \cdot \frac{N \cdot \sum u_i \cdot b^{N - N u_i}}{N^2 \sum u_i^2} \cdot e^{-\frac{(u_i^2 N^2) \cdot N^2}{x}} \cdot e^{(1 - u_i^2) \cdot \frac{N^2}{x}}$
 $\exp \frac{N^2}{x} \cdot \sum_i (u_i^2 (1 - u_i)^2)$

None of these other terms are well dependent on x .

$(a^2 b^2)^{R^2} \cdot \exp \left(kN + \frac{N^2 \sum u_i^2}{x} + \frac{\sum (1 - u_i^2) N^2}{x} \right)$

so I still look like $\frac{1}{x}$ must be ∞ for large R - which is impossible!

Putting in the $-\frac{1}{2}$ from 40.10 doesn't make much difference.

So, if I could really prove that ϵ formula for G has to be > 0 for very large R - that would prove that I couldn't be the correct formula!

Another possibility! (very likely!) that a wider convolution factor should be like $\sqrt{\frac{u_i(1-u_i)}{R}}$

This just cancels out the R^2 , because I think I'm right!

so in **Stem 40** $-\frac{1}{2} \rightarrow +\frac{1}{2}$ i divide by R !

Stem 41, Bas - Divide by $\epsilon \sqrt{\epsilon}$ as in ϵ from $\frac{1}{2} \log(F/A/B)$
 From $R = 1$ to 8.3M, G is ~~not~~ **basic** function of R ! $R = k$ for M
 Above $R = M$, ϵ **basic** ~~was not~~ **was not** word! $R = k$ for M
 for $R > 1000$. \rightarrow 2 non-monotonic G (check 262k \rightarrow 524k) \uparrow plateau

I should be able to show that $R \approx 0$ is worse than $R = \infty$.
 In fact, I know that! I.e. $R = 0$ means we use $M_i = u_i^2$!
 $R = \infty$ means we use $M_i = \bar{u}$, which is better.

Maybe do a double precision Power Base

2-14-99 SMAT ST (\equiv STern)

$\binom{A}{B} = \frac{A!}{B!(A-B)!}$

42
3422

ST.42

Contrast 2 ways of deriving data: \blacksquare about common \bar{u} & about individual u_i ($\equiv u_i'$). See if they are fairly or whether normal, punchy is

Needed: Remember that method of deriving \bar{u} (Binary) Bar isop. of unknown "logos": $\frac{n! m!}{(n+m)!}$

P.C. was

$\frac{n! m!}{n+m!}$

Wrong! - See 43.01

$\frac{n! m!}{(n+m)!}$

SN

0, 1, 2, ... procedures, 0 would give a new set of codes. - must of them \equiv odds \in "0,1" codes.

So contrast 4. 2 ways of deriv:

$\frac{x+y!}{x! y!} \approx (2^b)^{-R}$

$\frac{x}{x+y} \approx \frac{R \times x}{R \times x + y}$

So 2 \bar{u} method \rightarrow

$\left(\bar{u}^u (1-\bar{u})^{1-u} \right)^{NK}$

u_i' method \rightarrow

$\prod_i \left(u_i' u_i' (1-u_i') \right)^{N_i}$

$\frac{x! y!}{x+y!} = \frac{x! y!}{NK!}$

$\frac{x}{x+y} \rightarrow \frac{x+1}{x+y+2}$

; here, omit this term, to save

u_i' method

$Z = N u_i'$

$H = Z; L = N - Z; F = N$

Modifer of STern 9 (ST9.9)

\bar{u} method: $K=1$

$U = \bar{u}$

u_i' method: $i=0, 1$

$\frac{1}{2} \ln \left(2^N u^u (1-u)^{1-u} \right)$

So just do perm twice:

$K=1, u = \bar{u}$

$K=18, N=35, u = .05 + A(2,3)$

u in loop, $u = .05 + A(2,3)$

Modifer of STern 9

for u_i' : $G = -494.9771$

for \bar{u} : $G = -464.9104$

So $\Delta G = 30$

Success

CRAZY

\bar{u} is $\approx e^{20}$ times of codes $\{u_i\}$

$\ln \frac{10! 4!}{50!}$

$(.2, .5)$

Woops! u_i' $\bar{u} = .25$ $G = -492.06$

So $.25$ is better than $.265$

$.2 \rightarrow -401.97$ $.5$ is worse, 0,1 best.

$u = .001 \rightarrow -557.87$ $.0001 \rightarrow 1.16$ 0 prob $\rightarrow 0$.

$.5 \rightarrow -557.87$ woops! $.8 \rightarrow -491.9708$ as it should.

