

Report on nary 2 softyd CMI

411-104

73

74

Def: The set of provably convergent (PC) seqs, $\{P_i\}$, may be r.e. (?) If so, then a set of MSMs corresponding to these $\{P_i\}$'s are r.e. → (2.01) "reasonable large"

03
04 [SN] → Hvr: On + Gödel results! (1) Gu. a set of axioms. There is no "proof procedure" that will prove or disprove all provable terms. (i.e. terms for which finite proofs exist.)

To show this: Say one listed all poss. finite proofs (they are r.e.). Then one checked them in order, & picked the first legal proof. The reason this wouldn't work; proof checking probably takes an overly long time. If t. set of axioms plus t. proof correspond to a pgm. for a TmC, t. proof checker corresponds to t. TmC. & t. checking of t. proof corresponds to t. running of that pgm. into that TmC. If t. output of t. TmC. when it stops, = t. desired term, then it is proved.

Well, in general there exists no routine for ordering from trial proofs to be tested a C.B.'s on those proofs, that will eventually "catch" all legal proofs.

On the other hand, one can devise "proof procedures" that are fairly good. Perhaps a proof of t. form: Gu. any set of axioms is a proof procedure; I can find & thru a proof that would I think t. form. may be what people are thinking about when they say Gödel showed that humans can do things that machines cannot. On the surface of it, this conclusion seems unwarranted - if that's what Gödel showed - it seems like

combination outside the "window" of the proof procedure

28
29 The other Gödel result: If one has any reasonably large set of axioms, then there will be terms that actually cannot be proved or disproved w.r.t. that set of axioms. I.e. no finite proofs exist - it is not a question of not being able to find them as in .04 - .28. In this

33 sense, no (reasonably large) finite set of axioms is "complete". It corresponds, in the language of .04 - .28, to a TmC, and a r.e. set of pgms. But there exist finite output sequences for which no corresponding input pgms exist. Clearly t. TmC we are considering is not UMC! Perhaps t. proof is exhibiting of a non-provable or disprovable term by a diagonal argt.

1.03: Hvr, in view of 1.04 - .28 (i. perhaps 1.29 - .40), this idea of "provable convergence" will have to be refined a bit. The idea of "provability" is ~~not~~ apparently about the same as \forall halting problem.

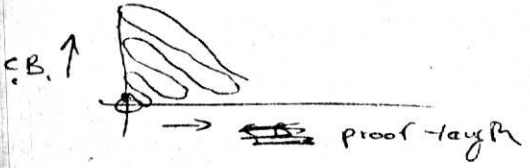
— so ~~the~~ p.c. only has ~~meaning~~ a.c. meaning if one states the "proof procedure" (\equiv search, test, \subseteq B, relation).
Anyway — \forall moral seems to be that \forall set of "provable"

MSM's is not ~~the~~ r.e.

→ 3.01

1.26 → On second part 1.09 - .28 may be wrong. Consider \forall 2 dim scan in \forall . (proof-length (\rightarrow decm. length), \subseteq B.) plane;

132/82



If a proof exists for \forall term. or its negation, it will be found this way.

— If neither exists, one can never be sure of this via this procedure.

So: Modified Conclusion for 1.04 - .28!

Given a reasonably large set of axioms \exists a Term: If \forall Term has a proof, then \exists a proof finding procedure that will find it, ^{eventually}. (e.g. 1.10 - .16). Hvr, if there ^{are} no proofs for \forall term or its negation, there is no way (in general) to tell.

The second part Term (1.29 - .40) holds as it stands. This first part says that while "independent" Terms exist for any reasonably large axiom system, one can in general, never be certain that a set of axioms is, indeed, independent, or ~~more~~ consistent. → hvr. see 9.01

There is some business about finding a model or representation of an axiom system, that is supposed to prove its consi. I guess \forall pt. of \forall first Term here, is that very often, a "model" for a set of axioms can't be found — so one doesn't know if they are consi. ~~or not~~ and that in genl. no procedure for model construction exists that will always work.

Apparently, hvr, it is felt that a model proves that ~~if~~ \forall \forall a set of axioms, \forall negation of any of \forall axioms has no proof within that system.

In case of certain axioms sets: (e.g. truth tables) one can tell if a set is ^{of axioms} consi or not. In this \rightarrow case, there are only a finite no. of situations to check — \exists one can check all of them. Just how this type of analysis fits into \forall discn. of 1.16 - .20, is unclear. See Formal Computation by Immerman pp 225-226 (8.12.3) for a limited discn. of this.

9.10
Spec
3.01

1274 R

01; 2.09: About MSM's : They are of 2 types :
02 → ① One can prove they are MSM's : i.e. that they always eventually converge. U1OM's are a subset of this class.

If one has a gn. Trunc., — if it happens to be in this class, one can eventually prove it by a 2 dim. scan (like 2.10.-.16.
Hvr., in finite time, if one hasn't found a proof, ~~it means~~

(or a disproof), it can still be in this class. — It might also be in this class, or it could be a non-MSM.

09 ② They are MSM's, there exists no proof of this fact. (That such a class exists is made likely by a form of Gödel — i.e. 1.29-.40.)

It would seem that MSM's (even class MSM's) are more powerful than U1OM's. The problem is still 464.29-32; 464.35-.40 — i.e. can one simulate do almost as well as in induction with a U1OM as a MSM?

Hvr., since MSM's are more powerful than U1OM's (463.35-464.10) — it can express functions that U1OM's can't — I think this is shown in For that reason, ~~it~~ ^{unc.} it may be poss. to show that there are "limit forms" that U1OM's can't do well with — or that they will do ably poorly with.

25 → Hvr. one can't use a MSM's & their assoc. set of $\{P_i\}$'s to generate a stochastic sequence — as one can w. any r -CPM or CPM. A universal MSM (if such a thing exists) can simulate any other MSM i.e. "cover" any PEM that that MSM expresses. ~~How~~ But, because of .25-.27 this may be of no great import!

perhaps just as we associate a r -CPM w. each FOR, we associate a ^{convergent} $\{P_i\}$ set w. each MSM. We can ~~also~~ have CB's on MSM's & make these CB's FOR's. ~~This is a~~ Thus a seq. of ^{in order} CB's that \rightarrow an univ. ∞ , gives us a $\{P_i\}$ -set that \rightarrow some kind of "universal (if ∞)" — ~~whether~~ i.e. CB's over on a MSM's or U1OM's.

Def. 30 It is clear that no UOM (\equiv U1OM) can exist ~~such~~ such that all seqs. of FOR's $\{R_i\}$ are CB's on it — because $\{P_i\} \equiv \{P(R_i)\}$ can be $>$ their limit, but $p^{(UOM)} \equiv$ must be $>$ $p^{(R_i)}$ for every R_i . Note that this is true before normalization only, but ~~that~~ 4.01

3.40 it is also true after normaliz. i.e. one can have a seq. of normalized probys, $\{P_i\}$ that $\rightarrow P_0$ & are often above $> P_0$ at some points
 T. Q. is any non-tonic before normaliz? I think ~~no~~. They need not be. In fact, it's possible to have a seq. if $\{P_i\}$ are normalized, then using w's Thm 12, ~~the~~ $\{P_i\}$ will also be normalized. Hvr. can we devise a set of R_i such that $\{P_i\}$ are not normalized & are monotonic, & $\{P_i R_i\}$ become $\{P_i\}$ when they are normalized? 4.59.15-30 suggests that for an arby $\{P_i\} \rightarrow P_0$, this is impossible. - i.e. a normz constant would $\rightarrow \infty$ & so for finite Q (which it is), one couldn't do it.

Can one show that one can get a seq. of $\{P_i\} \rightarrow P_0$, $\rightarrow P_0$ differs from any monotonically achievable P , by an arby large factor? Well, select an arby ϵ (v.m.c.). Then after it's known that its P value for a certain $A^{(e)}$ will be at least ϵ , make $\{P_i\} \rightarrow P_0$ arby \leftarrow that for that $A^{(e)}$ value. If $\{P_i\}$ is normalized, normaliz of this will approximate to inequality $P > \epsilon > k P_0$.

Hvr., even if one could do this - consider this P 's attempts to "cover" a Perm $A^{(e)}$ (P^x) that has $P^x(A^{(e)}) = 0$. In this case $P(A^{(e)})$ is arby $> P^x(A^{(e)})$, but that's O.k. - it gives no problems when Expected values of broadcast error of E (\leq sq error) are considered.

What we ~~can~~ would have to show is that P_0 can be arby $> P$ for a certain $A^{(e)}$. This is hard to show, because we really can never know the max value P can attain. Well - we can to some extent - i.e. by looking at the P values assoc. w. ~~other~~ all other $A^{(e)}$ pts., for the same ϵ . Hvr., this doesn't help either: Consider, say, $l = 100$, or some very large value of l . There is, say an input string (for the v.m.c.) of length l , S , that hasn't converged yet - which would give an enormous amount of probty to a gu. $A^{(e)}$ or could cut down its ^{upper bound} ~~value~~ value a lot. For every long string, $A^{(e)}$, there is ~~an~~ instead for say $\epsilon B < \epsilon A$, a shortest input string that hasn't converged yet, whose output starts out like $A^{(e)}$ does - that with $P(A^{(e)})$ enormously, & that limits the amount by which some other $P_0(A^{(e)})$ can be $> P(A^{(e)})$.

01:40: So, for large l & large C.B. ($\equiv \mathbb{Z}$), one finds the string, $A^{(l)}$, for which its uncoupled code is of minimal wt. Well, I think this can be pretty short: i.e. consider ~~at~~ some large l value (say $l=100$). Consider t \mathbb{Z} ^{output corpi} ~~input~~ ~~corpi~~ of 3 bits each. say all \mathbb{Z} of them have at least one ~~not~~ ^{never} convergent code for the next output bit. This means that all corpi of length > 3 will have uncertainty of at least $\frac{1}{2}$ ^{code length} in their proby values — no matter how long t corpi. So one couldn't simply devise a P_0 with $P_0(A^{(l)}) = 1$ ~~uncoupled probly~~ ~~of length l~~ for $t \in A^{(l)}$ for which $P(A^{(l)})$ is min. [~~More~~ $P \equiv P^{(M_{\text{min}})}$] $P_0 \equiv P^{(M_{\text{min}})}$ $\hat{=}$ be sure ~~it is~~ ^{it is} would eventually ~~become~~ $> P$ by an arbitry large factor, ~~Amount~~ P .

Def's

17

AH! O.K.! : we want to devise an Untractable seq. for the $p^{(M_{\text{min}})}$ limit. Say ~~some~~ $P_{i,l}$ ~~($i \in \mathbb{Z}$)~~ is the i^{th} approx. ~~then~~ ($P_{i,l}$ is for corpi of length l). Find $A_i^{(l)} \Rightarrow P_{i,l}(A_i^{(l)})$ is min. Let $P_{i,l}(A_j^{(l)}) = 1$, all other $P_{i,l}(A_j^{(l)}) = 0$ ($P_{i,l}$) is t . proby limit seq. we are trying to make.

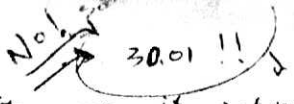
No!
But

woops! $P_{i,l}$ must be determined for all l — so, for a given i value, we sequentially generate a deterministic seq. for which $P_i(A_i^{(l)}) = 1$ & all other $P_i(A_j^{(l)}) = 0$. — We do this by computing $A_i^{(1)}$ then $A_i^{(2)}$, etc. in such a way so that $\frac{P_i(A_i^{(l+1)})}{P_i(A_i^{(l)})}$ is min.

30

There are some ambiguys w.r.t. $p = \frac{1}{2}$ situations — what "min" means ~~when~~ when several probys are =, etc. It may be that as $i \uparrow$ one may have to base one's choice partly on ~~on~~ previous choices (previous i , l choices) so that the limit of $p^{(M_{\text{min},i})}$ exists — this sounds a bit like Blom's argts. in their recent "Inductive inference" paper.

Hvr., I think this is unnecy, because of r. way $p^{(M_{\text{min}})}$ (6.01)



1.5. to ϵ approaches its limit — it achieves its limit suddenly, and then stays there.

So it does seem like routine 5.17 ff would generate an untractable seq. of P_i values that does \rightarrow a limit $P_0^* \Rightarrow$ \Rightarrow P_0 given umc, uom does catastrophically badly by it.

Wrt ϵ . "limits" involved, note that for every ϵ value $\exists z_0(\epsilon)$ so large, that no more uom cb's converge for $i > z_0(\epsilon)$. T. existence of this $z_0(\epsilon)$ assures that ϵ . limit of ϵ .

"untractable" seqs. exists \Rightarrow that it's "untractable"

31.01
for comments
out. Forgo
proof, 0
see 37.01
- .18 for
a clearing
up of this
point

What ϵ means is that if we have an arby seq. of

points $[P_i] \rightarrow P_0$, then it is not true that \exists a $umc(uom) \equiv M$

such that $P^{(M)}$ gives ϵ bound for all seqs. that is within a / constant / of that

gu. by P_0 .

If .15 - .18 were false \Rightarrow a $umc(uom)$ could "cover" all $[P_i] \rightarrow P_0$'s, then these P_0 's could not be better than $P^{(uom)}$'s by more than a constant factor. (Hvr., .15 - .18 is true).

I think that what I want to show is that no $[P_i] \rightarrow P_0$ can do / significantly better than $\frac{P^x}{P_0} < K_x$ for all P^x .

This "significantly better" idea is rather vague!

More specifically, — say $\frac{P^x}{P_0} = K_{x,\epsilon}$ then we would like

$$\exists P^{(uom)} \Rightarrow \frac{P^x}{P^{(uom)}} \leq K_{x,\epsilon}$$

Note, however, that $P^{(MSM)}$ is always at least as good as $P^{(uom)}$'s, since uom 's are a proper subset of MSM 's.

Given an untractable seq. for a gu. / umc , it is clear that it must be untractable for all uom umc 's! — say its untract. for M_0^1 . Then if its tractable for M_0^2 , M_0^1 could simulate M_0^2 \Rightarrow seq. \Rightarrow would be tractable for M_0^1 also.

Well given this untract seq., there is at least one MSM that can cover it. — \therefore if there exist univ. MSM 's, not all univ MSM 's can cover it. So for at least this one untractable seq., (and any computable functions of it, perhaps) \uparrow MSM 's are much better than uom 's.

8.90
2.90 space

Actually, maybe there is only 1 term here — i.e.

