perhaps Late 1951 or early 1952 — Relatively Probable reviews!

T. M. Review (T.M.R.)

This will be an ~~many~~ explanation of the history of the analysis, starting from basic concepts. The decisions made, and the reasons for various investigations and "study problems" will be given.

Outline of important ideas:

1) What is probability? ~~[illegible]~~

2) " " life?

3) How does evolution proceed?

4) What is "thinking"? How can one judge when a machine is "thinking"? Give some intuitive ideas on this. Give a few problems that a T.M. should be able to solve: e.g. synthetic geometry problems. Also problems in same general field should be solved more quickly after machine has solved ~ problems. This should all be done in an un-ad-hock way. I shall be the judge of ad-hockness.

5) Difference between living thing and thinking machine. i.e. the goal of life is fertile reproduction; the goal of T.M. is quick solution of the problems fed to it.

6) How does memory work? Just what determines what it is about a partic. situation that we remember?

7) Learning and Conditioning. Just what determines how a present experience will modify future behavior? This is linked to the problem of memory.

8) Antibodies. How do antibodies adapt themselves to destroy a partic. kind of germ? How does previous "experience" with that germ help? This is a simple, low life level case of adaptation and learning.

9) Adaptation: How do organisms learn to adapt to complex environments in ways to further their goals?

10) Languages — how do they grow, and how does one determine what the words will be.

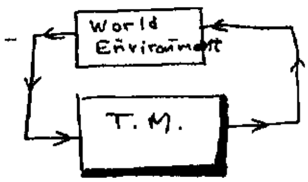
11) How does one make a decision from several conflicting lines of evidence?

Started!
in 1951, or early 1952,
I believe.
—Up to Z 22 by Ap 2, 1952 ~~middle of~~ (Z 10 is Feb 6, 1952) Z 16 is March 1, 1952)
Z 22 Ap. 2, 1952

T. M. — A Survey — *

The simplification of the T. M. problem lies in its parallel statement in various fields of inquiry. Each of these fields has an apparently different problem, yet any progress in one of these problems is translatable into progress in each of the others. It will be the purpose of this paper to outline each of the problems in the various fields, and show how the parts of the respective problems correspond to one another.

(1) The first problem is the Thinking machine proper. To construct, with existing equipment, a machine that will "think". More exactly:



— T.M. Has an input and an output — These may be of any form that conveys information.

— T.M.'s output goes into the input of the "world Environment", and the W.E.'s output is the input of T. M..

— Now T. M. has a certain set of inputs which it regards as "good" — with varying degrees of goodness.

— The purpose of T.M. is to give an output such that the total "goodness" of its input is maximized. To do this, it must make experimental outputs and observations on its resultant input — in order to determine the nature of W.E.

The exact nature of T. M.'s "goodness criterion" is rather uncertain. Suppose it associates with each input $I(t)$ at time t, an amt. of Good, $G(I(t))$, and T. M. tries to maximize some $\int_0^{t_0} F(t, G(I(t)))\,dt$ where F is some funct of G and t, and the integration limits are birth and death of T. M. [Note: $\frac{dG}{dt}$ and $\frac{d^2G}{dt^2}$ may be under the $\int$.]

— What T. M. must do at each moment, is to act so as to maximize the expected value of this $\int$.

This involves a definition of probability. T.M. must be able to associate with every future life plan of action, — and every possible value of the $\int$, — a probability ~~that~~ density, that such a course of action will ~~lead~~ to such a value of the $\int$.

— But this is an excessive simplification, since T. M. will make decisions in the future, which will be made on the basis of information not now available.
What one does is associate each "plan of behavior," "integral value," pair, with a probability.
A "plan of behavior" is a system which tells one what to do at time t, upon the basis of all inputs up to time t. [this concept is identical to one used in the "Theory of Games"]
E.G. Given a certain "plan of behavior" for scrutiny, T. M. must be able to tell the probability that the "'good' integral" will be between .7 and .8.

See footnote at bottom of page 3

But, may these "behavior plans" include such statements as "put the following plans into the plan evaluator: at time 175: 13, 12 and 27, and at time 178, start to carry out the one with the hyest expected value of the "Good $\int$""?
This problem seems to be identical with the one about "expectancy maximization in a Capitalistic Economy."

② The problem of "what is probability?" Given a set of objects. Given the n first series of them. What is the "probability" that the $n+1$ th is a certain one of the set?

Actually, probability is an elementalistic concept. Proby. is used to divide up a more complex problem into solvable parts. In some problems where elementalistic methods fail, one occasionally can ask for a probability where no such probability exists.

Also, there seems to be the idea of "certainty of probability" or "probability of probability". — since probability is gotten by observing a series of events, one would expect a short series to yield a less certain value of "mean frequ" or "probability" than a long series.

The crucial factor in proby. is "abstraction". One observes the first n events. One observes the frequency of abstractions A, B, and C, upon those events. Now say element ϕ_i has abstractions A, B and C.
To find the proby. of event ϕ_i at the $n+1$ th time period, one uses the observed frequencies of the abstractions A, B and C. But given these frequs, what is the "proby. that they will occur together" is an unsolved problem.

③ The problem "How may abstractions be most readily and 'naturally' be constructed?". This is a key to the problem of probability as stated above, tho it is not the whole solution. The most generalized concept of abstraction is simply a listing of all the objects in th. universe that have that abstraction in common.

Perhaps the important problem is, given an event, which abstractions from this event will most probably be most useful? — Perhaps a soln. to this is afforded by the following: Consider the set of all abstraction methods — now those of the set that give hyest reliability in probability estimates — i.e. those which are most significant in singling out events — or, less elementalistically, those abstraction methods which have, in th. past "led" to greatest increase of the "good S", are the best methods to use. ("in the past" leads to ad-hock methods)

Seems like a good non-El. idea.

