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The (a, q) data modeling in probabilistic reasoning

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Abstract: This article considers a critical and experimental approach on the attributive and qualitative AI data modeling and data retrieval in computational probabilistic reasoning. The mathematical correlation of X≈Y in the d=dx/dy differentiations and its point based locations and matrix based predictions in Markov Models, Rete's Algorithms and Bayesian fields, with the further development of non-linear 'human-type' reasoning in AI. The new approach in the ternary system transition (decimal↔binary) of Brusentsov-Bergman principle by its bound allocation in the 'mirror-based' system in t^{n-1}… t^{n+1} powers, and hereon considers its further data retrieval for suitable matching and translation of probabilistic data differentiation. The causation/probability matrix of this paper regards not only bound/free variable in x1,x2,x3, x^n variables, but discovers and explains its further subsets in a^nXq^n formula, where the supposition of d=X/Y regarded not as a mathematical placement of the variable X, but as its attributive (a) and qualitative (q) allocation in a certain value/relevance cell of the Probability Triangle of the ternary system. From where the automated differentiation retrieves only the most relevant/objective a^nXq^n data cell, not the closest by the pre-set context, making the AI selections more assertive and preference based than linear.

Keywords: Probability, Reasoning, Computational Logic, Abstraction Modeling, Probabilistic Reasoning, AI Reasoning, Automated Differentiations, Probability Calculus

1. Introduction

The schematic computational reasoning existent today regards the TRUE/FALSE operands in conduct differentiations in computational logics; nevertheless the mathematical consistency of such reasoning requires a different type of differentiations.

We may interpret and even improve certain logical matching in computational reasoning, however creating certain 'virtual consistency' of AI reasoning is a task of program reasoning and imagining, which we pertain to the Interpretation system of logic in probabilistic reasoning.

By correlating numerical value of an *attribute* (*a*) and *quality* (*q*) to the numerical Consistency of X we allocate its subsets (a, q) in certain alphabet of transition in decimal↔binary (ternary principle).

Particular perception and particular experience could contain an (a, q) data allocated in the triangle of Data Allocation (See Triangle 2) in where the most referred AI selections would become prioritized in 'human-like' stereotypes.

Another 'human factor' to have simulated in AI reasoning is the multiple abstraction modeling, which we explain in the modeling of abstraction Interpretation and Condition in abstract leveling.

The X, Y correlation of variables in any type of logical solutions needs to be graded and out-branched not only by the logical exclusion, but by the quality of its consistency of being objectively and subjectively assessed at certain extent. So any human-type implications would bare a reasonable doubt of being credible 'well enough', unlike the formal-logical execution of TRUE/FALSE.

2. Abstraction Modeling in Artificial Reasoning

2.1. Abstract Logic in Mathematical Applications

Alike in Bayesian probability we conflict not with frequency of referral and induce the (*a*, *q*) qualities in computational logic. The (*a*, *q*) allocation and priority scale (Triangle 2) has no limits in order of probability, however sifts off the least referable/non-referable options as on obsolete/actual in the abstraction system of AI, hence the requirement of probability appropriation and ordering in abstract logic modeling.

The mentioned [1] levels of:

- conjunction
- disjunction
- negation
- consensus
- recommendation
- ordering

require understanding of the System shift and its further Interpretation not only for a developer but for an AI as well.

The current problem remains relevant: the AI advancement in practical developments pertain to the mathematical ordering and equation of probability reasoning merely on technical levels of their own expertise, bolstering operands of the same order and not providing the value of it in abstract consistency. Such sub-complications require sub-programming in abstract modeling, automatic/binominal differentiations and other levels depicted below:

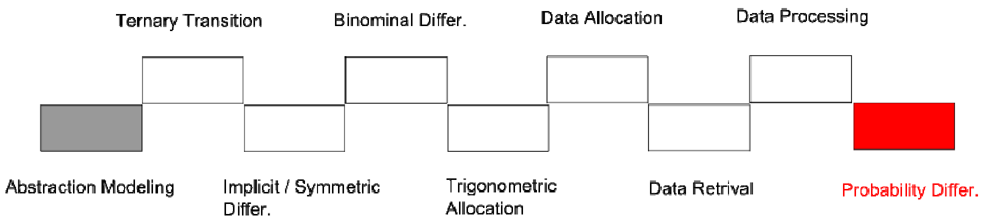


Fig 1. *The sequence of (a,q) data modeling.*

The understanding of what exactly is the certain abstraction of X, Y, Z, in particular sequence of dx/dy differentiation of AI reasoning, requires cohesion of mathematical rules and computational logic of selection in order to supersede the level of linear reasoning. Instead we presume the Bayesian model differentiation of free variables in conduct with dx/dy calculus in abstract models of stereotype reasoning, as well as the HMM.

Therefore, we get into the variable generalizations subdivided by their (a, q) grades of probabilities and causation, not functions. The likes of such we see in the *Opinion Triangle* (ibid p.7) concept, which has its own angles of limitations and needs to vary by the free operands of priority and not by bound or universal ones.

2.2. Free and Bound Variables

The scope of quantification [2] presumes different types of variables and their solutions. In proceeding of IA 'human-like' reasoning would be the way of free variables existent in any subscales possible, in our case its (a, q) sub-variables of mathematical operands, however, the ordering (stacking) of the mathematical data preceded by the differentiation calculus.

$$\forall x[P(x, y) \Leftrightarrow [(\exists x \exists z Q(x, y, z)) \Rightarrow R(x, y)]]$$

In the example of:

$$\text{IF } \forall x\text{=driver}$$

$$\text{THEN } \forall x\text{=aXq}$$

In where we specify what kind of driver (a) and how many of them (q).

2.3. Categorical Value

On whether it is applicable for AI to appeal to the formulistic logic or to the pure mathematical computation we shall decompile some principles of both fields of sciences separately.

Reduction to the mathematical (categorical) value considers a formal-logical or mathematical appeal of its value to its factual consistency, to its own definition and hence, for its further logical construction.

The method of comparative value based on the attributive consistency of the initial sample of cognition and its correlation with the unknown integer X by its internal and external consistency further on to be considered as (*a,q*) differentiation.

Hence, the mathematical differentiation of X and Y is a difference not made by a common inference, but by the inner (binary matrix, see Table 1) consistency of X and Y, in where we do not presume the meaning of X and/or Y logically, but merely their formal and qualitative consistency. The prediction/probability of X being Y or vice versa, nevertheless, could lead us into inference of what it may or might be IF or THEN X and Y arise or occur on the same alignment of deduction/induction or any general conclusion depicted by circles hereinafter.

2.4. The Sequencing

The methodological understanding of certain conditioning, which in mathematical reasoning of law compiled of simultaneous and sequence based equations of $x1$, $x2$, $x3$ (by Fred Kort) [3].

However, the concern of the numerical sequencing in the trigonometric function of positioning and artificial reasoning least probable with categorical (Fuzzy) logic.

In the event of the decimal-binary transition we presume only translation of one numerical value system to another (S cons → S cons^2), the sequence, therefore is obsolete in human reasoning simulation, however the probability/causation grade and the choice selection is where the priority sequencing needs to be modified to the automated differentiation (implicit differentiation).

We consider certain categorical value of ‘A’ related to its numerical counterpart of 0 and 1, both in binary and decimal (and in any other system). However, the grades of ‘A’ being a ‘driver’ predicted by the matrix of causation/probability in 0 or 1 needs to be negotiated, automatically inferred by the AI on the grades of (a,q) probabilities of whether the certain ‘A’ is better to have in $dx=A1^{21}$ and B in $dx= B2^{5}$, and so on.

2.5. Identification and Fuzzy Logic

The chronological identification of X1, X2, X3 in a certain numerical values represented by the grades of causation/probability for approximate reasoning (Fuzzy logic) requires certain identification inside the machine system as well.

While creating abstract forms of different levels, placing them into trigonometric triangle of priority selection, we assign the prioritized choices to the artificial definitions of ‘principle’ and/or ‘morals’. In where the lowest value of X provides the value of precision and objectiveness to the mentioned categories:

$$\text{in } Xq\text{; e.g.: } X=1$$

In where the unknown abstraction of X gains the qualitative (q) value of 1 (TRUTH). Therefore, applying computational differentiation of strict logic in comparison to Fuzzy logic requires the Bayesian principle of free variable differentiation to the abstractions of sporadic levels of sequencing such as:

$$X1/Y2 \text{ or } X4^{n}/Y6^{n}\text{, so on.}$$

In where different levels of abstractions have different values for subjective perception as well, and would also construe a basis for the (a, q) automated differentiation and data retrieval.

The problematic aspect of the AI reasoning development in the consistency of Fuzzy logic remains on its linear triangles [4], in where the certain grades of the same abstraction differentiated by exclusion by IF/THEN operands strictly.

For example: IF ‘hot’ THEN ‘not cold’. The solution of the linear exclusion or logical conjunction prevails only on the data coexistent with the pre-condition, however, any logical pre-condition is not graded as causation/probability of it and, therefore not reliable by a ‘human-like’ thinking.

2.6. Numerical Consistency and Observation

“How can conclusions at one level be related to conclusions at another level?” [5]. The self-reference, or the ‘mover’ of abstraction in the AI systems, needs to be equated mathematically from one form of conclusion to another and considered in the Interpretation transfer (basic shift):

Abstraction → Form → Preconditioning = Processing

Such Form shift could be graphically explained by the example of M. Minea [6], however the question is not in the graphical depiction and graphical interface, but in the basis of reasonable selection of computational data and the criteria the AI would prefer over it in probabilistic reasoning. And we do logically presume the subjective Condition of the AI surmise, or the Consistency of its Pre-conditioning.