$\bar{u} = .2653889$

This seems to question the correctness of \bar{u} but $x \rightarrow x+1, y \rightarrow y+1$ correction.

$\frac{x+1! y+1!}{(x+y+2)!}$ method of coding

Web. Mid. ed. Section Sec. for ratio am. py

6.28318

abcdef

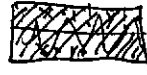
$45 \times 19 = 855$

$9.5 \times 2.4 = 22.8$

290 to 240.

ABC DEF

01 $\frac{x \cdot y + 1}{x + y + 1}$ vs. $\frac{x \cdot y!}{(x+y)!}$: $\frac{(x+1)(y+1)}{(x+y+1)(x+y+2)} = \frac{x+1}{(x+y+1)} \cdot \frac{y+1}{(x+y+2)} \approx u(u-1)$

which would make $\{u\}$ even worse!
 Actually, $f.c$ is $\frac{x \cdot y!}{(x+y)!}$  which is much lower than $\frac{x \cdot y!}{(x+y)!}$
 ...factor of $\left(\frac{1}{x+y+1}\right)$: in this case $\frac{1}{45+1}$
 So mult by $(N+1)$

02 T. differences: between 2 pc's should be $\frac{1}{\sqrt{2\pi C(u-1)N}}$ for \bar{u} : $\frac{1}{\sqrt{2\pi C(u-1)N}}$ $k \cdot N$
 IN $5+4$: I used $k=88, \bar{u} = .265$
 $N = 278.2789$
 For $N=250$, both \bar{u} & σ were $\frac{1}{\sqrt{2\pi C(u-1)N}}$ $\frac{1}{\sqrt{2\pi C(u-1)N}}$
 So $\Delta N = 2000$ \rightarrow $\Delta \sigma \approx 0.00097$
 So G_{u_i} is always better - which occurs in real life
 Tryd $\left(\frac{1}{R+1}\right)$ term.
 : Same group result $\left\{ \frac{1}{R+1} \right\}$ is always ahead's
 distance difference $\rightarrow 0$ as $N \rightarrow 0$.

N	$G_{u_i} - G_{u_j}$
260	-3.06
250	-4.72
270	-1.39
280	+1.39
278.2789	+0.00097
300	109.35
50	43.3
11	22.5
4	.1528
N	$G_{u_i} - G_{u_j}$
100	-16
200	-1.66
270	10.02

$\frac{x \cdot y!}{x+y! \cdot (x+y)} = \frac{(2/6)^k \sqrt{2\pi k R}}{R+1}$

23
 30
 This latest result is so crazy! That the transition of \bar{u} is $[u_i]$ should be so sharp, is certainly not expected, which is what I expect the "crossing" to be!
 So $N \neq 10 \rightarrow$ factor of 5 below \bar{u} is $[u_i]$.
 For $\bar{u} = 0.265$ \rightarrow $\sigma = 1.65$ or 1.6 for $\Delta N = 1$
 $\exp(1.6^2) \approx 7.5$
 So with $N = 200$, I observed u_i ≈ 2.0 \rightarrow equally unexpected (they to have been done by a simple beam sep. only 1/5 beam sep!)
 But $N = 200$ is only $1/2$ of 450 !

For by program $\frac{1}{x} \ln x = x \ln x + \frac{1}{2} \ln(x \cdot 2\pi) - x + \frac{1}{2x}$
 in $\frac{x \cdot y!}{x+y!}$ \rightarrow x cancels out but $\frac{1}{2x}$ doesn't \rightarrow $\frac{1}{x} + \frac{1}{y} - \frac{1}{x+y} = \frac{y \cdot (x+y) + x \cdot (x+y) - xy}{xy(x+y)} = \frac{(xy)^2 - xy}{xy(x+y)} = \frac{x^2 y + y^2 x - xy}{xy(x+y)}$
 $\frac{1}{x} + \frac{1}{y} - \frac{1}{x+y} = \frac{x^2 y + y^2 x - xy}{xy(x+y)}$
 For $x=y=2$ \rightarrow $\frac{1}{2} + \frac{1}{2} - \frac{1}{4} = \frac{3}{4}$
 $\frac{3}{4} \cdot \frac{1}{12} = \frac{1}{16}$

Actually, the formula for pc of Bern. string is just using "Laplace's rule" for each bit.

The "gamma" of 0.1, say, is just a way of making it easy to remember.