④ The Problem of Life: Each living organism is a device which must reproduce, in order to survive as a species. Reproduction, then, is the ultimate "good" for a living I. M., and the number of fertile offsprings is a measure of the "good". Actually, the exact problem of "Good" for a living creature, is a difficult one. Essentially, it implies the ~~most~~ largest number of fertile decendents in the "long run" — but statement of this criterion in terms of the individual T. M., is more difficult. Maximum no. of fertile offsprings is a good approx. (tho clearly, a fertile offspring with sterile ~~offsprings~~ is useless — which explains why this is only a rough approx.)

not exactly

See footnote page ⑤ see also bottom of page ⑦

Footnote — to top of page ②. The problem is: shall one consider action based on expectancy of a) expected courses of action or b) expected "plans of action" or c) expected "plans of action" which include refrence to the plan evaluator or d) some more complex method? Is method a) actually the most general possible — presupposing that reevaluation is made at each step in time? Very probably, th. following is a soln: (to page ④)

② The problems of learning and memory: These are spoken of together, since there is probably a close connection.

In memory, we have input data from the world. This data is abstracted before it is stored (probably). Data must be filed in such a way that it will be useful in future problem solving. The manner of filing (what abstractions are used for filing) is quite important, and what factors determine the manner in which an item is to be stored, is important.

Also, in conditioned response "learning", we have abstractions made. What are these abstractions? Also what governs learning rate?

from Bottom of ③

Footnote, continued: Consider T.M. and The Environment having discrete alternate moves, as in chess. Let an "Action plan" for T.M. be defined by the following: A correspondence betw. each ordered set of moves by Env. and a corresp. set by T.M. in reply. These correspondences are limited in that if 2 sets of Env. moves are identical up to time t_0, then T.M's replys in the "Action plan" must be identical up to $t_0 + 1$.

An "action plan" for Env. may be similarly defined. Each action plan has a certain time t_1 after which it is to come into effect.

An "action plane" for T.M. and one for Env. both defined after t_2, define a game after t_2.

Now say the "Good integral" is a functional on the set of games.

Let ${}^{t}A^{i}_{T.M.}$ be the set of T.Ms "action plans". ~~next~~ After time t. Let ${}^{t+1}A^{j}_{E}$ be the Env's " " " " $t+1$. Let ${}^{t+1}A^{i}_{E}\,{}^{t}A^{j}_{T.M.}$ be the game after t, resulting from these 2 plans.

Let $P({}^{t+1}A^{i}_{E}, X^{k})$ be the probability (based on T.M.'s observations of the game up to $t-1$) that if T.M. does move X^{k} at time t, then Env. will use Action plane ${}^{t+1}A^{i}_{E}$.

Let $G({}^{t+1}A^{i}_{E}\ {}^{t}A^{j}_{T.M.})$ be the value of the good functional for the entire game considering the known game up to $t-1$, and the game defined by ${}^{t+1}A^{i}_{E}\cdot{}^{t}A^{j}_{T.M}$ after time $t-1$

Then $\sum_i \sum_j P({}^{t+1}A_E^i, x^K)\, G({}^{t+1}A_E^i, {}^{t}A_{T.M.}^j)$

(where i runs over all values of i, and j runs over only those plans which begin with the move x^k) is the expectancy in G, that will result from the move x^k. We want to chose x^k to maximize this expectancy.

Note: after the probys. are computed this problem is quite similar to the chess-playing Machine problem of Shannons, and can probably be similarly programmed.

I think that this solution is rather non-elementalistic. Actually, before the game starts, an action plan can be devised by T.M. once and for all time no computation need be performed after that time, or at each move. Computation of the probabilities of each of Env's action plans is a very difficult task. I involves, at each move of each plan, the computation of the probability of the future behavior in terms of the past. [Note: Actually, before the game starts, T.M. computes the action plan, once and for all time. — At this time, T.M. has some data on probabilities, which is in the form of evolutionary selection of abstractions. (E.g. sound, sight, touch, smell) also many more complex abstractions and abstract methods] A-priori, Env's first move is arbitrary, and probably Env's 2nd move is also almost arbitrary. But as the game continues, T. M. begins to see possible systems in Env's moves, and these systems make better probability estimates possible.

Actually, the above soln. seems to be complete — "action plans" describe T.M's and Env's actions as completely as is possible. — It is desirable to elementalize the computation of the probabilitys of Env's "action plans".

Footnote to (4), page 3: The problem of "what are the desirable traits that evolution selects for" is the problem of "what is the "Good functional"" for life (as refered to abstractly on page 4)?

Actually, in the case of social animals, not the individual, but the society as a whole, is selected for, by evolution. Here, we can treat the society as a whole, as a T.M., with a certain "good functional" (its reproduction rate), which it must maximize.

The problem of T.M. then completely reduces to the following: Given the moves of the game up to t_0, what is the probability that Env's move at t_{0+1} will be x^k?

(6) The Problem of "Scientific Method": In science one must make a-priori guesses at theories. Given

a set of phenomena, one can make an inf. no. of theories that satisfy ~~the~~ all of those phenomena. Out of all of these theories, one must chose the "most probable" ones — i.e. those which will be most likely to give valid extrapolations of the observed phenomena. Then after chosing th "most probable" theories, one tests them empirically. — This whole problem is identical with th. problem of of "what is probability?" (see ②, page 2)

⑦ The problem of Antibodies, or <u>Adaptation</u>: Normally, with inanimate life, adaptation is by conforming. E.G., if a river runs thru a gorge, the gorge will wear away. Contrast this with a tite shoe. Instead of wearing away the skin, a callouse (thicker skin) may form. — Similarly, it seems that anti-body production is a simplified kind of "negative conforming" that is typical of "life." — Instead of the animal giving in to the insurgent organisms, the animal's blood puts up a fight. — Actually this entire problem isn't very clearly stated, and its connection with "life" should be made clear. It is felt that "negative conforming" shows the great and <u>varsitile</u> adaptability to <u>environment</u> that is so characteristic of life.