One can do a scan of 2, 10-16. If a proof or proof-of-negation

1, 2, 9 R

exists, then this will eventually find it. The important thing, then, is 1. 2nd term — (4.29-40) that there usually exist terms for which one can prove neither term nor negation.

10 : 2.90: Around 1962 or so, a perhaps still, a major big. problem area in Math was 1. Q. under what cond. could one show that a set of axioms was (a) consi. w/o (b) complete. Th. "consi." Q. See 1962 or 63 conf. on Automata Theory for some papers (a refs to papers) in this area. H. W. was a big work in this area.

I would like to know more about 1. Q of how one can show that a set of posts is consi. — i.e. gn. a set of posts, that a gn. ^(negative) them cannot be proved — Just what the sig. of a "Model" is, etc.

Another thing that I don't understand, (i.e. this is assoc. somehow w. Gödel's work) is the notion of a "system being able to prove itself consi."

01:40
8:40 spac

The input to M_p is the set of axioms, and the input string I ,
 is a deriv of M_u . Another input is an integer i . The output
 of M_p is an integer, $F(i)$. The significance of $F(i)$ is
 that after M_p has tried the first N proofs, it has proved
 that the first $F(i)$ output symbols of M_u all "converge", for input I .
 ($F(i)$ can be zero for all i), for certain values of I .

Let $G(i)$ be the output string of M_u , after i computation steps.

12

The output of M_s is first, the first $F(1)$ symbols of $G(1)$ probably $G(1)$ is meant
 next, it is the first $F(2)$ symbols of $G(2)$
 $F(i)$ " " $G(i)$ to $i = \infty$.

So, there is no output for a particular element position, until
 it is certain that that position converges. After this time (if it
 ever occurs) the output is simply that of the machine, M_u .
 We could have $F(i)$ and $G(j)$ being computed simultaneously
 asynchronously. The output of M_s at any time is the
 first $F(i)$ symbols of $G(j)$. i & j need not be =,
 but they both $\rightarrow \infty$ at their own rates.

The foregoing device is "universal" in the sense that if it is set
 up to simulate a probably convergent MSM, it will do so, after
 finding the proofs of convergence.

In general, the device will be made more powerful, by
 including more & more axioms. — One can usually insert
 an inf. no. of axioms, but one is never sure that they are
consi! — And an inconsi set of axioms could prove anything! (6.10)

35

Suppose I prove that: If a seq. of $[P_i]$ can be
 proved to \rightarrow a limit, P_0 , then I can construct a MSM
 that will give P_0 as a limit, with R_i 's that are
 all CB's on this MSM $\Rightarrow P_i = P^{(R_i)}$. This would then
 give me the if and only if thm. that I want. (11.01)

10.40: It would involve that stuffin

458.22 - ~~459.12~~ 459.12; 460.14 - .90.

~~XXXXXXXXXXXXXXXXXXXX~~

Re: 463.35 - 464.10 : [How to get a MSM to do non-a.e. computations]:

on 463.35 - 37 I say that I can get a MSM \Rightarrow t . convergence time for f . nth seq. of output is $>$ any a.e. funct. of n . \rightarrow I'm not so sure of this now - in fact it looks false! t . convergence time can be either bounded by $F(n)$ (where $F(n)$ is non-a.e.) or it can be ∞ .

If we are sure it is some $F(n) < \infty$, then $F(n)$ must be a.e. \checkmark No

fixed NO! I was thinking we could then run it until it converged - But we never knew when it has converged! (UOM)

Well - try this: take some finite corpus, use some UMC.

to determine ϵ ϵ f . proby of that finite corpus. As t . C.B., \uparrow 's \uparrow , we get a monotonic \uparrow value of t . approxn. to P_i .

Consider f . n 's bit of P_i as a function of i . Since $P_i \rightarrow$ a limit, t . n 's bit must settle down eventually, but

this "settling time" is incomputable (The not nearly " $>$ any a.e. function")

Hvr, using f . method of 463.38 - 464.10, I can construct a MSM umc. that can "compute" this "settling time."

Hvr, check this \uparrow \rightarrow It sure looks O.K.

I think that is some how is - If it is \leftarrow some computable function then CMT would be a.e. if we used this a.e. C.B.

~~Over and over I also note that the untractable seq. of 5.17 - t . untractable seqs for CMI via UOM's~~

So: write out new plan of Review paper - w.

~~Some~~ results on non-Runs about limits $\hat{=}$ Runs on MSM's

- Their greater power than UOM's is t . untractable seq. of 5.17

Some old ideas to perhaps mention: ① 69TM 228 Plan Rev: List of impl. things that CMI accomplishes. ② People based Report to

69TM 128 // ③ Also list of things to treat in report (5) Plan Rev 69TM 128.22 - Also see 69TM 130.01 for discuss. of what review should contain. \sim 731.40

③ on SFOR's 1bid 235, 266 ④ on Provably Convergent Automata 1bid 227.01

④ some not silly work on t . ~~seq~~ necessity of CMI 1bid 222 ff also 70TM 35 (in 89 folder)

11.40

11.40: Ont. Q: Are there any induction methods better than CMI?

Consider t . Here $l \in$ - Best of corpus w.r.t. True Fdss + Best of corpus w.r.t. CMI.

~~For~~ For CMI, this is bnd. For any B method of induction

it must have a lower bnd; i.e. it can't be zero for small l , because there simply isn't enough info to "identify" t 's Fdss.

For larger l , $-G$ must be a non \downarrow function, since one can't do systematically better than original Fdss model.

How might an induction method be better than CMI?

Well, its constant G bnd can't be \leq that of CMI.

(2) Its $-G \uparrow$ may be rapid for small l , then ~~it~~

~~it~~ get very close to its final value very rapidly —

Thus giving very small errors for large l .

It might be possible to get a theoretical upper lower bnd. for Expected value

~~of~~ of $-G$ by considerations like Play Rev 69TMI 224.06-15

e.g. consider $l=10$; consider a wfn function $w(F_j)$ on all

Fdss's F_j . Then if we chose $P(A^{(10)})$ (this is proby that the 11th bit will be 1) so as to

~~minimize~~ minimize $-G$, i.e. so $\sum_j \text{err}(P(A^{(10)}), F_j) \cdot w(F_j)$

is minimal, we will have a certain expected predn. error that is unavoidable. This "unavoidable error" will depend much on t .

form of $w(F_j)$.

Now, note that in CMI, our "expected error" is indep of t .

form of $w(F_j)$ — so perhaps ~~in~~ in t 's analysis, keep $w(F_j)$

in a literal, changeable form, and then do t 's analysis for

Expected error w.r.t. a given fixed F_j — see how it's.

2.7.88
3.17.28

19:40: O.K.: So, Pairs defined by MSM's probably are "nary" - in

Y. sense that if a seq. of pairs \rightarrow a limit \rightarrow best error is bndd for ever. Fdss, then that seq. of pairs is expressible as a set of CB's in a UMC MSM, using suitable probability mechanisms. To probability of Y. convergence of Y. seq. of pairs implies Y. convergence of Y. coversp.

set of MSM's. But I still have to go thru some thing like 460.14th to ~~construct Y. MSM~~ that correspond to Y. seq. of Pairs.

Even so, ~~say we have~~ a "Limit Pair" $\equiv \lim [P_i] = P$ (for i. j. f dss). Say we can construct a set of whose CB's $P^{(M's)}$ give

the same / best error, B_j . It is not clear that this

probability limit pair is as good as "the it is" using

This particular Gore. 14.01-18 suggests other Gores will be used.

On the use of MSM's for induction: It is clear that MSM's are

at least as good as UOM's & better in at least one case (i.e. Y.

Up to now, I don't think hypothesis as good as MSM's have been

used in science. One might say that (MSM's) are hard to use,

because one never knows how far from Y. limit one is - that is

UOM's one at least has a monotone & probly. In fact,

UOM's, this latter is not so. Y. normed probly is not at all

monotonic. Y. devry of a new short code can change Y.

expected probly values by a large factor, either way (up or down).

The 2 figure there is even more uncertainly

about Y. limit to be expected from MSM's.

Y. Main argt. for (UOM's) is the unprov. set of ideas about expected ξ ($\equiv \text{step}_{\text{best}} / \text{symbol}$) in my work on SVMH.

01:15:40: which gives us an idea of ~~unknown~~ what we can expect in the future, using a non-unc. uom. (i.e. C.B. $< \infty$). — Hrs, it may very well be that corresponding Thms can be devised for MSMS. — in fact one can, trivially, devise corresp Thms — that using MSM w. finite C.B.'s, the expected future brst/symbol will be about that observed in the past — with perhaps various refinements corresponding to those that I introduced for ~~uom's~~ uom's.

— So really, the 2 methods may not be so diffrnt. as far as this limit is concerned.

As for the limit of provability. At any point, one uses only MSM's in which one can prove that convergence ~~occurs~~ occurs, and output seqs interact.

Hrs, for provability, one usually doesn't know if one's set of postulates is consi — so one should look for proofs of inconsi of the set of posts, & loge w. a proof for the convergence of the approxn. seq. One will drop the search if ~~an~~ proof of inconsi occurs, & drop one of the postulates & try again. If a proof of convergence occurs, one may still want to continue the search for proof of inconsi, while one is continuing out the seq. of approximations.

One apparent good pt. of uom's: One can, for some C.B., find a pem that is ① known to converge for all Q ② one knows how long it will take (what C.B., T^l) to get a given accuracy in probty w.r.t. that pem. E.g. one has 4. coif. linear regressn. — one knows past $\frac{\text{brst}}{\text{corpus symbol}}$ & one can estimate ξ .

It's not clear as to whether there is a corresp. situation for MSM's. — 26.31 spec.

Edwy
Will
Sci Co.
Products
Pyrex
600ML
~ 60¢
Ac. Acid
12/16.
1 pt.
Dextrose
85¢/lb
1 lb
40¢/lb -
25¢/lb.

01:16:10;

The Main Bottlenecks in a "Proof" of r. adequacy ^{or} sufficiency or necessity of CMI for induction:

1) The MSM problem: While UOM's are good (budd Brost error) for FdSS's, it is not clear that MSM's are not better - certainly MSM's are at least as good w.r.t. Brost error. However, the disch. of 15.21-16.40 suggests that UOM's ~~are~~ are better because one ~~can~~ can estimate ξ for them - i. I haven't found a way to do this for MSM's.

Actually, I haven't proved that my ξ estimates are "correct" - more important, I don't have any (concrete) trials on them that tell when my ξ estimate techniques are applicable. ξ ξ

2) The LC (log. convergence) Problem: In general FdSS's are not what are used in models for science - (Even if FdSS include all CPM's - not only r-CPM's). Just how this fact is to be treated, is unclear. ~~All~~ All sci models that I know of, have been based upon a finite no. of params. These params were involved in 4. models in such a way, that $E(\sum(\text{err})^2)$ is probably predicted

= $(\sum A_i \delta_i^2) \ln L$ [$L \equiv$ corpus length, $\delta_i \equiv$ error in i^{th} param; $A_i =$ constants]

Models of this sort are certainly not r. only kinds conceivable,

i. I should perhaps draw up a few other kinds.

Another type of model uses ^{potentially} ∞ coeffs. (See LC 403, 404, 405, 410 -

(See 410.28-35 for a final, good, disch. of N-coeffs) - The key disch. is for linear regression, & analysis is identical for any continuous functional form if there is lots of data (L large) - i.e. the function is locally linear.

So, thus far, we have 3 ways that errors may converge, assoc. w. 3 kinds of Models:

- 1) FdSS (probably never used in Science)
- 2) finite no. of coeffs : Most often used.
- 3) ^{potentially} ∞ no. of coeffs : Sometimes used - perhaps always used,



if one considers the whole of scientific observation & prediction as corpus & potential. params, resp.

18.40 : On γ . Q of whether a u.m.c. MSM can always simulate γ . limit ~~M20~~
(when its known to exist) of a seq. of ~~MSM~~ e.c. pairs, $\{P_i\}$.

Well, I think its clear that for every such $\{P_i\}$ \exists MSM
~~constructively~~ ~~Tho I should verify this again~~ $P^{(MSM)}$ is identical to ~~MSM~~ γ . limit of $\{P_i\}$.
does / exist ~~MSM~~, so its

Just what was it I wanted to show about this limit ~~MSM~~,
around 460.14 ff, & why was it imp.?

Also, it implies that at ~~MSM~~ ^{least one} ~~MSM~~ MSM is at least as good
as any limit $\{P_i\}$ of e.c. pairs. Also, since u.m.c. MSM's
exist (which I've shown in / work on ^{recent} Provably Convergent MSM's ^{ie. 8.35 ff})
any u.m.c. MSM is at worst only an additive constant worse
than ~~MSM~~ any "limit" $\{P_i\}$.

So γ . problems: ① what was I trying to do on 460.14?

② UOM's are better than MSM's because of γ . possy of \mathcal{S} upper bound
estimation in UOMs. can I state this in more exact form - ~~Ex.~~

e.g. For any ~~MSM~~ CPM, in which one can get a reasonable
upper bound on \mathcal{S} , the ~~MSM~~ u.m.c. limit, UOM is γ . best one can do.

③ See 18.01-40. for γ . problems of new!

A possibl. outline of t. report:

1) This paper is ~~about~~ a commentary on Willis' "Comp. Compl. & Prob. Consts". Willis has proposed a mathematical solution to the problem of induction. We shall now try to determine to what extent it is indeed a solution, and to what extent it is unique.

Defn. of induction in terms of probn. of x . next symbol of a long, finite seq. of symbols.

W's definition of a FOR is an assoc. of a CPM w. each — His use of FOR's of ↑ power to get better CPM's.

It is possible to assoc. w. Univ's a seq. of FOR's of ↑ powers, & the CPM's assoc. w. these FOR's → a limit. Prob. measure. While t. limit exists, it is not c.c. — ∴ not a CPM.

W. defines prediction error for any CPM w.r.t. ~~any other CPM~~ ^{for a gn. corpus} any other PM. This is one ~~of the~~ explanations of

t. "difference" betw. x & measures. W. shows that for sufftly large c.B.'s (sufftly powerful FOR's), the mean error in prediction must → 0 as $\frac{k}{L}$ ($L \equiv$ corpus length), k is some const.

Diffy w. his mean error is that t. error can sometimes be +, sometimes -, so ^{knowing} that its mean value is zero, does not make ~~us~~ us feel that it is usually very small.