Using \bar{u} alone for pc. would give $(\bar{u}^u (1-\bar{u})^{n-u})^{Nk}$. By not needing to specify \bar{u} , we improve

to pc of $\sim \sqrt{2\pi} \bar{u}^{u-1/2} (1-\bar{u})^{n-u-1/2}$ $\left(\frac{\sqrt{Nk}}{\sqrt{Nk+1}} \right) \approx \sqrt{\frac{Nk}{Nk+1}}$ $\sqrt{\frac{2\pi}{Nk}} = \sqrt{2\pi} \frac{1}{\sqrt{Nk}}$

$\int \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{Nk}} \frac{1}{\sqrt{Nk+1}} \approx 1$ \Rightarrow it is $\left(\prod M_i \right)^{1/2} \approx A$, $\left(\prod (M_i) \right)^{1/2} \approx B$

Then $\frac{A}{A+B} \approx A'$!
 A' is also $\approx A$, but not as close as

OH 13.09-140: Just how did it vary N? Oh! easy! It's $\frac{1}{2}$ that's difficult to vary, there is something peculiar going on here!

using the oldie So far code, I got pc of $\sim (a+b)^N \frac{\sqrt{2\pi}}{N}$ for a N-bit corpus.

Using the statement of a $(\sum u)$ followed by E. deriv of ϵ corpus

E got $\sqrt{\frac{2\pi}{N}}$ for pc of deriv "a": Its a $\frac{1}{\sqrt{N}}$ width

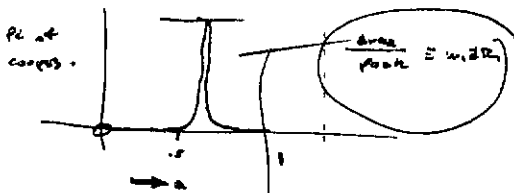
so $(a+b)^N \cdot \sqrt{\frac{2\pi}{N}}$; so how come extra $\sqrt{2\pi}$ here? (≈ 2.5066)

2.5066 is more reasonable if $\sqrt{2\pi} \approx 2.5$ times that is more exact

It could be that ϵ of the d.d. is \approx closely related to its width - in fact $\frac{1}{\sqrt{2\pi}}$ would be closer!

And it may well be that if one takes 2 wtd mean of all codes, one will get $\sqrt{2\pi} \approx 2.5$.

There is probly a very easy exact way to get the desired figures.



$$\left(\frac{\bar{u}^u (1-\bar{u})^{n-u}}{(a+b)^N} \right)^{Nk}$$

$$\text{pc} = \left(\frac{\bar{u}^u (1-\bar{u})^{n-u}}{(a+b)^N} \right)^{Nk}$$

$$\text{area} = \frac{\left(\frac{\bar{u}^u (1-\bar{u})^{n-u}}{(a+b)^N} \right)^{Nk} \sqrt{2\pi}}{\sqrt{2\pi \bar{u} (1-\bar{u})}}$$

so $\frac{1}{\sqrt{2\pi}}$ width may indeed be just $\frac{1}{\sqrt{2\pi}} \approx 2.5$.

$$\int_0^1 \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{Nk}} \frac{1}{\sqrt{Nk+1}} dx = \frac{X!Y!}{X!Y!+1!} \approx \frac{2\pi}{Nk}$$

So, the moral is, we may get just about exactly the same result if we use either $(a+b)^N$ for Bernoulli or (ϵ) base rule for \bar{u} , multiplied by its width times its pc of ϵ corpus wrt. just \bar{u} , to get its pc of a Bern. seq.

A source of systematic Error in football data: Players who low scores at the start of season tend to be discarded, so they have fewer times at bat for E. result to be seen

So, is a present problem; According to recent analysis for $n \ll 210$ (say $N=95$) the u_i are essentially useless for predn. of u_i . \bar{u} is much much better!

How, in fact, the u_i were useful. I.e. the ordering of u_i was useful for ordering of the sample u_i . only 3 cases out of 9 of players in top 9 to start, going to bottom 9 is "good sample".

SEE 140.05 - 140.40 (more specifically 140.32ff) for a good discussion. & understanding of this problem

114

130

132

2.10.99 SHAT STAM:

$\frac{1}{x!y!} = \frac{1}{x!} \frac{1}{y!}$

So maybe write re-view:

- I nature of problem.
- II Stark's soln (s)
- III My solns:

- (a) using Guesswork.
- (b) " $f(-n)!$ etc. — stick very fast. seem to work very well. $\frac{1}{s_1 z^s} = \frac{1}{s_2 z^s} - \frac{1}{s_3 z^s}$
- (c) " Sol 67b: sort of weird but 49.32 suggests maybe $\frac{1}{s!}$! (c) as special case of $\frac{1}{s!} = \frac{1}{s!} - \frac{1}{(s+1)!}$; convergingly $\frac{1}{s!} = \frac{1}{(s+1)!} + \frac{1}{(s+2)!} + \dots$

IV Give Main Math results in easily readable form:

$\frac{x!y!}{x!y!}$; $\frac{x+y!}{x!y!}$ etc. width of d.f.s. Start about $\phi(x)$, etc.