Summary so far: It can be ~~see~~ <u>seen</u> now that problems ④ (Thinking Machine) ⑤ (Probability) and ⑥ (Scientific method) are intimately related and identical.

③ (methods of Abstracting) is related to ② (Proby) in th. following manner: One has a game up to time t_0. to find ~~proby~~ proby. of Env's move X^k: X^k is a member of abstraction A_x. Now in the past, it has been found that if ~~they~~ 3 successive moves were a member of abstraction A_3, then the proby that the next move would be a member of A_x, is .25, with ~~Mean~~ a certain number of observed cases (say 23). Now the t_0-2, t_0-1 and t_0^{th} moves are members of A_3, so the proby of X^k at t_0 is .25 — from <u>this</u> abstraction <u>alone</u>. Methods of combining data from various abstractions is a difficult problem (see Qb48 for an attempt)

Also, consider how evolution behaves as an Affective ~~tone~~ Mechanism — Try T.M.'s in which any decision ~~or~~ say, abstraction methods, or any methods of operation is made "preferable", if it is found to lead, soon, to an increase in "good" —— This kind of T.M. presupposes a certain kind ~~of~~ G, that's in the form of an S, or some similar condition — but it may be a condition ~~that~~ is almost always found to be true.

7
2

Here, again, we have th. problem of ad-hock abstractions. If we eliminate the possibility of an "origin" in time (a natural zero point), then this reduces the poss. of many ad-hock hypothesese. Also, for a very long run of moves (and all "life" has the moves of the ancestors incorporated into its system to some degree) it becomes almost impossible to discribe certain ad-hock abstractions with the limited, finite nervous system of the organism. Perhaps this idea, with the idea of abstraction methods on ~~page~~ page 3, will solve the problem. [see Bottom of 8]

Note: By taking simple T. M.'s like Coupling's ~~and~~ or The Homestat in its various orders of complexity, one can, by working backward, define probability.

Also, for any simple definition of probability on can construct a T.M. — Now then, simplify or ~~other~~ otherwise improve this T.M., Then go back to the proby it defines, simplify and/or improve that def. of proby, then go to its T.M. and improve it — and so on back and forth. — This is a trick that can be similarly worked ~~with~~ between any of the many aspects of this problem.

Try to construct a T.M. or Homeostat or a def. of proby. based on Wiener's Affective tone mechanism. — I did devise a T.M. for this mechanism. — by using rate of change of "Good" as well as absolute amount of good, this T.M. can be improved — see what ~~kind of proby.~~ it leads to.

Note: Chess or Checkers, to show th. redundancy of: for the first move, white must chose an action plan. Either ① there exists an action plan such that Black always loses or ② There exists only action plans in which Black occasionally wins.

— If ① is true, white will, if he is "perfect player", chose a winning plan. If ② is true, and Black is ~~perfect, than Black will win.~~ [this does not prove it: see X 15.1]

From ④ Page ③. The problem of what characteristic of an individual are maximized so that net reproduction rate is maximized is helped along by the following.

For each individual construct, for the n^{th} generation, an n-dimensional matrix. the $(a_1\, a_2\, a_3 \cdots a_n)$ element —

of this matrix will be 1, if the a_nth offspring of the a_{n-1}th offspring of the a_{n-2}th offspring ..... of the a_2th offspring of the a_1th offspring of the individual exists. That element will be zero if that offspring does not exist. (order of offsprings is in order of time of conception, since 2 offspings of a man by 2 women, may be born simultaniously)

Now consider the aggregate of all such possible matrices. (all such matrices are limited — i.e. if the rth offspring exists, then the $r-1$th offspring must exist). Each matrix characterizes completely the possible character of the nth generation. **To each such matrix assign a probability, P,** that this matrix will represent the true state of the individuals nth order ancestors

If an animal is limited to A offsprings (A is quite large for most animals if artificial insemination is allowed), the nth ancestral matrix has A^n elements. The set of all possible nth ancestral configurations are of number 2^{A^n}. So the probability distribution will be a 2^{A^n} dimensional vector. ~~— Not all but only 1 of these vector components will be indipendent, since if 2 matrices are identical~~

or we may look upon the probabilities as a scalar field in the A^n dimensional Vector space, where each vector ~~component has the~~ values **0 or 1, only.**

[see top of 7] **Probabilty in a T. M.:** Start out with any "reasonably good" method of proby. evaluation. Then use this method to find a better method of proby. evaluation. And use the "better" method to find a better one yet, etc. ... Now there is a minimum "reasonable goodness" that is required for this to be possible, also, all initial methods may not converge to the same, or to equally good methods.

This "Bootstraps method" operates as follows: Take the origional method, then modify it arbitrarily, and determine the "probability" (by the initial method) that this modification is an improvement. — Try different modifications untill one is found which is very probably an improvement, and test it empirically. This may be a very slow method of convergence, but "mother

Perhaps this method could be used to find the optimum form of warmaps within [illegible] nature" has had so much time to work at it ~~that it may~~ be an O.K. method for her.

(8) The information Packing problem. See ~~[illegible]~~ Ta 9 for discussion. Here, the problem is to construct a language that is as "compact" as possible. Information Theory gives exact meaning to "Compactness". The idea of constructing a language is to have abstractions, and methods of combining abstractions (see #3) — probably in ways other than the Boolean algebra way.

If (3) is solved, we can solve (8) in th. following manner. First start out with a basic set of abstractions. Now, whenever any abstraction is used (not ness. a "basic" one) (must it be used in what turns out to be an expedient manner?). Keep a running account of the rel. frequ. of use of each abstraction. We have (by (3)) a method of combining old abstractions to produce new ones — Use this method in a random way, utilizing the most frequently used of the old abstractions (Note: if sentences (abstractions) are constructed at random, the short (containing few old abstractions) ~~abst~~ new abstractions are most likely. cf consider that one of the abstractions used is "end abstracting process now" — if the proby. of this abstraction being chosen is p, then the proby of ~~[illegible]~~ a new abstraction ~~[illegible]~~ containing n old abstractions is $(1-p)^{n-1}p$) The hyer apriory preference to short abstractions is in accord with hyer apriori probability of ~~[illegible]~~ briefly stated scientific laws.