2.7. The Data Condition

The non-predictable condition in AI to the ‘dynamic’ static data application is possible by the derivative functions of free variables transition as well explained as observatory transition [7]:

Factual data → Observation → Set of goals

In the following shifts of abstractions the prime numbers (Euclid’s P_n) vary in the derivative (X, Y) accordingly and infinitely:

$$\forall X_{pn} \in\equiv Y_{pn}$$

However, need to be allocated and retrieved as a pre-set data of the certain logical meaning by the means of such (a, q) subsets:

$$\forall Xan \equiv Yan$$

$$\forall X_{qn} \equiv Y_{qn}$$

In the derivative meaning of abstraction IF P+1=q, THEN we reduce the meaning of N to 1, the objectiveness number, for its simplicity of allocation and tagging in the AI pool.

We devise the value of X as of X in (a, q) probability/causation by the certain value of P_n graded as p1 p2 p3… p^n, to the consent of the causation matrix, pre-set in AI abstraction by its developer.

In more practical value we ask ourselves, which (a, q) could be pre-set for an integer X before it gets differentiated mathematically?

In aXq, in where 9X is a certain level of attributive abstraction that could be deciphered into many mathematical differentials as of P= -10000 or 1/-1000, in $N^{2,3,4}$, so on.

In $9^{2x-11}X$, or $6^{2x}+4^{-65}X$, or any other high level differentiations we predict the consistency of 0 and 1 only.

2.8. The Consistency

The known numerical consistency and the letter follow-up in sequential triggering of automated differentiations and computational reasoning provide certain arithmetical conjunctions of A,B,C,D,…1,2,3,4, levels into the sequence of logical operands IF/THEN; in where we may exclude ‘B’ if it is not ‘C’, and ‘C’ if it does not confer with ‘F’, so on.

However, the numerical degree of certain ‘F’ and ‘B’ for the practical reasoning in the subjective logical computation could only devise a philosophical rumination (cycling), therefore needs to get stipulated by the developer on credibility and probability of such data.

The consistency of a number is the definition and the consistency of the definition is the letter by the follow up of its cohesion and transfer unison:

$$A,1,\ B,2,\ C,3,\ D^{n=}X^{nx1}$$

$$X1,\ X2,\ X3,= P^{n}$$

$$P_{n} = p1,\ p2,\ p3,\ p4, = Rn+1\ldots n-1=Xn\pm1$$

$$Xn\pm1=a^{n}Xq^{n}\pm n1=1$$

$$\text{IF } X=Y=1, \text{ THEN } 1=1^{n-1}$$

$$\frac{(n1 - n1)}{x^{n1}} = x^{2}\ x^{n1}$$

And we don’t confront the Bayesian logic by pre-setting the trigger of information in the sequence of objectiveness, X1, X2, XN, X-N.

2.9. Observation, or the (POMDP) System

The artificial observation system of non-determinist analysis, or the ‘blind observation’, requires a set of duality. While operating with IF/THEN we construe determinism as if it is a strict data. The fluctuation of the universal operant ∀, considers the consistency shift of S→S1 by the observer not by the formulistic pre-set.

While POMDP system considers reward (R) triggered for observation (as for the Result) the AI shall be triggered by the certain *q*uality of satisfaction of credibility not an award of the successful programming.

The automated differentiation of numerical value of the variable (*a*X*q*) considers the logical Consistency shift from one trigonometric dimension (allocation) to another for *q*uality and *a*ttributive discernment of *a*X*q* =1 OR 0.

Making the abstraction movement more natural and less ‘rewarded’, unlike the Markov Model. As soon as the habitual observation considered as a computational solution, the machine would ‘observe’ everything observable only IF there is a connection to the existent abstraction:

IF A=driver AND B=bus,

OBSERVE C and D allocation.

IS B and/or D $\in$ Z?

IF not/ THEN match B $\in$ Y

IF yes/THEN observe Z.

If going by the rules of implication A→B, then an observation is already rewarded to the AI in the implication.

Meanwhile, the example of the Lisp, which traverses the list of CAR → (ABC) [8] and does not remove the first item in the list, but instead moves further to the consistency of the ‘CAR’ proves the opposite logic. However, the (a, q) of such expressions as A, B, C, → ABC listed only by the context of meaning, (car '(rose violet daisy buttercup)). In where the singularity mode evident in x,y,z but the grades of reward and quality are lacking in mathematical value.

3. The (a, q) Data Interpretation in AI Reasoning

Various transfer shifts form System 1 of numerical value to the System 2, transfer of decimal↔binary and adaptability of such consistency to the general field of AI reasoning.

3.1. The List of Equivalence and Model Transfer

A model of interoperation of formal systems by G. Kreisel explains transition from the model $S_1 \rightarrow S_2$ in Consistency ($Cons_1 \rightarrow Cons_2$) [9] applied to demonstrate provability logic in computable systems by defining its core; we presume the numerical (N) shift by abstract depiction.

Alike the Lisp principle of the data list of equivalence the data of concurrence in where (a’ a’)=TRUE we construe the graphical overlap in aXq=aXq±1 = (eq 'a 'a)

In order to simulate the thought pattern of ‘human-like’ reasoning in AI abstraction modeling, it needs to be represented by the principle of linear $Cons_1 \rightarrow Cons_2$ shift, in where the numerical value grades in x1 x2 x3….-x1, -x2, -x3 and where the consistency of S_1 does not overlap the consistency of S_2 as well.

Inducing the n± grade of X, X=Xn±1 we stipulate the adjacency or the relevancy of an abstract model in the ‘side-by-side’ correlations by A,B,C,= ABC, which would help us in future to overcome the binary transition from 01 to 0,1.

As soon as we do not occupy the same factual spot of the Consistency, but only have a consecutive adjacency to it, we would have to be adhered in trigonometric order as by *x1 x2 x3* in descriptive systems such as Lisp:

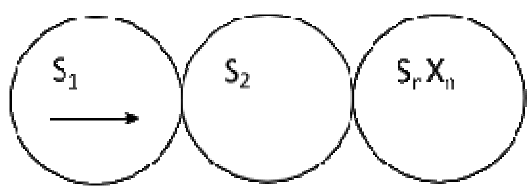


Fig 2. *The linear abstraction transfer*

It was also proposed by Daniel L. Schwartz and John B. Black models [10] in where we revise a closed chain transfer of probability selection as an effective, but still insufficient one:

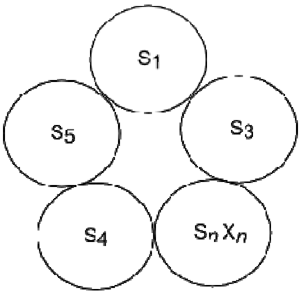


Fig 3. The 'closed chain' transfer

We state the System as P (positive) in where it is proposed in Kewen Wang [11] that the R is a model of P as of R ∈ P, and, therefore P is a degree of S (S^P). Whereas we construe the shift of: P∈Rn+1=k1, k2, k^n in binary system as well, in where, S ⊆ K^n and in where the P does not exclude R (P←R).

In the proposed model of S^P the transfer of one abstract Conclusion based on a previous Conclusion would be mingled and interlaced into N^{th} interpretation of R only - linear identification only.

3.2. The Sequence and the Linear Interpretation

The system sequence explanation is short – it's self-ordered. If we construe the sequence of p1, p2…k1, k2, so on, in certain formulas or numerical relations according to the differentiation or linear principles, the extension of computational logic would rather operate with categories of nt1, nt2…, and its relevancies to the subject of ntX1, ntX2….

However, the dynamic data allocation in the System of Interpretation from Cons1 → $Cons^N$, would be chained as k1, k2… kt1, kt2, kt^n as in ternary shift (decimal↔binary shift):

$$\text{IF } X=S_1\rightarrow S_2$$

$$\text{THEN } X=S_2\rightarrow S_3\rightarrow S_N$$

RETURN. transition reversed

$$\text{IF } S_1\rightarrow S_2 = S_N$$

$$\text{THEN}=S_N\rightarrow X_N$$

3.3. Anticipation Model

In certain X of unknown in AI reasoning there would rather be a qualitative selection to find such X by its consistency than by pure math rules. The AI would consider it from different $Cons^N$ by (a, q) allocation in its database. However, the matching of an existent data with an 'incoming' one needs to be correlated in a pre-set Anticipation Model (AM).

So, we're allowed to presume that in many S $cons^N$ there are hypothetically N options of AI reasoning and conclusions, hence N types of conclusions may be inferred by AI in bound variables.

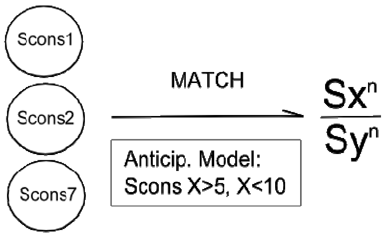


Fig 4. AI modeling matching

In where the AM could rather be the reasoning model in computation logic, whereas the AI pool data would intersect S $cons^N$ in order to pre-set a 'stereotype' of reasoning.

By selecting the consistency variants from Scons1→Scons9 we consider the stipulation of, X>5, X<10 whereas, Scons 9, for example, ranks in low/high priority of selection.

We presume not only the logical implication of A→B or wA→B with the consideration of t(time), but also the calculus differentiation of d=X/Y in its matching.

In where the matching of *int.* and *ext.* time models [12] would rather be redundant for the AI at the moment of perception, and instead presumed for an internal meaning (X) first, before it could matched with the 'incoming' one (Y). The computation of the t itself could be basically alleviated to the query model.

3.4. Query Methods Interpretation

How is it possible to move abstraction form of Scons1→$SconsX^n$ in practical application? Or if we presume a chain sequencing of X_n $Scons_n$ what and how would trigger the probability of selection of choosing certain SconsN in certain X_n of abstract reasoning?

