

# An Introduction on Cognition System Design

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*Abstract: Present work is an introduction on cognition system design. This work is structured in two parts: the first consists on a phenomenological analyze of Artificial Intelligence collocation which will generate seven questions needed in cognition system design; the second part represents possible answers for the first questions. The last part represents also is the opportunity to present the plausible reasoning theory and to solve two examples.*

*Keywords: plausible reasoning, Bayesian theory, model*

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## 1 Introduction

In 2002 by IST – 2002 2.3 2.4 (*published in the Official Journal of the European Union*) the European Union decided that the researches in cognitive systems design are considered strategically objective. The cognitive systems are defined by [1] like a system which understands, learn and are developing by social or individual interaction. These interactions include subsystems for perceptions and actions, which are already known like robots. The third element of the cognition system is the reasoning subsystem which will manage the first two. This is the biggest challenge of the cognition system design because it implies the modeling of human reasoning.

Modeling the human reasoning is an interdisciplinary problem because involves also philosophical and psychological knowledge [11-15]. The Artificial Intelligence (AI) domain covers a part of these problems [2, 3, 4]. This is the reason why we intend to start our study on cognitive system by a better understanding of (AI). We think that it is important to reveal – here in a phenomenological way – what we aspect from the science which is named Artificial Intelligent. Usually the first step of such analyses is to find the appropriate questions which will make deeper the phenomenon understanding. The results of the phenomenological researches on artificial intelligent (AI) collocation are seven questions which can drive to intelligent product

construction. The second part of the paper intends to answer the first questions: *Are there known theories that have as object the human knowledge?* and *How can we use them in order to develop a human knowledge model?* One possible answer could be ‘The Laplace model of commune sense’ or ‘The Bayesian theory’. The named theory is based on reverend Thomas Bayes and on mathematician Pierre Simone Laplace results [5, 6] and was developed in [7].

The backgrounds of the present work are E. T Jayne’s probability theory [7] and also the related works of Cox and E. T. Jayne, where the rules of the mentioned theory are presented. We will mention also the work of E. Yudkowsky [8] where an epistemology based on Thomas Bayesian result is presented and also J. Pearl work on causal reasoning [9]. The bridge between the Bayesian plausible reasoning and mobile robots has been inspired by the work of C. Pradalier, where the navigation of a mobile robot is controlled using Bayesian’s filters [10].

Our intention is to transform the rules of ‘Laplace model of commune sense’ into postulates, and to present theoretical results which are obtained from these postulates (the Bayesian theorem [7] and the Bayesian filter [10]). In the end we will present two examples of plausible reasoning solutions.

## **2 The Phenomenological Analyses of AI Syntagma**

### **2.1 Definition of AI**

The Artificial Intelligence is a syntagma composed by two terms (intelligence and artificial) that through their nature generate an interior stress, because the term of intelligence is in the ontic acceptance bound by the human or at the most by the living being and the *artificial* attribute comes to underline the fact that we have in mind a human creation or more precisely a product achieved by the human being. In this way the Artificial Intelligence becomes a human product that imitates the intelligence features (human, eventually naturals). We must recognize that from a psychological point of view this comment amplifies the mentioned stress. In our word the intelligence has become a fetish and has generated, in this way, a psychological complex. We will remember that all the people wish to prove intelligence even many of them don’t know exactly what the intelligence is. Because of that behavior, we accept hardly that intelligence can be associated with an object.

After all this considerations if we have accepted that AI is a product that copies the human intelligence, then we must understand what means *intelligence* and what means *to copy*.

## The Intelligence

The intelligence is defined in several ways, from this richness we will start with the following work definition: *The intelligence is the capacity of understanding the experience and the capacity to take benefit from this understanding.*

The enunciated definition articulate causally two attributes: the experience understanding and the benefit of this understanding. If we focus at the *experience understanding* we will discover that is a tautological expression, because the experience assumes a certain understanding. For example, the experience in the Kantian sense it is more than a sensations assembly, including a certain base of knowledge.

