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BASIC KNOWLEDGE ON RELATIONSHIP BETWEEN CONCEPT OF PROBABILITY AND POSSIBILITY THEORY

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Abstract: This work examines natural-language computational tasks involving substantial uncertainty. It reviews debates on uncertainty modeling in probability and possibility theory, including Zadeh's claim that some Computing with Words tasks are unsuitable for probabilistic treatment. It proposes a constructive probabilistic approach using specialized Kolmogorov-measure probability spaces to clarify the relationship between the two theories. Introduced by L. A. Zadeh in the late 1970s, possibility theory models flexible restrictions from vague information. As a non-classical uncertainty theory, it differs from probability theory while remaining closely related to it. The discussion also highlights key similarities and differences between possibility theory and other uncertainty frameworks, especially probability theory.

***Index Terms* -** Natural language, Possibility theory, Probability theory, Relationship.

I. INTRODUCTION

Introduced by Lotfi A. Zadeh in 1978, possibility theory is an uncertainty framework based on fuzzy set theory. It represents vague, incomplete, or imprecise information by assessing how plausible an event is, rather than assigning probabilities. This is especially useful when statistical data are unavailable but expert or linguistic knowledge exists. As a non-classical theory of uncertainty, possibility theory differs from probability theory. Probability measures likelihood based on randomness, while possibility measures compatibility with available knowledge. Their related mathematical structures make them easier to compare than fuzzy sets and probability theory. Its main concepts are possibility measures, which express plausibility, and necessity measures, which express certainty. The Minimal Specificity Principle favors the least restrictive possibility distribution consistent with the available information.

Overall, possibility theory provides a mathematical framework for reasoning with vague or incomplete information and is useful in artificial intelligence, expert systems, decision-making, and knowledge representation.

II. WHAT ACTUALLY POSSIBILITY MEAN?

Possibility has overall interpretations, commonly grouped into four main meanings. First, feasibility refers to how easily something can be achieved or whether a solution satisfies given constraints. Second, plausibility concerns whether an event seems likely or reasonable to expect. Third, logical possibility means consistency with available information; a proposition is possible if it does not contradict what is known. Fourth, deontic possibility means that something is allowed or legally permitted.

Possibility may be objective or epistemic, and both feasibility and plausibility can be understood in these ways. Objective feasibility concerns what is physically achievable, as in "Suman can eat six bananas for breakfast." Zadeh (1978) used this notion of physical possibility to justify the axioms of possibility measures: the feasibility of A or B depends on whichever action is easier. Feasibility is also tied to preference, since among mutually exclusive alternatives, the most feasible option is often preferred. Thus, subjective feasibility reflects an agent's willingness to choose an option, linking possibility with preference.

From an epistemic perspective, plausibility measures how unsurprising an event is in light of an agent's knowledge. An event is more surprising when it conflicts with what is known and more plausible when it is consistent with it. In this sense, plausibility expresses agreement with available knowledge. Decisions often rely on what seems possible as well as probable, especially when probabilities are unavailable. This shows the subjectivist role of possibility in modelling uncertainty, although possibility can also have an objectivist interpretation. Early frequentist approaches helped relate possibility theory to probability theory.

Plausibility is dual to certainty: an event is certain when its opposite is not plausible. This differs from probability, which is self-dual. Saying "not A is not probable" implies that A is probable, but saying "not A is not possible" means something stronger: A is necessary. However, the possibility of A does not determine whether not A is possible or impossible. Thus, possibility and necessity form a dual pair.

Necessity can be analyzed similarly to possibility. It may be physical, as in natural laws, or epistemic, as in accepted beliefs. Objective necessity refers to what must occur, while subjective necessity reflects priority, belief, or acceptance until new information disproves it.

A key issue in possibility theory is choosing a formal way to express levels of possibility and necessity. Unlike probability theory, this setting is not unique. Possibility theory has qualitative and quantitative forms; in the latter, numerical degrees require clear interpretation and justification. Possibility may mean feasibility, plausibility, or consistency with knowledge. It can be objective, referring to physical capability, or subjective, linked to preference and decision-making. Epistemic possibility reflects how well an event agrees with known information, making it useful when exact probabilities are unavailable.

Necessity, the dual of possibility, expresses certainty: an event is necessary when its opposite is impossible. It may be objective, based on natural laws, or subjective, based on belief accepted until contradicted.