Also tell what about Stark rem. rs. Maybe use 19.95 to change names from $\left\{ \begin{matrix} s_1, s_2, \dots, s_{D-1}, 2D \end{matrix} \right.$ to $\left\{ \begin{matrix} s_1, s_2, \dots, s_{D-1} \end{matrix} \right.$ for some $\phi(x)$ then.

Stark to "S". (The things not in etc., new but disappearing off to project.)

V Tell what major sillys & conclusions were.

Paradox! Consider 26.03:

.02
$$G = \prod_{i=1}^k \frac{x_i y_i + 1}{x_i y_i} \cdot \frac{x_i^{u_i} N^{y_i + N - u_i} (1 - u_i)^{y_i + N - u_i}}{x_i^{u_i} N^{y_i + N - u_i} (1 - u_i)^{y_i + N - u_i}}$$

"width" = $F_2(M_2)$

for each i , for each of the A_i factors there is a peak value of M_i : $\frac{x_i^{u_i} N^{y_i + N - u_i}}{x_i^{u_i} N^{y_i + N - u_i}}$; if u_i is not a value of u_i , it's

.05 width $\frac{1}{u_i}$, since $\int_0^1 F_2(M_i) dM_i = 1$, (Ti width being defined \Rightarrow width peak = $\int_{-\infty}^{\infty} f(x) dx$)
 See (1) for resolution of this difficulty.

One immediate difficulty w. this app. is that it is used usefully in 4.16-33 to show equivalence of 2 ostensibly different ways to get 6i pc of a bin. Bernoulli seq.

\rightarrow from 4.1.01 $\frac{x^u y^v}{x^u y^v}$ is 1. pc of a bin. Bernoulli seq. w. x^u 's; y^v 's.

\rightarrow hence $\int_0^1 p^x (1-p)^y dp$. — $R \rightarrow S$ is the sum of all different poss. params, p , being used in code sequence.

.14 So perhaps, for each $x+u_i \leq N$, $y+v_i \leq N$, in (02), 1. pc should be $\frac{x^{u_i} N^{y_i + N - u_i}}{(x+y+N \frac{1}{2} + 1)!} = \frac{x^{u_i} y^{v_i}}{(x+y+N \frac{1}{2} + 1)!}$

Instead, I used $A_i u_i \leq N$; $B_i v_i \leq N - A_i u_i$

$$\left(\frac{A_i x}{x y + N} \right)^{A_i x} \left(\frac{B_i y}{x y + N} \right)^{B_i y}$$

ln $\frac{y^{u_i} x^{v_i}}{x^{u_i} y^{v_i}} = x A_i \ln \frac{x}{x y + N} + y B_i \ln \frac{y}{x y + N} - x y \ln \frac{1}{x y + N} + \frac{1}{2} \ln \left(\frac{2 \pi x y (x y + N)}{(x y + N)^2} \right)$

ln $\left(\frac{u_i v_i}{u_i v_i} \right) = u_i \ln u_i + v_i \ln v_i - (u_i + v_i) \ln (u_i + v_i) + \frac{1}{2} \ln \left(\frac{2 \pi u_i v_i}{u_i + v_i} \right)$

I used instead, just $\frac{2 \pi (x y + N)^2}{(x y + N)^2}$, summing up to factor $\sqrt{\frac{2 \pi}{x y + 1}}$

which amounts to 2π in x by $\frac{1}{2}$ & y by $\frac{1}{2}$ & also a factor of $\sqrt{\frac{2 \pi}{x y + 1}}$

so it's like $\sqrt{\frac{2 \pi}{x y + 1}}$; which is "width" of Ti distribution

which I may have already included: **So This Seems to Resolve the difficulty of .02-.05**

So the exact expression we want is:

.28
$$G = \prod_{i=1}^k \frac{x_i y_i + 1}{x_i y_i} \frac{(x_i + A_i)! (y_i + B_i)!}{x_i y_i + N + 1}$$

Some notes:

$G = E^{x y}$

$$E \ln E - x \ln x - y \ln y + \frac{1}{2} \ln \left(\frac{2 \pi x y}{x y + 1} \right) + \ln(E+1)$$

$H = x + A_i$; $L = y + B_i$; $F = x y$

$$+ \frac{1}{2} \ln \ln H + \frac{1}{2} \ln \ln L - F \ln F - \ln(E+1)$$

ST 46 from ST 41

From it we $x = u R$, $y = (-v) R$ $u = .25$

$R = 100$ to 9500 , G has -484.056 min
 $R = 320$ -483.762 max

$R = 10$ $G = -489.9$

$G = 47.5$ $G = -484.8$ (4 by 1 from peak at $R = 320$.)