Because of this reason will replace the *experience understanding* through a term more comprehensive that transforms the work definition in: *The Intelligence is the capacity of knowledge and the capacity to take benefit from this understanding.*

If we wish to analyze now what *take benefit* means, we have to admit that this collocation assumes ethical approaches. Because in this moment we intend to avoid such ethical approaches we will reduce the significations of the benefit and will replace this expression with: *the facility of knowledge accessing* (inclusive the ones that mention the possibility of benefit).

In this way the work definition has become: *the intelligence is the knowledge capacity and the facility of access these knowledge.* According to this definition an intelligent human being is the one that can know easily and can use this knowledge (fruitfully).

## The Imitation

We will return at the *artificial* term content in the AI syntagma. We intend to copy the intelligence features of the human being and for that is important to understand what means *to copy*. To copy in an ontic sense is the operation in which the original is transposed with approximation into a product. Then, when I copy, I don't claim to perform an identical, but only to transpose certain features that I consider to be essentials. I'll give up, in this way, at all that seems to be accidental and I will perform a representation accepted by the original object concept.

To imitate is an activity that it's bounding by the knowledge because I don't imitate the object himself but I copy my knowledge regarding this object. Furthermore, when I imitate I decide that certain notions are important and other don't, and these decisions are based on my knowledge.

After that, to imitate means the approach of a certain technology. The technology assumes the knowledge of some procedures, the existence of some tools and objects (materials) where I will implement my copy. So in the knowledge process imitation I must identify all these elements.

Therefore we can conclude that when we mention the AI syntagma we refer at the copy of our knowledge about knowledge and about the access of this knowledge.

## 2.2 Opinions about Knowledge

The above analyze has underlined our capacity to know about knowledge process. We must mention from the beginning that the human knowledge sources are of various forms: mythical, religious, artistically, scientifically etc. and we must specify our position regarding this problem. Therefore bellow when we mention the cognition about knowledge we will understand the scientifically cognition of the human knowledge in her generality. Now it is natural to analyze what we understand through scientific cognition. The subject vastness and the space allowed to this article will be balanced trough the *opinion* term used in the following description. Also we will formulate certain opinions on the subject (see Figure 1):

- Scientific knowledge divides the reality in quasi independent domains (the systematic vision);
- For a certain domain it's start from a minimum number of fundamental troughs. When these principles ore axioms are proposed we desire that they are independent and in minimum number. The principles are carried out inductively, this process is induced by the experience and are after that adjusted through the theory results that they generate;
- Based on the principles, through deductions, theories are constructed. A theory represents the knowledge that can explain the phenomena from a certain domain of the reality;
- Based on a certain theory, a particular phenomenon is represented through the model. The model is a peculiar knowledge assembly, obtained by approximation process, that aspire to become operational;
- Scientific knowledge must be validated continuously by the experiment;
- It has as aim the a priori knowledge, more precisely we wish to know how will ensuing the phenomena before the experimentation (*voire pour prevoire*).

Conclusively the scientific knowledge has as operational element the model. The model is defined as being an approximation of the phenomenon which is constructed starting from a theory by elude the *non important* from the *important* of the phenomenon. This process (the separation in important and non important) is a subjective decision (depends on the subject – human – that know), but we have the hope that the experiment will infirm the bad decisions. We have mentioned that the model is operational, this means that the model can be used directly for obtaining the mentioned purpose: the a priori knowledge.

We can describe the phenomenon of model using in two ways: first if the model is simple we can use it directly (mental experiment), but if the model is too complicated to be used directly we must use technologies in order to obtain results. This technology contains methods (mostly mathematical), tools (mostly

computers) and support objects (paper, computer screen, etc.). We have named this operation as simulation.

It is important to approach the fact that when we imitate, we will not imitate the subject himself or the phenomena but the imagined model.