Possibility theory has qualitative and quantitative forms. The qualitative form ranks events without numbers, while the quantitative form assigns numerical degrees, usually between 0 and 1, depending on the available information and application. Below we outline semantics of possibility in the logical language

- For an event A, $Pos(A) \geq 0$.
- The event A is possible if $0 < Pos(A) \leq 1$.
- The possibility of A is a unitary possibility, $Pos(A)=1$.
- $Pos(A) \geq Pr(A)$.

III. Example to Understand Possibility

Consider the statement: "Radha is middle-aged". It is assumed that neither probability nor possibility distributions are given and use judgment to identify by answering questions for specific ages:

(Q1) What is your estimate of the probability that Radha is 38?

(Q2) What is your estimate of the possibility that Radha is 38?

Zadeh noted that, if asked Q1, he would not be able to give an answer. He argued that others would also struggle to answer Q1 based only on their perception of "middle-aged." By contrast, Q2 is easier because possibility can be treated as a grade of membership. For example, a value of 0.6 means that age 38 fits the concept of "middle-aged" to degree 0.6. Thus, Zadeh is effectively answering:

(Q3) What is the grade of membership of age 38 in the fuzzy concept "middle-aged"?

This follows from interpreting possibility as membership grade. In the Natural Language (NL) the major difference is in "will happen", "has happened" associated with word "probability" and "might happen" associated with word "possibility". Respectively questions Q1-Q2 can be reformulated into equivalent NL forms:

(Q1.1) What is your estimate of the chance that Radha is 38?

(Q2.1) What is your estimate of the chance that Radha might be 38?

(Q3): "What is your estimate of the grade of membership that middle-aged Radha is 38?"

- contains term "grade of membership" which is a part of the professional language not the basic NL.

IV. WHY SUM OF POSSIBILITIES MAY BE GREATER THAN 1?

Consider a probability space with two events A_{m1} and A_{m2} .

A_{m1} = "A may happen", A_{m2} = "A may not happen",

Thus, for A = "rain" we will have events

A_{m1} = "rain may happen", A_{m2} = "rain may not happen",

Respectively for A = "no rain" we will have events

A_{m1} = "no rain may happen", A_{m2} = "no rain may not happen",

Next consider another probability space with two events without "may" and "may not", A_1= "A", A_2= "not A". Denote probabilities in spaces with "may" and "may not" as P_m and without them as P_e respectively. In both cases in accordance with the definition of probability spaces sums are equal to 1:

$$P_m(A_{m1}) + P_m(A_{m2}) = 1 \quad \& \quad P_e(A_1) + P_e(A_2) = 1$$

Consider $P_m(A_{m1})$ = 0.3, $P_m(A_{m2})$ = 0.7, and $P_e(A_1)$= 0.1, $P_e(A_2)$= 0.9. In this example

$$P_m(A_{m1}) + P_e(A_2) = 0.3 + 0.9 = 1.2 > 1$$

The probability of "no rain" refers to a physical event. By contrast, the probability of "rain may not happen" refers to a mental event. It depends not only on the physical chance of rain, but also on the subjective interpretation of the word "may." This mixing of events from different probability spaces can lead to the claim that possibility theory differs fundamentally from probability theory, especially when the sum of possibilities exceeds 1.

V. POSSIBILITY DISTRIBUTIONS:

A possibility distribution is usually associated with a variable x ranging on U and then denoted π_x. This variable x represents the unknown unique value taken by one or more attributes describing states of affairs. A possibility distribution expresses the available state of knowledge by distinguishing more plausible or expected values from less plausible or surprising ones. The associated π_x acts as a flexible restriction on the variable's x under the following conventions:

$\pi_x(u) = 0$ means that $x = u$ is rejected as impossible;

$\pi_x(u) = 1$ means that $x = u$ is totally possible

$\exists u, \quad \pi_x(u) = I$ (normalization).

The quantity $\pi_x(u)$ therefore gives the possibility degree of the assignment $x = u$, indicating that some values u are more possible than others. Clearly, if U is the full range of x, at least one of the elements of U should be fully possible as a value of x, so that strictly speaking, a possibility distribution can be seen as a generalized characteristic function of a fuzzy set. Zadeh's main point is that, just as characteristic functions represent equal possibility in ordinary sets, fuzzy-set membership functions express degrees of possibility. Still, fuzzy sets and possibility distributions are not the same. A possibility distribution partitions U into classes of states with equal possibility. Each such distribution has one comparative counterpart, whereas a comparative possibility distribution can have infinitely many unit-interval representations. In particular, a purely comparative ordering is less explicit about impossible values than an absolute possibility scale, because plausibility ordering alone does not reveal whether the distribution is dogmatic.