We shall, hvr, show that in general, the expected value of ~~the~~ ^{total} the probability error ~~is~~ squared is bounded, so its mean must → 0. This makes it very likely that for long corpi, t. ~~prob. pu.~~ probty pu. by t. method will be in error by a vanishingly small amt.

W's badd error criterion implies badd ~~is~~ \leq sq. error.

It is natural to ask if they are not equivalent. They are not. W's badd error is a stronger condition than badd \leq sq. error.

We will show that it is possible for a CPM to satisfy the badd \leq sq. error criterion, but not ~~the~~ W's badd error criterion. (23.01)

11774 \underline{R} \leftarrow untractable self for UUM's.
 01:23,40 \rightarrow 6) \exists a sequence of CPM's P^T , w.r.t. properties! } TM 24

a) for every $A^{(l)}$ $\lim_{T \rightarrow \infty} P^T(A^{(l)})$ exists \Rightarrow call this limit $P^\infty(A^{(l)})$.

b) ~~for all~~ for $\forall l$, \exists at least one $A^{(l)} \Rightarrow$
 $-\log_2(P^\infty(A^{(l)}))$ is ~~...~~ $-\log_2(P^{(M)}(A^{(l)}))$ differ by $l(1-\epsilon)$.

* for ϵ any other UUM , M_0 , ϵ difference is $l(1-\epsilon) \pm \text{constant}$.
 See 47.01-18 for proof - P^∞ is UUM "untractable seq." for UUM's.

7) \exists a seq. of CPM's $P^T \Rightarrow$ a) for every $A^{(l)}$ $\lim_{T \rightarrow \infty} P^T(A^{(l)})$ exists - call this limit $P^\infty(A^{(l)})$.
 See 47.01-90 for remarks on this Thm.

b) For any P^∞ w. properties .01-.03, ~~...~~
 $-\log_2(P^\infty(A^{(l)})) - \log_2(P^\infty(A^{(l)}))$ has a bnd (that's indep of l)
 (P^∞ may also be a CPM, of course) \leftarrow (P^T is \forall set of C.B.'s on a UUM \rightarrow See 39.20 for stuff on UUM's).

20:23,23 ($\approx 2.5'$) If P_0 is in a known complexity class (e.g. it takes $< \epsilon \cdot l$ or $\epsilon \cdot 2^l$ steps to calculate $P_0(A^{(l)})$ or any other functional bound on the no. of steps needed to calculate " then we can construct a CPM, $P_2 \Rightarrow$ the best error for P_2 ~~...~~ wrt P_0 is bnd (for any l) by the best of P_0 wrt. M_0 .

127 8) Conjecture $\left\{ \begin{array}{l} \text{An upper bound for } T \cdot \text{ expected value of the best of the next symbol of a corpus} \\ \text{is } -\log_2(P_0(A^{(l)}) \times P_{\text{best of } P_0}) \end{array} \right.$
 $A^{(l)}$ wrt. a gn. CPM, P_0

b) If $P_{\text{best of } P_0} = 1$ (explain what this means) and $P_{\text{best of } P_0}$ is some sort of "unbiased estimate".

$\frac{d}{d\epsilon} -\log_2(P_0(A^{(l)}))$ is meaningful, then this expression is bnd by

$$\frac{d}{d\epsilon} (-\log_2(P_0(A^{(l)}))) = -\frac{1}{\ln 2} \frac{d}{d\epsilon} P_0(A^{(l)})$$

c) for a) we can break the best of P_0 into $P_0(A^{(l)})$
 2 parts: 1) part decided on before l : corpus was seen 2) part decided on after l : corpus was seen. \therefore the best of 1) is zero; the best of 2) is usual. \leftarrow Easiest to compute if we use the best rather than best!

d) Other expressions for $P_{\text{best of } P_0} < 1$ but > 0 .
 This "Expected value" is wrt. to the a priori assoc. w. all CPM's

i.e. $P_{\text{best of } P_0}$ \leftarrow trivially true see SUH 409.15ff for each l .
 If best - best is bnd either form is correct. If not, then I bet on best!

36 c) The SUH Thm! If one always selects uses for prediction, the $P_{\text{best of } P_0}$ \rightarrow 29.01 spec 25.01
 of l can length $< l \Rightarrow$ its best (or best) + the best of l - corpus wrt that $P_{\text{best of } P_0}$ is min., then one will end up with predictions about as good as those of CPM. \leftarrow This Thm is trivially true: see SUH 409.15ff

01:29:40 For Term, show that if $\text{brost error is } k(l)$, then
 E value of $\Sigma \text{ err}^2$ is $k(l) \ln 2$; This paves way for
 L Conv. analysis.

When unc UOMs are in power to MSM's, we get some
 new codes — but all $\left(\begin{matrix} \leftarrow \\ \leftarrow \end{matrix} \right)$ of these new codes are such that
 one never knows how close one is to convergence.
 So, in the sense of estimating ξ , MSM's would probably
 be no better at all, ~~than~~ than UOM's.

Alon
 Maron,
 Lawyer
 Rollin

~~XXXXXXXXXXXXXXXXXXXX~~

Req: A bound on $(\text{brost} + \text{keost})$ for uncs!

Using r. methods of Thm 5 , we can construct a
 MSM M_s that has t. same ~~prob~~ ~~measure~~ ~~as~~ ~~any~~ ~~UOM~~ (say unc). Furthermore, by using CB's
 on ~~any~~ unc MSM M_{s0} , we can get a M_{s0} that has t. same
 proby measure as this unc MSM , but has $-\text{brost} + \text{keost} \leq 1$.

→ Whether this M_{s0} has to be unc is unclear. If it is,
 then ~~at~~ M_{s0} ~~unc~~ ~~has~~ t. property / $\text{keost} - \text{brost}$ ~~of~~
 any string is bound by a no. characteristic of that M_{s0} unc .

Well, perhaps because MSM's do have simpler properties
 than UOM's, I might want to study them more.

The main advantage of UOM's over MSM's for prodn, is that
 I can get this ξ value for UOM's.

How: At any pt. int. ~~the~~ MSM limit PEMS — I
~~can~~ would have a CPM, so I could use t. same ξ computation
 method as I'd use w. UOM's.

Def: UMSM & UUOM : are respectively Universal, (Mildly sequential)
 & Unidirectional Output Machines

→ But, if this is "legal", then we would use (brost of part
 brost of corpus w/ part) as a fork & select a "best" pem on
 this basis — which by-passes t. idea of MSM's entirely

27.40: The ratio of ↑ of $\square \subset B$ (or T) with \square ~~measure~~ can be adjusted as one desires. TMZ

Anyway 27.10 (non UMSM's) are probably better than 27.18 (UOM's) for induction, because for every $p^{(UOM)}$ is every $p^{(UMSM)}$
 $\exists \alpha > 1$
 $\exists \epsilon$
 $p^{(UOM)} > \alpha p^{(UMSM)}$ (for all $A \in \mathcal{A}$)

But it is not true for UOM's & MSM's the other way — This can be shown by 1. untractable seq. (\equiv Prob. Measure) of 5.17

9) General discn. on induction problems in RW:
 Show how analog induction, hybrid induction (analog-digital),
 operator induction, clustering, grammatical induction, are all covered
 by CMI - or by the problem of extrapolating a long seq. of
 symbols.

10) RCPMS: Some new RCPMS: A list of RCPM types

appear in RW.

- a) v. CPM (rare)
- b) CPM (rare) Bernseq w. $p = \frac{1}{2}$ (or $p = \frac{1}{3}$ to binary machine)
- c) RCPM w. a finite no. of "random params"

Example linear regression. w. $y(t) = ax(t-1) + bx(t-2) + noise$

a, b, c all "random" w. betw 0 & 1 (random means long term)

b) models w random params. e.g. linear regression.

$$y(t) = \left(\sum_{i=1}^n a_i x(t-i) \right) + noise$$

all a_i 's, c are random nos.

19. [Is this non-parametric "statistics"?] \rightarrow 39.15

20: 23.40 (5.5) B. At this point CMI looks "very good". It is natural to ask, does CMI (23.21) give one better induction

possibl. More exactly, if P_T is a seq. of pairs \rightarrow for all $A \in \mathcal{A}$, $P_T(A) \rightarrow$ a limit and $P_\infty(A)$ never has

> a bad best error for any fixed source (i.e. a RCPM), then there always exist a UOM, $M_U \neq$

$\Rightarrow P(M_U)$ is as good as P_∞ in terms of best error. While I don't know the answer to this Q, RCPMS (23.21) have

relation. The theorem says \exists a seq of P_t 's that \rightarrow a limit P_∞ such that P_∞ is at least as good as P_∞ in certain circumstances

cases, is better than P_∞ . Whether P_∞ is better than P_∞ for any RCPM's is unknown or open Q. I.E. it is conceivable that it may have smaller best error than P_∞ - but I don't know.

Also note that P_∞ is assoc. w. a special kind of universal Turing. That is in some sense, more powerful than UOM's.

12074
29.40

in 1. Proof of r. untractable seq. See 3201-18 for way to get around this dirty. Herit. forag. discs (which don't prove what I wanted to prove) are still interesting.

6/4/50: $R_0: T$ way $p^{(000)}$ its limit. I don't think it has to \rightarrow its limit suddenly. I had the idea that for each $A^{(k)}$, \exists ϵ was $p^{(M^T)}(A^{(k)})$ was indep of T .

$\rightarrow T_0 \rightarrow$ for $T > T_0$, \rightarrow ~~Mean~~ $p^{(M^T)}(A^{(k)})$ was indep of T .

\rightarrow This T_0 being, of course, not e.c. — I think now, that this is wrong; There are always new very long codes for $A^{(k)}$ that can be computed in as T grows. [e.g. a non ricpm could have non-terminating ~~real nos.~~ for its probes]

W.r.t 5.30: It would seem that $\lim_{i \rightarrow \infty} A_i^{(2+1)}$ had not exist if it is defined this way!

Suppose $k=1$;

$$P_i(0) = \frac{1}{2} - \left(\frac{1}{2}\right)^{\lfloor \frac{i}{2} \rfloor}$$

$$P_i(1) = \frac{1}{2} - \left(\frac{1}{2}\right)^{\lfloor \frac{i+1}{2} \rfloor} - 1$$

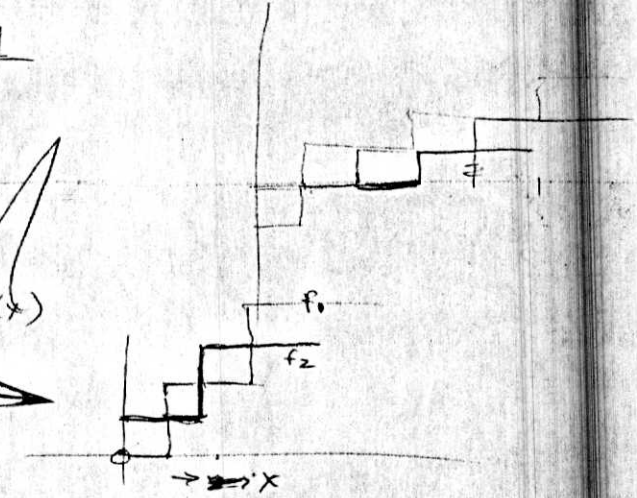
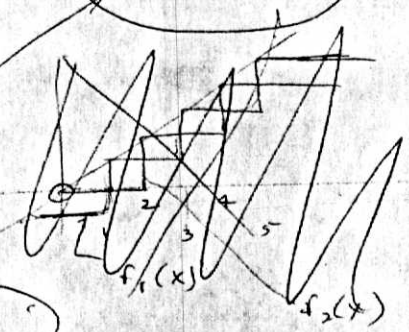
$\lfloor X \rfloor \equiv$ largest integer in X .

~~$P_i(0) = \frac{1}{2} - \left(\frac{1}{2}\right)^{\lfloor \frac{i}{2} \rfloor}$~~
 ~~$P_i(1) = \frac{1}{2} - \left(\frac{1}{2}\right)^{\lfloor \frac{i+1}{2} \rfloor} - 1$~~

$\lfloor X \rfloor \equiv$ largest integer in X

$$f_1(x) = \lfloor \frac{x+1}{2} \rfloor$$

$$f_2(x) = \lfloor \frac{x+2}{2} \rfloor - 1$$



$$P_i(0) \equiv \frac{1}{2} - \left(\frac{1}{2}\right)^{f_1(i)}$$

$$P_i(1) \equiv \frac{1}{2} - \left(\frac{1}{2}\right)^{f_2(i)}$$

So \rightarrow alternate i values, first $P_i(0)$ is then $P_i(1)$ will be larger so ~~$A_{\infty}^{(1)}$~~ would not exist!

How. both $\lim_{i \rightarrow \infty} P_i(0)$ & $\lim_{i \rightarrow \infty} P_i(1)$ exist, & \therefore ratio of Base limits is \therefore limit of i ratios. So, using a binary machine,

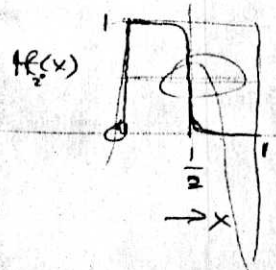
Consider $\frac{P_i(0)}{P_i(1)}$. It will \rightarrow a limit as $i \rightarrow \infty$. If $\frac{P_i(0)}{P_i(1)} \leq \frac{1}{2}$

$A_i^{(1)} = 0$ — what well, tho $\frac{P_i(0)}{P_i(1)} \rightarrow$ a limit, it can still oscillate about that limit indefinitely. If we happened to choose γ_c threshold here to be that limit, $A_{\infty}^{(1)}$ will not converge. (i.e. instead of $\frac{1}{2}$ here we could use $\frac{1}{2} - \epsilon$, for $\epsilon > 0$.)

B on untractable seqs, for limit Pams (cont) $\xrightarrow{\text{is normalized}}$ so $P_i(0) + P_i(1) = 1$
 Auction tack: say $P_i \in \mathbb{R}$

Then, instead of an untractable seq., let us construct a proby measure, $f_i(\cdot)$

$P_i'(1) =$ a very sharply n.l. funct of $P_i(1)$



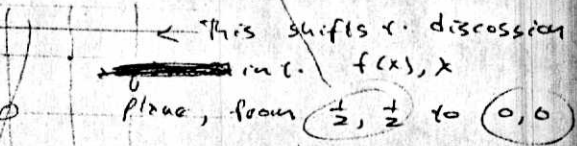
In fact, let $f_i(x)$ be always continuous for all i , but let $f_i(x)$ become sharper as $i \uparrow$.

so $P_i'(1) = f_i(P_i(1))$.

