

Willis' Induction Mechanisms — A Review and Some Corollaries.

see (28.01) for ^{terrible} ^{69 P. 100} ^{some mention}

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This memorandum ^{will be} ^{brief} ^{is} ^a ^{review} ^{of} ^{what} ^I ^{feel} ^{are} ^{Willis'} ^{most} ^{important} ^{results,} ^{present} ^a ^{few} ^{corollaries} ^{to} ^{his} ^{system} ^{and} ^{discuss} ^{the} ^{significance} ^{of} ^{the} ^{work.} ^{My} ^{present,} ^{very} ^{strong,} ^{impression} ^{is} ^{that} ^{it} ^{describes} ^a ^{both} ^{necessary} ^{as} ^{well} ^{as} ^{sufficient}

~~set~~ ~~of~~ ~~systems~~ ~~for~~ ~~inductive~~ ~~inference~~

i.e. Given a sequence of ^{discrete} symbols generated by some finitely describable stochastic source, the systems will, for sufficiently long samples, be able to predict the probabilities of the next symbols, with ^{errors in} probability approaching zero.

Since the systems are usually ^{run} ^a ^{bit} ^{awkward}, it is natural to ask if there are other, ^{more} ^{simpler}, systems that will do about as well. In a certain well defined sense, ~~there~~



no ^{other} ~~system~~ can do ^{as} ^{well} ~~as~~ ^{the} ^{ones} ^{Willis} ^{describes}.

Willis' work was ^{part} ^{of} ^{the} ^{outgrowth} ^{of} ^{some} ^{of} ^{my} ^{own} ^{work} ^{on} ^{induction} (3,4).

I described a method for evaluating the probability of any finite sequence of discrete symbols, by considering the lengths of various ^{input} programs for universal Turing machines that might have given this sequence as output.

The probability was the sum of the weights of ~~all~~ the possible corresponding input programs. A program of length n , was given weight 2^{-n} , if the machine had a binary input alphabet.

I ^{outlined} ^{some} ^{reasons} ^{why} ^{the} ^{probability} ^{assignments} ^{should} ^{not} ^{depend} ^{much} ^{on} ^{the} ^{exact} ^{specific} ^{universal} ^{machine} ^{that} ^{was} ^{used}, but I gave no real proof. I also gave various arguments to show it was likely that the probability values obtained were close to those that one expected for various

intuitive reasons, and I gave some examples of application of the system in which the results seemed reasonable. 412

Later, (3) I devised a criterion for the adequacy of an induction system and proved that no system ~~can~~ while it was clear that no system could satisfy this criterion, it seemed reasonable that the one I had proposed, would approximately conform. I shall discuss this criterion later in regard to Willis' ~~work~~.

~~Points~~. A most serious deficiency in my own work ~~was~~ surrounded Turing's "halting problem". It was clear that the system of probability evaluation proposed was not "computable" in a rigorous sense — and though approximation methods readily suggested themselves, it was not clear as to how this affected the accuracy of the results.

The ~~thing~~ ^{thing} that first stuck me in Willis' paper was his ~~method~~ ^{method} dealing with the halting problem by defining a set of Turing machines for which ~~normal~~ there is no halting problem, and ~~defining~~ ^{defining} a prob associating with each such machine, a computable probability method, of the type I had previously described. ~~That~~ None of these machines, of course, ~~are~~ ^{are} universal, but there are an infinite number of them, and one can, by selecting a sequence of them of increasing computing power, obtain a sequence of probability measures of greater and greater accuracy.

called. (FOR) → Willis calls these limited machines "Frames of Reference" perhaps since they relate their ~~output~~ ^{described} ~~to~~ ^{inputs (descriptions or coordinates) to} ~~the thing described to~~ ^{their outputs (the thing or point described)}.

(see page 1 of Willis' for his reasons for calling them FOR's)

The FOR is a tape Turing machine with unidirectional input and output tapes, and bidirectional memory tape. ~~Always~~ of input symbols

though willis considers machines with any number of symbols in their alphabets, there is no loss of generality if we allow only 2 ordinary symbols, 0 and 1.

It never gets into an infinitely long computation sequence without reading or printing. If it ever reads a square of its input tape, it will eventually write on ~~it~~ at least one more output square. ^{True e.g. when it gets in S or U loops} Conversely, if it ever writes on an output square, it will eventually read again on its input square. ^{True} for any finite input sequence, it will have only finite output sequence. ^{No. of U loops} ~~By using a general use of measure theory willie assigns probabilities to each possible output sequence.~~ ^{for any finite output sequence, it will have only a finite input sequence.}

Then it would never stop.

The FOR has, in addition, 2 special symbols, S and U.
 If it ever prints S, then it will continue to print nothing but S's for the rest of its output sequence.
 If it ever prints U, it will correspondingly continue with U's only. ~~The S sequence corresponds to an ordinary machine which stops.~~

When an FOR has been devised to partly mimic the behavior of a more general (e.g. universal) machine, the S sequence corresponds to the machine stopping; the U sequence ~~indicates~~ indicates uncertainty in whether the machine is in a infinite computation sequence or not.

A very simple, ~~yet~~ yet powerful, set of FOR's is that based on the time limited universal machine. ~~The~~ ~~universal~~. The ~~is~~ ~~T~~ such machine acts exactly like a specific universal Turing machine for all computations that take T steps or less, ~~except~~ except that it prints S's when the universal machine would stop. ^{in infinite sequence of} As soon as a computation ^{takes} longer than T steps, it prints a sequence of U's.

To assign probabilities to sequences, willis uses measure theory in an ingenious way that insures that these probability assignments satisfy all of Kolmogorov's axioms for probability. ^{well, it often prints U's} Perhaps of more interest: A CB in which computation time allowed is a function of output symbols printed thus far.

25
 Ref. →

This is done by associating with each of the ~~number~~ infinitely long input sequences, the point unique point on the interval $(0, 1)$ ~~that can be done by considering each~~

~~As a function of the sequence of bits, which is the infinite binary expansion.~~

that corresponds to the ~~fraction~~ ^{real number} of which that sequence is the binary expansion. It is clear that the total measure of all such points is 1.

The probability associated with any finite output sequence, α , is the total measure of all input sequences, that give output sequences that start out with the sequence, α .

It is clear then, that if $P(\alpha)$ is the probability assigned to α , then $P(\alpha\hat{0}) + P(\alpha\hat{1}) = P(\alpha)$.

— Since all sequences that start out with α , must also start out with either $\alpha\hat{0}$ or $\alpha\hat{1}$.

The Possible and The Impossible in Inductive Inference.

TH415 106/63
128 Sept 21
234 Nov 21
63
120
1.6
1.7
6.8
102
1.7

I will briefly review my own ~~work~~ ^{and} work in induction ^{explaining} its ~~main~~ ^{description} ~~main~~ ^{description} deficiencies, ~~and~~ ^{and} how it overcomes these difficulties. ~~Finally, I will discuss the significance of this work in relation to some theorems on what cannot be done by any inductive system, and an illustration of a few systems that do this.~~

~~and will conclude with a list of solutions to the induction problem that constitute~~
It is possible to show, that given any computable method of ~~evaluating~~ ^{evaluating} the probability of successive symbols of a sequence, in terms of the known part of the sequence, one can always devise a stochastic source of symbols for which this computable method ~~will~~ ^{will} fail miserably. In fact, if it were to be used on a binary sequence, its probability ~~assignments~~ ^{for each conditional probability} would always err by a factor of at least $(2-\epsilon)$.

Fortunately, ~~one~~ ^{one} need not limit ~~itself~~ ^{itself} to computable probability methods. ~~Any~~ ^{any} ~~sequence~~ ^{infinite} sequence of computable probability evaluation methods can be used in which the limit ~~exists~~ ^{exists} but is not computable. A certain ~~set~~ ^{described} equivalence class of such sequences will be ~~discussed~~ ^{discussed} that give optimum in a certain defined sense, optimum predictions for ~~any~~ ^{any} ~~fixed~~ ^{fixed} sequence. Any sequence of methods not in this equivalence class will give ~~significantly~~ ^{significantly} arbitrarily worse predictions for sufficiently long sequences. Two ~~arbitrary~~ ^{specific} members of the ~~class~~ ^{equivalence} class will be ~~discussed~~ ^{discussed}.

comment: ~~we~~ ^{we} have but ~~may~~ ^{may} be excluded later.

30

This ^{acquaintance} class of sequences of probability evaluation methods ^{is the class well defined.} ~~is the class well defined.~~ \rightarrow sense, a unique, optimum / solution to this

inductive inference problem. \rightarrow Members of the class predict as well as well as can be ~~shown~~ ^{predicted} and no non-member of the class can ^{predict} as well.

Two specific representatives of the class will be discussed. By using other criteria of optimality, other, less well defined

classes of probability evaluation methods can be described, and these will be discussed briefly. (2.32.12)

(3) ~~is~~ \rightarrow there is a certain well defined sense, ~~an~~ optimum solutions for the ind. prob.

O.k. ; T. above looks like an adequate abstract.

Oh to meaning of this optimum soln. to f. ind. inf. prob.!

+ Ann Rev 69 129.35 - 131.04 ²⁴ (Sept 1969)
gives one f. idea that I really didn't have any
clear I did on how to prove it ~~on~~ Sept 24.
Hvr. - ~~2~~ ² more months to Nov 26!

what was f.
2 examples?
Time is memory
limitation,
what other
classes of
prob. soln.
methods?

Solution to the problem of Inductive Inference. or Unique Soln to Prob. of Ind Inf. (1)

~~It is shown that the formulation of in~~
A particular general form of the induction problem is discussed. TM 417
~~It is shown that while it is known that effectively~~
computable solutions do not exist, it is shown that
the limit of a sequence of computable approximations
~~can~~ indeed exist - ~~but it is not~~ ^{though} this limit is
not itself effectively computable.

Willis' treatment of induction is shown to be a sequence
of computable induction methods whose limit gives an approximation
to probability values whose total squared error converges
to a finite value for ^{sample} sequences of arbitrary length.
~~These sequences~~ This limit also possesses a stronger
convergence property.

It is shown that the only ~~the~~ sequences of approximations
to probability ~~values~~ having this convergence property are
of the type described by Willis, so that his
formulation is both necessary and sufficient for this
~~convergence~~ convergence property.

The question of obtaining optimum approximations
to probability values using a bounded amount of computation
is discussed.

A unique solution to the problem of ind. inf.

~~The inductive inference problem is defined to be~~
ABSTRACT. This paper presents several corollaries of
Willis' theorems that reveal the extent to
which his work constitutes a unique soln.
to the problem of ind. inf.

All forms of induction are said to be reducible to
the extrapolation of a ~~the~~ sequence of symbols containing
all of the information to be used in the induction.

~~While it is easily shown that no~~
While it is easily shown that no effectively computable
solution to this problem exists, Willis has proposed an
infinite sequence of effectively computable approximations
whose limit exists, though ^{the limit} ~~itself~~ ^{not effectively} computable.