$G = 2.265$ $G = -483.997$ at $R = 800$

$R = 60$; $G = -484.95$

$u = .250$ max $G = -484.0606$ at $R = 290$
 closer to peak here $u = .275$ max $G = -483.997$ at $R = 1146$
 $u = .270$ max $G = -483.997$ at $R = 1146$

$G \approx -484.5$ at $R = \infty$, but T. put it. G is probably not correct for $R > 12000$. I used double precision.

$U = .225 \quad G = -483.3765 \text{ at } R = 40.36.$

$U = .230 \quad G = -483.44 \text{ at } R = 13576 \text{ but } R \text{ is highly not accurate}$

Looks like $U = .270$ is best (w. $R = 114$), which gives lots of U .

→ The broadness of the M exposure suggests something is wrong.

$U = .2$ gives max of -488.74 at $R = 28.28$ — so the problem U is somewhat sharp.

Check approximations.

The pool is so broad, that it's beyond 5 or 6 digit precision using in R .

.10	Work: Stain 41 had a "+2" from its $M \cdot L$ ($\frac{40.10}{1.1}$), and 38.33
.13	This is inappropriate in present PM . <u>rounded</u> . Now, $U = .270$ gives n / pool, but <u>loses</u> (not $R = 114$) $R = 114$ $G = -469,716$ at 1900 $.26$ " <u>General</u> max at $R = 563$, $G = -468,7065$ (low precision error) $.25$ " <u>max</u> at $R = 238$, $G = -469,0483$ $.265$ " " $R = 672$, $G = -468,6654$
.17	
.18	$N = 300$; $U = .265$ peak at $R = 47.5$, $G = -3087.97$ $R = 24$, so for $\Delta G = 1$ $U = .25$ " " $R = 47.5$ $G = -3087.867$ so <u>super</u> peak. $U = .26$ " " $R = 47.568$ $G = -3087.846$ $R = 24$, so for $\Delta G = 1$ $U = .255$ " " $R = 47.566$ $G = -3087.81$ $R = 24$, so for $\Delta G = 1$
.20	<u>Max</u> → $U = .255$ <u>Wierd</u>
.21	$N = 600$ $U = .255$ <u>max</u> at $R = 40$ (24, 67)
.22	$N = 1200$ $U = .255$ " " $R = 40$ (24, 67) ↳ See 94.14 for <u>How</u> on large N

But peak R should be f.
 Same, is not unreasonable;
 T. relative wts. of \bar{u} & M_i
 are being mult by 2, lev.
 See 75.20-23 for More on P_{ij} .

the results of .10-.17 are kind of wierd! — but loss

So Plan before! The peak in G is very mild. T. app of 95.23 is quite simple in theory.

— Likely to be correct. If we had a convergent opt for R , we could get "expected values" for the estimators.

What we want is $E \left(\frac{R \bar{u} + M_i \bar{u}_i}{R + N} \right) = E \left(\frac{R \bar{u} + M_i \bar{u}_i}{R + N} \right)$

.29 Max $\int_0^\infty \frac{R \bar{u} + M_i \bar{u}_i}{R + N} \cdot P(R) dR$: where $P(R)$ is unimodal R . \bar{u} product
 of \bar{u} prop of R and \bar{u} prop of R is given by $\exp(-R)$ [via Bayes]
 Because of the flatness of $\exp(-R)$ as a function of R , \bar{u} prop we use will probably converge actually
converge for large R . Using $2^{-\log_2 R}$ may not be inappropriate
 R^{-1} maybe O.k. for large R , but its unclear as to what to do near $R=0$.

Notes

1) Try to find expected values of U_i 's: On way: for each x, y selected, we have this d.f. for U_i : $(4602; f(x)u_i^{x+1} (1-u_i)^{y+50})$

The expected value of U_i is $\frac{\int_0^1 u_i (1-u_i)^{y+50} u_i^{x+1} du_i}{\int_0^1 (1-u_i)^{y+50} u_i^{x+1} du_i}$

T. ~~factor~~ factor is $\frac{(x+1)! (y+50)!}{(x+y+N+1)!}$; t. factor is $\frac{(x+1)! (y+50)!}{(x+y+N+2)!}$

So ratio is $\frac{x+1}{x+y+N+2}$

If we let $x = \bar{u}R, y = (1-\bar{u})R$ then $E_{U_i} = \frac{R\bar{u} + 1}{R + N + 1}$ To get final Exp. Value, we then use 47.29.