Consider $\lim_{i \rightarrow \infty} X_i \rightarrow \frac{1}{2}$

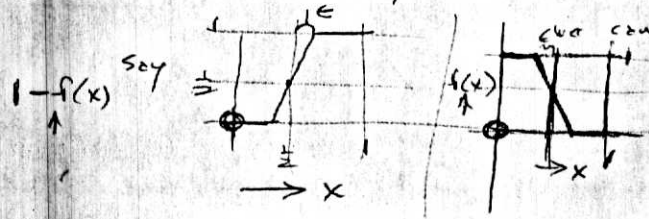
Does $(i X_i)$ have to \rightarrow ~~any~~ limit?

I think not: say $X_i = (-1)^i \cdot \frac{1}{\sqrt{i}}$
 or $X_i = (-1)^i \cdot \frac{1}{i}$



in both cases, $X_i \rightarrow 0$
 $i X_i$ oscillates finitely and in \mathbb{R} , unitarily.

Not $i X_i$ but a funct of i that has an obs value w.r.t of $\frac{1}{2}$: still the results of. right are correct.
 So we may have to keep $f_i(x)$ indep of i .



o.k., so we set

$$\frac{P_i'(A^{(l+1)})}{P_i'(A^{(l)})} \equiv F \left(\frac{P_i(A^{(l+1)})}{P_i(A^{(l)})} \right)$$

So this defines P_i' in terms of P_i .

Now, how much best error is remembered P_i (in trying to approx. P_i')?

If we find sequence for which P_i assigns (probs deviating

from $\frac{1}{2}$ by $> \epsilon$) to N conditional probys of symbols,

then best error for A is $\geq N$.

Ah so! Consider d_i & z sequences \blacksquare Proby measures

- 1) P_{∞}
- 2) ~~the seq~~ To proby for \forall seq. of all 1's $(1^{(\infty)})$ is 1
- 3) all other probys are zero

I think P_{∞} must ~~have~~ have best error of $\sim (1-\epsilon)l$ (for large l) for \forall seq $1^{(l)}$ w.r.t. either $P_{\text{am } 1}$ or $P_{\text{am } 2}$

33.90: Note that in P_{∞} , $P_{\infty}(A^{(l)}) > k(\frac{1}{2})^l$, since we have at least 1 coin for $A^{(l)}$ (i. seq. itself) of length $\sim l$. This means that if $P_{\infty}(A^{(l)}) = \frac{P_{\infty}(A^{(l)})}{P_{\infty}(A^{(l-1)})} = 1$ conditional probab of i. last symbol of $A^{(l)}$ wrt. P_{∞} .

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Then if $P_{\infty}(A^{(l)}) = (\frac{1}{2})^{l+S(l)}$ then $\sum_{l=1}^{\infty} S(l)$ must converge. or if $P_{\infty}(A^{(l)}) = (\frac{1}{2})^{l-S'(l)}$, $\sum_{l=1}^{\infty} S'(l)$ must converge.

To see $P_{\infty}(A^{(l)}) = \prod_{i=1}^l P_{\infty}(A^{(i)}) = \prod_{i=1}^l \frac{1}{2} \times \prod_{i=1}^l \frac{1}{2} S(i)$

$\prod_{i=1}^l \frac{1}{2} S(i) = \frac{1}{2} \prod_{i=1}^l S(i) = \frac{1}{2} \prod_{i=1}^l \frac{1}{2} S(i) = \frac{1}{2} \prod_{i=1}^l S(i)$

Also, have $\frac{1}{2} - S'(l) = \frac{1}{2} (1 - 2S'(l))$ $\left| \prod_{i=1}^l (1 - 2S'(i)) \right.$ converges to > 0 , iff $\sum_{i=1}^{\infty} 2S'(i)$ converges.

Here, because of 33.36, ~~even if $\sum S(l)$ converges~~, we could still have $k(l)$ be $< S(l)$ & get \emptyset or untractable seq.

For every value of l , there must be at least 1 seq. $A^{(l)} \rightarrow P_{\infty}(A^{(l)}) < \frac{1}{2}^l$. (They couldn't all be $> \frac{1}{2}^l$, since this would sum to > 1) \therefore there must be an infinite no. of l values for that seq. for which $P_{\infty}(A^{(l)}) < \frac{1}{2}^l$. (Can I make any limit to i. rate at which $\sum_{l=1}^{\infty} S(l)$ can converge? - i.e. can I say that $S(l)$ must converge slower than a certain ~~minimum~~ rate?)

Well, we know that there are seqs of length l (for any l) that have $P_{\infty} > \frac{1}{2}^l$ (These are deterministically decodable seqs, like (∞)). So there must be at least 1 seq. of length $l \rightarrow P_{\infty}(A^{(l)}) < \frac{1}{2}^l - \frac{k}{2^l - 1}$. (There are $2^l - 1$ seqs of length l to share ~~between~~ the deficit of k due to i. surplus of k in one $A^{(l)}$ sequence).

$\frac{1}{2} P_{\infty}(A^{(l)}) < \frac{1}{2}^l - k (\frac{1}{2})^l = (1-k)(\frac{1}{2})^l$ which doesn't help.

Would it be poss. for all $A^{(l)}$ to have $P_{\infty}(A^{(l)}) \geq \frac{1}{2}$ for $l > \text{some } l_0$?

So far, I only have 2 kinds of bounds on how ~~large~~ large $P_{\infty}(A^{(l)})$ can be: ① $\sum_{l=1}^{\infty} \log_2 P_{\infty}(A^{(l)})$ must be bounded above, because $A^{(l)}$ has $\left. \begin{array}{l} \text{by a certain constant characteristic} \\ \text{at least 1 dec. of (length } l + \text{const).} \end{array} \right\}$ t. unc. So $\approx P_{\infty}$ is bounded below - it can't be $< \frac{1}{2}$

② P_{∞} can't be $> \frac{1}{2}$ for all A sequences, since then \sum probab would be > 1 . 35.01

01:34.40 : Well: I don't see how to do it! — it may well be, Part
 while there are says. w. $P_{\infty}^c(A^{(l)}) = \frac{1}{2} - f(l)$ w. $f(l) > 0$,
 $f(l)$ is not computable — is a lower bound on $f(l)$ is not computable!!!

Consider t. Bern seq. $P \text{ of } 0 = .1$, $P \text{ of } 1 = .9$.

Consider some ~~can~~ typical seq. obtained by this ~~is~~ CPM. For large
 l values, P_{∞}^c will give values very close to $.1$ & $.9$ to 0 & 1 resp.
 say we have a P_{∞}^c that gives ~~near~~ $.95$ & $.05$ to 0 & 1 resp.
 Actually, for all t. 2^l seqs of length l , for large l , ~~the~~ P_{∞}^c must
 give values arblly close to $.1$ & $.9$ for at least one $A^{(l)}$.

Just try any PAM defined by ^{essentially} UMSM's show that ~~the~~ UUM
 machine can't deal w. it well. I think I did show somewhere that
 there exists at least one ~~the~~ limit PAM, in which \forall limits all exist.

(2) They are not computable (3) they are not representable by ^{CB's on} a UUM.

Maybe not — I did show that there are functions "computable" by UMSM's
 that are not computable by UUMS. (463.35 — 464.10.)

for this look at 3.37 ff. In fact, go back to those discuss, for ideas
 on t. present problem.

Conjecture: ~~the~~ UMSM's can compute functions that
 UUMS can't (463.35 ff)! \therefore assoc. w. each such function, should
 be a limit PAM assoc. w. t. UMSM, that UUM's can't deal w..

An analog is v's Thm 15, in which if a FOR, R' , can't
 "cover" ^{in a sub} another FOR R , then $P^{(R)}(A^{(l)})$ is arblly $>$ $P^{(R')}(A^{(l)})$ for
 at least one $A^{(l)}$. \leftarrow (This follows from t. Thm 12, but isn't Thm 12, itself)

455.35 ff has some marks on t. poscl. falseness of P 's]

\leftarrow This is certainly false: $P^{(R)}$ & $P^{(R')}$ can be identical, yet
 R & R' need not be able to cover one another — e.g. Prog can
 have difent. input alphabets!

But say R' can cover R : that R' can generate a function
 that R can't: i.e. \exists a seq., "a", $\Rightarrow R'(a \Delta n \Delta)$
 (Δ is punctu., n is arbitrarily finite no.) will calculate $F(n)$ ^{and then stop;} yet there
 is no such "a" for R — so R can't calculate $f(n)$.)

(Note R is UUM, R' is a UMSM)

R generates U's for R (2010), but for any input to R that gives a non-U output, R' ~~gives the~~ gives the same output w. that input.

Suppose that $F(n)$ increases more rapidly than any function computable by R - (I think that such funct. exist - i.e. 463.35 may tell how to generate such a function). - Then this means that ^{of} the codes that R' can interpret but R can't, some of those codes add cost to ϵ . ~~than~~ very long $A^{(2)}$ (i.e., large ϵ) much more rapidly than any codes of R could.

Her., note that R has a bunch of finite inputs w. infinitely long outputs. For R' to add to ϵ cost of those outputs, would ~~be~~ probably not \uparrow their cost by an arblly large factor.

The function $F(n)$ is able to give ~~me~~ relatively large costs to very long corpi. ~~than~~ It is able to give ~~more~~ do this to a greater extent, than any single ^{non-U} input sequence for R.

There are at least 2 ϵ troubles w. ϵ again disc:

1) Those finite inputs to R w. infinite outputs. We must be sure that there are an ∞ of UUM $F(n)$'s outputs that are diff. from those in ϵ .

Way they start.

2) Even if $f(n)$ is able to bestow cost on a long $A^{(2)}$ ~~but~~ using ~~much~~ much smaller values of $\log_2 n$, than there are ^{short} codes for R, with length $< \log_2 n$ - it is still poss. that very many, very long codes for $A^{(2)}$ will get lots of cost from R via ~~the~~ very many, very long codes for $A^{(2)}$.

2) Note that arg. 2 would be mitigated if we had an upper bound for (kcost - bcost (of any seq.)) - for each UUM, characteristic of that UUM.

3) There are also a large number

Specifically, other than ϵ diff. of 2, if b is ^{one of} R' 's codes for some long $A^{(2)}$, then R has no codes ^{for $A^{(2)}$ much shorter} than b is ~~shorter~~. - If this were true (i.e. kcost - bcost were bound), then I think this would dispose of diff. 2) (i.e. 24).

I'm assuming that $F(n)$'s exist which \uparrow ~~are~~ substantially faster than any of R's functions.

Perhaps to help w. 22 - show that for every such finite code w. ∞ outputs, I can find at least 2 functions for R' that \uparrow arblly rapidly.

01:36.90: SN While the value of $P_i(A^{(2)})$ as a function of i , does ^{does} not approach its limit with suddenness, I think that each bit of ϵ 's binary expansion of $P_i(A^{(2)})$ limits. This may make some of my old proofs ~~based~~ based on ϵ 's "suddenness of convergence" patchable.

Well, .01 looks pretty good! In the "undractable sq." problem, all I need to do is compare ϵ 's first 5 (say, or any fixed finite no.) signif. bits of ~~AAAAAA~~ $P_i^c(A^{(2)})$ w. those of $P_i^c(A^{(2)}_i)$. This comparison cannot oscillate indefinitely / ^{as $i \uparrow$} the first (unnormalized) 5 bits of these nos. can change at most, 32 times! (well, not necessarily — if ϵ 's first 18 bits are zeros, ϵ 's signif. bits can change 2^{18} times! — But in all cases ^{they can change} only a finite no. of times. Note that ϵ 's most signif. bit for $A^{(2)}$ can be at worst, the n th bit.

If .01 ff is ok, then I do have a undractable seq for UOMS. ~~woops!!~~ ^{39.25}

(Good! ☺). Then ϵ 's argt. of 36.22 + .90 makes it somewhat more likely that UMSM's will do significantly better than UOM's in predicting fdss's. On the other hand, it would seem that UMSM's could only do finutely better than UOM's, since UOM's are only boundedly worse than ϵ 's original generating form of a fdss! — so things are certainly a bit confused! → 41.40

Perhaps I can use ϵ 's "paradox of .25 ff" to "go around ϵ 's back way" & prove some other things (e.g. the finite or infiniteness of ϵ 's best - best for UOM's.).

Take a look at my ~~old~~ ~~old~~ ~~old~~ construction of ϵ 's "undractable seq" for UOM's. I may have used .01 ff — but I just forgot about it recently! See 5.17 ff ^{later} → Apparently I was not at that time aware of this diffy — but ϵ 's idea of ϵ 's nth bit of $P^{(UOMS)}(A^{(2)})$ converging suddenly, certainly is an old idea — I ~~think I~~ ^{think I} recognized this when I realized that $P^{(UOMS)}$ exists as a limit of $P^{(RT)}$; for $T \rightarrow \infty$.

37.40: R Out. "krost - brost" thru"; Perhaps use f. idea in Willis' ~~79~~ Jan 2,

latter in this way: T. trouble I had using his idea was specifying the C.B.

1) It may be poss. to "specify" γ . C.B. - even tho it's a non-computable no. (like t. time it takes for t. nth bit of $P_{20}(A^{(2)})$ to converge (for any ϵ : (ϵ is irrelevant)).

2) Actually go thru t. construction in Thrm 5; ~~unnessary~~ exact knowledge of t. C.B. may be unnecy. - One may have to modify γ . construction a bit, hvr. Perhaps I can tolerate/^{temporary} uncertainty about which of 2 sub corpi has greater probab. by using γ . method of 37.01 - .18.

My impressn. is that it may not be hard to show that ~~UNNECESSARY~~

krost - brost is bdd for UMSM's: ~~UNNECESSARY~~, ~~UNNECESSARY~~

I think ^{VHM} (12.30) shows this. Essentially, from a ~~UMSM~~ M_0 , we construct t. sequence of FOR's $R^P(R_t)$ where R_t is t. ~~UMSM~~

~~UMSM~~ C.B. on M_0 . So, assoc. w. M_0 , is t. MSM, $R^P(R_{\infty}) \equiv M_M$

To [k cost of a ϵ string via M_M] is \approx [(brost of that same string via M_0) + k] where k depends on M_0 [only] & is indep of ϵ -string involved.