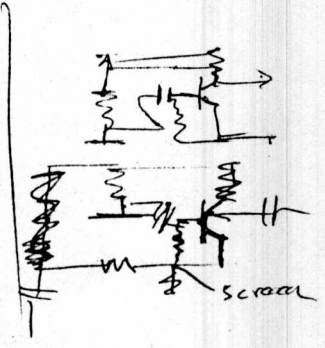
This limit satisfies a certain very strong convergence
property - which ^{in turn} implies the convergence of the sum of
the squares of the ~~errors in probability estimates~~ ~~estimated~~
deviations of the estimates from the true probabilities.

It is shown that the only sequences of probability approximations ~~having~~ the strong convergence property are those of Willis. In this sense, they ~~are~~ ^{constitute} a unique ~~Michaelson and sufficient~~ solution to the induction problem. ^{Convergence of} The total square error ~~is~~ is, however, a weaker

The use of these sequences in practical approximation of probabilities ~~is discussed~~ and ~~also~~ ~~of~~ ~~criteria~~ and it is possible to have a sequence of induction methods that approach this as a limit, that are not one of Willis' sequences.

The effect of this formulation on various difficulties in induction and scientific method is discussed, as well as the application of these ^{approximations} ~~methods~~ to practical prediction problems.

- For Kellogg's address try
- 1) Willis
 - 2) McCarty.



- Discuss various constraints on soln. e.g. CB & Length
- 2) The case of infinitely long being, (i.e. down length \propto ^{or} in corpus length)

Title

The Uniqueness of Willis' solution to the Inductive Inference
or: A unique Soln. to the problem of Inductive Inference. **Problem.**

~~The~~ ~~pres~~ This paper presents several corollaries of Willis' theorems that ~~show~~ ~~that~~ ~~his~~ ~~work~~ ~~to~~ ~~the~~ ~~general~~ ~~problem~~ ~~of~~ ~~induction~~ ~~and~~ ~~that~~ ~~it~~ ~~is~~ ~~the~~ ~~only~~ ~~one~~ ~~that~~ ~~provides~~ ~~a~~ ~~unique~~ ~~solution~~ ~~to~~ ~~the~~ ~~problem~~ ~~of~~ ~~induction~~. ^{reveal} ~~the~~ ~~extent~~ ~~to~~ ~~which~~ ~~his~~ ~~work~~ ~~constitutes~~ ~~a~~ ~~unique~~ ~~solution~~ ~~to~~ ~~the~~ ~~induction~~ ~~problem~~.

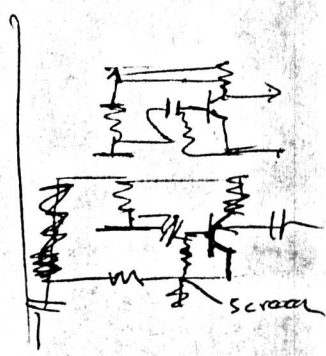
73.

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The use of these sequences in practical approximation of probabilities is discussed, and their off criterion and it is possible to have a sequence of induction methods that approach this as a limit, that are not one of Willis' sequences.

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- For Kolmogs address try
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Discuss various constraints on soln. e.g. CB & Length

2) The case of infinitely long being, (i.e. Devn length \propto ln corpus length)

Title - **The Uniqueness of Willis' Solution to the Inductive Inference or A unique Soln. to the problem of Inductive Inference. Problem.**

The ~~pres~~ This paper presents several corollaries of Willis' theorems that ~~establish~~ ^{show} his work to the general problem of induction ~~and that~~ ^{show} ~~the~~ ^{extent} to which ~~his work constitutes~~ ^{his work constitutes} a unique solution to ~~this problem~~ ^{the general prob. of ind inf} the induction problem.

T2

Introduction

It has been known for quite some time, that certain forms of the inductive inference problem are unsolvable. ^{very in one rather} Specifically, ~~if~~ ~~is~~ given an arbitrarily long sequence of symbols that has been generated by a ^{fruitfully describable} stochastic source ~~that~~ has a finite description, ~~and it is required~~ that one estimate the probability distribution for the next symbol. There exists no algorithm that will do this for all possible stochastic sources, since, given such an algorithm, it is easy to design a stochastic ^{sources} ~~experiment~~ that will frustrate it.

~~_____~~

I will give an expression for a kind of algorithm that ~~does~~ ^{frustrates} this impossible thing — but the

~~expression itself~~

values of the expression are not ^{frustrates} ~~the purpose of counter example construction~~

effectively computable. ~~so it is impossible to construct~~ and it will be shown that the expression actually ~~does~~ ^{gives} very good predictions and that ~~no other expression of this sort can do better.~~ ^{counter examples that will frustrate it}

The expression itself is the limit of an infinite sequence of algorithms, each of which is effectively computable, ^{directly}

- While the limit is itself not usable for induction, the manner in which this limit is obtained suggests various approximations that ~~might~~ ^{computational complexity} be used. [If the stochastic source is limited in almost any way, a computable solution to the problem can be ^{demonstrated} shown.]

It is ~~impossible~~ ^{usually} impossible to compute useful upper bounds on the error in probability estimates made ~~by~~ ^{by} these approximations. I shall, however, give some ~~conjectures~~ ^{strongly felt conjectures} on other measures of expected future ^{prediction} accuracy of these approximations.

The present paper will first ~~then~~ give an expression for the "limiting algorithm" and will show that the limit, indeed, exists — though it is not effectively computable.

Next, the error properties of the limiting algorithm will be investigated. Willis has devised an error criterion for induction algorithms. I will show that if Willis' ~~error~~ total error ~~is~~ ^{some} constant, k ,

then the total squared error of probability estimates ^{for sufficiently long sequences} must converge to $\leq k \ln 2$. k is always less than the Kolmogorov complexity of the stochastic generator. k is ~~the~~ ^{or some n thing} ~~of the~~ ^{I will then} stochastic generator.

~~An example will then be produced to show that Willis' error criterion is stronger than the total squared error criterion, by producing an example of an induction algorithm that satisfies the total squared error criterion but not Willis' criterion.~~

The last theorem will show that any limit of inductive algorithms ~~that satisfies Willis' criterion~~ for which Willis' total error is bounded by a constant, must be one of the kinds of algorithms that are being described in this paper — i.e. that this limiting algorithm is, in this sense, a unique solution to the inductive inference problem.

I will then give some expressions that I feel are likely to give ~~estimated~~ upper bounds on the expected future "information content per symbol" of the sequence

Outline of Paper:

- 1) Introduction: This reviews history of problem:
- a) Ancient, classical.
- b) My work
- c) ~~W's~~ W's work.

Some Unsolved Probs in Induction Theory.

Then tells what state of problem was in after Willis.

Then tells what f. present paper shows: i.e.

- ① W's expressn \rightarrow a limit as $CB \rightarrow \infty$
- ② $\sum \text{error}_w < k$

Discn. of W's error defn. — that it can be + or -, so, superficially ^{direct} ~~stated~~ that $\sum \text{error} < k$ does not insure that r . individual errors are small.

③ That $\sum \text{error}_w < k \Rightarrow$

$$E \left(\sum (p_i - p_i')^2 < k \cdot \frac{1}{n^2} \right)$$

④ Willis' error criterion is stronger than since E will give examples that satisfy S but not

⑤ ~~Agreement~~ If r . ~~limit~~ seq. of pams \rightarrow a limit, & this limit ~~has~~ has an error as small as W's \leftarrow , then this seq. of pams is one of W's kinds.

Or: the only kinds of sequences of pams whose limit ~~has~~ ^{satisfies} property are t./pams ~~proposed~~ proposed by W.

$$p = \frac{n}{1+n} \approx 1 - \frac{1}{n}$$

$$= \frac{1}{1 + \frac{1}{n}}$$

$$= 1 - \frac{1}{n} + \frac{1}{n^2} - \frac{1}{n^3} \dots$$

$$\leftarrow \frac{n}{1+n} \approx \frac{1}{1+n}$$

$$\sum \frac{1}{1+n} \text{ diverges}$$

38 — ⑥ That Lap's rule & other rules of w form are wrong in t. case of non-probabilistic seqs. Is One of few "hard" results.

7 More practical results.

- (a) Laps rule is wrong for determ. seq. Also, its wrong if ~~prob ratio is 1/2, 1/3~~ or any computable expression. ← not so clear, hvr. - I'm not sure.
- (b) If f . corpus is of bnd complexity - bnd in practically any way, then we can devise computable Pams that converge as fast as possl. a.g. $CB \propto T^{\epsilon}$, ϵ length of f . seq.

(c) Most laws in the sciences (prob. or determ) ~~do not~~ do not have finite decus. In ~~most (perhaps all)~~ such laws, there is a simpler modifi. of W's results to deal w. them - i.e.

Σ error $\rightarrow \epsilon \ln T$

Give example of simple Bern. seq.

→ Hvr, if $p_n = \frac{1}{2}$, say, $\Sigma(\text{error})^2 < \text{const}$,

$\Sigma(\text{error})^2$ diverges in conventional statistics.

So this is about i. same as f . $p=1$ case

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Thru Oct 21

Perhaps after (5) : (i.e. 9-38) : Have long section on t. significance of t. results

To start on Laps rule on 110, on ~~prob~~ laws of nature that have comp. bnds like ~~linear~~ (linear in T or some known $f(T)$).

Note that all of t. sci. rules proposed thus far are probably of ~~small~~ relatively "small" c.B. (i.e. not much $>$ linear in T) (?).
— Perhaps not so for mechanics of Gases - in which comp. may \uparrow exponentially.

Q. of whether there are other ways to limit t. search algorithm \rightarrow a "soln" is possl. (i.e. $E(\text{error}) \rightarrow 0$ as $T \rightarrow \infty$). Blum have solved this for t. ~~det.~~ deterministic induction problem. For deterministic induction, there is ~~a~~ simple soln. if t. set of allowable seqs is recursively enumerable (\equiv ~~v.e.~~ \equiv countable).

(SN) Politics: It might be well to give a talk at a ~~semp~~ meeting related to "Computational Complexity" \perp At t. Detroit meeting Hartmanis has an invited talk on this. - Anyway, it sort of ~~is~~ is related. [Abstract in By Dacl]

Another possy. is Phil. of Sci. - symp. } ← [Perhaps AAAS Meeting or That New England Party thing.]
Also statistics Symps.

So anyway: This is a good way to present part of Y.

conclusion: i.e. ① w. no restrictions on Y. spec algorithm, there is no soln. ② if Y restriction is a suitable CB as a fact of T (or 'inducibility' in C or exponentiality) then I have this very rapidly converging method ③ T. general Q is: what are some other constraints on Y. set of alg's that give convergence - & how fast do they converge? will if Y. alg's are r.e. will this do it? Since this constraint of ② gives ~~the~~ perhaps as fast convergence as one could ever get, one suspects there are much weaker constraints that will give slower convergence -

15

So that one part of Y. conclusion - its a

statement of what has to be done.

T. second part is on practical induction.

T. Third part is trying these results into Y. probs. of scientific method -

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Given a certain computing capacity and a

certain sequence of data - how can we best

use that comp. cap. to do induction on that data seq?