How is a certain PROBABILITY arises at a specific moment of the *int.* time or in a certain order?

For example, the notion of QUERY in *Computable Probability Theory* by Cameron E. Freer, [13] and the measure of the *countable space* of it would hypothetically suffice to predetermine the Consistency of Interpretation in AI. In where we schematically presume:

Conditional Time → Consistency → Interpretation = Probability Application

However, such QUERY methods also could exist in uncountable spaces of S_n, X_n that would take an Interpretation transition from S_1 to S_2 infinitely. And in the solution of this problem Mr. Freer refers to the Solomonoff induction in *Sequence Prediction.*

So, if we would mathematically presume the *Sequence Prediction* [14] of Solomonoff then the system wouldn't be self-cycled:

Conditional Time → Sequence Prediction → Consistency = Interpretation

The shift in binary system as:

$$\text{IF } S_N \rightarrow X_N$$

$$\text{THEN } S_N = 1 \text{ OR } 0;\ X_N = 1 \text{ OR } 0;$$

In where the 'IF' holds the probability value = 1 OR 0, THEN S_N =1, AND X_N = X_N in the numerical value grade from -1 to 9^9 ($X_N^{-1 \text{ to } 9(\text{in } 9)}$)

$$\text{IF } S_N = 0, \text{ THEN } X_N = X_N^x$$

If it's computed by Solomoff principle then requires a branch-out to different mathematical equations and even if executable thence after all, the attributive (*a*) and qualitative (*q*) identification of what is '1' and what is '0' in the bound variable of X need to be Interpreted in transition of Scons1→ Scons2 as computational reasoning but not as data retrieval/ allocation.

We can't say that the listing [15] proposition is adjustable to the issue of this paper, because it considers only linear programming, therefore the (*a*, *q*) of bound variables in the dynamic data allocation would be irrelevant.

However, it was also proposed to distinguish the separate order Queries in order to indicate an *active assertion* (ibid 112), and, henceforth make the probability matching by the strongest argument.

The similar situation in non-linear programming we propose by the induction of *a*X*q* dynamic data allocation in the grid (see the Triangle 2) QUEUED only by the PRIORITY of data retrieval, but not by the ACTIVE ASSUMPTION (access), as soon the active assumption (in before any differentiation occurred) is an access list and could be pre-conditioned wrongly in advance.

4. The (*a*, *q*) in the Subjective and Objective Recognition

4.1. Bayesian System and Joint Distribution

Subjective reasoning of AI precludes not only propositional or mathematical logics but principles reflected in Bayesian probability. The data evolving from the hypothesis or even active assumptions may preclude mistakes, false, stereotypes and whatever else happens to the human-type reasoning.

The Bayesian system of P/H/D [16], or of the knowledge before and after hypothesis, actually compliant with the same principle of the Consistency shift from the Pre-conditioned knowledge to the Anticipated one.

The problem of Bayesian theory still revolves around the actual question of how an AI would apply the correct set of causes and solutions of its inferences. The *generative model* [I7] was depicted in a simple chain causation by Bruno A. Olshausen, however we would try to elaborate it in the Fig 5.

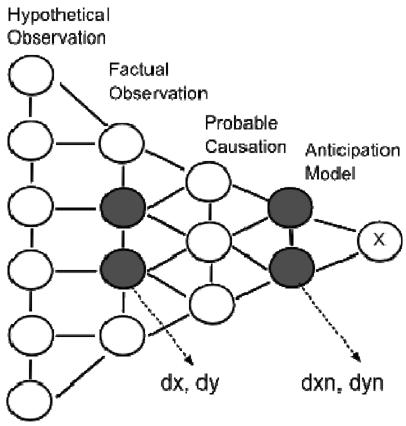


Fig 5. *The causation matrix differentiation*

A match or a mismatch of certain cell is the question of certain Xn, Yn, in (*a, q*) degrees of free variables.

If a certain cell of, let us say, 'Factual Observations' has an X in the (a,q) degree e.g. in a^2Xq^1, which is higher in 'objectiveness' than for example, the $a^{12}Xq^{11}$ in the 'Probable Causes', then the selection would revert to the 'Factual Observation' cluster and vice versa. And as an advance of variable computation existent in probability equation we presume the Xn, Xyn, Yn, Yxn substantiation of *r!*.

$$\text{IF XN}, \text{Xyn} > 0$$

$$\text{THEN Yn} = -1$$

Sub-leveling resolves the probability of subsets in x,y,z > or < 0 as following:

$$\frac{n}{r!(n-r)} = \frac{Xn}{X!(n-1)}$$

The number of the possible outcomes predetermined by the Xn strictly.

4.2. The Joint Probability Distribution

In the Bayesian nets P (x1, x2, x^n) $\prod_{t=1}^{n} P x_i$ = Parents (X_i)), a small change in the variable of *x* indicates the angle ^ of its variation, but not the *x* in allocation/retrieval. We conclude and exclude the other elements that don't match preclusion. In the proposed [18] examples of Bayesian nets were used no subsets:

(A^F^G^H^J^K¬B¬C) =

(A│F)(G│H)(J│K)P(¬B)P(¬C) so on, in conjunction of X it would be more like:

P (x1 x2, xn… y1, y2, yn), (X1^X2^X5^X4¬X3¬X6)=

(A│F)(G│H)(J│K)P(¬B)P(¬C))

However, by adding the (*a*, *q*) subsets to X:

P(x1 1x1 2x2 3x3…$a^n Xq^n$)

(X1^1X1^2X2^3X3¬1X4¬1X2)

In computational differentiation (d):

IF X1=1X1 IN LINE1, THEN 1X4,1X2 = FALSE

IF 1X4, 1X2=TRUE, THEN, 1X4 d 1X2 = x.

4.3. The Transformation Concept

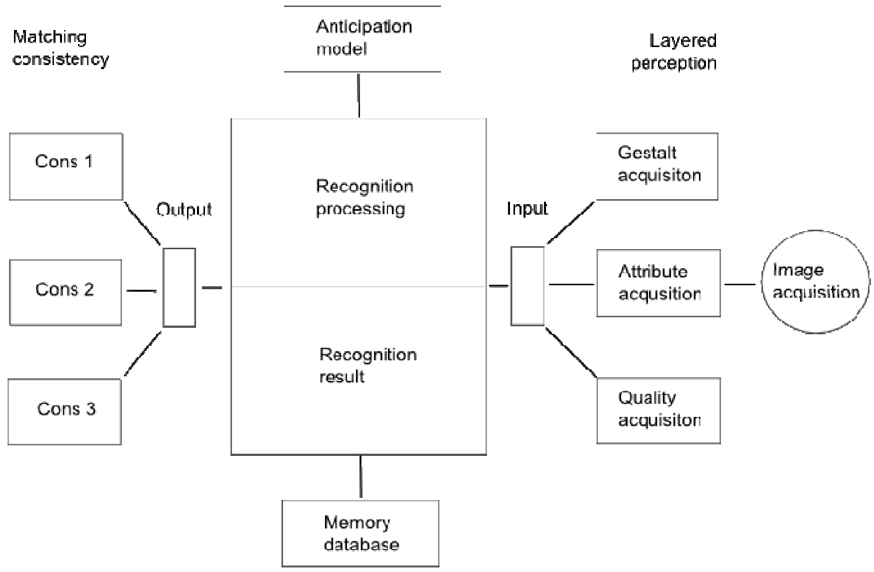


Fig 6. *The image perception model*

The transformation concept of mathematical data in the example of AI facial recognition [19] sublimed by its 2d-3d combinations of human-factor emotions derives an idea of direct and indirect Input/Output of visual perception, in where we could stem out our probability of Subjective perception in the Objective meaning of AI by subjective selection of types.

The *Block Diagram* [20] by Mr. V. Bettadapura is the schematic interpretation of 1 leveled processing and digital pattern recognition; though currently outdated, instead we would construe the model of it in two levels of visual data processing (Fig 6.).

Herewith, we consider the image perception as a data allocation and would rather split the Image Acquisition on 3 types of secular perception: Gestalt, (A) and (Q) than having one objective pattern.

The 2 levels of Recognition Processing would rather split 2d and 3d patterns into 2 different pools of matching. And whether it is abstract or facial recognition we receive reciprocal non-linear net of matching between the layers of Anticipation mode and the layers of Recognition Processing.

4.4. The Problems to be Solved

How could we predetermine the AM in Causation Matrix and in the image/sentence recognition is the question of (a,q) matching of Anticipated (Preconditioned Cons) with (a,q) of Hypothetical or Perceptual reasoning/vision?

In a perception of a ‘dog’ in the AI’s hypothesis would combine (a,q) of a ‘dog’ by the (a,q) of the factual dog observed, also by its abstract implication and not by its literal coordination, transitive implication.

For example, in the sentence of: ‘Mr. Example is a fury barking animal and he didn’t pay my bills’

The match of literal (q) and (a) of Mr. Example with (q) and (a) ‘hairy’, ‘barking’ would rather construe that ‘Mr. Example didn’t pay the bills’ and that is why he is somehow related to a ‘dog’ in transitive meaning, rather than ‘Mr. Example is a dog that can pay bills’

4.5. Notes

The role of the (a, q) processing in the consideration of Consistency Interpretation and Choice Selection conducted not merely by mathematical equations but by the programming preset of System transfer and System Prediction (Solomonoff), basically presume the cybernetic biology in simulation of subjective perception, which is existent in the development of Image Acquisition.

The differentiation of subjective-objective reasoning/recognition in causation and object perception, inflicted in visual dependency of abstract levels to understand what is the object or the idea is, requires non-linear simulation of 2D simplifications in mathematical reasoning, q and a consistency of which would only simulate complicated human brain reasoning.