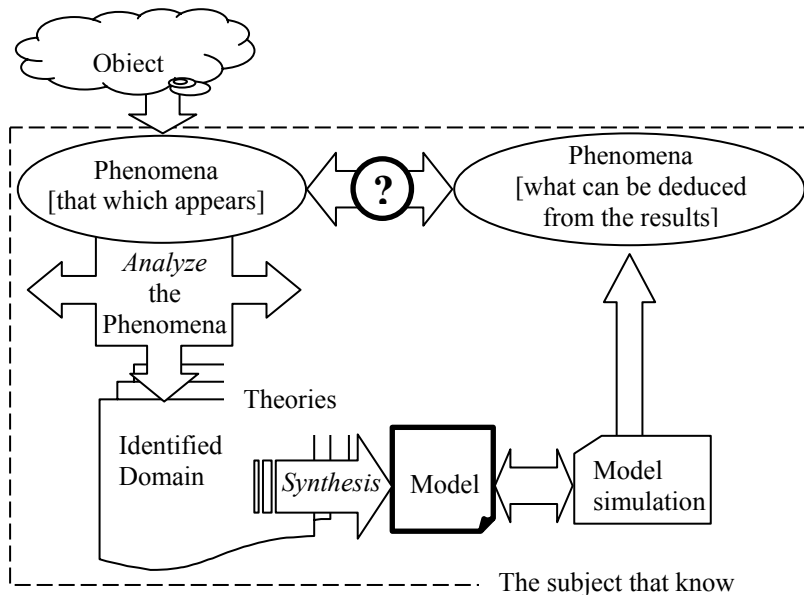


Figure 1  
The model creation

### 2.3 Results of Phenomenological Analysis

If we will resume the previous results we can say that when we mention the AI syntagma we expect to find a science which contains the technology to copy the model's of human knowledge and the access to this knowledge. In order to construct such models this science must be linked to cognition theories.

Starting from these conclusions we can find now the appropriate questions which allows the possibility to deep the understanding of the AI and which drives to intelligent product construction.

- 1 Are they known theories that have as object the human knowledge?
- 2 How can we use them in order to develop a human knowledge model?
- 3 How can we simulate this model and how can we improve it?
- 4 What is the technology – the methods and the tools – which can be used in order to copy the model?

- 5 What are the properties of the object that can be transformed in intelligent object?
- 6 How can we experiment the intelligent object?
- 7 What are the ethical aspects of the intelligent object construction?

### 3 The Theory of Plausible Reasoning

The second part of the present paper intend to answer to the first questions: *Are they known theories that have as object the human knowledge?* and *How can we use them in order to develop a human knowledge model?* One possible answer could be ‘The Laplace model of commune sense’ [2]. The background of a particular theory consists on principles or axioms. The difference between these two concepts consists on the fact that the axioms are self evident fundamental and the principles are accepted fundamental reason. This is the reason why we have chosen to name the next fundamental reasons principles.

#### The Principles of Plausible Reasoning

- 1 The representation of degree of plausibility is given by the plausibility function:

$$p : \Phi \rightarrow [0 \ 1]; \quad p(A | X) = y \quad (1)$$

where:

$\Theta$  is a set of sentences

$p(A | X)$  is a continuous and monotonic function which associates a particularly degree of truth for the sentence A in the condition that sentence X is true;

- 2 The consistence of the commune sense requires the following property for the  $p$  function

$$p(AB | X) = p(A | X)p(B | AX) \quad (2)$$

$$p(A | X) + p(\neg A | B) = 1 \quad (3)$$

$$p(A + B | X) = p(A | X) + p(B | X) - p(AB | X) \quad (4)$$

$$p(A_i | X) = \frac{1}{n} \quad i = 1 \dots n \quad (5)$$

where  $\{A_i\}_{i=1 \dots n}$  is a complete set of mutual exclusive sentence.

Some comments are necessary:

- by consistence we mean:
  - every possible way of reasoning a sentence must lead to the same result;
  - the equivalent sentences have an equal degree of plausibility;
- in order to obtain the degree of plausibility for a sentence we must take into account all the evidence available;
  - $p(AB | X)$  means the plausibility of sentence **A and B** in the condition that sentence **X** is true;
  - $\neg A$  means **non A**;
  - $p(A + B | X)$  means the plausibility of sentence **A or B** in the condition that sentence **X** is true.