T. use of CMI directly seems to be very wasteful -

probably hopelessly so. Hvr, Y. method does suggest practical techniques for induction -

~~One~~ One of these involves a Goodness Criterion:

for induction algorithms wrt a given data seq. The simplest

~~algorithm~~ is of these is $\frac{A+P}{S}$; where A is ~~the~~ length of descn of Y. algorithm one has been able to find &

P is Y. probty of Y corpus wrt. that Algorithm. (A is Kol compy)

A' + P is another where A' is ~~an~~ with an approxn. to w. complexity (A' ~~is~~ is always < A)

~~the~~ better yet is $\frac{P}{S-A}$ where S is Y. no. of symbols (binary) ~~in~~ inpt

in Y. data seq. ; there are other refinements that one can make.

These Goodness criteria give an upper bound on how bad

our expects to predictions of that algorithm to be in the future. 425

Since ~~the~~ ~~MI~~ ~~inherent~~ No inductive method can give a good estimate as to how much a proposed algorithm differs from the correct one, but the Goodness criteria I've described are useful in many cases ~~and of even more value than~~ of about equal value.

→ The problem of deciding which inductive algorithms to test. ~~has been~~ ~~is also~~ MI also suggests solutions to

These will be algorithms that ~~are at least~~ ~~do~~ have the simplest forms. The concept of "simplicity" ~~is~~ ~~while~~ Ordinarily the simplest forms will be those having fewest symbols - but in order to do this properly, one must assign costs to each symbol, based on its frequency of use in the past. In general each symbol will be the abbreviation of a subroutine that was used in the past.

Another trick to obtain simple algorithms is to modify or "mutate slightly", algorithms that have been much used in the past. If it has been used much in the past, its ~~abbreviation~~ ~~is~~ ~~then~~ ~~symbol~~ ~~is~~ ~~the~~ name or "symbol" is inexpensive. The name of the mutation used ~~must~~ should also be of low cost (i.e. frequent past use) to help form a new inductive algorithm of low cost.

~~A third area in which much work~~
The Goodness criteria for algorithms that I've described are of uncertain value. ~~MI~~ The reasoning behind them is plausible but inexact. I've tried them on some induction ~~on~~ algorithms involving linear regression. They give reasonable results. Certainly much work needs to be done in this area.

90

The selection of algorithms to test

While the methods I've outlined for selecting algorithms for testing seems reasonable, I have not really tested it in any practical cases. I have done some work on the cost of defining symbols and subroutines (I & C part 2 - give pp), but certainly (much work needs to be done here).

07

08

A third ~~more~~ direction of research suggested by CMI is in the philosophy of science.

Q. of confirmational; ^{of hyp. by gn. evidence.} Theory construction methods; wt. of a priori info., ~~Fit of the~~ ^{Attractiveness of} ~~Goodness of~~ Theory v.s. wt. of exptl. evidence, etc.

20

6:05
6:22 P
6:35 P
6:45
6:53
freq. of various symbols.
Ngn. traps
upon transition traps

So anyway, the paper will be:

Introduction Abstract:

Introduction: [redacted] (401 ff)

History

what paper shows in more detail than Abst.

signif. of Results

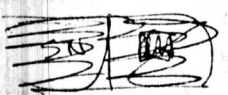
A. To what extent is it a solu. } 6.01 - 15
what other kinds of solns. Prev are.

B. Applies to Phil of Sci., Sci method, etc. 8.08 - 20

C. Applicn. to practical inductions A.F. 6.20 - 8.07
Also mention Kol's ~~cat~~ complexity used in part discry by T. Cover.

D373 : \Rightarrow I may want to include a proof for the "all items" method.

This is because in this form, CMI is closer to what one does in science. — it is a wtd Σ of a bunch of hypth —
Hvr., I'll have to note various approx. forms of it, & tell which ones are bad. — Also perhaps mention SVH "results".



At the end, list some "Open Problems": e.g.

1) If one uses the "best" pair for each predn., will this method converge as corpus length $\rightarrow \infty$, & if so, how fast.

\Rightarrow (Would it be possl. to show this is identical to a non a.c. "Willis" method & \therefore have ∞ error convergence?)
 \rightarrow or show it is not equivl. to a Willis method so ∞ error must be $>$ that of Willis). ^{in proof of deriv.}

2) Show that $\epsilon \leq \frac{A + f(s)}{s}$

Thms: 1) $\Sigma \epsilon^2 < k$

2) $\Sigma \epsilon^2 < k$ does not imply $\Sigma \text{cost} < \alpha k$

3) $\Sigma \text{cost} < \alpha k$ imply CMI

4) All pairs method. (Mention that Σ of a few pairs w/ "prefer" wts. is W.G.)

5)

Open Probs:

1) If best "pair" is selected does this converge as $s \rightarrow \infty$?

2) Is $\epsilon \leq \frac{A + f(s)}{s}$ true or approximately true? (Is it true for $A = \log_2 \text{pcost of pair}$)

or for $A = k \text{ cost of pair}$)

3)

(Note that "expected value" can be defined! But may be true only for stationary seqs. — i.e. seqs $\xrightarrow{\text{slow}}$ which \exists exists.)

T. idea of a seq. of machines "approaching Universality" — I think my idea was that if $M_i = \{ \dots \}$ were r. seq. of machines, then for any finite machine M' $\exists j \Rightarrow (i \geq j \Rightarrow M_i \text{ can simulate } M')$.

Hvr, this defn. will not work if we allow M' to be any non-univ. machine: E.g. If we use $M_i = \text{unc. w. } \uparrow \text{ bound of } i$, then

M_i is a FSM & it has a finite memory. — There are lots of non univ. ^{having inf. memory} trms that any FSM can't simulate.

Hvr, ~~155.10~~ 155.10 (Willis) gives a defn. of universality that is probably Ok.

I'm not yet sure that r. \uparrow limited times "approach universality" in an usable sense. Furthermore if we allow τ to be a function

of S , ^{FCS} f. corpus length, we still can't get a sequence of $F_i(S)$'s, \Rightarrow r. result that \uparrow LU's approach universality!

Hvr, for a fixed corpus length, S , ~~with~~ r. \uparrow LU's do approach universality.

Without r. restriction to fixed S , there is no sequence of r.e. FOR's that eventually "covers" every specified FOR (i.e. approaches universality).

T. uniqueness thrm. is proved for ACPM's only. (if proved at all!)

From 155.05 $\forall R \left[\lim_{i \rightarrow \infty} \sum_{arr} (P_i, F, R) \leq k \right]$
 I'm assuming these are interchangeable! "E" involves a finite sum.

$\forall A^{(2)} \left(\lim_{i \rightarrow \infty} \sum_{arr} (P_i, F, A^{(2)}) \leq k \right) \rightarrow$ is stronger than

155.30 / If $R_F \neq R_j$ then $\left(\forall k \exists F' < k P_j' \right)$ is false for any $k > 0$ $\left(-k \neq k \right)$

$\therefore \exists \forall k \exists A^{(2)} \Rightarrow \text{~~... ..~~} F(A^{(2)}) > k P_j'(A^{(2)})$

155.37 seems to be in doubt: $A^{(2)}$ is of measure (wrt. F), > 0 & ~~... ..~~ P_j & F differ by a really large factor wrt $A^{(2)}$,

- But does P_i 's mean that P_i 's would be untrue? Certainly P_i 's would be untrue, but r. falsity of .33 does not imply r. falsity of .38.

So Thm. 33 is wrongly true: Also any seq. of P_i 's for which .33 is true, imply that $R_i \rightarrow$ universality.

D 1373 : The idea here is that the "Expected value" Eqn. (10.31) means that $F(A^{(m)}) \left(\log_2 \frac{1}{k} \right)$ is arby large. We can get k arby large, but ~~the~~ choice of $A^{(m)}$ depends on k , and $F(A^{(m)})$ can be very small — even zero — since F is an arby. CEM — Tho P_j' would also have to be $\leq \frac{0}{k} = 0$ also.

Anyway, 10.33 is a strong theorem about CMI. It is stronger (i perhaps more useful) than 10.31 (which 10.33 implies).

But 10.33 is v.g. by itself, it gives us more direct confidence in a CMI than 10.31 does. 10.33 works for ^{all} individual sequences, $A^{(i)}$ of any length, l . So for large l we expect mean "error" to be small.

T. lemma needed around 155, 30:

$$\text{If } R_F \neq R_j' \text{ then } \forall k, \exists \forall \Rightarrow F(A) > k P_j'(A)$$

This is true because $\left\{ \text{If } R_F \neq R_j' \Rightarrow \forall k > 0, \exists \forall A, F(A) > k P_j'(A) \right\}$
 i.e. $\forall k > 0, \exists \forall A, F(A) > k P_j'(A)$. ~~It is false that~~ $\forall A, F(A) < k P_j'(A)$.

This is true because of the 2nd part of Willis ACM Thm 15.

Order of presentation

So: 1) First show that assoc. w. each Umc, (of W's type of Umc), ^{is "provable"} computable. That this proby measure is uniquely defined for that Umc.

(i.e. that it doesn't matter how the FOR's approach universality). $\left\{ \text{I think I must prove "Uniqueness"} \right\}$

omit this is included in 2) \rightarrow 2) ~~for any~~ for any cpm, ~~is independent of A~~ $P'(A)$; $\frac{P'(A)}{P(A)}$ is bounded, for any A . This bound is $k(P')$ — i. prob of A deriv of P' wrt to Umc. This implies "mean error" of $\frac{\log_2 A^{(l)}}{2}$.

3) say $P(A)$ is t. limit of a ~~seq~~ seq of cpm's, $P_i(A)$.

then \forall cpm's $P'(A)$, $\frac{P'(A)}{P(A)}$ is bounded ~~if and only if~~

$P(A)$ is a t. limit seq. of R ~~approaches~~ $\left(\frac{P_i}{R} \right)$ approaches universality as a limit.

D1373 : \mathbb{E} since $P(A)$ of 11.30 is f. ratio of 2 limits,
 it may be that $\frac{P'(A)}{P(A)} \leq K$ is not so easy to prove.

$P(A)$ may give some non-zero probs to Unobservable events —
 which may screw up t. proof!

This is an interesting Q: Does t. prop. imply that t. 345P

~~the measure~~ measure of all unobservable events is somehow limited?

Say $\leq \frac{1}{2}$? In W's Thm 12 (ACM 252.17) in $\text{Pam} \rightarrow \text{FOR}$:
 If t. Pam, P , has ~~unobservable~~ measure > 0 for only obs events (i.e. no
 U 's ~~ever~~ ever show up) then ~~the measure~~ we have no U 's in t. corresp.
 FOR if it's constructed in accord w. Thm 12.

Well: say $P_0(A)$ is t. $\lim_{i \rightarrow \infty}$ of t. max CPM's assoc. w.

t. ~~time~~ U. $P_0(A)$, hvr, is not normed: i.e. \neq

$$P_0(B^0) + P_0(B^1) \text{ is not necessarily } \equiv P_0(B)$$

— $P_0(A)$ t. limit for observable ~~events~~ (i.e. ^{eventually} converging) events.