We may be able to do t. same kind of construction,

starting with a UMSM, M , then have R_t be t. ~~UMSM~~ C.B. on M ,

then the MSM $R^P(R_{\infty})$ will be a MSM ~~UMSM~~ M' , that M can simulate. So for M , krost - brost is bdd.

This "proof", hvr, does need some clearing up.

01: 38.40
29.40 spac

So, anyway, it looks like the UMSM limit is certainly adequate for induction on all Fdss. So this form

of CMI is a vac. & suffx form. ~~What is, at least, a~~
~~UMSM's~~ ^{seem to be} of some interest in themselves — e.g. 7. kcost - bcost
bnd term. (38.18) — 7. untractable seq. wrt. UUOMS (5.17 ^{38.01} & ~~38.01~~)

The suggestion in 37.20-25 is to just now UMSMs with a give hyper
prosts than UUOMS, using very rapidly \uparrow functions accessible to UMSM's
but not UUOMS. → 40.01

05: 29.19 11) If kcost - bcost is bnd for any one UUOM, it is bad for all UUOM's.
" " " " un bnd " " " " " " " " " " "

12) Kcost - bcost is bnd for all UMSM's (see 38.18-40 & 12.30ff).

13) Define MSM's; show that \exists UMSM exists, show that \exists UMSM can compute
funct. that a UUOM can't. Link UMSM w/ "term?" 24.11


What I want to do now is really get all these proofs, defs, etc. in
good, vigorous form. Go over them carefully — particularly the most
recent ones (i.e. stuff on untractable seqs., kcost - bcost bnd for UMSM's, etc.)

25: 37.18 : 37.01-18 assures that $\frac{P_i^c(A^{(i)} \rightarrow 0)}{P_i^c(A^{(i)} \rightarrow 1)} > 1$ (say) w. ϵ accuracy —
but ϵ is always > 0 . This would probly have to same diffy as

ny typical function of 31.20ff. Well - ~~the~~ perhaps not.
In 31.20ff, the problem was that I wasn't sure
that ~~the~~ $f(i)$ would $\rightarrow 0$ or 1 as $i \rightarrow \infty$;

— in fact it was quite poss. it would $\rightarrow \frac{1}{2}$, thus yielding nothing of any
use. In the present case, however, we always end up w. a zero or
 ≥ 1 . If the first 5 (say) bits converge so that $P_i^c(A^{(i)} \rightarrow 0) \geq$
 ≥ 1 . first 5 bits of $P_i^c(A^{(i)} \rightarrow 1)$, then we decide on $A^{(i)} \rightarrow 1$ for
the contin. of our "untractable seq."

Note that "almost all" seqs are on $P_i^c(A^{(i)}) = \frac{1}{2} \pm \text{a very small } \epsilon$
for just about all i . I.e. — most seqs are "random" w = probly
for 0 or 1. Any "non-computable" method of decyng. a seq. will then
probably yield a seq. that is "untractable" to UUOM's.

39.40 : 39.14 spec → Actually, ~~the~~ I was worried that this report would have too little material in it, but the 13 items from 23.18 to 39.20 are really a lot of material — most of it rather exact theorems or some import — in the rest, ~~the~~ no more conjectural (the 4 items in 8) (24.27) are of much more direct importance for practical induction. 

Furthermore, the stuff on induction w. UMSM's is a "necessiff" soln. to t. induction problem. — Superficially at least, it seems like an adequate "theoretical soln." All I've been able to show, hvr., is that 1) it is a v.g. soln. 2) No "limit type" soln. is better. I have not been able to show that there are not other, simpler, solns. that are about as good — e.g. UUM limit pm.

What I want from this review ~~now~~ Report is partly for myself. — a clear statement of ^{hard} results, w. proofs, then a statement of imp. conjectures & open problems, & indication why these open problems are imp.

There are, hvr., imp. topics on CMI that I'll not review in this report — e.g. linear regressn., operator & program induction, applics of CMI to "clustering", ~~an~~ optical pattern recogn., etc.

One of t. imp. ideas of this report, was to get other people working on CMI, because there were many Q's that I didn't understand. Hvr., in t. past 6 months, I've cleared up a lot of ~~myself~~ so that it really isn't so essential to get other people to work in this area! There are still 4 "conjecture" statuses of several imp. Q's (24.27, e.g.), but I can probably work on practical induction w. t. answers to them pretty rapidly!

10.40
37.28 spec. → Trouble occurs only if (relatively) by pres's are added to f dss's whose breasts ↑ rather rapidly w. l (i.e. are like αl),

(this ~~includes~~ doesn't include non-deterministic seqs, but includes seqs w. several "random" coeffs & perhaps even an inf. no. of "random" coeffs.)

Anyway: f dss's constitute an almost negligible fraction of all seqs. (I believe)

So it's quite poss. that the "short codes for very long seqs" generated via $F(n)$ (~36.01 ff) may never add anything to these f dss's.

There is, however, a big Q about the rigorous basis of the "paradox" of 37.25.

There is an upper bound for how good any program can do wrt to the "expected value" error (or best error) in prediction — wrt to the "true" program that would produce a gn. ensemble.

I.e. the program that produces the ensemble is best. This does not say anything about the best of any individual seqs.

So this whole paradox must be put in more rigorous form — if it is to be regarded as a paradox at all!

Also, the boundedness of $(\text{best} - \text{breast})$ (36.28, 33) looks like another imp. pt. in the paradox. Perhaps this paradox constitutes a disproof of this!

Actually, the situation is even more complicated! I had assumed that for most CPM's, that all copies $A^{(i)}$ were gn. & breast $\approx \alpha l$. In fact, this is not so. A CPM can assign probs subly close to 1 — e.g. $P(A^{(i)} = 1) = 1 - 2^{-i}$ for all $A^{(i)}$.

This makes the seq. have a breast that grows very slowly w. l.

By letting $P^{(i)} = 1 - f(i)$ where $f(i)$ ↓ or bly rapidly w. l, we can get with the breast of $1^{(i)}$ to ↑ or bly slowly w. l.

But — no matter how slowly this ↑ w. l, $F(n)$ (of 36.01 ff) will ↑ so fast w. n, that the breast will be unbly modified by an unbly large amount. So argt. 28 is irrelevant.

If the bound $\text{best} - \text{breast}$ is true, then 36.01 ff constitutes a proof of existence of a untractable seq. for UODM's — unless for every value of $F(n)$ ∃ a finite decm. of an infinite seq. that

01:41:40: start out like f_n , but has a den of length $< n$.

Even if 41.90 - 42.01 were true - would there be any paradox to explain? The main paradox involves CPM's: UMSM's would

somehow assign greater prob to certain seqs than f . CPM

"that generated" that seq. - (if this is at all meaningful) -

2 somehow this is impossible, because f . "generator" of a

seq. gives us by a prob to f . seq. as possl.

Déf SN LPM Limit Prob Measure: A prob measure defined by

$$P_{\infty}(A^{(n)}) = \lim_{i \rightarrow \infty} P_i(A^{(i)}) \quad \text{where } \{P_i\} \text{ are all CPM's.}$$

01: 42.40;
40.90.Spac

A sort of new Abstract or introduction to the report:
Title: A ^{Formal} Unique Solution to the Problem of Inductive Inference.

The inductive inference problem is first defined to be the extrapolation of a (usually long) sequence of symbols — this sequence having been created by some unknown stochastic source.

~~It is well known, that if the generators of the sequence is allowed to be any finitely describable stochastic source, then there is no effectively computable solution (in the sense of Turing, Davis - etc.)~~

The solution ~~employed~~ that will be given, is the limit of a sequence of effectively computable approximations. While the limit exists, it is not, of course, effectively computable.

It is shown that this solution ~~provides~~ gives probability values that converge rapidly to the ~~actual~~ values generated by the ~~unknown~~ unknown stochastic source. ~~Two~~ kinds of error criteria are considered. The ~~first~~ "Information Error" ~~was devised by Willis and is the more stringent~~ ^{called} "Information Error".

The first is the total sum of the squares of the probability error. This sum converges and is bounded by a constant that can be estimated if the nature of the stochastic generator is known.

*It is not sure
this is what
Willis
defined
that way*

The second is a more stringent error criterion devised by Willis, called "Information Error", having, however, less direct intuitive meaning than the first type of error.

A third kind is ~~proposed~~ proposed, and some strong conjectures are given as to how to evaluate it, if the ~~unknown~~ underlying stochastic source is not known. It is shown that there is no limit of probability approximations that is better than the one given.

This particular solution to the induction problem is compared with that of Willis. ~~It is shown that~~ the present solution is at least as good as Willis' in all cases — ^{it is} usually the more difficult to ~~approximate~~

(paralogical) (?)
untractable

TM44

01:43:40 compute the approximations. For certain kinds of stochastic sources, the proposed solution is far better than Willis' — but for stochastic sources that actually appear in the Real world, it is not clear ~~as to whether the proposed solution~~ it is significantly better. ~~than Willis'~~

~~Some problems are involving~~ The application of these induction techniques to ~~practical~~ practical problem is discussed first in terms of the adequacy of a ~~sequence of~~ symbols extrapolation as a complete formalization of the induction problem —

Note 14
So good
to 15
in t.
abstract

Secondly, in terms of using the proposed solution to solve problems in ^{general} pattern recognition, numerical series extrapolation, clustering / in pattern recognition, ^{techniques} geometric probability, ~~and~~ human concept formation, etc

Say: instead of .14-.19: ~~we solve specific prob~~
Secondly, in terms of examples of how the proposed solution ~~would~~ can be applied to specific induction problems

01:49.40: On T. defn. of MSM's: I'm not so sure that I really have a rigorous defn. It was first defined on 461.25

463.35: How a MSM can compute a function incompatible by a UOM.

11:02-11:20 || 3.01: 2 types of MSM's.

3.37: Proof that there are seqs of P's & no set of C's on a UOM can express them.

5.17: An untractable seq. for UOM's.

7.02: Out. Defn. of a MSM. Also see 8.17-20

8.17-20 probably has most of the defn. I've been using.

At present, My impressn. of a MSM:

for every infinitely long input seq., it will eventually converge to a finite output seq. If the machine (stops), it is regarded as having an ~~infinite~~ loop following its ~~infinite~~ first out

printed symbols. ~~This means that every $n > 0$, $f(n)$ a $f(n)$ (computable) \rightarrow by t . time $t = f(n)$ the n th output seq. will have converged.~~

For a finite input seq., I don't know what to regard as its output. I could regard a blank as a special input symbol, so even finite input seqs are really infinite. Also we can make a special

input, it knows that the following squares are blanks

Here, note that for a finite I comp. bnd., only inputs of length $\leq T$ are readable - so we normally consider longer inputs as $C \cdot B$.

So - if we consider inputs of length $= T$, then we don't have

to consider blank squares on the input tape. But, ~~we should consider~~ if we always have all inputs

be of length T , for $C \cdot B \cdot T$, - Now ~~we~~ do we get our

posts to be based on input code length?

Consider we have a LPM, $[P_i]$: we are dividing a MSM, M $\rightarrow P(M) = P_{00}$. We want the I/O behavior of M : of bits, say we have n as input, the finite string S followed by blanks.

Using M 's terms, we first print out $R(P_i)$'s output as input

(i.e. the response of $R(P_i)$ to S ; $R(P_i)$ being the assoc. w. P_i)

Next the output is changed to $R(P_i)$'s response to S , ... to $R(P_i)$'s response to S .

R

0.1: 46.40: $\lim_{n \rightarrow \infty} p(\text{UMSM})$ (29.11) This does not show that ~~it is~~ $p(\text{UMSM})$ is as good as one can get. It merely shows that for any P_{lim} that is $\lim_{n \rightarrow \infty} P_n \equiv P_{\text{lim}}$ $p(\text{UMSM})$ will do as well, within a constant boost.

0.04 I would like to do a little better, i show that ~~if~~ P_{lim} has ~~limit~~ $\exists \text{UMSM}, M_{\text{UMSM}} \rightarrow P(M_{\text{UMSM}})$ is identical to P_{lim} .
~~limit~~ P_{lim} has ~~limit~~ $\exists \text{UMSM}, M_{\text{UMSM}} \rightarrow P(M_{\text{UMSM}})$ is identical to P_{lim} .
 boost error for all ~~limit~~ P_{lim} , then $\exists \text{UMSM}, M_{\text{UMSM}} \rightarrow P(M_{\text{UMSM}})$ is identical to P_{lim} .

While 0.04 is very probably true, I don't think that for practical purposes it is much stronger than 29.11. I.e. If one uses a randomly chosen ~~MSM~~ UMSM to do induction, both 0.04 & 29.11 would say that one will get a bndd boost error.

Hvr. 0.04 also says — if you use any ~~MSM~~ P_{lim} that gives one a bndd boost error, in these circumstances, it will be based on a UMSM.

So ~~the~~ One way to prove 0.04: Show that if "clearly" a P_{lim} that will get bndd boost error w. all limit perms, must be based on a ~~MSM~~ UMSM. T. Q is — must it be a UMSM that its based on? If not, then there must be some MSM that it cannot "cover".

Proof: It is a UMSM || Hypoth: its not a UMSM (try to prove false)
 If it is not UMSM, then \exists a MSM it can't "cover".
 Now it is possl for $P(R_1)$ to be $\geq \frac{1}{K} P(R_2)$, yet R_1 ~~doesn't~~ ^{need not} cover R_2 , which is a precont ~~normal~~ situation.

~~The~~ T. forog. approach is incorrect if followed as above, hvr., I'm not sure that there isn't a way to prove it using these sets of dyts.
 Another entirely difunt way to prove 0.04 is that of ~ 960.14 ff.
 — This is a constructive way to get the desired UMSM.

01: 47.40
 46.40 spec
 changed to ~~47.40~~

If we have an infinitely long input, S , then
 we first do $R^{(P_1)}$'s response to 1. first bit of S . T. output is then
 $R^{(P_2)}$'s " " " " 2 bits " " " " "
 ... $R^{(P_i)}$'s " " " " " " " " "

TM48

05: In response to a finite input, if P_{∞} exists (i.e. $P_i \rightarrow$ a limit) M keeps changing its outputs until at a certain point, the output changes no more, but M continues to calculate. We ~~do~~ not, hvr., ever know that M will never print again.

0: A notable thing, is that if the response limit response of M to input $S \sim$ Blank is A , then the limit response of M to S (some ~~input~~ ^{input sub} string) is A (some output substring). In this sense, M is a "Mildly Sequential Machine".