We have a bunch of info. to express via our abstractions, and we try various abstraction methods, to find some (or one) that will most consisely express our data. The ad-hock abstraction would, of course express our data perfectly, and most briefly, but if we must ~~[illegible]~~ build our abstractions probablistically from old abstractions, then our ad-hock abstraction is extremely improbable.

Feb 6, 1952

~~This~~ a return to a survey of T.M.

Thinking about T.M., at first, seems an imposs. task. It appears that because of Nature's method of developing T.M. being optimal [I.E. to repeat, if ϕ_{ij} is a T.M. op. (ϕ_{ij} is the j^{th} offspring of the i^{th} generation - all T.M.'s reproduce on Jan 1 only - each year) - each T.M. dies as soon as it reproduces] The number of offsprings of each T.M. is $\propto$ th. "Goodness" of that partic. operator form. Each set of offsprings is a gauss distrib. about th. parent in Operator space.

This seems to be a very good way to develope T.M.S, if one has many resources. - Perhaps it is, in a sense, th. best way.

Even if man had th. resources, he would be limited because he doesn't know th. "metric" of Op. space - i.e. for a gn. Op., how probable is a mutation to another op?

This is th. problem of structure of genes

To repeat: Genetic structure determines the "metric" of TM operator space. By knowing it, one could plot a probabablistic distribution of T.M. on, say the N^{th} generation.

To do this - (1) One has th. metric of op. space (2) one has an environment defined by a point function on op. space, giving th. no. of kids for that point in op. space.

Suppose th. op. space could be so distorted that "distance" was identical with Geom. distance.

For simplicity, let op. space be 1 dimens. let $P_n(x,k)$ be th. probability that upon the n^{th} generation, there will be k individuals alive, of operator structure, x. Then, if one knows $O(x)$, the no. of kids x will have in th. gn. environment, one can, from $O(x)$ and $P_n(x,k)$, find $P_{n+1}(x,k)$

Note: Here we assume no interaction between operators after birth. - Certainly, recognition of such a factor would change the soln. entirely.

We have taken th. simplest problem and we have, in principal, written a mathical

11

Z

expression for its soln.

Now, can we add any complexities that make th. problem more interesting and/or useful?

There is changing environment.

There is simple Malthusian interaction, in which $p_n(x,k)$ is multiplied by $[\int p_n(x,k)\,dx\,dk]^{-1}$ for large n to normalize $p_n(x,k)$ – so as to keep th. expected population constant in accord with a limited food supply. Since $p_n(x,k)$ seems to increase exponentially with n, probably this constant renormalization would result in $p_n(x,k)$ consisting of a few δ functions in x – no since th. p_{n+1} resulting from such a distrib. would not $= p_n$. Th. = lib. condition gives, with renormalization, $p_{n+1} = p_n$

It appears that Nature had a good metric to start with, and/or a good initial point.

Side Note: A realistic added complexity is $p(x,l)$, The probability that x will have l offsprings in th. g. n. environment

This has some relevance to th. black box problem, with time delay. I.E. one puts an input into a black box at time t, and gets an output at time $t+1$. One can put in 10 inputs per second. One tries to maximize the output. (As in Ub 50) $\boxed{Z\ 12-1}$

.25 The changing environment is important. If th. environment changes too rapidly per generation, then adaptation criteria for that generation are not relevant for the next Generation, and we loose th. effectiveness of our metric.

A serious problem: for a known metric, and a given starting pt. in op. space, under what conditions will

(a) $\lim_{n\to\infty} \iint p_n(x,k)\,dx\,dk \to \infty$

(b) $\lim_{n\to\infty} \iint p_n(x,k)\,dx\,dk \to 0$?

Just how does a rapidly changing environment make (b) more probable?

This enables us to ask – how good must a metric, init. conds, and environment be, for (a) to occure? $\boxed{Z\ 12-2}$

$\boxed{Z\ 11-25}$ $\boxed{\text{from page } Z\ 11\text{, line } 25.}$ The opportunity of having 10 investigations running almost simultaneously means that when one or 2 investigators have good luck, more manpower is allocated to their region of space. This is similar to the no. of kids being $\propto$ the "goodness" of a pt. in op. space. ["kids" ≡ "offsprings"]

$\boxed{Z\ 11-50}$ A good method of analysis is to make op. space have a finite no. of pts. in it, x. [$x = 1 | 1 | m$]

Let $N(x,k)$ be the proby x will have k kids.

Let D_{xy} be the xtn. proby from x to y.

— Usually $D_{xy} \neq D_{yx}$. [tho it may in Genes, due to Q.M. symmetric matrices]

$$P_{n+1}(x,k) = \sum_{l_1} \cdots \sum_{l_m} \Big(\prod_{i=1}^{m} \cancel{P_n(i,l_i) D_{ix}} \Big) \quad \text{for } \sum_{i=1}^{m} l_i = k$$

~~this is~~ wrong; $N(x,k)$ has been forgotten.

This is a summation over all possible ways in which one can have transitions to x giving a total of k individuals at x. — i.e. l_i kids from i going to x, with proby D_{ix}, and $\sum_{i=1}^{m} l_i = k$, so that the total transfer is k.

A "Good" metric is one in which D_{xy} is ~~large~~ small if $\sum_{k=1}^{\infty} k\,(N(x,k) - N(y,k))$ ~~large~~ small. $\boxed{Z\ 13-16}$

The important problems, then are

- For a gn. metric, and environment and init. conditions, will the species die out or expand? — Vary all 3 paramaters.
- How does changing environment with time affect the above? — Can this effect be simulated by a constant environment and a "poorer" metric?

Metric $\equiv D_{xy}$
Environment $\equiv N(x,k)$
Init. conds $\equiv x_0$

One can try a few simple distributions for metrics, environments, ect.