### Theoretical Results

Analyzing the mentioned postulates, theoretical results can be deduced. From the beginning we will mention that because the probability function has the same properties (1..5) it can be accepted that the plausibility function is synonymous with the probability function. This is the only reasons that theoretical results from probability theory can be transferred to the theory of plausible reasoning [7].

It is obvious that we do not intend to present exhaustive theoretical results. We will resume presenting the Bayesian theorem which can easily deduce from (1-5). If we name by  $d$  the evidence of an experiment and by  $h_{i=1..n}$  a set of mutual exclusive hypotheses the Bayesian theorem tells us that the plausibility of hypothesis  $h_i$  in the condition of evidence  $d$  is equal with the plausibility of hypothesis  $h_i$  multiplied by the plausibility of evidence  $d$  in the condition that hypothesis  $h_i$  is trough and divided by the sum of the same product made for all the hypotheses of the set.

$$p(h_i | d) = p(h_i) \frac{p(d | h_i)}{\sum_{k=1..n} p(h_k) p(d | h_k)} \quad (6)$$

The plausibility of hypothesis  $h_i$  in the condition of evidence  $d$  is named the a posteriori knowledge, the plausibility of hypothesis  $h_i$  is named the a priori knowledge and the plausibility of evidence  $d$  in the condition that hypothesis  $h_i$  is true is named the likelihood. The sum from the denominator is named the marginalization sum.

In order to converge to the model construction we will link this theoretical result to the Bayesian filter [10]. A Bayesian filter allows to estimate the state  $X_t$  for a Markovian system in condition of knowing the observation  $Z_1, \dots, Z_t$ . In order to solve this problem several steps are necessary:

- variable definition:

$\{X_i\}_{0 \leq i \leq t}$  the system states;  $\{Z_i\}_{0 \leq i \leq t}$  observations;

- decomposition

$$p(X_0 \dots X_t, Z_0 \dots Z_t) = \prod_{i=0}^t p(X_i | X_{i-1}) p(Z_i | X_i) \quad (7)$$

- initial knowledge:

- the initial state distribution;

$$p(X_0) \quad (8)$$

- the transition **model** from state i-1 to state i

$$p(X_i | X_{i-1}) \quad (9)$$

- the sensor **model**;

$$p(Z_i | X_i) \quad (10)$$

- the question

$$p(X_t | Z_t \dots Z_0) \quad (11)$$

## 4 The First Case Study

In order to exemplify the mentioned theoretical results we will consider the case of a mobile robot which modifies his state (position) and – from time to time – make observations (measure his position), see Figure 2.

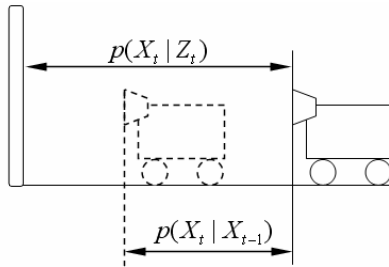


Figure 2  
The mobile robot

The dynamic model of the robot is very simple (the robot has a constant speed):

$$x_k = x_{k-1} + \Delta \quad (12)$$

where:  $x_k$  is the position of the robot.



We know that this model is only an approximation of the reality and from moment two developments – knowledge improvements – are possible:

- developing our model eventual by adaptation: adjust the appropriate value of  $\Delta$  or introduce new parameters;
- constructing the Bayesian filter over this model.

We have chosen the second possibility which can be mathematical described by the following equations

$$x_k^{est} = x_k + \pi^{est} \quad (13)$$

where:  $x_k^{est}$  is the outputs estimations;  $x_k$  is the model output;  $\pi^{est}$  is the model perturbations.