2) I could improve accuracy of f_i formula by putting in the $\frac{1}{(2x)}$ term in to f_i $X!$ approx. so $X! \approx \sqrt{2\pi} X^x \cdot \sqrt{X} \cdot e^{-X} + \frac{1}{2X}$ - so $\frac{1}{2X}$ is an addition to $(X!)$

3) Try this "fitting" from using f_i data for f_i entire season. T. present form could be readily modified to deal w. players who have different SSZ's.

4) The value of u_i used ~~should be~~ so simply $\frac{\text{no. of hits}}{45}$; "No straight rule" & better value would be $\frac{\text{no. of hits} + 1}{45 + 2}$ (Laplace's rule)

Since f_i hitting averaged over $\sim .25$ this amounts to \sim only 11 hits, so the correction

is usually large $(.25) \rightarrow \frac{.25 + .01}{46} = .2663$; so $.25 \rightarrow .2663$ is a fair increase. ($\Delta = .0163$)

The season average was $.27$, so this could be error appreciable.

On the other hand, the observed value of $.265$ itself is not very accurate; its d.f. is $\sqrt{\frac{.25 \times .75}{810}} = .0152$ which is about same size as "Laplace rule" correction. $(.21)$

5) On Arrive for R: If $f(R)$ is $\Rightarrow \int_0^{\infty} f(R) = 1$, then

$\int_0^{\infty} F(\alpha R) dR = 1$ $\int_0^{\infty} \alpha F(\alpha R)$ expand $F(R)$ in the F direction & contract in the R direction

Any normalization $\left[\text{constant } \frac{1}{\alpha} \text{ which is invariant} \right]$ can be done this way, - (well, almost all say $\alpha F(\alpha R) = F(R)$)

one soln. is $R \geq \frac{1}{\alpha}$; are there any other solns? $F(\alpha R) = \frac{1}{\alpha} F(R)$

From $\int_0^{\infty} F(\alpha) = 1$ no $F(R) = \frac{A}{R}$. So this is the most genl soln: $F(R) = \frac{A_0}{R}$.

Could I use $\frac{R}{A}$ for norm? If \rightarrow fact to be normed was $\int_0^{\infty} R dR = \infty$. Function $\frac{R}{A}$ ~~doesn't~~ approach 0 at $R = \infty$, \therefore product could "converge" \rightarrow what value of "A" do we use?

T. only reason to use $\frac{1}{R}$ is that it can't be distorted by $.25$ - it has no inherent "size" in the R direction - but the "A" factor does it "size" in the $f(R)$ direction.

I was considering using $2 \sqrt{1 + R^2}$ but I still have diffy $.25$.

6) A way to use $P(R)$ (if $\int_0^{\infty} P(R) = \infty$) for ~~normalization~~ approx.

do $\lim_{R \rightarrow \infty} \frac{\int_0^R F(R) P(R) dR}{\int_0^R P(R) dR}$ if $F(R) = \frac{1}{\sqrt{2\pi R}}$ then $\lim_{R \rightarrow \infty} P(R) = \alpha$ then this $\rightarrow \alpha$

$$\left(\log \left(\frac{1}{2} (.265^R + .735^{(10^R)}) \right) \right) * 810 = -468,6812 \text{ for } G_{20}, R=200, \text{ which}$$

13 slightly worse than G_{10} - 468,6657 but not for $U=.265, R=672$ or 47.17 slightly

Using $U = .265389$ = best point of N - 468,671 at $R=672$

6 but = 60

So precision is important.

$\left. \begin{matrix} -468.6702 \text{ at } R=800 \text{ and } (15) \\ -468.6718 \text{ at } R=981 \end{matrix} \right\} !$

Using P. B. at 25! peak for $G = 468.6666367$ at $R = 800$

For large R $G = 468.680845$ $G = 468.680845$ slowly \downarrow
 $R = 4.54$ $G = -468.6808988$

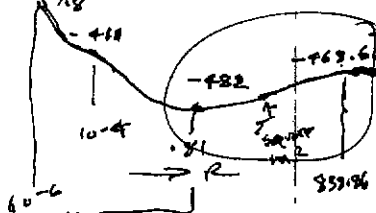
The peak at $R=800$ is very small wrt. 9.54

Woods! G_{20} is a small peak of -468.67899 at $R=1892$

Woods! $R=10^{-4}$ $G = -468.3213$
 10^{-3} $G = -468.545$

I'm getting crazy stuff (8.20)! $R=10^{-4}$ to $R=.81$; G from -411 to -482

From it \uparrow G_{20} is 838.88 peak slightly \downarrow to 0 .



so for $R \rightarrow \frac{R}{2}$; $\ln G$ does $-G.3$.

$$\frac{G.3}{18} = .35 = \ln \sqrt{2} ; \text{ so for small } R ; G = \frac{1}{R^{.35}} = R^{-.35}$$

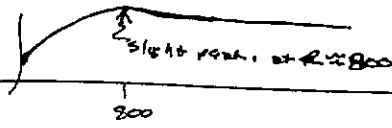
This section is invalid

Stamps!