By definition $p(M)$ (if M is a MSM), is obtained by the limit of the ~~sequence of LPM's~~ LPM, $[p^{(M_i)}]$, M_i being the i 'th C.B. on M .

So, in general, I think a MSM can respond to a finite string (followed by $(\text{Blank})^{(\infty)}$) by a finite amount of printing, and then possibly an infinite pure (not printing) calculation. Its response to an infinite input involves reading part of the input, doing some writing (perhaps rewriting) ^{↳ that's probably unnecessary} then reading more & writing more & perhaps rewriting some - then read some more, etc.

For finite input, a UOM can have inf. output. So, in a way, for finite input followed by $(\text{blank})^{(\infty)}$, a MSM can print infinite output.

T. constraint of .10 looks like it may be significant, but it need not be if we never give it finite inputs!

35: Another impl. idea I haven't gone into: I considered various C.B.'s on a MSM to be FOR's. In general, I don't see how this would be so ~~easy~~ - unless we only allowed certain kinds of C.B.'s, perhaps

49.01

01:48:40: It may be possibl. to get ~~CPM's~~ CPM's from machines that are not FOR's:

We can use deBasque Measure - as W does.

02
03

Say we use a T limited MSM. These are all ^{a sub-set of} FSM's. ~~Each~~ maps
t. set of (all info. input strings) into a set of finite output strings, so we
do have \sum of all probys = 1 (including outputs w. S & U in them) - but in t.

Def

present case, we have not U's or S's - we just have those finite
output strings. ^{we do, hvr, have "B" (= Blank) symbol, which so follows all finite strings.}
T. machine can be in a comp. just after having written

- t. 8R. symbol (t. 9 B & 10R have been written, already) when
- t. T limit occurs - or - it can stop after rewriting
- t. 8R symbol - in either case, t. output is identical.

110

Look at 76.30-40 & 78.01-05: This decbs t. response of a MSM that
is "simulating" a particular LPM, Poo. If we put any CB, T, on
such a machine, it will give fine Proby measures if T is \Rightarrow
t. machine has just finished writing a complete $R^{(P_i)}$ output. If
T is \Rightarrow t. machine is only partway thru such an output, then I
don't know if we get a Proby Measure.

20

22

23

\Rightarrow well! These CB's on a MSM may not yield proby measures -
This will be because of t. lack of "sequenciality" in t. outputs.
Hvr, for large CB's most of t. output will be sequencial
in t. proper sense (like a FOR is). For large CB's - only
~~t. first~~ t. first n symbols (for fairly large n) will
have proper probys assoc. w. them - furthermore, these
probys will not get into t. diffy of .20 - .22, because those
only ^{output} symbols will not change as t. C.B. \uparrow !

So: when t. CB's on a MSM do not yield a "true Proby"
- This will only be for t. latter ~~the~~ symbols of t. output. By suitable
X-PMS, these number assignments to output strings can be
changed so as to yield numbers that do conform to t.
conds. that proby measures conform to. Only t. latter
symbols will have these nos. changed, hvr, since ^{nos. for} earlier
~~was~~ symbols will be probabilistic, since these earlier
~~was~~ symbols ~~are~~ have a suitable "sequencial
property".

01: 49.40: Out: So now go thro this lack of sequentiality — say, as described in 49.20-22 — desc. in detail just how it occurs — is just how it does not occur in the evolution part of the output that has "settled down".

I think it very likely that 49.23 ff will patch up this trouble w. getting proby measures out of MSM's!!

Renormalizations, using ^{t. constraint} $P(A^0) + P(A^1) = P(A)$, $\sum_r P(A^r) = 1$ may be adequate. It may well be that if one has any ~~numerical~~ (non-zero) numerical function on all finite strings, one can renormalize via .10 to obtain a "probly measure".
— A zero pre norm, with for a given string A, will give zero norm'd proby for all strings of form A^x where x is any string (including the null string).

Negative pre norm probys would probly give no trouble — but look into this! ~~Work I think it would work~~ It will be ok, sometimes if the fully norm'd rule is used!

Say P' is pre norm'd
 P'' " post "

Then
$$P'(A^0) = P'(A) \cdot \frac{P(A^0)}{P(A^0) + P(A^1)}$$
$$P'(A^1) = P'(A) \cdot \frac{P(A^1)}{P(A^0) + P(A^1)}$$

This is an adequate recursive norm'd rule. We also need to know that $P'(\text{null seq}) = 1$.

From a more practical view pt., one can save trouble re norm'ing, if one only uses (unnorm'd) proby values that have been constant for at least $k \geq 2$ most recent CB increases. (This is w.r.t. MSM's referred to in 49.20-22, 49.30-35, 48.01-02)

So, w.r.t any particular CB on a MSM, we can, using 49.03, obtain a "probly measure" (positive semi-definite) & using .25 we can re norm' if necessary. Thus we can get CPM's from CB's on MSM's.

Next, we define the PM assoc. w. any MSM as being the LPM assoc. w. the seq. of CPM, assoc. w. the ^{successive} "T", CB's on that MSM.

From this, it is clear that we need ~~not~~ never consider finite inputs to MSM's — i.e. we don't have to define what MSM's must do when they see the blank at the end of the input string. This is because we are only interested in them because of the LPM's assoc. w. them — in obtaining ~~probys~~ phrase limits, we only use

50.40: inputs of length T , $T \rightarrow \infty$

49.03

As for t. CB's assoc. w. MSM's - we again only use T-type CB's - so we consider only inputs of length T , - so again we don't have to worry about ~~how~~ how machine will react to a blank square.

Going back to defining a MSM

Time computation ends
T CB'S on MSM's. 49.02 - 10 decbs behavior of

Let us insert an inf. string into a MSM. It will, typically, continue computing & printing, forever. It can, however, stop at any time, or go into an infinite/compu. loop (no printing)

at any time - thus printing out a finite string. In either case, it would satisfy t. defn. of a MSM, since each output symbol would \rightarrow a limit.

If it ~~never~~ never stops or gets into an inf. compn. loop, then we require that every output symbol \rightarrow a limit eventually. This means that each symbol cannot oscillate indefinitely - but must eventually (often at a not a.c. time) settle down to 0 or 1.

If it never stops or gets into inf. comp loop, I think it ~~must~~ must print an ∞ of ~~non-B symbols~~ non-B symbols. - so it can have no B's on its output tape.

The "sequential property" of MSM's arises as a ~~trivial~~ trivial ~~consequence~~ consequence from t. defn.; It is clear that for any fixed inf. input, then ~~eventually~~ eventually, every output symbol up to $T_0(n)$ will eventually converge. (i.e. $\exists T_0(n)$ so large that for $T > T_0(n)$ the first n symbols of t. output will remain invariant)

In most cases of interest $T_0(n)$ increases more rapidly than any a.c. function.

If it should become necessary to define t. MSM response for finite inputs, then look at 46.30-40; 48.01-05. \rightarrow 55.01

T. mode of analysis of ~~MSMs~~ ~~MSMs~~ of 49.02 ff. using TCB's

w. only inputs of length $\geq T$ can be applied to UUM's to yield a ~~simple~~ simpler (less background needed) development of Willis' paper. However, TCB's are certainly less general than t. CB's he treats & will perhaps ~~not~~ make certain of W's terms. inaccessible.

ol: 51.90! Perhaps it would be well to varyate the difference betw.
 a) $\text{FOR} \neq \text{FSM} \neq \text{TCB}$ [By FSM I mean unidirectional I/O tapes but no work tape.]

1) FSM & FOR's do not include one another either way.
 2) A squaring machine is an FOR but not a FSM - since it needs potentially infinite memory. A permissible input to a squaring machine is a no. followed by a Δ (concn. symbol).

3) A FSM can get into infinite loops: a FOR can't - but I think a FSM that can't get into inf. comp. loops is a FOR if f.s & U symbols are added.

4) A copying machine is ~~not~~ a TCB, it is a FOR & FSM.

5) A TCB is a kind of FOR.

6) I don't think a squaring machine of this sort is a FOR. One that is: Input is string of n 1's, followed by a 0. Output is a seq. of N^2 1's, then machine stops. If no blank follows the input seq of n 1's, machine prints (n^2) then stops also. If a 0 follows, it stops permanently; if a 1 follows, it prints $2n+1$ more 1's, then stops.

or the machine may print (in radix 1) the ~~total~~ total no. of 1's appearing in the input thus far.

When we are doing a FSM to simulate a LPM, [LPM]

In some ~~cases~~ simulating a FOR assoc. w. a gn. CPM (ie. R_0, P_i of the LPM), our output could get into a U or S loop. We can simply have the simulation stop rather than print 0's or S's. This will result in a non-normal PM, but that's O.K., because we renormalize anyway.

01:0240:

I may want to issue a preliminary Progress Report, for my own as well as that of various correspondents:

Plan In the report, give a general statement (introdu) of the way things look, then list various Thms. & call which seem proved at the present time.

- 1) Thms: 23.18ff: Define LPM's.
- 2) Define $P^{(M_{uom})}$: show it exists.
- 3) $P^{(M_{uom})}$ has ~~bound~~ bndd best error for all CPM's.
- 3.5) If f. sat of poss. Pans in a known complexity class, then \exists a CPM that has bnd best error.
- 4) If a Pcm has ~~bndd~~ best error of k , for \forall gu. CPM, then $\exists \epsilon (\epsilon \text{ err})$ is bnd by $k \cdot \frac{\epsilon}{\ln 2}$ or whatever const.
- 5) If a Pcm has $\exists \epsilon (\epsilon \text{ err}) < k \cdot \ln 2$, then its best error (or expected best err) need not be bnd.
- 6) $P^{(M_{uom})}$ ~~is~~ does not have bndd best error for all ~~CPM's~~ LPM's.

Give example.

6.5) pot PMS have: discussion of realizability then that thm, then t. disc on ?

- 7) a) Define MSM's
- b) Thm: \exists UMSM's exist.
- c) Define $P^{(M_{msm})}$:
- d) Thm: $P^{(M_{msm})}$ exists
- e) Thm: $P^{(M_{msm})}$ has bnd best err for all LPM's.

see 95.30 - 96.10 for bibliography proof - the thm may be for better refs.

conjectures, disproofs, partial thms, remarks: 7.5) Say Pcm is a LPM that has bndd best error for all LPM's. Then \exists a UMSM, M , $\Rightarrow P^{(M)} = P_{oo}$, probably true.

8) State SVH thm: That choosing "best" Pcm (best of Pcm + best of corpus wrt that Pcm is max) will yield result as good as $P^{(M_{uom})}$. I \leq trivial. - This plan yields $P^{(M_{uom})}$ identically!

9) $k_{\text{best}} - \text{best}$ is a k_{err} bnd for all UOM's
unbnd " " " "

I don't know which.

R

10) For VMSM's, I think Kraft - brost is bad

11) The ξ terms (unprov'd) : a) $E(\text{brost of next symbol})$ is

$\frac{\text{brost of pair} + \text{brost of corpus w.r.t. pair}}{L (\equiv \text{no. of symbols in corpus for pair})}$

b) How to divide brost of pair into an a priori (zero cost) part & a a posteriori (regular cost) part.

c) Arg't of using brost here rather than k cost:

i.e. for 2 pairs, P_1, P_2, \dots ; P_1 has k cost c_1
 P_2 has 2 codes of lengths $c_1, c_1 + 1$; I think P_1 & P_2 are equally good

12) Discn. of r cpm's, cpm's rates of ^{brost} convergence of diffrnt. PM types (see 29.07) - various stochastic model types.

13) Discn. of relative goodness of $P(\text{MUMSM}), P(\text{MUCOM}),$ cpm if ~~a~~ cpm to be dec'd is of known complexity class, etc.

14) Discn of use of various umc's for proby evaluation -
If the umc is chosen before t. sequence is seen (or chosen in a way that is likely to have zero correl. w.r.t. seq) then t. expected error in predn. may be very small. (?) Certainly there will be no a.h. error or "systematic error" (whatever that is in t. present case).
The "A" in $\frac{f(s)+A}{s}$ will be zero.

5:40
5:51
5:51

Some Problems Assoc. w. having no defn. for output of MSM w. finite input: 1) If best-best is bad for MSM's I must have a defn. for MSM's output for finite input! (Note 56.27)

TM 55

This defn. may not be so diff. The MSM must be capable of reading blank squares & reacting to them. The blank can be regarded as a regular input alphabet-symbol. However, since a blank is always followed by a blank, there is never any reason a machine would want to read a symbol followed by the first blank - so we will use this to limit the form of γ . Traces finite state transition rules.

As for the rest of γ . MSM's behaviors it would be restricted as before, so that it would have to eventually converge for the n th output symbol - no matter what value n has.

So, w. finite input, a MSM could compute forever, compute and print forever, or eventually stop, subject only to constraint 14-15.

We also want a more genl. defn. for a c.B. on a MSM. So far I've only been using a TCB. We want a more genl. c.B. because: We want to use a set of "stronger" c.B.'s on a UMSM as γ . generators of a LPM. No claim that LPM's based on UMSM's are more powerful than those based on c.B.'s on UMSM's - but this claim is very narrow, if c.B.'s on UMSM's are a rather broad class of c.B.'s - but γ . c.B.'s on UMSM's are narrowly restricted to TCB's. (Not so narrow - see 56.32, 57.01)

Some properties we'd want for a c.B. on a MSM:

1) ~~It's output~~ Its output (in response to a given input) is exactly the same as γ . MSM its γ . c.B. of, except at a certain point it does a new & different thing - so one can easily tell where the simulation of γ . MSM stops. for γ . c.B. to stop at that pt. would perhaps be an adequate "identification of behavior"

2) We would like the behavior of the c.B. to be "e.c." in the sense that several input Q's about its response to various input types (finite input, certainly) are e.c. E.g. T. PM assoc. w. a c.B. is e.c. - so its very likely that we don't want a c.B. of a MSM to be as general as how a MSM can be.

3) Perhaps for 2): for every finite input string, γ . output is e.c. (in γ . c.B.)
b) (I'm not sure I need anything so restricting, but): for every l , $\exists n(l)$ 56.01

R

01: 55.40: \Rightarrow for every output string of length $l \exists$ there are no input codes of length $> n(l)$. [I'm not sure this is meaningful.]

I still don't think t. prog. is envf.