5. The Simulation of Logical Perception or Rete Algorithm

From prediction, hypothesis and probability we believe to acquire the different levels of logical reasoning, even though the computational leveling and sub-leveling alone would not solve the problem of reasoning simulation, we consider to attribute some functions to its interactive automation, conducted not only by the visual dependency (layered Gestalt recognition), but by the separate mathematical (a, q) equations.

Considering the qualitative (a, q) consistency of a factual visual object perceived by AI, we get through the abstract inversion, which comprises its attributes as a mere fact of that *all A's are A's and not B's, and so on*. However, the semantic work of the Rete's principle could be layered further to specify the (a, q) not by its type only; but by its PREFERENCE!

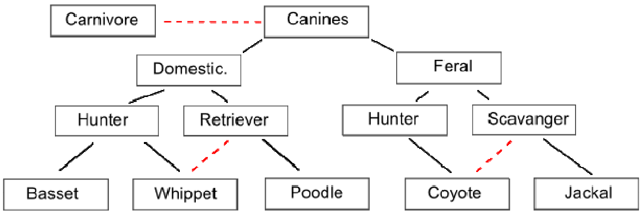


Fig 7. *Semantic network 1. Example*

If we guess that Poodle is more likely retriever than a hunter, it would be stereotyped in the AI reasoning as well, unless proven the opposite.

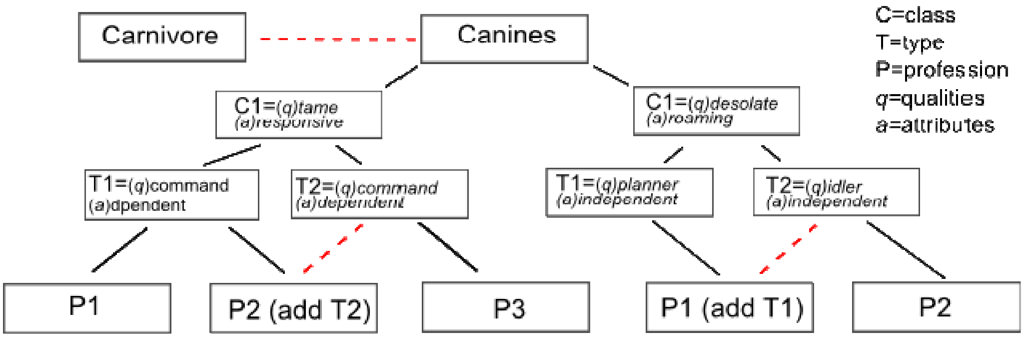


Fig 8. *Semantic network 2. Example*

So we could infer by exclusion, IF P=2 and 3, THEN P1=T1 =C1= Domesticated.

5.1. Logical Selection in AI Reasoning

The logical type selection and levels of computation require reproach from linear understanding to the non-linear application as well.

In abstract reasoning or in the reasoning of the Semantic Networks we judge the physical condition of 'A' as of any existent physical object and from its (a, q) consistencies proceed to the formal-logical condition:

Object → Formal Recognition → Attributive differentiation → Condition = the Fact

The logical question is whether it is reasonable to consider the Condition of the formal-logical referral as a Consistency of it, or as a sequence/consequence of (a, q) differentiation? We presume that the Rete's principle is a subject to expand from the 'Preference leveling' to the direct assertion by the definitions of the Forms and (a, q)'s of the AI data, even before it evolves from schematic abstraction to graphical interface of 2d/3d recognition.

Object → Form → Attribution = Condition,

Condition → Assertion = Result

It means that the visualization of the machine reasoning would rather be a sheathing of the pre-computed data in the logical perception and not the cognition.

5.2. Numerical Sequencing

The sequencing of semantics in binary or in any numerical system requires transfer and reason for such transfer.

If we presume that the machine mainly operates in binary, then we would probably perceive its translation as:

HUNTER = 01101000 01110101 01101110 01110100 01100101 01110010

However, the 'motivation' of an AI is strictly limited by the AM, and by its Consistency of (a, q)'s. So, what requires a transfer from binary to any other numerical system?

5.3. Differentiation

We state that the AI Anticipates, Considers, and Selects, however, the basis of provability logic requires an inter-disciplinary sequence of perception, in where a word perceived as a word, but parsed by its binary consistency for further semantics:

Sequencing → Binary application → Differentiation → Multiple choice selection = (a, q) Value of Selection

For example, if '1' is the physical quality (q) (degree) of volition, then we suppose to have its counterpart of attribute (a), (intensity) of volition in '2', the inner X and the external consistency X as the shape of it – the form.

1X2 via nqXna

Hunter (q) = (a) Scavenger

X=Coyote, Fox, ADD Raven, so on.

The degree of volition is the degree of multiple choice of subjective reasoning, meanwhile, the intensity of volition could be an indicator of how many TRIES the machine applied before it made a RIGHT choice:

Data Acquisition → Perception → Choice Selection → Logical Conclusion → Alternation → Ascertaining = Application

A provable requirement of logic not always coincides with the antecedent, because it is fully dependent on valid proposition. In where the most valid proposition is always updated numerically, while in behind and under the inner perception (consciousness) of Bayesian fields, Markov's volitions, or Rete's algorithms packed into the differentiations and binary transitions, we see the (***a***)ttributive (***q***)ualities of what is 'right' and 'wrong'.

5.4. Cycling or Sequencing

In Bayesian fields the choice selection and AM revert the probability of IF/THEN multiple times if so required, the cycled logic would rather repeat itself and the sequence may even leave the main premise behind its original condition. Another intellectual problem - is whether it is possible to combine cycling after sequencing, so the machine won't be chaotically sporadic in complex equations?

And the antecedent model allows to presume it possible:

Antecedent about past → consequent about future [21].

In this case, the development of temporal logic (Fisher-Wooldridge) in temporal pool of data and of its consequent parsing required:

Preset Integer → Differentiation → Sequencing = Multiple Choice Selection;

Multiple Choice Selection → Logical Selection → Mathematical Differentiation = Data Appropriation

The axiomatic and propositional pacing of the basics of the AI reasoning, however, implies the sequential calculation of IF/THEN, whereas the cyclic logic defines and functions in the closed logical surface by multiple restatement of IS/NOT:

#1 IS D is a sequence of C?

#2 IF C IS succeeding D then YES

#3 IF C IS prior to D THEN C = *X*

#4 IS C in a sequence?

#5 IF sequence THEN BACK to #1

By defining the S cons. of 'D' and 'C', we define that 'C' succeeds 'D' and 'D' precedes 'C', so there is a chance of that they're either conjured, either completely different objects. The machine reasoning would rather require a stipulation on whether 'C' is an *anXqn* data or not.

And if it's known, then what (*a*)'s and (*q*)'s in particular it has in correlation to its counterpart, in order to establish that 'C' is a part of 'D', and 'F' might become a part of 'C' and 'D' as well on the base of logical precedent and analogy.

5.5. Notes

Cycled mathematical differentiation and composition of reasoning based on its operational *propositional calculus* [22] and predicaments have to be bridled by sequential argumentation and selection pattern of Causation Matrix in details; however we apply theoretical and methodological specificity of current developments.

Hereinafter, we attempt more practical, mathematical explanation of (*a*, *q*) data differentiation and modeling.

6. Mathematical Application of (a, q) Differentiations in AI Reasoning

In this part of the research we evolve from the abstraction modeling to the precise application of sentence recognition in artificial reasoning, in where the sentence structuring in AI relied not merely on abstract or practical logics, but also on mathematical pre-sets, differentiations and equations.

6.1. The (a, q) Differentiation of Mathematical Reasoning

In the example of contra-positive equation of p – Lp [23] in where we consider that IF a person is not *guilty* THEN *innocent* is a certain requirement of advocacy. In where judging by the contra-positive inversion we could also presume that and the *guilty* and *innocent* for the AI is contradictory, hence not logically equal.

The logical and mathematical equations need to be 'unbiased' in the decision–making by giving to a degree of *guilty* and *innocent* same initial validity in numerical value of a*n*Xqn:

Guilty = 1 Innocent = 1

Guilty = *an*X1

Innocent = *an*Y1

IF *an*X1 = 1

THEN *an*Y1 = O

For example, if the degree *of an*X1 = 1 (*guilty*) could be 5X1 = 1 and the degree of *an*Y1 = O (*innocent*) 9Y1 then we differentiate the validity scale of *guilty* in 5X1 and innocent in 9Y1.

The scale of validity and objectiveness would be the final result on how the mathematical reasoning matches the current understanding of laws by human logic.

6.2. Binary Devaluation and Re-Adaptation

Before proceeding into differentiation of *an*X*qn* in probability/causation matrixes of logic we would have mathematically pre-set the system for certain pattern of recognition at certain numerical levels.

The adaptability of the sign with an integer and qualitative description of such mathematical integer is problematic, because the abstraction modeling coexists in the Consistency of mathematical reasoning.

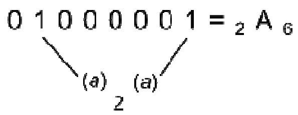
For example:

All *A*'s are letters including A1, A2, A3, etc.

Whereas: A (logical category) 1,2,3 (its attributes) and all A's are letters even in A1, A2, A3, decimal combinations.

While in the attributive consistency of any decimal (binary) number preceding the letter is a qualitative attribute of the letter and the opposite:

A= 01000001, and 01000001= A.



6.3. Mathematical Preset of Decimal Differentiation

In case of getting closer to the decimal system we presume that the logical differentiation of machine REASONING (not pattern recognition, not computer processing, not any type of machine calculation) in simulation of 'human-like' reasoning would rather be applicable to the simplified mathematical-programming equations of (a, q) consistency and their correlations.