At! could be due to error in approx of K !

Her. X ! appears to not work well for $R < 1$; So this part really coincides w. $R < 1$ area!

From 49.20 ff. + plot probly looks like



$R = 792.7$ \pm $K.1$ is a peak

$G = -468.66669270322$

$R=4.54$ $G=-468.6808988$

-468.6808988 . very slightly worse.

ST & INSD. 605!

Print $G - \log G \rightarrow$ has peak \rightarrow close to $R=80$!

Print $G - 2 \log G \rightarrow$ has peak \rightarrow sharper than \rightarrow

down \rightarrow 36
 down \rightarrow 26

for $R \rightarrow 200 \times 2$; $\Delta R = .5$.

The ideas that $\ln \ln$ in original D.P.

(ST 46.6) T.P.D. because constant > 0 for large G ; R is a reasonable function.

Model. If R is by, we know S fixed at \bar{U} , and the value of e^G is $\prod \bar{U}^{A_i} (1-\bar{U})^{B_i}$

which is $\left(\frac{\bar{U}^{\bar{A}} (1-\bar{U})^{\bar{B}}}{\bar{U}} \right)^K$

ST 11: (8, 10) Checks χ^2 by integrating

ST 11: "no" correction

ST 5: compare G_{20} means of χ^2 , $(-U_i)$

ST 6 \rightarrow to 5

ST 7: χ^2 calculates χ^2 means of χ^2 count;

ST 8: χ^2 \rightarrow so χ^2 \rightarrow Grand mean. (Kps)

$\bar{U} = .265389$

ST 9: compare G_{20} means of χ^2 , $(1-U_i)$ \rightarrow is χ^2 mean.

$$\frac{6.3}{18} = .35 = \ln \sqrt{2}$$

$\ln \sqrt{2}$.

50.20 is 50.33 about 10%: In 50.20 we have an \uparrow of ~ 13.33 in G .
 w. a 1000fold change in R : $\ln 1000 = 6.9$; $\frac{13.33}{6.9} \sim 2$ so $e^G \uparrow$ by
 R^2 for $R = 816$ $R = 8336$. If we mult ~~by~~ subtract $2 \ln R$ from
 G we should have no peak! - Not flatness!

Oh! T. really rep'd w/o of G was from R : $\rightarrow 481.8$ to $R = 259 \rightarrow 471.5$
 $\Delta G = 10$ $R = \times 16$; $\ln 16 = 2.77$; $\frac{10}{2.77} = 3.6$; so e^G was like $R^{3.6}$
 so $\frac{e^G}{R^2} \rightarrow R^{1.6}$. so it will peak.

Anyway, the moral: Peak is position of peak depends much on our approx.
 This assumes ~~also~~ that $R > 1$, (not unreasonable)

Also, for some $\frac{1}{R}$, even no there is a peak, if one takes expected values of
 U_i ; $R = \infty$ gets all of the work (I think). (using the "brill" "renormal" method)

SP: T. behavior of the A approx used in the papers (ST 46, 50 \pm previous) don't work at all for $R < 1$.

Here, for $R=0$, the analysis of 49.26 holds, is I think I can get a good approx for $0 < R < 1$.
 49.20 deals w. $R=0$.

Anyway: Since I'm fairly sure about behavior at $R=0$ & ∞ ; To criticize f .

System: Computer in a Gaussian System: which seems to work reasonably. Ways: I'm not so sure it did work!

Also ~~could~~ consider simpler Laplace analysis of 42.01-44.30
 essentially it uses 2 coding methods only: $R=0$ is $R=0$ is $\frac{1}{N} \sum_{i=1}^N \ln \frac{g(x_i)}{g(x)}$
 $(R=0$ wins so all jobs \approx all work, for $N < 210$ (probably $R=0$ def all work for $N > 220$;
 there is a small transition region of comparable wts)

Mainly, I'm interested in the corresp. betw. $\frac{1}{N} \sum \ln \frac{g(x_i)}{g(x)}$ & 0 : Why does Gauss seem out, but
 Laplace not a.k.a. : Is it some problem w. approx [Laplace] Gauss?