I may need to talk for ~~CB's~~ MSM's, as well as a modification for MSM's; ^{unrestricted}
for every infinite input string; ~~for every~~ $l, \exists n(l) \Rightarrow$
~~Symbols of t. output string~~ up to the l^{th} are indep of t. nature of
input string after t. ~~all~~ output symbol. - So, t. finite part of t.
the n^{th} symbol, yields t. finite part of the output up to t. l^{th} symbol.
For c.B.'s on MSM's, $n(l)$ is always bndd - (i.e. it exists).

For Full MSM, $n(l)$ must exist also, because if it did not, then for the l^{th} output,
there would, for every value of T , no matter how large, be a seq. that could
change t. ^{all} output symbol after T . I think this ^{may} mean that t. l^{th}
output symbol need not converge - but I'm not sure - perhaps not!

Consider t. MSM! Its first symbol is a zero, as long as t. ~~input~~
input starts out $0^{(k)}$ - as soon as $2^{1/k}$ appears, it erases the 0 &
writes 1 & leaves it that way.

T. \odot is, is t. prog. a MSM? The first symbol doesn't oscillate. For every
input string it will eventually converge to 0 or 1. It converges to 0 for ~~(input)~~
- it converges to 1 otherwise.

I could, if I liked, define MSM's so that for every $l, \exists T_0(l) \Rightarrow$
after $T_0(l)$, t. l^{th} output symbol of t. machine converges.

Do I need this restriction? If I had it, would ~~every~~
every LPM have a MSM associated with it?

It is not nary that t. keust of a ^{finite} corpus be definable for MSM's.
Best, hur, must be definable *

Note that in 19-24 the ~~prob~~ ^{prob} of $0^{(n)}$ is zero. I don't know
if this ^{sort of thing} must always be true for ~~MSM's~~ ~~any~~ ~~kind~~ ~~of~~ ~~seqs.~~ all sets of seqs.
of this sort. Well, t. seq $0^{(n)}$ has ~~prob~~ 2^{-n} , $T \geq$ wt. of all seqs
of that sort is ~~1/2~~ $\frac{1}{2} + \frac{1}{8} + \frac{1}{16} + \dots = \frac{1}{2}$ (?) $01; 001; 0001, \dots \rightarrow 71.01$

Every CPM is ~~approximatable~~ ^{approximatable} ~~or~~ ^{or} ~~well~~ ^{well} by a FOR. So if
c.B.'s on a UMSM are FOR's, then ~~perhaps~~ ^{perhaps} ~~any~~ ^{any} seq. of
CPM's that \rightarrow a limit, is representable as a seq. of c.B.'s on a MSM.
In fact, if we just use T c.B.'s, this is true! - Since by using
suitable values of T limits, we can obtain a seq. of CPM's from
t. MSMS of of 46.30-.90, 48.01-.05.

What we really want, is to be able to devise various seqs. of
CPM's, that can be regarded as c.B.'s ~~that~~ ^{that} "approach universality
UMSM" - so we are sure ~~that~~ ^{that} approach t. strength of p(UMSM). 57.01

01:56:40: The TCB on a UMSM will do the desired thing, but it would be better if we could have a wider variety of CB's, so we could devise a wider variety of seqs of CPM's that approach P(MMSM).

Hvr., It may well be that w. things as they are, using only TCB's on a UMSM, I am able to show that this seq. of CPM's is, indeed, stronger than that based on a UUM, i.e. that this new kind of seq. can "do" any LPM w. but b/c error.

For the present, I can leave it at that pt., & explain that probably ^{more general} better CB's could be devised, so more general seqs of CPM's could be used.

(also (C) 46:30-40 & 48:01-05)

Note 56:30-32: This means that any seq. of CPM's that converges (i.e. ^{LCM} ~~is~~) is expressible as a seq. of TCB's on a MSM. So ~~any~~ ^{any} ~~LCM~~ ^{LCM} is expressible as a seq. of TCB's on a UMSM. **No!** ^{Probably true, but I have not proved this.}

But anyway: a set of TCB's on a UMSM is a fairly genl. kind of LPM - probably the most genl. kind possl.

21 Hvr., suitable defn. of CB's for MSM's might be obtained by modeling them after FOR's, to some extent. ~~two~~ 2 kinds of FOR's are

- (1) TCB - which works O.K. for MSM's
- (2) FSM (Finite Memory) w. the additional constraint that the machine cannot enter a state it has ever been in before, unless it has a different input symbol, or is on a different square of the input tape (these latter restrictions prevent int. loops - they may be too restrictive, hvr.)
- (3) More generally than (2): "no infinite compn. loops" allowed. This isn't so easy to define, hvr. - A machine might get into a write & ^{recompute} rewrite loop that goes forever all the time - (the MSM can't do this, by defn. - so a CB on it, can't) - Or, it could converge in this write, rewrite, loop - but not in e.c. time.

10.35: ; On 1. construction (is data?) of a UMSM:

8.35 - 10.35 show how to construct a UMSM in which its output is defined only for infinitely/inputs. We can take a finite input string i loop ∞ loop onto to end (or a Blank $\equiv B$) loop. The B (or ∞) symbol has this special loop property

In 10.12 - .35 we have $F(i) \neq G(j)$ "going at different rates". Will we ever run into the problem that Schubert did?

I think the relative rates of $F(i) \neq G(j)$ are irrelevant -

i.e. it is only necessary that both $i \rightarrow \infty$ & $j \rightarrow \infty$.

Say $i = j$. Then for every i , let $M(i)$ be either (a) length of $G(i)$ or (b) $F(i)$ - whichever is smaller.

If both $L(G(i)) \neq F(i) \rightarrow \infty$, then $M(i) \rightarrow \infty$.

If $F(i) \rightarrow \infty$ is bad ($F(i)$ must be ~~not~~ a non-decreasing), then $M(i)$ ~~will~~ has the same bnd. - i.e. $L(G(i))$ must ~~have~~ eventually get as large as $F(i)$.

So $\lim_{i \rightarrow \infty} M(i) = \lim_{i \rightarrow \infty} F(i)$.

I think the idea of this M_s is that it will print null for a particular symbol, until it has a proof that that symbol converges - at which time it just does regular compus. for that symbol. ~~M_s~~ M_s must therefore, converge for all symbols - either by staying at null, or by converging the way M_u does.

An alternate way of doing it: M_s first starts looking for proofs of convergence, via M_p . As soon as $F(i)$ gets > 0 , it then computes $G(i)$ - then continues with M_p computing until $F(j)$ gets large, for $F(j)$ say - at which point $G(j)$ is then computed. So we go back & forth between M_p & M_u .

2-12-74 R

TM 70

01:61:40 A perhaps unreasonable in the adequacy of 1. Limit recursive methods for deriv of all poss 1-lim rec. PEMS!

Return to set of all recursive (\equiv r.c.) PM's (\equiv CPM's) requires a hyper order - i.e. 1-lim rec. soln.

It would seem that 1-lim rec PEMS should require 2-lim rec. soln!

There is, hvr, a sort of lack of similarity betw. CPM's & 1-lim rec PEMS I'm considering. Each 1-lim rec. PEMS has a proof assoc. w. it (that it converges). Such proofs are of necessity, uncertain. CPM's have nothing corresponding to this.

Another ~~factor~~ factor! Regular CMI finds the "proper path" by a \geq lim recursive process. Each individual probty is found by a 1-lim rec. process. Perhaps ACMI (Augmented CMI) bears a \sim relation to the "untractable" seq. for CMI, that CMI bears to all ~~finite~~ Fdss. (Actually CMI will work for a greater class than Fdss - ~~eg.~~ e.g. random coifs - even on into no. of random coifs)

DEF

[SN] CMI or ACMI may not be the final soln. to the induction problem! In RW prediction, one has an ∞ infinite seq. of data one can use, to bear on any particular prediction. Just how does one ~~decide~~ decide what data to use when, in one's successive approxns to the probty?

2-16-74

Re: ACMI! Perhaps it would be well to show that ~~if~~ if a limit recursive seq. of PEMS can solve Fdss's then ~~this limit recursive seq. can be represented by a machine that is "universal" over all Fdss's.~~ This lim rec. seq. can be represented by a machine that is "universal" over all Fdss's.

Essentially, what I want to show is that the soln. must be at least as good as CB's on a UUDM. The idea here is that if someone proposes a soln. one can immediately test it for "minimal strength".

It's in the direction of generalizing the Minsky-Papert result on "perceptrons": i.e. to discover how what the inductive limitations of a language (or a means of representation) are.

I think Porgy is more like what I had in mind for the "Thrm" about the "nec. & suffy" of CMI.

15
70.40
56.29 spec

TM71

M responds to $0^{(n)}$ by printing 1 (even if $n=0$),
" " " $0^{(\infty)}$ " " 0.

Is $M \in MS_M$? If $0^{(\infty)}$ is inserted, M could never print 0, in any finite time. So, for $0^{(n)}$, ~~at least~~ M prints 1 after time n ; for $0^{(\infty)}$, it never prints.

It is impossible for M to print "0" in response to $0^{(\infty)}$.

So - for all inputs, I think f . first output sq. does converge.

M_1 responds to $0^{(n)}$ with 0 if n is even, 1 if n is odd, no print if $n = \infty$.
we can use any f of n that varies per f .

Is $M_1 \in MS_{M_1}$? For every input, f . first output sq. does converge,

(but there is no max length of input that need be examined to determine f 's first sq. (in contrast to FOR^2).

SN T. soln. W. does is ~~probly~~ probly not lim rec. solvable in γ . sense of Gold, - but is γ . limit of a set of recursive approxs. to γ . probly. Hvr, the n^{th} digit of f . probly that W obtains is lim. rec. solvable in γ . sense of Gold".

T. present work on MSMS & induction is perhaps in γ . direction of Blum's paper on γ . Q. of what broad classes of seqs are extrapolable. What I've found is that γ . class of extrapolable seqs is broader than had been ~~that~~ that - a result probly \sim to Blum's.

3974
59.90 spac
01:71.00

A summary of some recent results in Inductive Theory.

(Note: Unless otherwise noted, the terminology and notation will be that of Willis 1970)

1) Let M be a Universal Turing Machine. Let M_T be a c.f. on that machine, that allows only computations of $\leq T$ steps.

Let P^{M_T} be the computable probability measure associated with M_T .
Then for every string of length m , $A^{(m)}$,

Thm I: $\lim_{T \rightarrow \infty} P^{M_T}(A^{(m)})$ exists.

This is easily seen: $P^{M_T}(A^{(m)})$ is a non-decreasing function of T , and this function is bounded above by 1.

Call this limit $P^M(A^{(m)})$.

This limit is never ~~computable~~ effectively computable.

$I^M \equiv -\log_2 P^M$ is ~~now~~ called the "information in string" $A^{(m)}$

check Willis

Note at beginning: The following are a set of results that have presented ~~apparently~~ without proof — to give an idea as to ~~what~~

I will present here a set of apparently important results in the theory of inductive inference. Most of these results follow directly from the work of Willis (1970). I will use his ~~terminology~~ terminology

and notation, unless indicated otherwise. Although it is necessary to read Willis' paper to understand the present paper in any detail, it is still possible to get some idea of the present results without doing so, and such a reading will, hopefully, motivate the reader to do so. In the present report, few proofs will be presented.

A more detailed paper giving more detailed discussion and proofs ^{can be} expected to follow soon.

2) Theorem II For any computable probability measure, P_0 and any string of length m , $A^{(m)}$,

$$I_0(A^{(m)}) \equiv \log_2 P_0(A^{(m)}) \text{ and}$$

$$I^M(A^{(m)}) - I_0(A^{(m)}) \leq b + c$$

Willis' most important paper.



see 101.01-10 for a more exact def of b.

01: 85.40!

Have b is the length of the description of P_0 with respect to M , and c is a ^{positive} constant that is characteristic of M . It ~~is~~ is the length of a program that falls M how to construct a FOR that corresponds to P_0 .
 ~~M can be chosen so that c is always 0.~~
 Equation 86.40 suggests that for large values of m ,

(if b is defined by 101.05-10, then $c=0$)

$P^M(A^{(m)})$ might give very good approximate values to the $P^M(A^{(m)})$

value of $\frac{P_0(A^{(m+1)})}{P_0(A^{(m)})}$ - which is the conditional probability

~~that~~ that $A^{(m)}$ would continue as $A^{(m+1)}$.

To see this, rewrite equation 85.40 as

$$\prod_{i=2}^m \left[\frac{P^M(A^{(i)})}{P^M(A^{(i-1)})} \cdot \frac{P_0(A^{(i-1)})}{P_0(A^{(i)})} \right] \leq 2^{b+c}$$

write it in this form

$$\prod_{i=2}^m \frac{s_i'}{s_i} \leq 2^{b+c}$$

$$\left(\prod_{i=2}^m \frac{s_i'}{s_i} \right)^{\frac{1}{m}} = 2^{\frac{b+c}{m}}$$

where $s_i' \equiv$

$$s_i \equiv \frac{P_0(A^{(i)})}{P_0(A^{(i-1)})}$$

are conditional probs for P^M and P_0 resp.

$$\text{and } \left[\prod_{i=1}^m \left[\frac{P^M(A^{(i)})}{P^M(A^{(i-1)})} \cdot \frac{P_0(A^{(i-1)})}{P_0(A^{(i)})} \right]^{\frac{1}{m}} = 2^{\frac{b+c}{m}}$$

for large m , the right side is close to 1.

The left side is geometric mean of the ratio of conditional probabilities obtained by P_0 and by P^M .

The average of this ratio is close to unity. From this fact alone, it is not clear that the individual ratios need be close to 1.
 of the particular nature of probabilistic sequences, it is possible to show that s_i' and s_i are nearly equal.

It is not, however, apparent that the individual ratios are close to 1. Because the next theorem, however, makes this more likely.

values of i , very very close to unity for almost all values of i - which is the next theorem.

28 3) Theorem III for the conditions of Theorem II,

for proof see 7 fm willis, 1973, 1+1-14, 162

$$E \left(\sum_{i=2}^m (s_i' - s_i)^2 \right) \leq \frac{2^m}{m} \sum_{i=2}^m (s_i' - s_i)^2 \leq \ln 2 (b+c)$$

Here E is the Expected Value with respect to P_0 .

$A^{(m)}$ is the k^{th} sequence of length m . There are just 2^m of them.

s_i' and s_i are conditional probabilities for the i^{th} bit of $A^{(m)}$

for P^M and P_0 respectively.

87.40 This says that if one uses P^M (which is approximately calculable) rather than P_0 (which is unknown), then the ~~error~~ expected value to the total squared error will be bounded by ~~some~~ $(b+c) \ln \sqrt{2}$.