We don't know a priori the model perturbation but we can obtain, by experiments, the statistical distribution of  $\pi^{est}$ :  $p(\pi^{est})$ . This distribution accomplishes (1) so we can define the estimation plausibility like the degree of truth for the following sentence: 'the estimated output  $k$  for our model is  $x_k^{est}$ '.

From (13) we have:

$$p(\pi^{est}) = p(x_k^{est} - x_k) \quad (14)$$

We must note that using the model we will obtain the state  $k$  from state  $k-1$  so we can rewrite (14)

$$p(\pi^{est}) = p(x_k^{est} - x_k) \equiv p(x_k^{est} | x_{k-1}) \quad (15)$$

Using the Bayesian rule (6) we can write:

$$p(x_k^{est}) \propto \sum_{x_{k-1}} p(x_{k-1}) p(x_k^{est} | x_{k-1}) \quad (16)$$

where:  $p(x_k^{est})$  is the plausibility of the output estimation;

$p(x_{k-1})$  is the plausibility of state  $x_{k-1}$ ;

$p(x_k^{est} | x_{k-1})$  is the plausibility of the estimation when we know the state  $x_{k-1}$ ;

$\propto$  means proportional.

If during locomotion we measure (make observations). We can describe this process in the following mathematical form:

$$x_k^{mes} = x_k^{est} + \pi^{mea} \quad (17)$$

where:  $x_k^{mes}$  is the output measurement;

$\pi^{mea}$  is the measurement perturbation.

Once again we don't know a priori the value of the measurement perturbation but if we experiment our sensor we can obtain a statistical distribution of these values. We can write:

$$p(\pi^{mes}) = p(x_k^{mes} - x_k^{est}) \equiv p(x_k^{mes} | x_k^{est}) \quad (18)$$

Using (6) we obtain:

$$p(x_k^{mes}) \propto p(x_k^{est}) p(x_k^{mes} | x_k^{est}) \quad (19)$$

If we use normalized distribution we can transform (16) and (19) in equations.

For the purpose of the Bayesian filter constructing we will return to relation (7-11):

- variable definition:

$\{x_k\}_{k \in \{0, \dots, n\}}$  the system states are the position of the robot (see Figure 1a);  
 $\{x_k^{mes}\}_{k \in \{0, \dots, n\}}$  we will measure the position;

- decomposition

$$p(x_1^{est}, \dots, x_n^{est}, x_1^{mea}, \dots, x_n^{mea}) = \prod_{i=0}^t p(x_k^{est} | x_{k-1}) p(x_k^{mes} | x_k^{est}) \quad (19)$$

- initial knowledge:

- the initial state distribution, is obtained after experiments, in this case we have chosen the following Gaussian distribution;

$$p(x_0) \propto \exp\left(-\frac{(x - x_0)^2}{2 \cdot 0.1^2}\right) \quad (20)$$

- the transition **model** from state k-1 to state k, is presented in (12), the mathematical form of this distribution can be obtained from experimental measurement, once again we have chosen a Gaussian distribution:

$$p(\pi^{est}) = p(x_k^{est} | x_{k-1}) \propto \exp\left(-\frac{(\pi^{est})^2}{2 \cdot 0.2^2}\right) \quad (21)$$

- the sensor **model**: the mathematical form of this distribution can be obtained from experimental measurement, once again we have chosen a Gaussian distribution

$$p(\pi^{mes}) = p(x_k^{mes} | x_k^{est}) \propto \exp\left(-\frac{(\pi^{mes})}{2 \cdot 0.05^2}\right) \quad (22)$$

- the question is the plausibility of the each state when we know the transition plausibility and the measurement (sensor) plausibility; in order to compute this results we have used (16) and (19):

$$p(x_k^{mes}) \propto \left( \sum_{x_{k-1}} p(x_{k-1}) p(x_k^{est} | x_{k-1}) \right) \cdot p(x_k^{mes} | x_k^{est}) \quad (23)$$

The question response is a distribution for each  $k=0\dots n$ . This distribution has a maximum value which is the most plausible answer to the question. More precisely, each iteration we obtain a 2 component information: the most plausible answer (the robot position) and the value of its plausibility.