This is usually \leftarrow

Hvr, t. normn constant will always by $\frac{1}{\alpha_2}$: i.e. $P_0(A^{(0)}) \rightarrow \alpha_2 P_0(A^{(1)})$

$\alpha_2 P_0(A^{(0)})$ is normed & α_2 is usually > 1 , but always ≥ 1 .

— This is because the unobs. events always have a measure ≥ 0 .

Re: Normn: one way to think of it: T! UMC goes into $\geq U$ loop immediately if it would otherwise not converge at that pt. ("Magical")

Humm!! : Perhaps very impl.!! : Even for normn. of P_0 ,
 we have $\forall A \quad P_0(A) \leq K P_0(A)$.

If for normn, $P_0 \rightarrow P_0' \equiv \alpha_2 P_0$: $\forall \text{ all } A \quad P_0(A) \leq \alpha_2 P_0(A)$, since $\alpha_2 \geq 1$.

Hvr, I don't think that we can have $P_0 < P_0'$ ~~for all A~~ for all A $\frac{1}{2}$, since
 both are normed. So α_2 must be between 1 & K — for all θ values!

This means that there can be, at most, only a fraction $1 - \frac{1}{K}$ of
 U containing seqs. $\left[\begin{array}{l} \text{i.e. at least } \frac{1}{K} \text{ of t. seqs must be observable (i.e. no U's).} \\ \text{indep of } Q. \end{array} \right.$ Here, K can be ∞ .

Proof of deriving t. ~~simplest~~ ~~FOR~~ ~~that~~ ~~has~~ ~~no~~ ~~U's~~. — perhaps t. identity ~~is~~
 simplest FOR that has no U's. — perhaps t. identity ~~is~~
 FOR.

D 1473 : This is an extremely interesting theorem, if true!

TM 431

It means that for any l , there is a fraction $\frac{1}{k}$ of t . input strings of length l , which result in t . machine printing no U 's (i.e. stopping w. an "S" loop or stopping) ^{after having read} t -end of t . input string (= perhaps writing ^{after having read} t -end of t . input string?).

On second thought, it is trivial! Say it takes a 10 bit string to get this U into an S loop. Then at least a fraction 2^{-10} of all input strings (of length $l \geq 10$) will result in t . machine stopping.

Hrr, t . discn of 12.28 - .40 is of some interest: It ~~probably~~ ^{perhaps} makes it poss. to find a / smaller (certainly not larger) value of k ~~than~~ than 13.06 does.

Actually, t . machine of 12.28 - .40 is quite clear: Say

String S is t . simulation string for some machine that has no U outputs.

Then S^x as input to machine M_u has no U 's in its output.

These constitute a fraction 2^{-N_s} of all t . input strings

of length $\geq N_s$ ($N_s \equiv$ length of S)

A Q. about Normen: Can I have a / ^{single} normen constant for each value of l , or do I need something more complex? In addition

to $(\sum \text{all probs of all seqs of length } l) = 1$, I need cond:

$$P_n(\beta_0) + P_n(\beta_1) = P_n(\beta)$$

$$\text{for } P_u, \text{ we have } P_u(\beta_0) + P_u(\beta_1) + P_u(\beta^2s) + P_u(\beta^3) = P_u(\beta)$$

$$I \text{ think I want } P_n(\beta_1) = P_n(\beta) \cdot \frac{P(\beta_1)}{P(\beta)} \cdot \frac{P(\beta)}{P(\beta_0) + P(\beta_1)}$$

$P_n =$ normed

$P =$ un normed

un normed conditional probty

normen. const. for cond. probty.

$$\text{so } P_n(\beta_1) = \frac{P_n(\beta) \cdot P(\beta_1)}{P(\beta_0) + P(\beta_1)}$$

$$P_n(1) = \frac{P_n(1)}{P(0) + P(1)}$$

$$\text{So clearly } P_n(\beta_0) + P_n(\beta_1) = P_n(\beta)$$

My impressn: more complex: simple normen. will not preserve

Seq Probty ^{unnormed}

0	1	1/4
1	1	1/4
0	0	1/16
0	1	1/16
1	0	1/16
1	1	1/16

$$P_n(\beta_1, 0) = \frac{P_n(\beta) P(\beta_1) P(\beta_{10})}{(P(\beta_0) + P(\beta_1))(P(\beta_{10}) + P(\beta_{11}))}$$

Here $P_n(\beta_1, 0)$ depends only on t .
Unnormed probty of β_1, β_{10} & seqs. that deviate from these by 1 bit at the ends.
i.e. β_{01}, β_{11} .

IF hvr, we use t . simple norm \geq const that depends on l only,
 the const will depend on t . \in of t \neq unnormalized probabys of all seqs.
 of length l . I think t . Probab of all these other seqs are somewhat
 arby — so t . simple method wouldn't work: — e.g. t . simple
 table of 431.35 (Left) — would not work.

So 431.30 are correct ~~are~~ (finite) recursive defns. for normz.

All of t . \neq unnormalized probabys involved in t . defns are monotone \uparrow in t . C.B.
 \therefore are bound above by 1. \therefore they all approach limits.

Q. : Is t . limit in some sense unique? ^{No: see .39 ff} i.e. w. a gn Umc.

is it indep of how we \rightarrow 'universality' of this umc? I think it is
 equivl. (in unnormalized form \therefore in normalized form) to a ^{hypothetical} FOR in which

somehow, U's are ~~immediately~~ computed ^{for} all non-stopping seqs.

If so, this FOR is unique wrt: a gn. Umc. — (i.e. \rightarrow CB \rightarrow " ^{universality})

Def: A necy \neq quality ~~is~~ \forall C.B. must have in order for

.15 ff to be true! as CB is \uparrow , any particular seq. must either

(a) ^(i.e. print non-U's eventually) terminate eventually, if t . Umc does, or not terminate ever, if t . Umc. does not

~~CLAIM~~

(b) is true for any CB on a Umc. — since t .
 CB will never stop if t . Umc doesn't stop.

If (a) ~~is not~~ is not true, then there is at least 1 seq. for which
 t . Umc stops but t . seq. of C.B's does not. I think then,
 in such a case, this seq. of ~~some~~ C.B's would not \rightarrow 'universality'
 at least
 in my sense — since I think there would then be / one FOR
 that t . seq. of C.B's would never "cover". i.e. say it take

T steps for t . Umc. to ~~stop~~ stop. Then consider t . T limited UMC.

~~call it~~ M_T . I think that none
 of t . C.B's in this sequence can simulate M_T .

But I'm not sure how to prove this!

I think I can show a sort of counter example to something:

I.E. Give a Umc, M . We can have a seq. of C.B's on M

439.015P
433.01

Another Q: Suppose ~~the~~ we have a set of pages that are t . limits of seqs of CPM's — one diffrnt. seq. for each value of l ($l \equiv t$. order no. of t . corpus symbol) — a different Umc is t . limits for each l .

Say M_l is this l^{th} umc. That is approached as a limit.

Say we have a Fdss w. an associated FOR that has deriv. brost b_l from M_l . Is it poss. for $b_l \propto l$, say?

Well, if it is, then this means that if ~~each~~ ^{of this set of perms} each seq. of CPM \rightarrow ~~unity~~ ^{unity} then ~~t.~~ ~~brost error~~ can be $\propto l$ — which violates t . CDI

thru that I'm trying to prove.

On second thought, I don't think it's legal to have t . perm vary w. l .

Each ~~perm~~ ~~var~~ what ~~we~~ we have in t . E desired Perm. is

a ~~seq~~ single non-a.c. Perm, that is t . limit of a bunch of CPM's. These CPMs are each defined for all l .

— They may, hvr. give ~~to~~ unnormalized probys of zero for all $l > \underline{\underline{t}}$

some l_0 — (a \uparrow L Umc would do this).

01; 433.90j : that \rightarrow univ. but they do not "Approach M", i.e. the TM434

"FOR" that represents the limit of this seq. of CB's is not \equiv FOR
that is the "limit" of M (in the sense of 432.16-18) ~~(this would be the limit of a seq. of TLU's)~~.

Say M_0 is a univ. M_1 is the same as M_0 , except;
 $M_1(1^\infty) = M_0(\alpha)$; $M_1(1^0\beta) \rightarrow$ stop; where α & β are arbitrary strings.

So: M_1 looks at the first bit of its input: if it's a 0, M_1 stops.
~~It~~ (It may be waxy for M_1 to read the rest of the input before stopping, if it is to be one of W's "possible machines" — but this is modify).
If the first bit is 1, ~~M~~ converts itself to M_0 & performs $M_0(\alpha)$ on the rest of the input.

Consider the following seq. of CB's, ~~TM~~ M^T : If the first bit of the input is 0, M^T ~~goes into a U loop~~ goes into a U loop.
If the first bit is ~~1~~ 1, M^T "follows" M_1 for T operations unless M_1 stops (in which case M^T stops) ~~otherwise~~ If M_1 operates longer than T ops., M^T goes into U loop.

} M^T is a TLU on M_1 , unless the first input bit is 0, in which case $M^T \rightarrow$ U loop.

M_1 is universal, since it can simulate ~~any~~ M_0 .

M^T does approach ~~univ~~ (univ), since if M_0 can simulate $T+1$ iterations.

2 ~~is~~ ~~univ~~ FOR in time T, then M^T can, also 437.01

[SN] There was some Q in my mind as to whether ~~TM~~ M^T \rightarrow univ. (This is clear M^T is a C.B.). Since ~~all~~ all M^T are ~~FSM's~~ FSM's, & there are FOR's that are not FSM's, it would seem that no ~~TM~~ M^T would ever be able to simulate such non-FSM's.

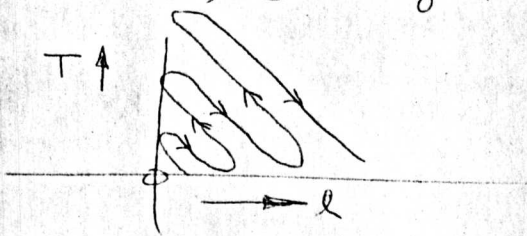
In general, I think that there does not exist a 1 dimensional seq. of CB's that \rightarrow univ. in the sense that I'd like. We can, however, have a 1/2 dimensional set of machns. For each value of $l \leftarrow$ (the output corpus length), we let $T \rightarrow \infty$.

Some quick, general results:

1) We have a seq. of Pams. ~~These~~ ^{Pams} can be regarded as functions; the domain ~~can~~ can be regarded as a 2 dim discrete point set; for each value of l , ~~the~~ (1 dim.) there are 2^l poss. values of the argument. The range is (0,1).
Anyway the seq. of Pams, p^T , converges to p^{∞} ~~(say CPM)~~ 435.01

1.434.10 But t . convergence is not uniform in l . I.E. for each value of l , the limit ^{may be} approached at a different rate. This corresponds to non-uniform convergence of a Fourier series, say —
 The a ~~series~~ series does "M's converge" (which is a single quantity assoc. w. t . interval.).