Unless I think of some very good ideas, this seems to be about as far as one wants to go, at present. The tie-in with the $\boxed{\text{"Black Box"}}$ problem is made in $\boxed{Z\ 11-20}$

The tie-in between th. "Evolutionary T.M." and Th. "Black Box".

On th. bott. of Z 12 we expressed the various steps in a study of how th. "Evolutionary T.M." works. Now, using Black box methods — i.e. the idea of an a-priori measure (not metric) on Op. space — functions space. Op. space funtion space is th. space consisting of all possible functions on operator space. A possible function on op. space would be $N(x, K)$ of $\boxed{Z12-9}$ — th. proby. that x will have K kids. The space of all possible functions, $N(x,K)$, is op. space funct. space ≡ OSFS.

If x is a discrete variable over m values, then $N(x,K)$ is a $m \times K_{max}$ dimensional vector. Any function on this $m \times K_{max}$ dimensional space is a funct. ~~on OSFS~~

$\boxed{Z12-22}$ A "good Metric" will, optimally, I think, have only one local max. (or min). Probably, then, one should try to find a transformation from th. metric one has, to a better one. Such a transformation does, I think, always exist. I.E. even in th. N-dimensional continuous case, on can place all pts. of = goodness near one another. — This involves, in general, discontinuous xfmns, but for th. "evolutionary T.M." we have a discrete operator space, and so this is no problem.

The lesson to be empirically learned from nature is — just what is her metric space? — Also, (to a lesser extent important, because we have some idea of an answer) what is her "environment" — i.e. "Goodness function" on Operator space?

Most important of all: What measure space is implied by Nature's method of solving her black-box problem? For each measure space there exists a method of soln. Just what measure space corresponds to Nature's method of soln? There may be no answer to such a problem, since th. measure space methods.

may be characterized by certain procedures that make them all different from th. method that Nature uses. If so, ~~pos~~ possibly nature should be improved upon - at least slightly, since the measure space method may, inherently, be the optimum method (not neccessarily) - the nature probably can be improved upon.

Perhaps Analogous - or even more than analogous - is the case of Probability. Suppose one has a ~~prob~~ method of assigning probabilities to any contingency on th. basis of any evidence. This method consists of a table with contingency - evidence pairs assigned probability values. Now one can, on the basis of ~~a few~~ relatively few members of the table, construct a / a-prior carnap probability of ~~___~~ various states of th. universe, and from this, derive the rest of the entries in th. table. But these derived values will not, in general Coincide with the true values in the table, unless th. "probability evaluation method by which th. table was constructed obeys (I think Carnap has a special name for such prob. eval. methods) certain laws - and there is no reason to [redacted] believe it does. It cannot (I think) be shown, that th. carnap - derived proby., is, in any sense, "better" than th. one in th. table, because it may turn out that actually all th. values in th. table were very good, except th. ones from which th. carnap probabilities were derived - these latter values being selected at random. - Suppose further that all these "good" values were derived from a Carnap set of basic probabilities, but not from th. ones in th. table.

In such a case, perhaps it is possible to modify all of th. probability values so that ~~__~~ they approach, more probably, a truer state of affairs. Suppose, for instance, that one could assign an a-priori proby to each Carnap type contingency - evidence - proby table, and one had some sort of idea as to what kind of distortion forces might produce this table, one could work back and find inverse proby - i.e. th. proby. that each Carnap-type

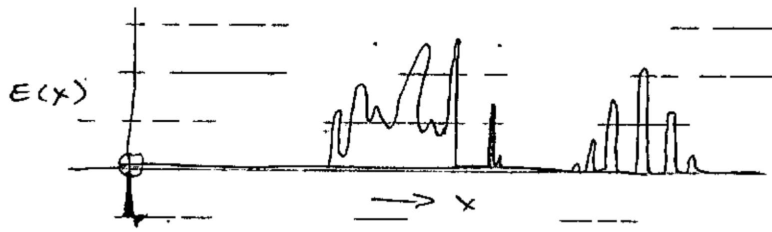
$\mathcal{F}(A \cdot B) = \mathcal{F}(\mathcal{F}(\mathcal{F}^{-1}A * \mathcal{F}^{-1}B))$

table was th. origional one. ~~This~~ This is an interesting problem — Given a Proby eval. method ($\equiv$ contingency - evidence - proby. table) to find, from this, the most probable "true" probabilities — if such exist. $\boxed{Z16:1}$

Getting back to th. Evolutionary T.M.: $N(x,k)$ could, as an approximation, be made a poisson distrib, and ∴ have only 1 parameter (remember variance of Poisson distrib $\propto \sqrt{\text{expected value}}$) — $\frac{\nu^n}{n!} e^{-\nu}$ is proby. of $\approx \frac{1}{\sqrt{2\pi n}}$ for large $\nu \approx n$ of occurance of n ~~[illegible]~~ kids, if ν is th. expected no. of kids.

~~[illegible]~~

Suppose $E(x)$ ~~[illegible]~~ $\equiv \sum_k k\, N(x,k)$ is th. expected no. of kids at x



let 

be the width of th. gaussian distribution of mutations

then we have a new $E_1(x)$ which is the convolution of $E(x)$ and $G(x)$, $E_1(x)$ is a ~~more~~ smoothed $E(x)$ and is more useful than $E(x)$.

Suppose each x had exactly $E(x)$ kids each time. Also, suppose th. x scale is distorted so that th. variance of ~~[illegible]~~ G is ~~constant~~ th. same for each x.

Let $P_0(x)$ be th. initial population density distrib. Then proceeding in a naive way, convolution integral

$$P_{n+1}(x) = (E(x)\, ~~[illegible]~~\, P_n(x)) * G(x)$$

$$\mathcal{F}\, P_{n+1}(x) = \mathcal{F}(\mathcal{F}(\mathcal{F}^{-1} E(x) * \mathcal{F}^{-1} P_n(x))) \cdot \mathcal{F}\, G(x)$$

Here we have avoided sex completely. This is a very important factor in The Evolutionary T.M. It would be interesting if one could show that the evolution of sex was very probable. Also th. presence of sex indicates something about th. metric.