In any way, this ~~is~~ is stronger than saying that the ~~error~~ error approaches zero as the length of the sequence approaches ∞ .

It is possible to choose ~~an~~ M so that ϵ is $\ll 1$. One can make ^{very rough} estimates of b by assuming that P_0 is of about the same complexity as computable probability measures that have been ^{empirically} observed in the past.

4) Theorem IV While any probability evaluation method P , such as P^M , that for which expression 87.32 is bounded,

~~must have a corresponding~~ M

for which $-\log_2 P(A^{(m)}) = I_0(A^{(m)}) \leq K$,

a positive constant, has ~~corresponding~~ constraint on its ~~total error~~ expected total square error

corresponding to eq. 87.32, the converse is not true.

(I may want to drop this then. In its present form, it's rather weak; the relevant PP are

see index 202, 20 for refs to this. I think ~~is~~ at MIT on my desk. (~ 163 - 185).

Actually this begins to look trivial in one sense - since eq. 85.90 is for any $A^{(m)}$ and 87.30-32 is for the expected value wrt all seqs of length m .

so certainly 85.90 is very strong in some sense - being a constraint on every $A^{(m)}$ - while 87.30-32 is a constraint on expected values only.

Avr, say we have a P , for which 87.30-32 is true for all P_0 . Then it is conceivable that 85.90 will be implied.

So check on just what was proved here! → see 97.01 for discn.

174 R
 90.40: 5) Theorem § V: It has been noted that $P^M(A^{(m)})$ is ~~never~~ never effectively computable. ~~It is probably the~~ ~~simplest~~ In general, there can be no effectively computable probability method that will converge for large m values, for all P_0 's that are effectively computable. However, if we restrict our possible P_0 's to be in some known complexity class, then ^{computable} a probability evaluation method P exists, ^{otherwise} similar to P^M , having the convergence properties described in Theorems III and IV.

Unclear as to what this refers to.

~~The~~ P is said to be in complexity class $F(T)$, (where $F(T)$ is a known recursive function), if it takes less than $F(m)$ steps to compute $P(A^{(m)})$ to some specified accuracy.

6) Since P^M is itself incomputable, and ~~is~~, superficially, it would seem that approximations to P^M require an enormous amount of computing, it is natural to ask if there might not be other probability evaluation methods that are ~~as~~ good as P^M , but perhaps ~~more~~ easier to approximate.

I feel that there are probably no such easier methods, if we consider methods that are limits of computable methods.

A theorem to this effect (which I have not been able to prove) is as follows:

Suppose that P_T ~~is a sequence~~ (T=1, 2, ..., ∞)

is an infinite sequence of computable probability methods such that $\lim_{T \rightarrow \infty} P_T(A^{(m)})$ exists for all ^{finite} $A^{(m)}$.

Also, suppose that $(-\log_2 P(A^{(m)})) + \log_2 P_0(A^{(m)})$ ~~is bounded~~ $< k$ upper bound ~~where~~ for all computable probability ~~measures~~ P_0 .

Here k ~~depends~~ depends on P_0 but is independent of m .

Then ~~for~~ ~~any~~ for every P_0 , there exists ~~such~~ so large that ~~T > T_0 implies that~~



91.40:

on R_T , ~~and on R_0~~ , sub ϵ T_0 so large that
 $R_0 \subseteq \epsilon R_T$ for all $T \geq T_0$.

where $p(R_0) \equiv P_0$ and $p(R_T) \equiv P_T$. $\rightarrow R_0$ and R_T are both **FOR's** (from set of resources)

SN At t. present moment, I'm not sure t. forge. Perm is false, I'm almost sure that perms based on UMSM's ~~will~~ will work for P in t. above case, but UMSM are (usually, if one has a reasonable postulate set) ^{uniformly} stronger than UOMS — ~~so a UMSM would satisfy t. conclusion.~~

The cause of the theorem is that if the sequence $[P_T]$ is as powerful as ^{stated} ~~is~~, then it must be derivable from a sequence of machines (FOR's) that "approach universality" — in the sense of being able, in the limit, to simulate any other machine.

N.B. This theorem can probably be strengthened by omitting R_0 here. I.e. R_T and T_0 exist as a function of any $R_0 \Rightarrow p(R_0) = P_0$.

But R_0 doesn't have to be choosable along with R_T .
 \rightarrow Once R_0 is chosen subject to this constraint, we can then find a T_0 and a $R_T \Rightarrow (T \geq T_0 \text{ and } p(R_T) = P_T)$ together imply $R_0 \subseteq \epsilon R_T$. $\forall R_0, \exists T_0 \Rightarrow \forall T > T_0$ we can find R_T .

When stated as 91.30-92.30, t. theorem may be false. I may be able to prove it! To prove it: show that t. contrary (i.e. for any $T_0 \exists \epsilon T > T_0 \Rightarrow$ There exists no $R_T, \epsilon \Rightarrow R_0 \subseteq \epsilon R_T$ and $p(R_T) \equiv P_T$) is imposs.
 $\Rightarrow p(R_T) = P_T$
 $\Rightarrow R_0 \subseteq \epsilon R_T$
i.e. $\exists \epsilon R_T \Rightarrow p(R_T) = P_T$
 $\Rightarrow R_T$ can simulate R_0

That if it were true, then P_T would not \rightarrow a limit, or if it did, then t. limit wouldn't satisfy 91.34.

\rightarrow Another trim out. Thm: in .06, the condition $p(R_0) = P_0$ is unnecessary. The idea is, that for any $R_0 \exists T_0$ and R_T and $\epsilon \Rightarrow (T \geq T_0, p(R_T) = P_T)$ imply $R_0 \subseteq \epsilon R_T$. 9301

1114 R
 .01; 95.40: { Proof (I think): A param like 95.30 can be directly associated with a MSM - i.e. one can devise a MSM ~~that~~ whose output is the outputs of successive FOR's associated with each of the Pams in the limit. Since a UMSM can "cover" every MSM, 95.38 follows, 46.30 - 40, 48.01 - 05 (49.02 ft - probably not past 51.40.) Deals w. LPMs \rightarrow MSMs]

- (1) At the next beginning, mention that M is a UOM
- (2) Try to make all ^{must} terms clear w/ refs to W's paper. (e.g. give defn of PM)
- (3) Introduce concept of LPM as soon as possible. So Q. Is PM most powerful LPM? (answ: No.)
- (4) If P_0 is a PM that is discoverable by a finite no. of params, a_i , then P_0 is continuous (or differentiable) w/rt the a_i , then P_0 is discoverable by PM. Here "discoverable" means $\sum a_i x^2 \rightarrow k \ln x$, not $\sum a_i x^2$.

I think continuity rather than differentiability is needed

A funct. can be continuous at a pt. & not be differentiable. e.g. $x \sin \frac{1}{x}$ at $x=0$. If a funct. is ~~not~~ not continuous at a pt., it can have no derivative. It may, however, have a 1-sided derivative.

Hvri, I think the only functions calculable by Trms are continuous functions!

96.90
90.90 spec

Discussion of the Thm's proof of falsity of converse of
Thm. III (87, 28)

Apparently, from 168.30 the Thm I proof was not exactly the converse, but

Recall $E \leq (S_i - S'_i)^2 \rightarrow$ does not imply $E(\ln p - \ln p') \rightarrow 0$

which would seem to be a lot different!

I'm not so sure of (9.1)
q was written
on 168.32

R_i (Willis; 141.04) $\equiv S_i \ln \frac{S'_i}{S_i} + (1-S_i) \ln \left(\frac{1-S_i}{1-S'_i} \right)$

$R_i = S_i \ln S'_i - S_i \ln S_i + \ln(1-S'_i) - \ln(1-S_i) - S_i \ln(1-S'_i) + S_i \ln(1-S_i)$

Also 141.20: $R_i = S_i \ln \left(\frac{S'_i}{1-S'_i} \cdot \frac{1-S_i}{S_i} \right) + \ln \left(\frac{1-S_i}{1-S'_i} \right)$

I think the idea of the proof of $E \sum (P_i - P'_i) < \ln 2k$ involves the

fact that $E \sum (P_i - P'_i) = \sum E R_i(S, S')$ where S, S' are

source points of the P_i, P'_i . — $\sum P_i$ & $\sum P'_i$ are probs for the entire seq.,

S, S' are conditional probs. Willis 145.31-36 summarizes this

proof.

Rec! Thm III: F_i is a ^{randly} probab of ~~seq~~ X_i with a limit of

seq. P_i is an attempt to approx. it. 181.20, 25

But I'm not sure — what are P_i & P'_i ?

In 184.18 $P'_i = P_i - h_i$ unless $P_i > h_i$

$P_i = e^{-\frac{1}{P_i}}$ ~~XXXXXXXXXX~~

Perhaps 181.16 ff explains the notation adequately. Anyway — my conception is:

\vec{F} is the seq. to be predicted, \vec{P} is a CM derived attempt to predict \vec{F} ,

so $(\vec{F} - \vec{P})^2$ is bndd. \vec{P}' is some function of \vec{P} . We try to design

\vec{P}' so that $(\vec{F} - \vec{P}')^2$ is bnd, but $\sum R(F_i, P'_i)$ is not.

on 184.15: If $F_i = \frac{1}{2}$ — can this be? This means that
for large i , the seq. is doing very unlikely things. If it is, then it
is probably not predictable!

Also in 184.17, we get $p = h_i$: Run 184.18 says let $P'_i = P_i - h_i$
unless $P_i \leq h_i$ — well! what about it?

Anyway, I'm not sure h_i is relevant.

01: 97.40 This is beginning to look unreasonable! First, 97.30-32; Then, consider that F_n must have very many different sets of values — one for each of 1 to 2^m , sequences, $A^{(e)}$ — ; we must sum over them.

184.23 $P_i' = e^{-\frac{1}{P_i^n}}$; $R(F_i, P_i') = (97.10) = \frac{1}{2} (\ln 2) - \frac{1}{P_i^n}$
 $\approx \frac{1}{2} e^{-\frac{1}{P_i^n}}$ I think. $+ (1-\frac{1}{2}) (\ln(1 - e^{-\frac{1}{P_i^n}})) \rightarrow \ln(1-\frac{1}{2})$
 $R(F_i, P_i') = F_i (\ln P_i' - \ln F_i) + (1-F_i) (\ln(1-P_i') - \ln(1-F_i))$
 $= \frac{1}{2} (\ln 2 - \frac{1}{P_i^n} + \ln 2) + (1-\frac{1}{2}) (\ln(1 - e^{-\frac{1}{P_i^n}}) - \ln(1-\frac{1}{2}))$

For large i ; if $P_i \rightarrow 0$, it is $\approx \frac{1}{2} (\ln 2 - \frac{1}{P_i^n}) + (1-\frac{1}{2}) (-e^{-\frac{1}{P_i^n}} + \frac{1}{2})$

$\frac{\ln 2}{2}$; $-\frac{1}{2 P_i^n}$ are the largest terms. $-\frac{1}{P_i^n}$ is probably the largest of $1, 2$ — ~~and~~ and \sum of it diverges.

Anyway, I'm not so sure that Thm III is important at all.

- T. main terms of import: A) $\sum (P_i - P_i')^2 < \ln 2$; B) A \notin LPM that can cover all CPM's
- must be expressible as \sum of $\#$ of CPM's that \rightarrow unc. So: P^M will "do" for all CPM's ; it is about the simplest LPM that will do this.
- c) That all LPM's can be covered by P^{MM}
 d) " \exists at least one LPM that P^M does not cover.

I'm still not sure, but my impression of the "proof" of the "Thm" of ~ 185.40:

We took a particular sequence i a particular CPM, \rightarrow
 F_i (\equiv the cond. proby for i ; \mathbb{R} symbol) = $\frac{1}{2}$, say.
 Then, P_i is the proby obtained by CPI for i ; \mathbb{R} symbol.
 So $\sum (P_i - F_i)^2$, (I said) was bndd (The in fact, this is not exactly so).
 Then I devised P_i' as a function of P_i (\rightarrow perhaps of F_i),
 $\rightarrow \sum (F_i - P_i')^2$ was bndd "since" $\sum (P_i - P_i')^2$ was.
 Then I "showed" that $\sum R(F_i, P_i')$ was un bndd.
 This was supposed to show that $\sum (\ln F_i - \ln P_i')$ is un bndd. 101.01

would, I think, have to be bounded. — so choose a $\alpha_0 = \epsilon$.
 LUB of these α 's. It would be this, so would then be adequate for all T's assoc. w. that T_0 ;

so: Thm: If $\forall P_0, \exists K(P_0) \rightarrow I^{(P)} - I^{(P_0)} < K$
 Then $\forall R_0 \in A^{(m)} \exists T_0(R_0), \alpha_0(P_0) \rightarrow \forall T > T_0 \exists R_T \rightarrow (P^{(R_T)})(A^{(m)}) = P_T(A^{(m)})$ and $R_0 \in \mathbb{R}_T$
 Here we recognize that T_0 (B. not α_0) must be a function of m as well as P_0 . 102.01

an uncomputable limit that ~~over~~ limit can have.
 The ~~the~~ has the desired convergence properties.
 The convergence is quite rapid and the ~~the~~ ^{expected value of the} sum of the squares of R ~~is~~ \rightarrow 1 limit.

03.40: If the probability distribution of the source is not itself computable, but is expressible as the limit of a sequence of ~~prob~~ computable probability distributions, then a method exists for ~~measuring~~ predicting the symbol probabilities with very high accuracy as the sequence becomes very long. Again, as in the case of the finitely describable sources, such a prediction method is expressible only as the incomputable limit of a ~~set~~ set of computable prediction methods.

SN: Try to make a set of defns. so that the main 4 items are easily expressed in compact form.

Some concepts: κ limit recursive (or a.k.a. hyper-schubert defines)
 κ limit recursive Prags measures, ω limit recursive = recursive?
 or is ω limit recursive = recursive?
 Perhaps MSM's can be considered to be ω limit rec. machines —
 i.e. their behavior can be expressed as the limit of a set of UOM's.

Before going much further, write down just what
 the ~~terms~~ terms are, where the proofs are, what the weak pts in the proofs are, what the defns are & where they are written, & their poss. weak pts (e.g. MSM's, UMSM's, etc.) — Also ~~what~~ what a review of what that there is on why the ~~pr~~ $\sum (p_i - q_i)^2 < k$ is better than $E(\sum (p_i - q_i)^2) < 1/n \sqrt{k}$. — & why I probably wouldn't include it in the review.