2) If "Lim sup" rather than "Lim" is used, I think ~~we get uniform convergence~~ we can use $\delta \geq \delta_{min}$ over T, l to get convergence:



\neq \neq \neq \neq \neq

Unv

→ 437.20

3) That there exists no path in T, l space that will give uniform convergence (an old impedance term). This is due to the fact that there exist p.r. functs whose computation time \uparrow w. l faster than any n. function of l . (But not faster than any p.r. funct. of l , because assoc. w. every p.r. funct. of l $\int F(l)$ we can define a p.r. funct. of l whose value is t . computation time of $F(l)$. — This can be done via the unv. defn. of $F(l)$).

So, D.K. The thm about t . limit $\rightarrow P_o(A) \neq t$. param to be derivd) is o.k.

So look up some thms on ~~non-uniform~~ δ definitions on non-uniform convergence in "Analysis".

Hvr., it is clear that my definition of "Approaching Universality", must be modified. Perhaps: For any ~~fixed~~ $l < \text{some fixed } l_0$, M^T can approach ~~unv~~ \int (universality) $\int \underline{M^T \rightarrow \text{unv}} \int$. $\int \lim_{T \rightarrow \infty} M^T = \text{unv} \int$.

Say we know a seq. of param, \exists for all $l < l_0$, t . / brost error is $< k_l$. ~~SN~~ \int I think t . entire seq. of param is a finitely derbabla object

Then t . FOR's assoc. w. those param \rightarrow ~~unv~~ UNV for that l_0 .

A seq M^T , of FOR's \rightarrow UNV for l_0 , if for every FOR δ output seqs of $l \in l_0, \forall \text{for } \exists T_0 \rightarrow ((T > T_0) \Rightarrow (M_T \text{ can simulate } R \text{ for } l \in l_0))$

01: 435.40 : Note! in Willis's 135.09 y. idea that l must be fixed is mentioned. But in the defn. & descn. following, this condition is not mentioned.

Anyway — For the forward Thm. to be true, i.e.,

$$\forall l \left[\lim_{T \rightarrow \infty} \inf_{\text{broadcast}} (P^T, P_0, l) < K \right]$$

$P^T \equiv P^{(M_T)}$
 P_0 is any CPM.

M_T must be able to (for large T) to ~~simulate~~ R^{P_0} w. $\leq K$ bits, for all output strings of length l or less. This K must be indep. of l .

Now, i. Backward Thm: we have a seq. of Pems, P^T , a corresp. M_T 's.

~~1.04~~ T. limit of 1.04 exists for this set, i. for any P_0 ,

17 \exists a K \Rightarrow 1.04 is true. Then for t. seq. M_T has the property that for any FOR, R , M_T is able to simulate R for outputs of R that are of length $\leq l$.

20 Say 17-20 is not true — i.e., for at least 1 l t. seq. M_T is not (for large enough T) able to simulate R . Then clearly ~~$R \neq M_T$~~ $R \neq M_T$ for \approx all large T 's, i.e. for large enough a certain ~~l~~ l , $\log P^{(R)}$ & $\log P^{(M_T)}$ differ by an arbl. large amount — i.e. $>$ any specified K .

25 DEF

So — a defn. for: T. seq. of FOR's, $\left[\begin{array}{l} "M_T \rightarrow UNV" \\ "M_T \rightarrow UNV" \end{array} \right]$

~~1.04~~ $\forall R \left[\exists K(R) \exists R (\leq K) M_T \text{ for } T \geq T_0(l) \right]$ Some \uparrow funct. of l .

(i.e. K value depends on R , but not on l ; T_0 depends on l .)
 28 So: Thm: ~~1.04~~ 1.04 is true for an arbl. ~~FOR~~

n -CPM, P_0 , ~~1.04~~ iff M_T (y. FOR's assoc. w. P^T) $\rightarrow UNV$.

~~1.04~~ iff $\lim_{T \rightarrow \infty} M_T = UNV$.

iff $\lim_{T \rightarrow \infty} R^{(P_T)} = UNV$

SN In 1.04 we have " $< K$ " : for RW Pems! $< K \ln l$

is more like it. — but then, P_0 is not a n -CPM. So we prove Thm. 28

Then we discuss its applicability to Pems in the RW.

pl: 436.40, 434.20 spec

On the ^{lack of} uniqueness of $\lim_{T \rightarrow \infty} M_T = \text{unv.}$ Say M_T are a seq.

of CB's on M_0 , a univ. machine. Say M'_T are another seq. of CB's on M_0 ; both M_T & $M'_T \rightarrow \text{unv.}$ Are the limits of M_T & M'_T necessarily the same — i.e. " M_0 "? (By $\rightarrow M_0$, we mean the FOR of 432.16-18 assoc. w. M_0).

If the ^{counter} example of 432.39 — 434.20 ^(commit page 423) ^(but it does look o.k.) then a seq. of CB's on a univ. M_0 that $\rightarrow \text{unv.}$ need not \rightarrow ~~that~~ M_0 .

A set of CB's ~~that~~ on M_0 that always does \rightarrow that M_0 , is the ↑LU seq.

So, assoc. w. every univ. M_0 , is the "FOR" determined by the ↑LU assoc. w. M_0 . However, all CB seqs on M_0 that $\rightarrow \text{unv.}$ ~~are not that~~ do not approach the same "FOR".

Assoc. w. every univ. M_0 , is a FOR, F_0 , that is the limit of the ↑LU assoc. w. M_0 . ~~From~~ The F_0 exists it is not e.c. from M_0 . The sense in which it "exists" is not clear. It does not "constructively exist".

20, 435.15: Re: this 2 dim scan w. lim sup: Just what is one doing? l is changing during the scan. Is the lim sup of $\frac{\text{scost}}{2}$ taken? Suppose one goes thru this 2 dim scan, a retains at each time, t , coding for which $C = \frac{\text{scost}}{2}$ is min. Eventually, this C will be arbitrarily close to the max entropy of the seq.

However, it's not clear as to what one is trying to do here. If the goal is the best extrapolation for the next corpus symbols, ~~then~~ using a gen. cost, then perhaps the best way is to use the entire corpus & use all of the available cost unit.

If the goal is to find "the rite pair" then perhaps a 2 dim scan or some modifn. of it is best. In the 2 dim scan, one is ^{almost} sure that eventually the rite pair will turn up & be recognized.

There are, however, statistical Q's involved ~~when~~ when one is considering small l values for the l, T pair — since fluctuations ~~are~~ are then likely to give ^{typically} large C values.

However, my previous concept here was to assume a reasonable CB on the corpus (say $T \propto Kl$ or $T \propto A^l$). Then, by making my c.B. $\propto l^2$, say I'd be searching for a real soln.

In the 2 dim scan: If I were testing pairs in this way, I think it would work. In general, I think that pairs are like p.v. puncts — i.e. they are not r.e. 439.01 spec. 438.01

Some points to cover:

a) That CMI results are ~~in~~ relatively invariant under changes of lang. (info lossless changes \equiv reversible \equiv nonsingular).

b) How to use CMI for operator induction of induction in which order of examples is irrelevant (use Gram induction of I & C II as example) - perhaps mention special form of CMI for operator induction

c) How to use CMI for RW induction. Arby irreversible mapping of RW into corpus; A to D conversion. Semantics is not very simple. Goodness of induction depends in a pri. unknowable way on completeness of mapping.

d) One can (almost) never be sure one has found all reggs in a corpus - larger CB ^{always} may help

e) All reggs in a corpus are expressible as a compression of coding. (See I & C II for examples - also note work on coding for a noiseless channel of unknown statistics ~~is~~ - note that ~~the~~ CMI is a soln. of sorts to this problem).

f) Discussion of ~~perhaps~~ obtaining e.c. soln. of CMI by ~~putting an~~ assuming an arby (but reasonable) C.B. on \mathcal{L} -corpus - e.g. (linear or exponential) in \mathcal{L} .

g) Perhaps have a 3 part paper: (a) Hard Results, Thms.

(b) Signif. of these results (c) Conjectures, Open Q's, etc.

h) Perhaps submit (b)(c) to Phil Mag: Or perhaps submit 3 part paper to Phil Mag! They ~~do~~ have stuff like this - e.g. Oetingers early, foolish, ^{computer} "learning" paper, D Mackay's "Info" paper.

i) The $K \propto \ln \mathcal{L}$ phenomenon - how every CPM has assoc. w. it a r CPM that is arby close to it (~~the~~ Willis' Thm).

j) Some results in MML linear Regression.

(k) SVM ~~Thm~~ "Thm".

(l) Perhaps mention "All pairs Method" - Prop 1. (SVM Form ^{improved})

D1973 R

01: 438.90; (37.90 spec)! i.e. one can list all candidates for Pams, but the testing of one of these objects, to see if it's a pam, is never, for certain, possl. One can, hvr., use ~~certain~~ various C.B.'s for t. testing, to get more & more certainty.

Hvr., one can implement this C.B. Very easy enuf. All **CPMS** \rightarrow **FORS** i are C.B.'s on ~~some~~ a unc. (z?).

10 So perhaps: List all CPM's (this is simply a list of all FOR's — which is a list of all ^{finite initial} input strings to a unc). Assoc. w. each corpus length, l , consider all CPM of decm. length $\leq l$.

Do a \geq dim scan on T (\in C.B.) $\leq l$. Retain in many, t. CPM (or ~~the~~ set of CPM's) for which $\frac{\text{best}}{l}$ is max. (for suitably by l ~~to~~ ^{statistical} to avoid fluctuations).

T. logg. method (off) will probably ~~eventually~~ eventually give close to t. best CPM (i.e. \approx t. best predn).

Hvr., suppose one has obtained this CPM at some l, T point.

(say $l = T = 10$). One wants to use it for prediction at $l = 20$. What T value should be used? Its imposs. to say. The T value is as much \approx ^{proport.} decm. of t. CPM as its detailed code.

For a prediction at $l = l_0$, t. \approx best one can do is \approx consider all CPM's of ~~the~~ decm. length $\leq l_0$ & use all t. cost available.

443.01

25 **SN** ^{Gan.} An interesting pt. came up in this ^{off} \geq dim scan! One could use any radix one liked on t. corpus / ^{is t. thing would still converge as well.} This amounts to

clumping data chunks in arby sizes. It suggests that for best $\frac{\text{best}}{\text{cost}}$, one might want to ~~cluster~~ ^{"package"} t. data in reasonable ^{sets of} "chunks" — e.g. before one tries chunk to fit a ^{set of} linear regressn coefs to a corpus, one waits until a fair amt. of data comes in. This chunk of data can be regarded as a single symbol of large radix.

➔ Perhaps when viewed ² this way, a major objection to "sequencial coding" disappears.

One ~~major~~ part of t. objection to seq. coding, was that t. decm. of a complex coding system (like linear regressn) was very unlikely (very large best) — so ~~many~~ a large no. of trial codes would have to be stored. My impressn. is that when linear regressn. is to be tried, it is then of rather by likely hood's. ^{Gan} \rightarrow 440.01 ^{spec}

439.24: I think I have this iff thm. under control now. Best thing to do is write up the proof w. as much exactness as poss. — close as poss. to what it would be in the report.