Even the initial data are not crispy because we must admit that we don't know with precision this data (see Figure 3).

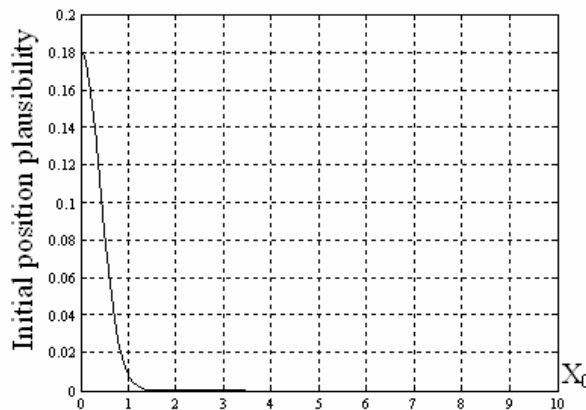


Figure 3  
The initial state

### The First Situation

The robot has several state transition and no observations are made during this transitions. Simulation results are presented in Figure 4. If we analyze this result the main conclusion is that even the translation value – according to (12) – remains constant, the degree of plausibility has decreased continuously from translation to translation. This means that the degree of trust decreases continuously. This is an obvious situation, because a scientist has already the feeling that using repeatedly a model the degree of confidence will decrease. In this case the benefit is that we can compute this decreasing and of course we can take decisions after these results.

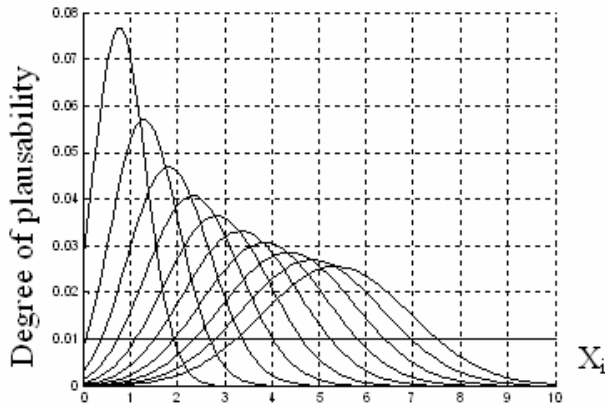


Figure 4  
Transition without observation

### The Second Situation

The robot performs several observations – without performing any transition. In Figures 5 and 6 where we have presented the results of this simulation we can see that the degree of plausibility increases continuously and converges to value 1 (absolute trust).

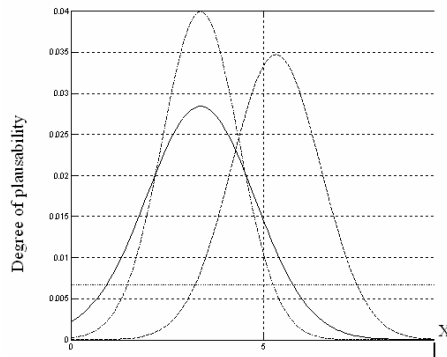


Figure 5  
Two observation (-.- and ---) which starts from the same state (-)

In Figure 5 two particular situations are compared. There are two observations which start from the same state. In the first case, when the observation reproduces the value of the state, we will obtain a bigger rising. At contrary, in the second case there is a difference between the observation and the state. This difference will rule to a smaller degree of true. If we realize several observations which have the same value the degree of true will increase continuously to one (Figure 6).

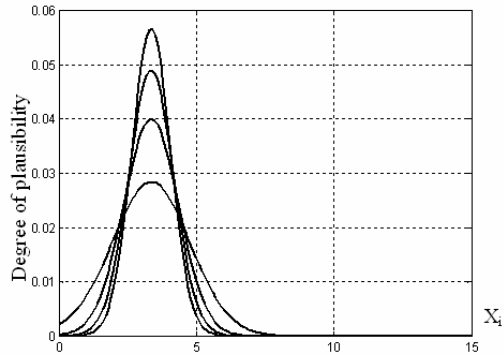


Figure 6

Increasing the plausibility by several observations

### The Third Situation

After these results the conclusion is that we can impose a minimum value of trust and perform observations only if we are below of this value. This is a more realistic strategy which is presented in Figure 7.