In the example of decimal pre-set of A,1 A2, A,3 above we proceed to:

$$A3 \succeq A1, \text{ but } 3 > 1$$

By analogue [24], or material implication [25] we presume:

$$A3 = A1,$$

In where we have a sentence of A3=A1 as an equality by type but not quality or/and attributive consistency. The differentiation of *A* type to its particles of binary system will help us understand the logical matter of any logical statement at its best degree of credibility and bias.

In all of the data concerning the (a, q) recognition and retrieval from binary to decimal (and vice versa) it is required to have a matrix of attributive consistency.

For example, the table of decimal (a, q) equation in where the 9th grade of decimal number is the maximum grade:

Table 1. *The binary-decimal (a, q) transfer:*

Decimal(e.g.)	Binary	A	Q	anXqn	Decimal Differ.
1	00110001	3	5	3X5	-
234	001100100011001100110100	10	14	10X14	1X4
1695	00110001001101100011100100110101	15	17	15X17	5X7

6.4. The (x, y) Differentiation of (a, q)

In alphabetical selection and type generalization in where the most commonly used verbs of operational language could be used in cohesion of phrases and expressions commonly used in law. For example, the phrase 'I strongly believe'.

I = 1, strongly = 1, believe – 9, interpreted as 9 grades of assumption versus certainty of 1+1, 2<9, 2X9. Linear data pool of syntax example:

Table 2. *The 9 grades of assumption in binary-decimal dx/dy*

Syntax	Log. Interpret.	Decimal = Binary = anXqn	dx dy; x=y	Differ. (d)
I'm sure	Definition/Fact	1-3 (123) = 001100010011001000110011=10X14 (1X4)	1X4; 1-3Yn	dX(1×4) dY(1×2×3)n
I'm pretty sure	Assertion	3-4 (34)= 0011001100110100=7X9	7X9; 3-4Yn	dX(7×9) dY(3×4) n
I think I'm sure	Presumption	4-7 (4567)= 00110100001101010011011000110111= 16X16 (6X6)	6X6; 4-7Yn	dX(6×6) dY(4×5×6)n
I think I might be sure	Assumption	7-9 (789) = 001101110011100000111001 = 12X12 (2X2)	2X2; 7-9Yn	dX(1×4) dY(1×2×3) n
I believe I'm sure	Anticipation	9-0 (90) = 0011100100110000 = 6X10 (6X1)	6X1; 9Yn	dX(1×4) dY(123) n

The dx, dy differentiation is created to depict a pattern of recognition based on the multisystem level in binary↔ decimal translations.

6.5. What If to Stay Only Decimal

Evaluating dx only by its decimal value with no transfer from binary via dx/dy complications and just by the use of linear simplifications of the 9 grade probability matrix we would get to another differentiation of X and Y but in programming. So, it would implement more logic of IF/THEN instead of having just numerical values.

For example, 'I'm sure' vs 'I'm pretty sure', I'm = 1, sure = 1, pretty = 6. We have differentiation of 2 and 8, or we could decipher into 2Xnq contra 2Y6.

$$X{=}2;\ Y{=}2Y6$$

$$D{=}X/YN{=}x$$

And if we would get the result of 2X5 contra 2Y6 we would probably see the > and < N in q straight away (5<6), so the probability matrix would rather state that 5 is more objective than 6, and so on.

However, if the machine would doubt itself into self-consciousness, would it rather retrieve the (a,q)N's back to the binary system to stipulate the source abstraction/object recognition?

In the transition to the abstraction modeling:

d=dx X2 dy Y(2x6)

d=x2/y12

d=xy10

10=1010 (binary)

7. The Probability and its Selection

Whether to apply implicit or symbolic differentiation it is a matter of a specialized approach and different level competency in various computational applications. We regret not having such competence in particular fields and, therefore yet apply to a more schematic and propositional and instigating methods of abstract formulation of probabilistic reasoning in AI cognitive systems.

Therefore, the next step for us is to understand that the mathematic (dx/dy) differentiations are rather pertinent to its own kind of 'space', while the cycled logics and abstraction modeling are more constrictive and limited.

And hence, requires the Subjective/Objective perception/reasoning simulation transferred from the high levels of math equations to the simplistic tenants of choice selection and probability.

7.1. Subjective and Objective Differentiations

The computation of dx/dy calculus in AI abstraction modeling would rather be transferred into derivatives of variables system than functioning independently, it means the abstract meaning of probability in AI choice selection would be modeled alike the system of the assumption grade above (See Table 1).

However, the logical preset and the mathematical differentiation in Sum selections of programming are merely commutative and d=dx/dy of them is still simulated.

We presume the data abstraction of multiple choice dx/dy by its decimal value of (a, q) in the context of aXq and aYq:

7.1.1. Binary Summation (X=Y):

OBJ = X; SUB = Y

Xqn = (1,2,4,5,n), Yan = (1,2,4,5,n)

The (a, q) grade in a pre-set of subjective data (SUB) and objective (OBJ):

IF OBJ qn = 1 THEN OBJ an = 4

THEN 1X4 = TRUE

In equation to:

IF SUB qn = 1

THEN an = 1, 2, 3, 4, 5, 6, 7, 8, 9, OR, n

We get:

1Yqn, (q) = float

Summating SUB to OBJ:

1X4 + 1Yqn = 2X4

SUBJ Xq = 4

Where 4(q) is the coefficient of the objective probability in SUB reasoning, then:

IF OBJ 2X = SUB 2Y

THEN OBJ a = SUB q

Which means that the SUB (a) probability matches OBJ (a) from 4-10 and excludes selection of 1, 2, 3. As in percentile probability it's roughly 60% out of 100%. Thus, we only get the coefficient of the subjective choice selection = 60%.

7.1.2. Binary-Decimal Differentiation (dx, dy):

OBJ q = X; SUBq1=y

q=X; A=y

dx dy = q1 THEN

d =x1 y1-9

d=x1/y(1×2×3×4×5×6×7×8×9)

y=362,880=01011000100110000000=6Y14=6Y4

Yq=4

In case of data discrepancy between the SUBq/OBJq matching we would stipulate binominal transition in SUBq↔OBJq consequentially and try to negotiate the medium range of it in probability matrix.

7.2. The (a, q) Probability Score

The coefficient probability of 60% needs to be matched with the coefficient of probability of another statement to make sure they have similar degrees.

For example, if the statement of a liar varies as 60-20-99-12-1-60-99, then we would see an unstable pattern of a preset argumentation, in where the speaker manipulates the facts and certainties of '12', '9' and hearsays '99' to make sure his subjective proposal '60' would be at good stake of being credible '1'.

Table 3. *The probability result matrix:*

Value (1-99)	Probability	Value (1-100%)	Grades of Probability %
1-29	Dn^{1-3}	1-30%	Definition 100-70%
29-39	An^{3-4}	30-40%	Assertion 70-60%
39-69	Sn^{4-7}	40-70%	Supposition 60-30%
Etc.			

For example, parsing the phrase, ‘I know it’, on the (a, q) probability:

$$d=Dn^{1-3}=Xn$$

$$\text{IF } n=2\ (20\%) \text{ THEN}$$

$$Dn^{2} = 80\%$$

$$\text{THEN } an^{1-9}D2$$

The definition (D) is valid in (2), in probability makes 80% and that is to be differentiated further on in na^{1-9} to find an attributive quality and the foundation of it.

While interpreting the 9D2 being objectively valid in (2), but based on the traditional or customary understanding of (9), so on. We differentiation the (a,q) data by its PREFERENCE, not by its consistency.

8. Automatic Differentiation

8.1. Symbolic and Implicit Modeling

For object perception we would presume an artificial space by the means of *trigonometric preconditioning* [26], which considers sin/cos alignment in abstraction. Basically any perception of AI could be contracted to the symbolic differentiation of dx/dy, the problem however, is that the mathematical reasoning could rely on differentiation that yet exists in before any subjective associations.

Abstraction Modeling → Logical Pre-conditioning → Mathematical Differentiation → Trigonometric Differentiation

Fig 9. *The consolation of the different layers of differentiations*

The similar problem was indicated in the Microsoft Research [27], and pertains to the concern of the Expression analysis time, which runs with delay. We see the cause of such delay in the reverse of the $R \rightarrow R^n$ modeling, which is a real number computation and in f=dx/dy the differentiation produces only P.

And if we are going to discover the (facial) expression recognition by graphical application of the AI we would rather construe the logical model set of what expression is and then its types by dx/dy instead.

The Product Evaluation in A. Griewank [28] is conducted by symbolic differentiation and could easily link for abstraction model differentiation in object perception in contrary to the $R \rightarrow R^n$ shift; however, the symbolic differentiation has to be set and done by deciphering the abstraction in simplified value of logic (decimal system):

$$\text{By A. Griewank: } X_{n+1}=X_1$$

While the calculus regarded as positive integer or negative the Microsoft Research stems out of the natural numbers of R→Rn+1. We presume that the symbolic differentiation of probability/causation could be found on the premises of the f=Xn, which does not confer with the substantiation on positive (+) or negative (–) numbers of R, rather extending the N to the X power of the probability matrix, limiting the calculus to the extension of decimal value.