Relatedness. (A metric space rather than a measure space.)

(1) evidence o proby.

Apriori

input event o output o

(2) evidence → proby

(3) $\xrightarrow{\text{input}}$ $\boxed{\text{T.M.}}$ $\xrightarrow{\text{output}}$.

optimization of reproduction proby.
can be done if p.e.m. is avail.
but existence of p.e.m. is an el. assumption.

(4) However, a human being is able to solve problems other than th. problem ~~of~~ reproduction — so that perhaps th. elementalism suggested by p.e.m. is not a bad one.
i.e. it would seem poss to learn from ~~a~~ human behavior, how to solve problems as a goal. we do not have to be so non-el. as to allow only reprod. to be a goal.

Alternation of moves between T.M. and env.

{Preliminary concept of "Good" which is elaborated upon as time progresses.

{Concepts of similarity of inputs. prelim. concept which is elaborated upon as time progresses.

2 ~~events~~ inputs are ~ when ~~they~~ are followed ~~[illegible]~~ s ~ outputs ~~[illegible] inputs~~ make them be followed by ~ inputs. ~~[illegible]~~ (and conversely about ~ outputs)

At first 2 inputs or 2 outs are ~ if they are usually followed by ~~[illegible]~~ good or bad.

temporal ~~dimensional~~ extremization

$\overset{in}{\alpha}$ $\overset{out}{x}$ $\overset{in}{\beta}$

$$\int_{-\infty}^{\infty} d\omega \; \exp - \left[\mathcal{F}\left(s(t) \right) - \mathcal{F}(p(t))\, e^{-i\omega t} \right]$$

Basic idea of learning is to know what strings of stim-resps. demand the same responses.

Generalized similarity:
if 2 situations containing many stims. and responses, are similar in detail, except event χ_1 (stim, or r resp.) of situation 1 and χ_2 of situation 2, and χ_1 and χ_2 are not $\sim$ or dissimilar — they have simply not been evaluated, — then χ_1 becomes $\sim$ to χ_2.

In addition to $\sim$ and σ for every S,S or R,R pair one must have a degree of certainty of each value, to tell how much weight it must be gn. when mixed with other evidence.

A general device that is less ad hoc and more general than 2 20 (top) would a mechanism to keep T.M. non-al. I.E. it would watch to see that the end-goals were being pursued, and that T.M. didn't become "perverted" in over emphasis of unimportant sub-goals.

This page has not yet been transcribed.

March 1, 1952

Z 15-4 ~~This is a very important point, i.e. the best proby. eval. meth~~ is probaby ~~not [illegible] "normal"~~ Z 14: 20 def. one. ~~I~~ Normal pr. ev. meth's are ones to which a measure space can be assigned. In the past, I have assumed that a p. ev. meth. using a metric space (like the one used by genes) was a "normal" one — but this is now (it appears) extremely unlikely.

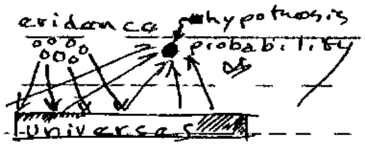
At the ~~present~~ time, an expedient course of action would be to investigate some P.E.M.'s (proby evaluation methods) to find out how "abnormal" they are, or just to get an idea of what they look like. Consider P.E.M.'s implied by variations on Wiener's "Affective tone mechanism". ~~It~~ It seems, at present, that ~~the [illegible]~~ looking at P.E.M.S from th. pt. of view of "Normality" is sterile — that examination of language and general scientific methods and learning theory, in attempts to get a metric space, would be better.

The idea of a metric space. This is a space of events or abstractions, such that if 2 events are close to one another, then they are also "close" in "goodness" value. I think that many living beings use a metric space in which space and time proximity imply closeness of G (goodness = G) value. For metric spaces, it is best to have one with only one maximum point for G — i.e. no local ~~[illegible]~~ maxima or even minima. Usually, of course, this is impossible.

Review:

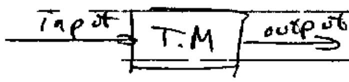
① A "normal" p.e.m. is one in which it is possible to assign a priori probies. to all th. possible states of the universe. When evidence is offered, certain of these universes become impossible. Then the probability of any statement is simply the sum of the renormalized probys of all remaining universes in which that statement is true.

One starts with the a-priori universes. The evidence modifies th. proby. distribution, and from th. new distrib., one can calculate probies.



② An "abnormal" p.e.m. is one in which th. proby assigned to any evidence, hypothesis pair cannot be derived from any such a-priori universe probability.

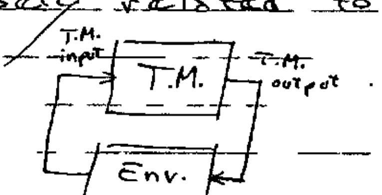
③ The problem of th. human T.M. is to maximize reproduction rate. If a complete p.e.m. is available this problem can be optimumly solved. However, that a p.e.m. is needed for th. solution of such a problem is an elementalistic assumption, and is probably untrue.



④ That the human T.M. can solve problems other than maximization of reproduction rates indicates that th. elementalism of ③ above may be O.K. Also, that one may be able to learn how to solve simple problems by observing human behavior.

Investigation of th. following kind of T.M. —
I think this is similar to Wiener's Affective tone mechanism.

① Alternation of digital moves between "T.M." and "Environment". Env. [def.]
(this may or may not be a simplification — but it isn't too closely related to the assumptions which follow



Note: In th. discussion to follow All inputs and outputs refer to T.M.