Another deriv method is to use $U_i = c_i \bar{u} + (-c_i) U_i'$: T. tricky pc's are of $c_i \bar{u}$. } this sounds quite rigorous!
 perhaps use uniform approx. for $c_i \bar{u}$ over i unit space; integrate over that space
 This gives us U_i for each data set $\{x_i\}$ \rightarrow $\frac{1}{N} \sum \ln \frac{g(x_i)}{g(x)}$ to make a guess, w/o computer

$P([U_i]^{(j)})$ $[U_i^{(j)}]$ is \approx same as $[U_i]$; but $U_i^{(j)} \rightarrow \frac{N U_i^{(j)} + 1}{N+1}$, $N_i \rightarrow N_i + 1$

A brief review of STEIN:

12.0) Down of STEIN effect from Sci Amer May 77 pp 119-127

I was uncertain about data of various variables in 4.20 vs, hvr. Later, I found out papers

f. Lofus. [Ref? 12.01 - 05; 8.01 - By 8.12 I had ~~multi/correlated~~ int. SA & RT.

10.01 starts to analyze our off. refs (Cook, Ralph) 2.20 pinpoints difference in my early use of that of 2 way.

By 10.20 - 23 I got a reasonable data. of σ^2 as used in SA, paper

So by 9.25 & 10.20 I think I understood what the SA records were.

3.01 is a billy, review of recent work of SOY in TM & SM.

2.20 is my early Gaussian version of ST. problem. 4.20 ff develops σ^2 & σ^2 .

1.01 : 1F.40 : On 15.01-.90! Consider expected ms error in producing r_{ij} for both methods.

1.02 Using μ_i , ty error would be $\frac{1}{L} \sum_{j=1}^L (\mu_i - r_{ij})^2$ / $\frac{1}{L} \sum_{j=1}^L r_{ij}$

1.03 simple case $L_i \equiv L = \text{constant}$: $\frac{1}{L} \sum_{j=1}^L (\mu_i - r_{ij})^2 = \frac{1}{L} \sum_{j=1}^L (\mu_i^2 - 2\mu_i r_{ij} + r_{ij}^2) = \mu_i^2 - 2\mu_i \bar{r}_i + \bar{r}_i^2 = (\mu_i - \bar{r}_i)^2 + \sigma_i^2$

1.04 $\sum_{j=1}^L (2\mu_i r_{ij} + r_{ij}^2) = 2\mu_i \sum_{j=1}^L r_{ij} + \sum_{j=1}^L r_{ij}^2 = 2\mu_i L \bar{r}_i + \sum_{j=1}^L r_{ij}^2$

1.05 $\sigma_i^2 = \frac{1}{L} \sum_{j=1}^L r_{ij}^2 - \bar{r}_i^2 = \frac{1}{L} \sum_{j=1}^L r_{ij}^2 - \mu_i^2$

So σ_i^2 (ms error if $L_i \equiv L = \text{constant}$) $\geq \sigma_i^2$ from 1.02, 1.03, 1.04, 1.05!

$$\frac{1}{L} \sum_{i=1}^k (\mu_i - \bar{r}_i)^2 + \sigma_i^2 = \frac{1}{L} \sum_{i=1}^k \mu_i^2 - \mu_i^2 + \sigma_i^2 = S^2 + \sigma_i^2$$

1.06 $S^2 + \frac{1}{L} \leq \sigma_i^2$; This is the ms error in using μ_i to predict r_{ij} .

1.07 $\frac{1}{L} \leq \sigma_i^2$; This is the ms error in using μ_i to predict r_{ij} .

1.08 So if L is of reasonable size, $S^2 + \frac{1}{L} \leq \sigma_i^2$ is always approximately $\geq \sigma_i^2$

1.09 \downarrow Hence omitted effect of non-independence (see 15.2.5-2.9)

Ent. error of 6 Baseball scores: $\sigma_i^2 = \mu_i(1-\mu_i)$ (1.02)!

One way of getting it is $\sigma_i^2 = \mu_i(1-\mu_i)$

So ms error is $\mu_i(1-\mu_i)$

$S^2 = \left(\frac{1}{k} \sum \mu_i^2\right) - \mu^2$; $\mu_i \equiv \frac{1}{k} \sum \mu_i$

$\sigma_i^2 = \mu_i(1-\mu_i)$; $\bar{\sigma}_i^2 = \frac{1}{k} \sum \mu_i^2$

$S^2 + \bar{\sigma}_i^2 = \mu^2 - \mu^2 = 0$

$\sigma_i^2 = \mu_i(1-\mu_i)$

Anyway, 1.09 means that to σ_i^2 's always go $\geq \frac{1}{L}$ of σ_i wh. - which seems unreasonable

also SA results of wt of μ_i .791 for $\bar{\mu}$ & .209 for μ_i .

(NB) Actually, the ratio is Not just 1 to 1+ α ($0 < \alpha < 1$)

It's 1 to $(1+\alpha)^k$! So if μ_i 's were used completely almost always!

This is a very poor coding method.

1.30.1

39.20 in other

21.15 for

2 between