Which basically means that on the developer level it has to be set on the automatic differentiation that would circle around for a while and in the case of FAILs in computation would rather limit itself with abstract assumptions and modeling, more of the human type reasoning.

$$\text{The Preset of: } \sum X_{n+1} + Xn = X1$$

$$\text{In where in object perception: } X = Y \text{ or } X \subset Y$$

In case of abstraction modeling we presume each part of X and Y as separate (see Fig. 1), in here the subset or junction of 2 or more models differentiates modal space symbolically.

$$\text{In where: } f=dx/dy \text{ is } d=aXq_{(n+1)}=aYq_{(n+1)}$$

8.2. The (a, q) Differentiation of the Symbolic Differentiation Modeling

In the symbolic differentiation of the X, Y, Z… X1, X2, X3…, if the X=X1 and Y=Y1, then we get the similar consistency in equation of X1=Y1, as soon as its binary $(1)_2 = (1)_{10}$, so we presume the (a, q) equilibrium of X = Y or X ⊂ Y.

We presume that defining an object merely by its external consistency is not sufficient and therefore, the internal attribute of an object (object-object) defines its qualitative consistency numerically in correlation to physical appearance.

The conjunction of abstract models into one definition of an object by the Scons1→Scons2 and so on, defines the ⊂ of Y in interpretation of decimal value of symbolic differentiation modeling

For example:

Reeled Wheels → Scoop → Diesel Supply = Tractor or ⊂ Tractor ≠ Bicycle

The *(a, q)* of an object modeling by its counterparts in conjunction prevail in (+) or (⊂) of the logical predicament and in the AI AM.

The symbolic differentiation f=dx/dy of X = Y or X ⊂ Y conditions are suitable for programming such abstractions.

8.3. The Logical Conjunction of Symbolic Differentiation

Another supposition of the object perception based merely on mathematical assumption not by its symbolic data.

If two or more objects of X, Y, Z (e.g. tractors, trucks, and other diesel powered engines), are combined in one sub-type of X_{n+1}^{n} then the decimal ∑ would lead us to the logical conjunction of A∧B, (Fig. 10).

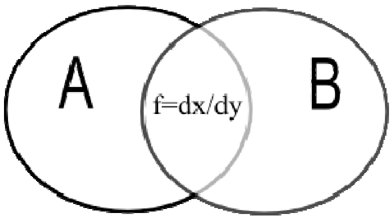


Fig 10. *The logical conjunction in dx/dy*

A∧B f=dx/dy∩dx/dy

In where the A∧B conjunction is subsequent to the intersection of symbolic differentiation (f=dx/dy).

In decimal conjunction:

$$(q)X2(a) + (q)X4(a) = 2X6 \wedge 2Y6$$

The external (q) in quantity = 2, internal (a) = 4, presume that 2 similar shapes of X (circles) have f difference in shapes of 2≤4 or 2⊂4 in dx/dy.

Whether to adjunct X to Y or to Z, the machine would specify its (a, q) in f=dx/dy, however, whether the X and Y are the parts of each other or the separate entities, decides the adjunction of the type specification via X_{n+1} in Markov Models and Bayesian Logic fields.

8.4. The Decimal Value of (a, q) in f=dx/dy

By defining an inner attributive value of abstraction/number we specify its external attribute value. We equate both integers by consolidating the artificial perception by the dx/dy differentiations in numerous logical combinations of Xn+1.

However, in the demonstration of (q)X2(a) + (q)X4(a) = 2X6∧2Y6, the decimal value of (a, q) of 2≤4 that specifies XY is a supplement of binary matrix explained above (See Table 2), therefore, it makes more sense to specify its trigonometric spacing for the AI in before of any technical equations.

The decimal value of f=dx/dy in where Xn+1 presume such conjunction (A∧B) as infinite only in the alignment of the positive values (+) as of the default ones:

$$f=(d1, d2, d3, d4, d5, d^{n})$$

$$dx/dy=(A,B,C,D,E,F,G,X_{n+1})$$

Which leads us to understand the Microsoft Research on $R \rightarrow R^{1}$ transfer is what we've explained in abstraction modeling of Scons→Scons2 in graphical mode.

8.5. The Vector Placement of Automatic Differentiation

The vector placement of derivatives (trigonometric placement of the automated differentiation) in the equation proposed by Mr. Neidinger [29] gives us an object oriented approach of the Xn integer placement in cos/sin spaces and it proposes to use a standard MATLAB 1×2 linear differentiation, which predicts the following:

if X=3 then 2×X+X+X+7 is 16, [30].

In where '16' is supposed to be the differentiation of [16,3], in the MATLAB.

We presume the mathematical application of trigonometric differentiation in visual formation of abstraction modeling by the following:

$$d1= \text{if } f(x) = \sin 16, \text{ then } f^{1}(x) = \cos 16$$

$$d2= \text{if } f(x) = \sin 3, \text{ then } f^{1}(x) = \cos 3$$

$$\text{Lim } f(x) = \sin x^{16}/\cos y^{3}$$

$$\frac{(-\sin x)\ \sin x - \cos y \times \cos y}{\cos 2x}$$

The Lim of its trigonometric depiction is set to bind the frame of visual perception in 'human-type' depiction for AI, unlike the abstract infinity of the $R \rightarrow R^{n}$.

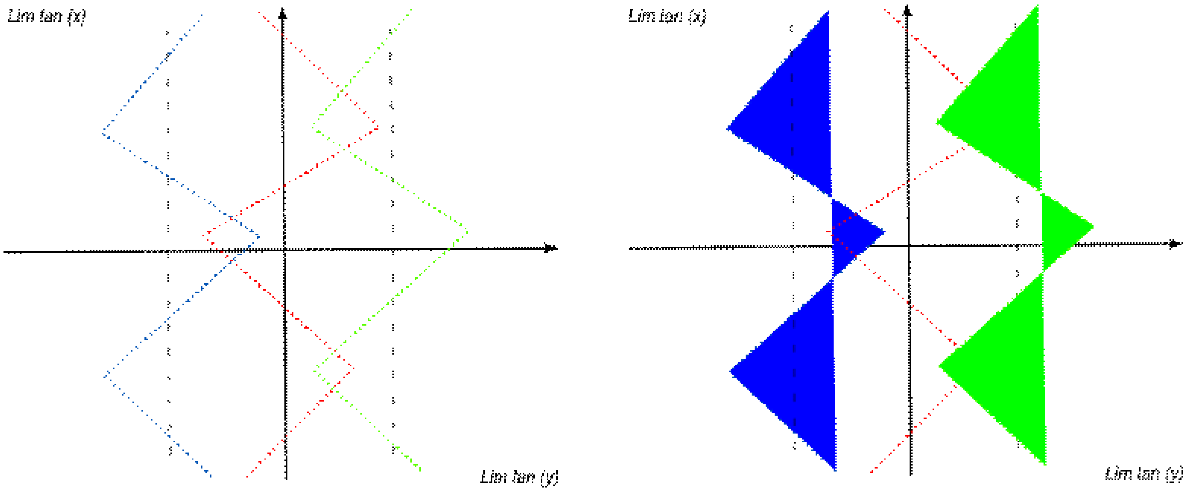


Fig 11. Trigonometric data allocation

The probable solution:

$$\frac{(\sin x+\sin x)^2\ (\cos y\times\cos y^2}{(\cos x)^2}=\tan x\ \ (\tan x^2)?$$

Our goal is to achieve an inverse and reverse tangents of trigonometric modeling of certain data allocation in practical reasoning. The understanding of trigonometric f(x)=dx/dy would rather be more effective in 3d depiction. However, our course is to define and design, the direction, the mathematical perception of AI that would work independently and via automated differentiation.

8.6. Further Differentiation Assumptions

The certain allocation on the vector of d = cos/sin=tan positioning would specify the symmetry of reason modeling and data depiction in AI, however the 'human-type' reasoning contains assumptions on the level of suppositions and reckoning.

In consideration of f(x) = sin x/cos y or f(x) = sin x/cos x we consider X for its (a, q) on the level of X decimal-binary application to the trigonometric positioning.

In order to make the AI system compatible both in trigonometric and binary applications it would require the understanding of d (sinx x) in fx = dx/dy and vice versa. Regarding the mathematical point precision (or point of X,Y,Z etc), the development of multiple level allocations is required.

For example, from trigonometric differentiations we know that:

$$\frac{\mathrm{d}\ (\sin x)}{\mathrm{dx}}=\cos x$$

As soon as the (*a*, *q*) may occur not only in 2d surface, we presume the following:

$$\cos x\ \mathrm{m}\ \mathrm{f(xn+1)}=\frac{\mathrm{d}(\sin x)}{\mathrm{dx}}=\cos x$$

The cos X allocation in the triangle of the 2d field, meanwhile the *a*X*q* would specify it's (*a*,*q*) (tensor) in 3d, 4d, etc

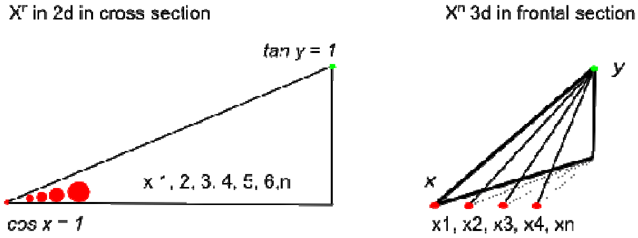


Fig 12. The Xn trigonometric allocation

While judging the allocation of dx/dy trigonometrically, its mathematical application could discover, perhaps more 'narrow' split of allocation for the AI.

8.7. Hidden Markov models in (a, q) Modeling

Another example of the sentence retrieval by its differentiation and product model was proposed in the *Phrase Model* [31] and considers the POS model with vectors *j, i,* which is an analog of *x*, *y.* It considers the angle (Θ) of sentence by its *x, y* and the recall of such positioning.

The attributive (*a*, *q*) differentiation of m (*i*, *j*) we present as X (*a*, *q*) in decimal with no Lim in ordering, therefore the Θ could be the variable itself.