In Figure 6 the minimum trust value is 0.1. We have started from 0.18 and after five transitions we are below this value. In this moment we have performed an observation which increased the confidence value to 0.22.

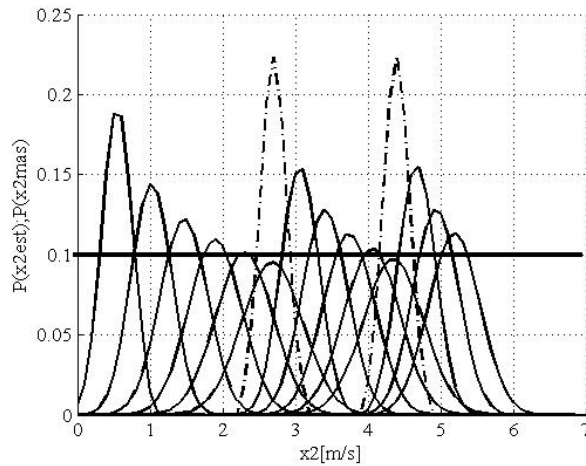


Figure 7

Transitions (-) followed by observations (-.-)

## 4 The Second Case Study

The second case study proves the ability of the Bayesian method geometry. The problem that we intend to solve is the following:

*Problem: If  $ABC$  is an isosceles triangle,  $M \in AC$  and  $AM = MC$  then  $BM \perp AC$ , a priori we know that if  $ABC$  is an isosceles triangle and  $BM, \neg \perp, AC$  then  $AM \neq MC$ .*

If we will rewrite the problem by using the plausibility function we will obtain:

$$p(\perp | \Delta, =) = 1 \quad \text{if} \quad p(= | \Delta, \neg \perp) = 0 \quad (24)$$

where:  $p(\perp | \Delta, =)$  is defined like the plausibility that  $BM \perp AC$  when we know that  $\Delta ABC$  is isosceles and  $AM = MC$ ;

$p(= | \Delta, \neg \perp)$  is defined like the plausibility that  $AM = MC$  when we know that  $\Delta ABC$  is isosceles and  $BM, \neg \perp, AC$ .

From (2-5) we can write:

$$p(\perp | \Delta, =) = \frac{p(=, \Delta, \perp)}{p(=, \Delta)} = \frac{p(\perp)p(\Delta | \perp)p(= | \perp, \Delta)}{p(\perp)p(\Delta | \perp)p(= | \perp, \Delta) + p(\neg \perp)p(\Delta | \neg \perp)p(= | \Delta, \neg \perp)} = \frac{\alpha\beta\delta}{\alpha\beta\delta + (1-\alpha)\varphi \cdot 0} = 1$$

Some comments are necessary: usually in the first moment will consider that  $\alpha, \beta, \delta, \varphi$  are 50%; but after a more careful examination we will realize that these plausibility are very smalls because there are many possibilities that are also plausible. The solution proves that these values are not important.

### Conclusions

Present paper consists from two parts. In the first a phenomenological analyzes of AI collocation is performed. The result of this analyze are seven question which intend to deep the understanding of AI. In the second part we tray to answer to the first two questions by presenting the plausible reasoning theory. This theory is proposed in [4], but we have structured it from a new point of view which corresponds to the description from the previous analysis. We consider that the main advantage of this theory consists in fact that it allows epistemological model which contains both inductive and deductive process. The first presented example underlines this aspect. Increasing the plausibility of a sentence by performing observation means to perform the induction. We will underline also two aspects which have been obtained from simulation. We will mention firstly the diminution of the trust, during repeated use of a theoretical model and secondly the possibility to increase the plausibility by performing observations. The second example underlines the possibilities Bayesian method in deduction processes.

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