Probably best to break it into 2 thms., because I'll want to refer to consequences of each $\frac{1}{2}$; e.g. \mathcal{P}_n forward (error $\leq k$ if $\mathcal{P}_i R^i$ is a seq. of \mathcal{P} FOR's that $\rightarrow UNV$) part implies ~~...~~ $\sum sq\ err < \mathcal{P}k$, ~~...~~ || How to make G_n a uinc., how to make ~~...~~ from it, a seq. of FOR's that $\rightarrow UNV$. || Thm: expected value of error(s), at.

O.k.: Thm: Given any r computable Prob. measure (r -CPM), \mathcal{P}_n .

If \mathcal{P}_i ($i \geq 1/\infty$) is a seq. of CPM's \rightarrow ~~...~~ $\lim_{i \rightarrow \infty} R_i = UNV$,

Then for any sequence ~~...~~ $A^{(i)}$ of length \mathcal{L} ,

- ① $\lim_{i \rightarrow \infty} \mathcal{P}_i(A^{(i)})$ exists for all $A^{(i)}$.
- ② $\frac{\mathcal{P}_n(A^{(i)})}{\lim_{i \rightarrow \infty} \mathcal{P}_i(A^{(i)})}$ is bounded ^{Above} \Rightarrow a constant k ,

$\Rightarrow \forall \mathcal{L} \left(\begin{matrix} \uparrow \\ < k \end{matrix} \right)$ ~~...~~

If M_0 is a uinc $\Rightarrow R_i \leq M_0$

~~...~~ $(\mathcal{P}_i \equiv \mathcal{P}(R_i))$ ~~...~~

and ~~...~~ $(\mathcal{P}_0 = \mathcal{P}(R_0))$; $R_0(\leq a) M_0$, then

$\forall \mathcal{L} \frac{\mathcal{P}_0(A^{(i)})}{\lim_{i \rightarrow \infty} \mathcal{P}_i(A^{(i)})} \leq 2^a$

Jan 31

Note: for any seq. of $R_i \rightarrow UNV$; there will perhaps be a minimal uinc, $M_0 \Rightarrow \forall i R_i \leq M_0$. To see this: say there are

n uincs, $M_{01}, M_{02} \Rightarrow \forall i R_i \leq M_{01,2}$.

Then take the largest $M \Rightarrow M \leq M_{01}, M \leq M_{02}$.

This is some Boolean-like operation on M_{01}, M_{02} — like \cap or \cup .

Th. \mathcal{P} operation is descr'd in ~~...~~ Willis (ACM).

Anyway, this minimal uinc will give us the smallest poss. a (?)

Maybe not: If M is a uinc, $\forall M_i$ (M_i can be uinc or not) $M \leq M_i$. Her., we still have an ordering via " \leq " in $M_i(\leq a) M_2$ (perhaps).

01: 443.40 : It would seem that perhaps the most relevant Q would be:

Given a fam, P_0 , how large will α be? α is the \subseteq brost of P_0 wrt. \mathbb{R}^{P_0} . α can be the LUB of α_i , where

~~UNIV~~ $P_0 (\subseteq \alpha_i) P_i$: since α_i is bounded above (by ~~UNIV~~ by hypothesis int. thm to be proved) it must have an LUB.

Daf

.10 In the thm of 443.10, $\lim_{i \rightarrow \infty} P_i = \text{unc}$ (This is identical to $\lim_{i \rightarrow \infty} R_i = \text{unc}$)

— But I don't think this implies $\lim_{i \rightarrow \infty} P_i(A^{(k)})$ exists for all $A^{(k)}$.

~~Pro~~ This is true if R_i are \uparrow LU's

If only $\lim_{i \rightarrow \infty} R_i = \text{unc}$, then $R_0 (\subseteq \alpha) R_i$ for some large enough i

~~UNIV~~ If the P_i are nested so $\forall R_i \subseteq R_j$ if $i < j$, then I think the limit exists for all $A^{(k)}$. This makes $P_i(A^{(k)})$ monotonic in i .

How, if $P_i \rightarrow \text{unc}$ then I think a subset of the P_i must $\rightarrow \text{unc}$, if such a subset could conform to the nesting,

Perhaps the trouble is w. my defn of " $R_i \rightarrow \text{unc}$ " :

as it is, it would seem that for a ga. R_0 , $R_0 (\subseteq \alpha_i) R_i$ for $i >$ some i_0 — but that α_i could $\rightarrow \infty$ as $i \rightarrow \infty$.

For $R_i \rightarrow \text{unc}$, we want α_i to be bounded for $i >$ some i_0 .

Note that i_0 is a funct of $A^{(k)}$ in genl. & k in particular.

→ This bounded α_i is included int. defn. of 436.25 ☺

Some Conjectures:

1) If $\lim_{i \rightarrow \infty} P_i$ exists, then I think the R_i 's must be nested

ie. either $R_i \subseteq R_j$ or w or $R_i (\subseteq \alpha) R_j$ for some bounded α , for large enough i, j . ($i > i_0(k)$)

2) If 1) is true, perhaps the by i R_i must be \subseteq B's on some unc.

3) If $\lim_{i \rightarrow \infty} P_i$ exists then $\lim_{i \rightarrow \infty} P_i = \text{unc } M_0 \rightarrow$ either 2) R_i are all CBS on M_0 or

④ $\lim_{i \rightarrow \infty} P_i' = \lim_{i \rightarrow \infty} P_i$ for $[P_i']$ some set of CBS on M_0 .

452.40 : Given P ($P = \lim_{i \rightarrow \infty} P_i$), perhaps one could construct $A \rightarrow Umc$ in the manner of Willis' Thm 12.

D2773 350P

Anyway, as $i \uparrow$, the P_i 's get arblly close together — so the R_i 's must get "arblly close together" in some sense. Consider fixed $Q, i \neq z$.

Conjecture: If $\lim_{i \rightarrow \infty} P_i$ exists for all values of i , except of $i \in \{P_i\}$,

then this limit corresponds to some kind of aguable machine.

A simple case would be that in which P_i was i . distribn. for a simple binary firm seq. w. p irrational. P_i would have i p value accurate to i binary places.

[However, this may not be the kind of example I want, since the thrust of interest ~~is~~ involve finitely ~~less~~ $i \in \{P_i\}$ terms w. finite i .]

Anyway: The problem is 452.10 - 16 — i.e. $R_i \rightarrow Umc$ doesn't imply

$\lim_{i \rightarrow \infty} P_i(A^{(Q)})$ exists for all $A^{(Q)}$. — I think \Rightarrow implies implies

~~is~~ $\frac{P_0}{P_i}$ is bounded (no matter how large i is) (if $i > i_0(Q)$). This latter may imply expected

mean best error $\rightarrow 0$, also that $\leq \text{space}$ $< \epsilon$ $\ln z$.

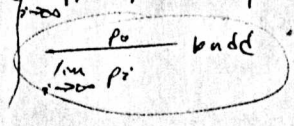
That $\frac{P_0}{P_i}$ is bdd implies, I think that $R_i \rightarrow Umc$.

How, if $\frac{P_0}{P_i}$ is bdd, this does not imply that $P_i \rightarrow$ a limit, so one ~~can't~~ can't make statements about "that limit". — However, one can say, that for large enough i , ($i > i_0(Q)$) the mean best error in P_i will be $< \frac{\epsilon}{2}$ & esp. err will be $< \alpha \ln z$.

30

So this may be O.K. if we have iff below. $R_i \rightarrow Umc$ is $\frac{P_0}{P_i}$ bdd \rightarrow 456.04

We would like iff below R_i are CB's on a Umc . $\lim_{i \rightarrow \infty} P_i \rightarrow P$ w. $\frac{P_0}{P}$ bdd.



While it may be true, I've not been able to prove it.

How, first check this.

A poss. Thm: If $\lim_{i \rightarrow \infty} P_i$ exists is $\frac{P_0}{\lim_{i \rightarrow \infty} P_i}$ or $\frac{P_0}{P_i}$ is bdd.

Then \exists a Umc $M_0 \rightarrow$ a firm defined by M_0 via a FLU seq. is identical to $\lim_{i \rightarrow \infty} P_i$.

01:453.90 : Assoc. w every p/mable macha. There is a ^{unique} PEM defined by
 f. limit as $n \rightarrow \infty$ of t . t limited CB's on that machine.
 T. limit always exists if t is f. same for \Rightarrow various other seqs of CB's.

Note that if ~~for~~ $P_2 \rightarrow P$, then we ~~cannot~~ probably cannot say very much about ~~any~~ set of R_i assoc. w. t . P_i . This is because 2 FOR's that $\rightarrow t$. some CPM need not have much in common. They can certainly differ in various permutations of b. input alphabet — but t . 2 FOR's can differ much across seriously. E.g. take an arby FOR ^{R_1} , find its CPM, then construct R_2 from this CPM via w . Perm 12. R_2 will (if t . input is binary) have only 21 code of length ~~for~~ n for any output seq. In fact, this will not be true of R_1 .

So: ~~It may be possible~~ It is possl. to map from t . ^{set} $\{P_i\}$ into a set $\{R_i\}$ via w . Perm 12, in a unique way. Can we use this $\{R_i\}$ to define a programmable machine? In princ., for an arby ^{infinite} $\{R_i\}$ seq. This is not possl. — but if t . R_i are derived from a $\{P_i\}$ that \rightarrow a limit, in a unique way via Perm 12, we might use $\{R_i\}$ to define a limit $\&$ p/mable machine.

One might define this "limit Machine" using t . construction methods of Thm 12. ~~One~~ One constructs a sequence of R FOR's, R_i . If its done properly, it may be possl. to show that ~~if~~ if $P_i \rightarrow$ a limit, then t . construction features of R_i must also \rightarrow a limit. A possl. might be that since w . uses tables to define t . R_i 's derived from P_i 's — one might be able to show that for large enuf. CB's, ⁽¹⁾ every table entry must eventually become constant ⁽²⁾ (i.e. there are only a finite no. of entries in t . tables).

AH! If $\lim P_i \Rightarrow$ exists, then there must exist a i_0 such that for ~~for~~ $i > i_0$, P_i changes by $< \epsilon$. This means that 455-01

01:45:40: after $i > i_0$, we know how to code t . first $[-\log_2 \epsilon]$ bits of t . input!

So, I think using 454.28 ff (i.e. 454.39 ff in particular), one should be able to construct a "limit machine" if $P_i \rightarrow \text{limit}$.

T. Q is: is this limit machine unique? I think it is -

output of limit machine not unique (i.e. P_i)

Note: P_i 's limit machine may be a true, but it is not a "probable" machine. it has not undirected output.

I. limit machine "exists" in t . sense that given any input sequence, I can eventually compute t . r_i symbol of t . output - but in general, I will not know when I've done so - eventually, I will give a first approx. to next r_i symbols, but I may change my mind after that.