The arg max used in HMM basically is the arg max = f(x) = dx/dy, the differentiation of the max *x* and *y* grades. We consider such aspect by the use of the 9 grades of causation/probability matrix in the sentence structuring and in recognition as well.

The curve positioning and the trigonometric data allocation from the results of the sentence structuring of AI is the automated process of the (*a*, *q*) supposition and preference in the model of IF/THEN exclusions. The conjecture, or the AI reasoning of guessing of any X^n variables we devise in the guessing of the Xn+n, the same manner Markov Model does and confers with binominal equations as well.

8.8. The Point Based Location of $a^n Xq^n$

The decimal grade of assumption/probability in X (*a*, *q*) would be geometrically presented as a depiction of proof in the example of 2X5.

In where 5 geometrically elapses 2, and postulates the dominant (a, *q*) in nXn+1.

For example, in $a^n Xq^n$ of 7X1 we have the objective quality of '1', while its internal attribute construes the '7', making a logical point of 'idea' or of 'hearsay'. In trigonometric depiction simplified to binary as the evaluation of 7>1, geometrically we perceive the postulate of '1' as smaller one, but in factual - as the point precision, h.e. as 'objectiveness'.

If the '1' has no fluctuations and alterations in space in opposite to '7', which has 7 points, then we would regard that the $Xa^n = 1$ as a stemming of cos/sin x. In correlation we construe the $d = Xa^n = 1/ Ya^n = 1$ as well.

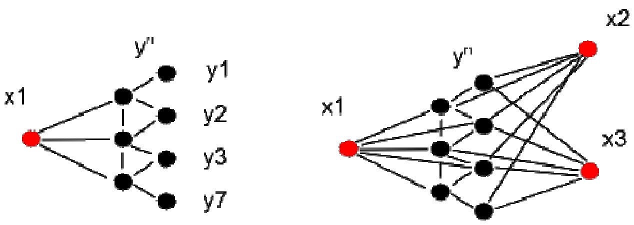


Fig 13. *The bond variable allocation*

Automated space differentiation in (*a, q*) data modeling developed as variable of dx/dy is actual only in mathematical equation of $x1, x2, x3, x^n$. However, the approach of not defining the value of X, but only complicating it into the value of its spiral consistency in trigonometric point location and decimal↔binary transitions would suggest to AI to have a non-linear parsing of X.

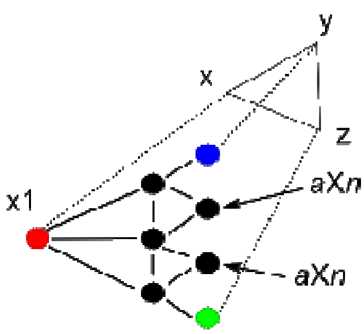


Fig 14. *The aXn appropriation*

It would be no longer regarded as an *X* variable, but as an *X* of an *X* with its own sub-(a, *q*):

$$Xd(f)y = X^{aXq}$$

Making it a differentiation inside of a differentiation, in where the AI reasoning would decide IF it is worthy to PROCESS a certain task OR to SKIP to another X^n in the QUERY modeling.

9. Binominal Differentiation and Positive (P) n+ (a, q) Data Retrieval

9.1. Binomial Differentiation

Another type of triangle spread in trigonometry is the Pascal's triangle bijection. The gradual numerical spread of n(n-1)… (n-k+1) chooses *k* in any *n*. In our case we devote $a^n\ q^n$ retrieved by the integer X subsequently for further AI processing.

If we'd received identities of a sentence by its n1, n2, n3, then we'd have to consider its sub-variables (x, y, z) as well.

Proposed in Pruce-Reid Mathematical Foundations [32] of binomial differentiation of x^k, the sequence of positive numbers and its derivatives looks as following:

$$R = \sum_{r=0}^{R} n + r - 1\, Cr = {}^{n+R}C_R$$

In where we propose that the numerical value in summation could have a variable of ${}^{n+r-1}Cr$ instead of (n-1), so we would presume that *n* is the variable X and it is differentiable. Here, in ${}^{Xn+n-1}Cr$, would rather lead us to ${}^{Xn1}Cr$.

In where from the equation of:

$$R = \sum_{r=0}^{R} n + r - 1\, Cr = {}^{n+R}C_R$$

we get:

$$R = \sum {}^{Xn+n-1}Cr = {}^{Xn+R}XC_R$$

${}^{Xn+R}XC_R$ demonstrates that the variable Xn could be variable only in +R as a suffix to it, and therefore, any derivative order of (n-r) would become (n+r), so the a^n/q^n, attributive data would summate the X*n*'s as for positive numbers only.

The recurrence theorem [33] of (–n × –n × n+1 × n+1…) has proved that the recurrence of both –n and n+ identical in summation.

Therefore, by simply allocating the (*a*, *q*) integers in Xn of binomial expression we expand $(x+y)^n$ to the expanded summation of it.

The infinite summation of positive numbers $\sum_{r=0}^{R} n + 1$ and it's further (*a*, *q*) data retrieval would help us to allocate certain positive numbers not only in trigonometric order, but also by its P (*a*, *q*).

By having in the result any decimal number from 1-0 we would consider its transfer to the binary and hence to the allocation of any artificial probability/causation matrix indicated above.

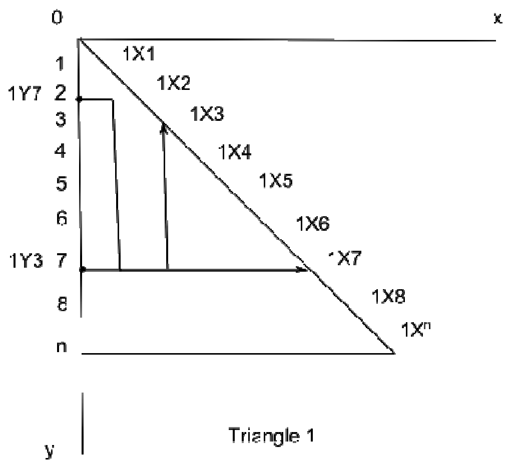
9.2. Positive Integral Summation and its Trigonometric Allocation

The possibility of data retrieval in conduct of mathematical exertion of P from the binominal nk/-nk or/and dx/dy differentiation formations in trigonometric allocations of user interface of AI still requires of a high-end level cohesion and adaption in both: programming and mathematical application.

However, the symmetry of the binominal theory and the sporadic dx/dy allocation in different AI spacetimes and considers the difference of two completely different mathematical principles. It plays a role of unison in trigonometric asymmetry and abstract symmetry of both functions.

The (n+1 n-k) principle in coordination of a triangle basis and its internal summation re-orders the binary stipulation in order to store data by its numerical consistency occurrence.

The trigonometric allocation of numerical occurrence of n→*aXq*:



Triangle 1. *The trigonometric allocation of n→aXq*

But instead of getting from any sequence of *n→k* according to the binominal theory, we get from *n* to (*a*,*q*) in X*n*.

While dx/dy differentiation is a perfect example of data retrieval and its further differentiation in the example of two and more probabilities in the AI reasoning that would consider *q*X*a* with the certain grade of (*a*, *q*) variables, matching the probability matrix.

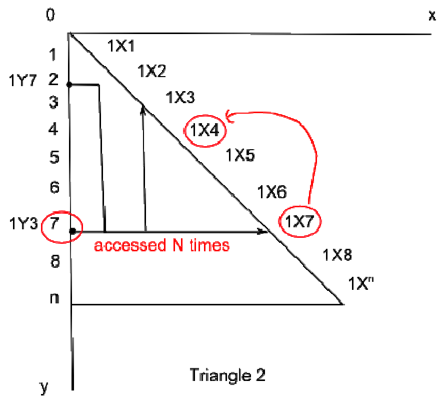
By stipulating the Y*n* ⟶ X*n* *(a*, *q)* referral, we ascertain the R probability of certain P→X in the trigonometric positioning.

9.3. Data Retrieval

The data allocation in such triangle matrix requires initial allocation and fragment allocation of the (*a.q*). In the example of the *Fragment Priority* [34], we consider the N of queries accessed to a certain cell. If AI accesses the same cell of data in the triangle more than 1 time, we would consider a cell RETRIVAL for further dx/dy processing.

The work also considers the *Cost Matrix* [35] intersection of S1→S2, which we've mentioned as Scons1→Scons2 transfer, and it could be seen from the triangle of binominal allocation that the cross-reference of X↔Y also considered graphically as cos x ⟶ sin y.

The priority of access and its frequency of referral may probably move a cell from the lower decimal value to the greater one.



Triangle 2. *The trigonometric selection/retrieval of n⟶aXq*

In the stemming of data of N- n_t+1, [36] the number of documents (n_t) and the number of occurrences (tf_{td}) QUERY the probability of the access result.

The proportion of data, time and occurrence presume the coefficient of ∑ probability we've mentioned before.

$$\text{Data} \times \text{Time}+1/\text{Occurrence N},$$

Or any other implications of n(n-1)… (n-k+1) pertinent to it.

9.4. The Brusentsov-Bergman Ternary Principle and its Allocation

As for the conclusion of a brief supposition on P integral of ∑ and allocation, we would try to construe the graph of the data transfer of decimall↔binary, as soon as we know that the AI programming involves binary applications of programming, so we cannot rely merely on mathematical and trigonometric differentiations.

The programming levels in cope with mathematical differentiation types (implicit, symbolic, binominal) acquire specificity of decimal R/N matching, regarding only its N preconditioning and integral (x.y,z, etc) solutions. The allocation of data of *aXq* in the temporary pool of AI needs to 'translate' the 'results' of such complicated differentiations into the binary language by the proposed 'Mirror Reflection' principle, which we would try to elaborate.