② T.M. starts with some rather vague, loose concepts of "good" and "bad". They assign a number to each possible input. They may be vague, and loose for one or both of 2 possible reasons:

2) Tho they cover all possible inputs, the metric space they define is largely on th. basis of proximity in time and/or space. I.E. 2 inputs have rather close goodnesss values (G values) when they are ~~the~~ similar in color, shape, Sound, position, texture, ect. "similarity" here is largely on th. basis of physical science meaning, and Bio-physics discrimination threshold — discrimination thresholds do define a connectivity of a space in a topological manner, and do give an ~~a~~ idea ~~as~~ to how to construct a metric.

These values are "loose" because they are usually easily changed.

Some G values like satisfaction of hunger, physical pain, ect. are ~~not loose~~ not "loose" but titely fixed.

The initial G function is the best that can be made, due to lack of knowledge about the specific universe that T.M. is to be born into.

To review: The G values are assigned first to such things as satisfaction of basic body needs, pain, ect.

Also G values are assigned to general things like temperature, texture, loudness, etc. Note that the latter qualities are general, so that "temperature" means average body temperature. G values would be the same for {warm hand and cold foot} and {cold hand and warm foot}

(3) Elementary, preliminary Concepts of similarity of inputs. Same as ② above. At first 2 inputs are similar if they have close G values. There is some differentiation, however, even at first, since certain inputs ~~them~~ may have equal G's, yet may demand different responses (outputs). ~~[illegible]~~ e.g. Hunger of infant plus presence of mothers teat in his mouth may produce sucking response; General body warmth and comfort without hunger, may ~~[illegible]~~ have equal G, but will produce no sucking response, Therefore must be recognized as different situation.

So at first "similarity" is on 2 bases.

a) 2 situations are similar if they have close G's.

b) " " " " " " demand the same response.

Actually 2) may, in a sense, be regarded as a more ~~important criterion in later life~~. [I think "similarity" is more important than G. G is an attempt to break down "similarity" into elements]

These are preliminary states of T.M. T.M. "Learns" in later life by modifying its concepts of G and of similarity.

In general, if 2 inputs are similar (demand the same response) then they usually have close G values. But if 2 inputs have similar G's, they need not be similar ($\sim$ ≡ similar).

How learning modifies:

1) 2 inputs, A and B are $\sim$, if: input A is followed by output α and produces input a
" B " " " " β " " " b
$a \sim b$ and $\alpha \sim \beta$
Then $A \sim B$

2) 2 outputs α and β are $\sim$ if:
A is followed by output α and produces input a
B " " " " β " " " b
$A \sim B$ and $a \sim b$
Then $\alpha \sim \beta$

This tells how initial idea of similarity can be expanded.

Notation: Capital Latin letters are inputs.
Greek " " outputs.
$A\alpha \to A_1$ means A is followed by α producing A_1 as an input.

An OLD PROBLEM of the Affective Tone Mechanism:

3) If $\exists\ \alpha \ni A\alpha \to B$, and B is Good, then A becomes Good.

The trouble was, that this led T.M. to seek A as a subgoal in itself. Altho we can find instances of this in human beings, as a perversion, e.g. the seeking of money as an end, rather than a means; it would seem that such perversions would occure even more frequently than they do, if, say, human beings were governed by this mechanism.

I believe that the following solution for the dilemma was proposed when it first came up, or some time after, or now for the first time: This resolution is largely ad-hock, and is tailored to fit observed human behavior. } is this non-committal!!!

if $\exists \alpha \ni A\alpha \Rightarrow B$, and B is Good than A becomes Good. Now suppose B is a very important, permanent good, like satisfaction of hunger. Then A will become good and retain its good only by virtue of $A\alpha \Rightarrow B$, so that if $A\alpha \not\Rightarrow B$ with reasonable frequency, than the "Good" of A begins to drop off. If, however the good of A becomes very firmly established (in infancy of a human being, say), it can become a perverted sub-goal in itself, so that even when $A\alpha$ no longer produces B, A retains its goodness.

Also - its a rather non-el. way of doing it - since B (which is the ultimate goal) controls the A.T., not A)

This hypothesis loses a little ad-hockness, when one considers that it works for conditioned responses, and for more general learning, as well. X 14.36

Remember, however, what Goldstein said about the lack of importance of C.R.'S. - Yet even tho they may be a parody of true learning, they may preserve many essential features of it.

An important question in any learning theory, is not if it explains C.R.'s with their many trials, but does it explain rapid learning due to insight? — i.e. Gestault — the "Ah Ha phenomenon".

A preliminary skirmish with the Gestault problem before we go out to lunch.

① As T.M. trys to decide what "move" to make, it evaluates ~~goodness~~ G of each poss move on the basis of "similar" moves in the past. When it suddenly finds a move of very great expediency and G value, this may be "Gestault"

② Gestault may be an entirely separate phenomenon from ordinary learning. This, of course, makes the mechanism very ad-hock.

Z21)

The Manner of operation of T.M., then, is as follows: At time t, T.M. has complete recall. It has ~~maxm~~ $D(x_1, x_2, t)$ the distance between outputs x_1 and x_2 at time t. It has $\Delta(\varphi_1, \varphi_2, t)$ the distance between inputs φ_1 and φ_2 at time t.
It has $G(\varphi, t)$ the goodness of input φ at time t.
Now T.M.'s next move, $x(t+1)$ will be made by evaluating the expected goodness of all possible next moves. This will be done by assuming all possible sequences of T.M. - Env. moves, which start with x_i and extend, ~~the~~ ∞ moves into the future. The a-priori probability of ev. responding each poss. way can be gotten by using entire ~~all~~ previous history of T.M., plus the φ and x distance functions. Since, in general, each proposed sequence has not happend before, one will have to ~~w~~ weigh it probablistically on the basis of sequences which are close to it. The degree of closeness is gn. by the φ and x distance functions.

Now - This determines T.M.'s next moves - but how should the φ and x distance functions and the $G(\varphi, t)$ funtion be modified by time? (perhaps it is unness to do so, since T.M. already has behavior which is based, in a very useful way, upon past experience)
{ — Yet I think time modification of these 3 functions is what gives Gestault!