That "t. limit exists" I interpret to mean "eventually, for $i > \text{some } i_0$, I will no longer change my mind (Also, the "settling down" is a sequential occurrence)"

($i_0 = i_0(l)$, I think) perhaps not a notation. Anyway - to show that t. limit machine is unique, just prove that

for any FOR, R, t. limit machine can simulate R. I think this is equiv. to proving its unique. I don't know if there's a theory to that effect, but assume so for t. present.

I may have been forgetting that there are 2 limits involved: One is the $i \rightarrow \infty$ limit, i.e. other is $t. T \rightarrow \infty$ limit. They are not necessarily identical - but they can be.

On second thought, t. rate at which $P_i \rightarrow$ its limit very probably depends on l . For large l , i.e. small P_i , to get an error $< \epsilon$ requires much larger i than if l is small (i.e. larger P_i). Perhaps Not. To get a best error $< \epsilon$ may require larger i if l is large.

Well consider $i \in T$. Suppose $i_0 = i_0(\epsilon)$ (for given ϵ error in P_i) is a funct. of l . Or, say T is a known funct. of i & l .

Given any input sequence, there will be, assoc. w. each n value (length of input) i_0 value, \Rightarrow for $i > i_0$, t . output r_i assoc. w. first n inputs, do not change. $i_0(n)$ will often be not a recursive function - it can be w. n , but not (having recursive funct.)

35 I may need to help. Lemma! If: $P(R_1) < 2^{-2} P(R_2)$ for all $A^{(l)}$ of $l \leq l_0$. then $R_1 \leq R_2$ for output seqs of $l \leq l_0$ i.e. R_2 can simulate R_1 w. $2 \times$ (in code of length l) for outputs of length $l \leq l_0$.

Actually, this lemma is false: T. fact is that for t. hypoth, there exist R_1, R_2 w. t. desired properties. \Rightarrow proof of 155.37 is wrong!! 456.01

01: 455.40 :

Re: 453.30

I think t. backwards thru is : t f



$\frac{P_0}{P_i}$ is bdd, (bdd is indep of \mathcal{L})
for large n and i ?

then \exists a seq. of $R_i \Rightarrow$ (a) $P_i = P(R_i)$

(b) $R_i \rightarrow \text{unc.}$

Going ~~back~~ ^{back} even further: I had this lemma: If R_2 cannot simulate R_1 ,

then for any k , \exists a seq. $A^{(k)} \Rightarrow P_{(A^{(k)})}^{(R_2)} > k P_{(A^{(k)})}^{(R_1)}$. This lemma is

false. R_2 may be unable to simulate R_1 , yet $P^{(R_1)} = P^{(R_2)}$ for all $A^{(k)}$.

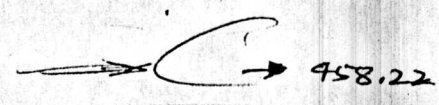
e.g. ~~ARLATA~~ $\left\{ \begin{array}{l} R_1(A) = A \\ R_2(A) = \bar{A} \end{array} \right.$ ($0 \rightarrow 1, 1 \rightarrow 0$ for every symbol in A).

Both machines assign f. same probab. to all seqs., yet neither can simulate f. other.

Or, more generally, consider any FOR. = R_1 ; let R_2 be f. same FOR except $R_1(A) = R_2(\bar{A})$. So both have f. same $P^{(R_{1,2})}$, but neither can simulate f. other (usually) w. x ltn. length zero!

say $P_1 \leq 2^{a_1} P_0$
 $P_2 \leq 2^{a_2} P_0$ etc.
 $P_3 \leq 2^{a_3} P_0$

can I construct $\Rightarrow R_i (2^{a_i} P_0) \dots ?$



I had been assuming that w. thru is said that if

$P^{(R_1)} \leq 2^2 P^{(R_2)}$ then $R_1(2^2)R_2$: which is false.

So, it really looks like I'm nowhere near proving f. backwards thru of .01 or any other backwards thru!

If $\frac{P_0}{P_i}$ is bdd indep of \mathcal{L} , (for large n and i). Then P_i need not

have been derived from a set of R FOR's that \rightarrow unc.

It may well be that .01 is true, but still, that doesn't make

CMI seem very unique! It would, hvr., mean that if there

is any P_i seq. that can do, then CMI can do at least as well.

Well: Maybe things aren't so bad! - Perhaps I can show .20-.22

for an orbly large no. of P_i 's.

01:456.40 :

T. 3 Thrus I mita prove!

1) 456.01 \Rightarrow If $\frac{P_0}{P_i}$ is bdd, then $\exists \{R_i\} \Rightarrow P_i = P(R_i); i R_i \rightarrow \text{unc.}$

2) $\textcircled{2}$ If $\frac{P_0}{\lim_{i \rightarrow \infty} P_i}$ is bdd then $\exists \{R_i\} \Rightarrow P_i = P(R_i)$
 $\textcircled{b} R_i \rightarrow M_0 \leftarrow$ this may be implied by $i.e. (P_0/M_0 \text{ is unc.})$

$P(M_0) = \lim_{i \rightarrow \infty} P_i$
 $P M_0$ is the limit of a \uparrow LU on M_0 .

$R_i \rightarrow M_0$ has the meaning of 454.28 - 455.01

\textcircled{b} if $\frac{P_0}{\lim_{i \rightarrow \infty} P_i}$ is bdd, then \exists a unc, $M_0 \Rightarrow P M_0 = \lim_{i \rightarrow \infty} P_i$.

3) If $\frac{P_\alpha}{\lim_{i \rightarrow \infty} P_i} \leq k_\alpha$ (for various α 's) — then \exists a unc, M_0

$\Rightarrow \frac{P M_0}{\lim_{i \rightarrow \infty} P_i} \leq k_\alpha$ i.e. \exists a CMT at least as good as $\lim_{i \rightarrow \infty} P_i$.

P_i are r-CPM's ; P_α are all r-CPM's
Actually, P_α can ~~be~~ probably be CPM's

possl. thm: If $\frac{P_\alpha}{P(M)}$ is bdd $\forall \alpha$ (some bnd for all α) for all α , $\frac{P_0}{P(M)}$

Then M must be unc.
say M is a sequential Machn.

If $\forall P_\alpha, \exists K \Rightarrow \frac{P_\alpha}{P(M)} < K$
then M is unc.

perhaps counter ~~example~~ example
say M_0 is a unc.

construct M_0' in the following way: It has the same I.O, except that inputs of the same length are rearranged — keeping, how, without ~~the~~ off sequential property

possl. thm: If $\lim_{i \rightarrow \infty} R_i = M$ then $P(M) = \lim_{i \rightarrow \infty} P(R_i)$
data in 454.28-455.01

Here, M is a particular Machine; $\left\{ P(M) \equiv \lim_{i \rightarrow \infty} P(M^T) \right\}$ where T is a $\neq T$ limit for a CB. i.e. M^T is a T limited machine, M .

The idea here, is that T limiting probably distribn. is somewhat indep

01: 457.40: A basic Q. is: what am I trying to show? Basically, the uniqueness of f .

CMI soln. Some thms. that would show this! $P_x \in \text{r.c.p.m.'s.}$

1) If $\lim_{z \rightarrow \infty} \frac{P_x}{P_z}$ is bndd for all x then $\exists \mu \Rightarrow \frac{P_x}{P_{\mu}} \leq \mu$.
i.e. CMI is at least as good as μ limit of a seq of p.c.m.s. This would also show that it is imposs (?) to get a convergence rate for Fd SS's that is better than CMI gets.

~~scribbled out text~~

Note that 1) assumes that $\frac{P_x}{P_z}$ is the μ of interest.

In general, it need not be ≤ 50 .

Define the problem: list poss. solns. & partial solns.

A soln. of 456.20 for an arb but finite no. of on's - would perhaps solve f genl. problem.

Note that the "limit machine" of 454.39 - 455.01 is not a P-computable machine since its output tape is not unidirectional.

353P

Another Q. is whether the idea is o.k. - in view of my previous misinterpretation of W 15. - One second thought - it doesn't use that thm - so it's o.k.

22

At first glance, it might seem easy to construct these R_i 's if $i=1, 2$ only. It is easy if $z_1 = z_2 = 10$. However, if $i=1, 2, \dots, z^{10}$ z_i 's are all < 10 , or ≤ 12 even, one can get interference betw the R_i 's. ($i > 0$). If there is no interference, one simply constructs $R_{1,2}$ in accord w. Thm 12's ^{proof} then constructs R_0 in accord w. Thm. 15's proof.

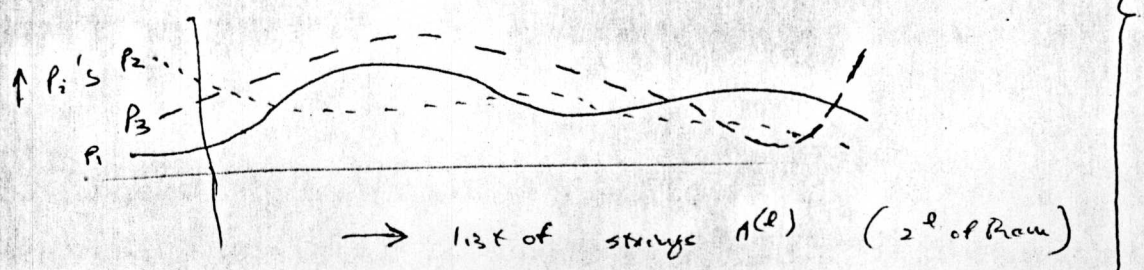
There are at least 2 impt. things one must deal w.

1) We are concerned w. r.c.p.m.'s of $l < l_0$. [$A^{(l)}$ is the string set]

2) We are concerned w. interference betw the P_i 's.

One good way to represent R_i 's "interference" is "interaction" in a way that may help solve the problem.

36



459.01

1: 459.40 identity machine ($M(x) = x$) — yet P_1 could be fairly complex.
 T. identity machine assigns = a prop to all strings of = length — but its simulation capabilities are minimal.

P_1 could be P_0 multiplied by some bounded function of $A^{(k)}$ & then renormed.

so ~~459.37~~ 459.37 is probly false. This seems like an impl. idea.

So, it looks like t. non-monotonicity of ~~P_1~~ ~~P_2~~ P_i 's ~~approach~~ approach to P_0 is t. Big problem

I. kind of non-monotonicity assoc. w.t. machine of 454.39-455.01 may not be so bad. Perhaps I can rewrite W's formulation in terms of that kind of Machine — rather than a "programmable Machine" → 461.13

14: 459.12: In t. picture of 458.36, one can also draw curves $2^i P_0$, for various 2^i values.

Now — T. idea is to conserve on the 2^i length simulation strings.

— If there were only a few 2^i values & 2^i 's were large, there would be no "interference" (458.22). How t. conservation operates:

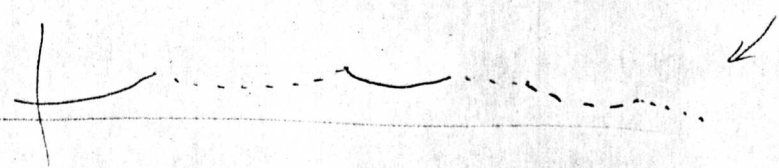
Say $n = 4$: $2^i (2, 2, 3, 4)$

first we construct t. codes for t. 2^i machines: they are identical except for t. last (= last) bit. If 2 P_0 's have many values in common, their codes are t. same for all but a few final bits (i.e. t. codes of t. leaves).