Although, existing software packages of such transfer mainly common in graphical software industries and based on user (human) interface perceptions, unlike the interface of AI that would rather have a schematic version of it.

As for the model of the existing presumption we refer to the closest solutions in Stakhov-Brusentsov-Bergman ternary principles [37], which is as well based on the principles of R property numbers, mentioned previously.

The sequence of natural numbers of a_{-1}, a_{-2}…a-m in the trigonometric alignment reflected, according to the Brusentsov-Bergman, in the weight of t^{-1} t^{-2}…. t^{-m} of negative powers in where the t^i used as a summation of bits.

We've covered the similar principle of binominal R = n(n-1)… (n-k+1), however, with no representation of binary. As soon as any classical mathematical differentiation does not consider bits, we'd rather simplify the allocation of such data transfer of decimal↔binary with the cognitive simulation of binary value $1=0^n$ in decimal, in where any natural positive number $R_{n=0}=1+n^{ti}$.

We take the t^i as for the 'golden representation' principle $t=\frac{1+\sqrt{5}}{2}=10$ (Ibid 223) and proceed from binominal principle R= n(n-1)… (n-k+1) to binary in the following conjecture of bits:

$$R_{n=0}=1+n^{ti}$$

$$nt=\frac{1+\sqrt{5}}{2}=10n^t$$

$$10n^{t=} R/t^{ir}$$

In where: R=0 i^r=0,0

In where the maxim for of binary and decimal would be P (in 0 and 0,0)

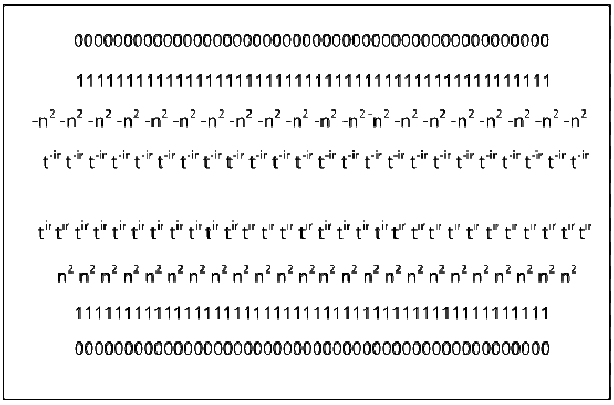


Fig 15. The binary-decimal transfer allocation

10. The (a, q) Probability Processing in *a*X*q* Reasoning

10.1. Direct Differentiation

By taking recourse from abstraction modeling, we've briefly covered complex differentiations and trigonometric allocations of free/bound derivatives, trying to adapt *a*X*q* to the existing mathematical principles of calculus, as well as proposing our own models and solutions. However, the basis of probabilistic AI reasoning in data allocation/retrieval crucially relies on the strict and Fuzzy logics in programming.

In abstract reasoning equation with no trigonometric allocation, we would subdivide (*a*, *q*) on SUB and OBJ data allocation/retrieval on the mere basis of its PREFERECNE and GRADES which make possible to simulate the probabilistic AI reasoning in detour to the implicit and strict one.

In the following:

IF X=Y

PROCEED to X

$X \subseteq a^n,q^n = Y$ u a^n,q^n

IF $Xa^n>Ya^n$, then Y

IF $\sum a^nXq^n>\sum a^nYq^n$ then Y

We presume the lesser (*a*) of one derivative (X) as the value of objectivity prevailing over the other (Y) in the AI choice. Meanwhile, the (*q*), quantity component is subsidiary to (*a*), in other words $q\subseteq a$.

IF aXq=aYq

THEN $Xq\subseteq a+1<aYq$

We remember, that we quantify the numerical value of (*a, q*) in binary transfer (See Table 2.)

We see that the binary↔decimal data would define the N of (*a*, *q*) according to the matrix of probability/causation, based on the abstract models of TRUE/FALSE operands, however, it is still troublesome to pertain such sporadic data to the factual speech and voice recognition of AI.

Let us assume that the AI pool of data is already pre-set on 2 or more choices of probable solutions and 1 of them is the OBJ data reasoning, e.g. OBJ 1X2, the other – is a hearsay, but also logically TRUE, e.g. SUB 1X7.

How would we rule out the probability of likeness? We assume the linear behavior of (*a*, *q*) differentiation in the non-linear situation:

IF OBJ 1X2 = 1

AND IF SUB 1X7 = 0

THEN 1X2 + 1X7 = SUB 2X9 (in SUB pool of data)

1X7 – 1X2 = SUB

X5 = the grade of SUB perception.

9 - 5 = 2

9/2 = 4.5, the probability of assumption.

For example, ascertaining the qualitative description of assumption:

Quality of TRUE = 1-4, ASSUMPTION = 4-8, FALSE = 8-10

IF OBJ 1X2 = SUB 2X5

THEN 1X2+2X5 = 3X7 (SUB pool of data)

2X5 - 1X2 = 1X3 (SUB coefficient)

SUB *a*(7-3) + SUB C. *q*(3-1) = 6

The statement of that OBJ. 1X2= SUBJ. 2X5 = 6, which stands as an 'assumption'.

In this case we presume that the OBJ (*a, q)* of 1X2 is probably too weak/strong to be subjectively presumed or perceived as 2X5. The subject is either 'delusional', either too ‘assumptive’.

The allocation of the results in the trigonometric allocation by the use o binominal equation of P numbers tends to grade the level of importance (see Triangle 2.)

10.2. Direct implication

The *a*X*q* direct implication:

IF X ⇒Y

THEN X⊂Y

THEN Xa > Ya (Y = OBJ>SUB)

BUT qX < Yq (X = SUB>OBJ)

The logic is the quantity (*q*) of X prevails over (*q*) Y, but the attribute (*a*) of sentence is hidden in Y.

10.3. Indirect Implication

The *a*X*q* indirect implication:

IF X≈Y

THEN X∪Y

IF $Xa^n \geq Ya^n$, then X = X and/or Y

IF $\sum a^n Xq^n \geq \sum a^n Yq^n$ THEN X=Y

Mediates X to Y, however does not exclude X.

11. Main Results

1. We logically prove that the probability/causation in abstraction modeling had to be reviewed from the linear interpretation to its sub-set differentiation of X, therefore presume the temporal data allocation by priority/preference differentiation and not by the direct logical ‘relevance’. As of demonstration of it such data allocation may be interpreted in computational logic e.g. in Lisp programming (the list of context meanings) by alternating the methodology on non-linear and non-context based assumptions and differentiations based on (*a*, *q*) of different level variables (x,y,z, etc)
2. The decimal↔binary differentiation of *a*X*q* in computable reasoning applicable to the probability matrix and to the further binary transfer in P and R of N consistency and in implicit ∑Xn+1, n(0). Both binary and decimal Xn dx/dy probability grading are possible in bound/free variables via the implicit/symbolic d(f), hence possible in trigonometric ordering.
3. We prove that the trigonometric allocation of the *a*X*q* data and its grades are applicable for abstract depiction in the Priority Triangle systems. In where the point based system could lead the binominal allocation of *a*X*q* of different variable levels of n(n-1)… (n-k+1).
4. The abstract methodology of N consistency of derivative order used by a linear pre-condition IF/THEN is applicant to the matter of SUB/OBJ data allocation in where the similar *a*X*q*/*a*Y*q* are not in reciprocal exclusion, but convalescent.
5. The advance of (*a*, *q*) sub-sets in differentiation is probable for dx/dy differentiations of bound/free variables and implies the different approach in the existent mathematical or computational differentiation that sub-sets the variable ‘X’, not by ‘x’ of ‘unknown’, but by the degree of two probabilities of its allocation/retrieval in the AI reasoning. De-coding the factual data in the sets of x1, x2, x3,… y1, y2, y3, deferrable on more or less obsolete grades of factuality/probability and hence represent ‘zipped’ simplifications of sentence allocations.

12. Conclusion

The numerical value of ‘TRUE’ is construed as an abstract tangent, numerical value and differentiation in decimal/binary languages of computational logic, may not puzzle or confuse a researcher with its ‘hybrid’ approach, however operates strictly on the mathematical premises of d=dx/dy algorithms.

The mathematical transition from S1 to S2 takes sporadic differentiation that defines only the shift from one logical definition to another however, does not constitute the reasoning or the meaning of a certain logical word/sentence at all.

The causation/probability matrix shift if matched mathematically to the f(x) = dx/dy differentiation could lead to a first order logic, but would never be applicable in the dynamic situations of high order logics, therefore, it has to be adherent to the causation/probability matrix of dynamic order allocation, which we’ve tried to demonstrate in the Triangle 2 briefly.

The $R_{n=o}$ in binominal differentiations in the sequence of binary of n+1…n-1 in the (*a*, *q*) data allocation/retrieval, is efficient and practical in the ternary fields (Brusentsov-Bergman) in binary↔decimal transitions, as soon as both theories presume the equivalence of data storage in t^i

The (*a*, *q*) differentiation in general comprises 2 levels of sub-derivatives of X and Y, in where the (*a*) of the logical sentence, or any binary/decimal number, quantifies as the ‘meaning’ grade in the probability/causation matrix and defines the objectives of (*q*).

The $a^n Xq^n$ grading computation helps us to shift from the merely mathematical dx/dy to the non-linear interpretation over the similar/multiple request of, IF X=Y THEN x1, x2,… y1, y1… z1, z2,...

And it is our duty to conduct a further research on AI reasoning innovations in more practical and narrow fields of its computational application. Such models as HMM and GMM in probability reasoning, as well as imaginary (*i*) number in cognitive computations of AI, and to provide more specific and more practical solutions over descriptive ones. Henceforth, to enhance and to develop a new approach in artificial cognition.

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