The variations of $D(x_1, x_2, t)$ and $\Delta(\varphi_1, \varphi_2, t)$ and $G(\varphi, t)$ with time can be gotten using the rules $\boxed{Z19-15}$ and $\boxed{Z19-20}$

~~An analysis of this T.M. could proceed in the following way.~~ Make the T.M. a black box problem, with ~~t~~ env. as the black box, and certain ultimate goods and sub-goods in T.M. Sequences of T.M., env. move alternations are inputs to the Black box and outputs of T.M. Successive outputs of the black box are inputs to T.M. and are evaluated by T.M.

For problems like mathematical problems, at first, the only "good" that T.M. can know is correct solutions. Then as ~~th~~ it works more and more simple problems, it will build up a store of "sub-goods".
At first T.M. should be fed simple problems with only a fewness moves for answers, so that T.M. will build up ~~a~~ metric

spaces and "Good" spaces.

Along with this mechanistic analysis, should proceed a constant reference to psychological data, and intuitive ideas about scientific method.

(05) Note: A less el. idea of Goodness and similarity would be for stimulus response pairs or SRS triplets or SRSR quad's etc. These would, of course, each have their own spaces, based (1) upon past history and (2) upon simple deductions from assumptions and data in lower order spaces. $\boxed{x20.10}$

April 2, 1952

The idea of sub-goals in T.M. is as follows: Suppose one has a black-box problem — i.e. an input and an output ~~happen~~. In a normal B.B. problem, each output can be immediately given a number, G, and one tries to find an input whose output gives the hyest G value. In T.M., however, only a few of the outputs have G values attached to them, and others have G values — but in the form of a probability distribution of large variance.

~~Again~~ In such a T.M. B.B. problem, a method to maximize G, would be to first fill in lots of the G values in the space of outputs, so that one could know in what direction one was going inside the box.

Even with the initial set of G values given, the B.B. may be a hard one to solve, if there are several local extrema.

Suppose one has a 2 dim. B.B. (fig. 1)

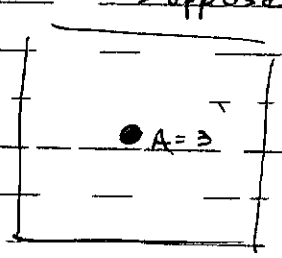


fig. 1

Say there is only one ~~point~~ small area, A, that is "Good", and one must try to find it by chosing pts. in the box at random. One would have a rather small proby. of finding it.

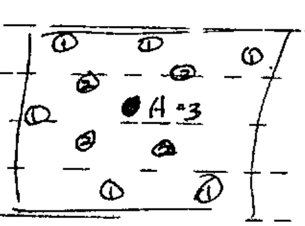
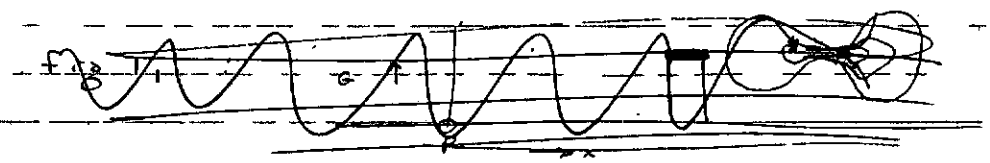


fig 2

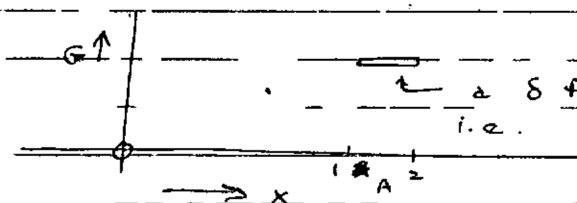
Now, suppose that in addition to A, there are other small areas with various G values as shown in fig 2. Then, Some random guesses will not give A, but they will give some idea as to where A is

Now, say that in addition to the ~~[illegible]~~ labled pts. in Fig 2, one has an idea of similarity, so that each of the areas shown with a "G" lable can be smeared out — but that the parts of the smear outside the origional area have variances > 0 in their proby distribs.

~~[illegible]~~ In 1 dimension:



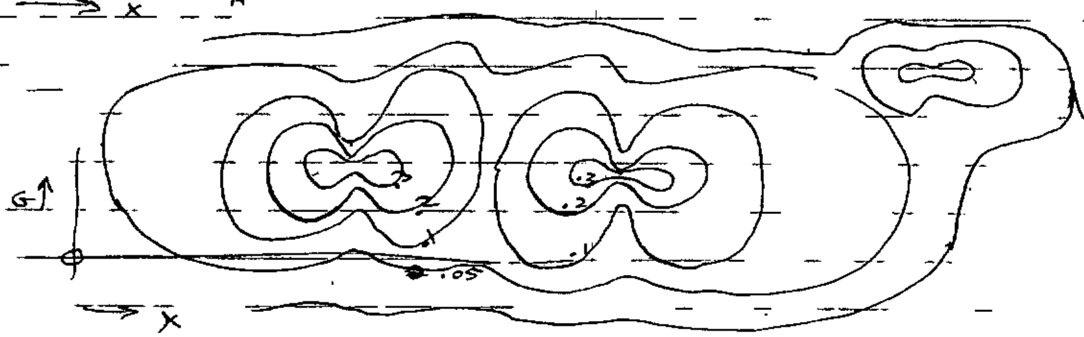
X is the 1 dim. the P axis is ⊥ the paper, and is the proby density of x having a certain G value. Contour lines of = G are shown.



← a δ function in the G direction, i.e. $P(X, G) = \delta(G-3)$ for $1<x<2$
$= 0$ " $1 \not< x \not< 2$

fig 1′

fig 2′



In such a case of smearing, one has even more probability of getting useful info from each trial point.

So one may have as a sub-goal, the realization of a ~~[illegible]~~ method to recognize when a pt. is near a really "good" area. The criterion is that these estimates of "good" should be ~~[illegible]~~ ~~[illegible]~~ instrumental in leading one toward one's ultimate goal.