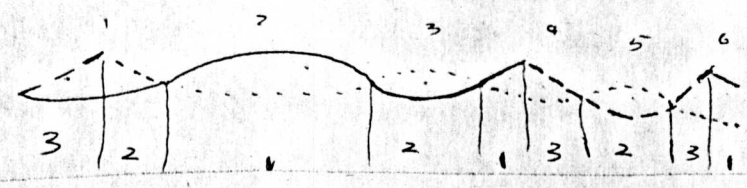
If P_3 is always $> P_4$, then P_4 's code can consist of P_3 's code concat w. some 1 bit out end.

[think its a kind of Boolean net problem;

From 458.36: consider t. lowest level: Its "code" is t. null code.



On t. next level, there are: 6 segments, but only, at most, 3 "basis" regions.



Well, I'm not sure as to how to proceed w. this code assignment, but t. Boolean idea (not nearly exactly as desc'd above) seems reasonable. 462.01

01: 450.40 Hvr., don't spend more time on it now! T. main problem is - is there any pt. to it in view of T. non-monotonicity of 459.13?

03 Note that with a gen. UMC, M_U , I can have a seq. of CB's on M_U that \rightarrow UMC, yet T. seq. of P_i 's assoc. w. this seq. of CB's need not be monotonic, T. monotonic condition is accy if $R_i \subset R_j$ for $i < j$ - but not if T. CB's don't have this property. Hvr., for each of the CB's R_i , $R_i \subset M_U$, also $P(R_i) \leq P^{M_U}$ - limit. If we have an arby $\{P_i\} \rightarrow$ a limit, it is certainly not necy true that $P_i \leq P$.

08 09 10 11 12 13: 460.13: One CMI formulation that may work! My old "fixed length coding method, using bidirection E, v. tapes. Random (\equiv All poss!) input strings we stop the Machine at Time T, to compute probys. We let $T \rightarrow \infty$. Hvr., even for fixed string length, is it necy true that a by fraction (or "almost all") of the output symbols would eventually stabilize? Perhaps not - but in the UMC Machine of 454-39-455.17 we would have convergence of this sort.

So, it seems quite poss. that CMI could be formulated in terms of machines having this "mildly seq. property" - rather than T. strict sequencibility of W's - "programmable Machines".

Def. 25 Note that is MSM (\equiv Mildly sequential Machine) is not the same as an unrestricted Tmac. (Tmac). An unrestricted Tmac. could write output 1111 then erase it, then write 1111 again, indefinitely. A MSM could not do this indefinitely - tho. it could do it for any finite time.

Since Programmable Machines are a (proper) subset of MSM's, MSM's can be UMC. T. prog. decn. makes a plea for T. introd. of MSM's in T. formulation of CMI as a more general form than W's SQPM's. T. Q. is - do I really need this?

Say $P_i \rightarrow$ some limit P . we can have $P_i = P(R_i)$; have R_i be CB's on UMC, M_U , yet P_i need not $\rightarrow P$ monotonically! \rightarrow ~~Monotonicity would ensure it!!!~~ i.e., .03-.12

08-12 suggests perhaps we do need it! i.e. for any SQPM, condition .10 holds, yet $P_i \leq P$ need not hold. So - I think its true that if $\lim_{i \rightarrow \infty} P_i = P$; $P_i = P(R_i)$; $P_i \leq P$ i. R_i are FOR's, then $\exists M_U$ (\in MSM) $\Rightarrow R_i$ are all CB's on M_U i. $R_i \subset M_U$ ($P_i \equiv P^{R_i}$; ~~REDA~~ P_i is an arby Pcm) 462.01

01:46:40: Ok, Ron! Say one is given one M_0 that's MSM.

02 so $P_i \equiv P^{M_0}$; does there exist a SQPM, $M_0^2 \Rightarrow P_i = P^{M_0^2}$?

03 It may indeed "Exist" in some sense - but I wouldn't be surprised if

04 it needs not be computable from M_0 's desc.

It is poss. to ~~know that~~ $P_i \rightarrow 2$ limit, yet have γ limit be not computable.

This is true as on computer $p(M_0)$ for $M_0 = SQPM$ - ~~in this~~ In this case P_i is monotonic \uparrow . We can add an oscillatory component $P_i \rightarrow 0$

$\rightarrow 0$ if we like, to give γ whole thing non-monotonicity.

If we took $\sin(1000 P_i)$, this would $\rightarrow 2$ limit, since P_i does, but it may or may not be monotonic. Presumably, for small enough 2 's larger enough value of "1000", one can always get some

non-monotonicity as $2 \uparrow$.

From .01 if I suspect that .03-.04 is true.

Hvr., another approach to CMI could use a sort of diffract. number system

from normal positive radices. E.g. radix 3, but γ coeffs can be

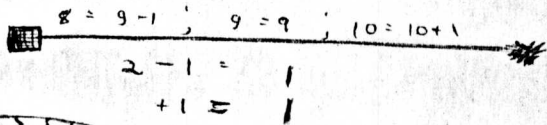
0 or ± 1 , rather than 0, 1, 2. Or base radix 2, but coeffs can be ± 1 only (not zero) (this latter is used in binary division algorithms).

In γ binary case $\pm 1 = 1_0 = +$, so there is ambiguous int. representation.

$2_0 = +$; $2_0 = \text{woops}$; Even nos. aren't representable!



$1 = 1$; $2 = 3 - 1$; $3 = 3 + 0$
 $4 = 3 + 1$; $5 = 9 - 3 - 1$; $6 = 9 - 3$; $7 = 9 - 3 + 1$



If M_0^2 or $.02$ existed, then, given an arby $P_i \rightarrow P$,

one could construct a new monotonic \uparrow , $P_i' \rightarrow P_i' \rightarrow P$ also.

If P_i is allowed to be an arby seq. that $\rightarrow 2$ limit (if I think it is), then

it would seem that constructing P_i' would be impossible in general.

It would mean that eventually for $\{P_i\}$, one could say that $P > \text{some } k$.

If $\{P_i'\}$ were constructable, then P_i'' , a monotonic ~~seq.~~ $\rightarrow P$ should be constructable. This would mean that one could construct arby close upper & lower buds for P .

- certainly unlikely for most general $\{P_i\}$ seq's!

Tom Mahone -
The "Vermont
Cowboy"
Pickup
careful of
Tom Mahone!

T. strange thing is that a SQPM can be an Umc - so how come it can't simulate a MSM? In Thm 3, W. defines a Univ. feasible machine as one that can simulate any other feasible machine.

A feasible Machine is a Tmc w. unidirectional I.O. tapes. Usually it has at least 1 work tape. If it has none ~~it's a FSM~~ its a FSM; if it has > 1 work tape, its of no extra capability than a 1 tape machine - other than possibly speed.

Browsing ^{thru} to old version of W. (pp 20-21) it looks pretty much like his proof for "Universality" would work only for a unidirectional I/O tapes ^{simulation of Tmc's w}

Actually, unidirectional input is not a constraint ~~in the original version~~
~~the~~ T. unid. ~~input~~ machine can simply copy its input onto its work tape, so its effectively 2 directional ^{ie. it can refer to earlier values on its work tape}
~~However, there may be certain non-computable long reading strings that cannot be simulated.~~

T. unid. output does, hrs., appear to be an actual ~~restriction~~ restriction on what can be computed.

T. MSM I'm thinking about, (when its doing what a SQPM can't do) never stops.

~~while~~ while a ^{univ.} SQPM can't exactly simulate an arbl. limit seq. $[P_i]$, perhaps it can get with say, a factor of $\frac{1}{2}$ of r. limit - this would be ~~about~~ about good enuf - but I don't even see how it could do that good. I think that as P_i approaches its limit, one can never at any pts, be sure about any ~~finite~~ finite range of where the limit can be!

Hrs, while there may not exist a ^{computable} method to go from t. seq. $[P_i]$ to a SQPM umc, this does not mean that such a SQPM umc does not

~~Exist!~~ ! ! !

Discussed SQPM's & MSM's w. Marr: He ~~did~~ did see just how MSM's could do things that one couldn't exactly ~~construct~~ ^{simulate} devise instructions for a SQPM to do. But he said he didn't know anything more about it. Said that there was some mention of this or a closely related phenomenon in Blum's (induction) report - suggested that I write them about this.

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D3173: O.K. I think I see how I could ~~make~~ ^{make} decb (effectively) a MSM \rightarrow t. convergence time for χ_k ~~sq.~~ ^{sq.} of output was $>$ any c.c. funt (= recursive funct.) of n. \therefore I think I can construct a MSM that would "compute" this non-recursive $f(n)$. The way it does it: We have this MSM that has a ~~time~~ time counter, which 464.01 \rightarrow seq 74TM 11.02 - 2.20 for this construction

463.40 counts t. no. of machine steps done since the start. (This counter can count by 10's or 100's - it need not be accurate to better than $\pm k$.)

Every time the n^{th} square of the "output" tape is changed, it writes down t. no. in t. "counter" onto ~~the~~ "output tapes" - So we sort of have 2 machines, and one of them does "compute" this uncomputable $f(n)$ - so if we relax t. rules on ~~changed~~ t. defn. of computability, this MSM is "more powerful" ^{unidirectional IO = willis' Programmable Machine.} ~~U10M~~ machine (\equiv U10M)

It seems likely that t. MSM's are not r.e. - i.e. that one can't always tell, from a decim of a Trunc whether it's a MSM or not.

w. a MSM, one does not have a useful sequential property - i.e. one cannot ^{over} discard a candidate decim. of a corpus, just because it differs in output w. t. corpus. - so, even tho one uses C.B.'s on a MSM to get successive approxns. to probability, one always has to consider all possl. input codes for each ~~successive~~ successive approxn.

One could take an arby Trunc & define it into a MSM, by saying it must print U ~~at~~ at a particular output pt. if it never converges ~~to~~ for that particular output symbol. This would, of course be imposs. to determine in genl. One could just as well ask a U10 Trunc to print U's under similar circumstances - thus simplifying most induction problems a great deal!

But, t. main point is - that since a MSM is more powerful than a U10M, & one can get a seq. of P_i 's that only a MSM can really "cover" - that probably a ^{universal} U10M cannot really completely simulate all seqs. of P_i 's exactly.

- Well, actually, we didn't expect it to - U10M's can only deal w. r-CPMs & t. like. W. shows that Trunc is a r-CPM arby close (bcast-wise) to any Perm (perhaps) - but check this.

- Anyway, I'm not so sure P_{13} is t. problem. I'd like to show, that given any seq. of perms, $\{P_i\}$, that \rightarrow some (uncomputable usually) limit, P_0 , that \exists a U10M ~~that~~ $M \rightarrow$ PCM) is just about as good as P_0 .