VI. INFORMATION IN POSSIBILITY DISTRIBUTION

Possibility theory is guided by the principle of minimal specificity. When constraints define a feasible set of possibility distributions, the preferred representative is the least specific one: the distribution that gives each state the highest admissible degree of possibility and therefore makes the fewest commitments. This reflects the idea that any state not proven impossible should be treated as possible. In some cases, however, a dual principle of maximal specificity is more appropriate. When available knowledge is too weak and minimal specificity would erase useful information, states not observed to be possible may be treated as impossible. This principle also applies when a possibility distribution serves as a weak approximation of richer information, where the goal is to preserve as much information as possible, as in possibility-probability transformations.

VII. Relations between concepts of Possibility and Probability:

A. Possibility versus probability

Consider the statement "Suman ate X bananas for breakfast," X = {1, 2, . . .}. A possibility distribution as well as a probability distribution may be associated with X. We may associate a possibility distribution $\{\pi_x(u)\}$ with X by interpreting $\pi_x(u)$ as the degree of ease with which Suman can eat u bananas for breakfast, $u = 1,2,3,\ldots X$ is in possibility theory called a fuzzy variable. We may alternatively interpret X as a random variable and associate a probability distribution $\{P_x(u)\}$, with it by interpreting $P_x(u)$ as the probability of Suman eating u bananas for breakfast (on an arbitrary day), $u = 1,2,3 \ldots$. The values of these distributions might be assessed as shown in Table 1. The values of $\pi_x(u)$ and $P_x(u)$ might be as shown in the following table :

Table 1

u	1	2	3	4	5	6	7	8
$\pi_x(u)$	1	1	1	0.9	0.7	0.5	0.3	0.1
$P_x(u)$	0.2	0.4	0.3	0.1	0	0	0	0

A high degree of possibility does not necessarily mean a high probability. However, if an event is impossible, it must also be improbable; in this sense, possibility serves as an upper bound for probability. Zadeh's (1978) possibility/probability consistency principle describes this relationship as a heuristic guide, not a precise rule for calculating exact probabilities or possibilities.

B. Situating Probability Spaces in Context

Consider the sum of the possibilities of events A and not A, Pos(A)+Pos (not A), and compare it with the probability sum Pr(A)+Pr(not A). In probability theory, Pr(A)+Pr(not A)=1 only when both probabilities are defined within the same context. If this requirement is removed, the sum may exceed 1. For example, if Pr(A)=0.7 for A = "rain" is calculated from data for the last spring month, while Pr (not A)=0.6 is calculated from data for the last summer month, then Pr(A)+Pr(not A) =1.3>1. A similar context shift can occur when computing Pos(A)+Pos (not A). For mental events represented by possibility measures, it is especially difficult to ensure that the context remains fixed. Therefore, sums obtained from such context-free questions do not justify rejecting probability theory or introducing a new possibility theory based on sums greater than 1.

VIII. Possibility and Necessity Measures:

A. Quantitative Possibility Theory: Connecting Probability with Fuzzy Sets

In the Bayesian view, estimation should use not only objective data, such as random samples, but also reliable prior information about θ_0. Prior information can improve estimation by narrowing the possible location of θ_0. If θ_0 is known to belong to a proper subset A of Θ, then estimates of θ_0 become more reliable. In verbal terms, prior information assigns different degrees of possibility to the values θ_0 that may take. Since random samples are mainly used to estimate θ_0, incorporating prior information creates a data-fusion problem: probabilistic data must be combined with possibilistic data. Such prior localization information is often represented by a probability distribution, such as a prior density $P(\theta)$ on Θ. However, a function such as $P(\cdot)$ also has a possibilistic interpretation because it expresses localization information. Treating $P(\cdot)$ as a possibility distribution rather than a probability density function can also avoid technical difficulties associated with improper uniform priors. This perspective helps explain the motivation for possibility distributions in uncertainty analysis and clarifies how they differ from probability density functions.

Fuzzy theory is not exclusively connected to possibility theory, and possibility theory is not limited to fuzzy sets. Probability and possibility distributions can both be viewed as special cases of fuzzy sets. Under this interpretation, any fuzzy set can be converted into a probability or possibility distribution by adding suitable normalization conditions: probability requires the total sum or integral to equal 1, while possibility requires the maximum value to equal 1. Thus, if $m(x)$ is the membership function of a fuzzy set on the interval $[a,b]$, it can be normalized into a probability distribution by dividing by S, the sum or integral of m(x) over that interval, giving $P(x) = m(x)/S$. Alternatively, it can be normalized into a possibility distribution by dividing by M, the maximum value of $m(x)$ on $[a,b]$, giving $Pos(x) = m(x)/M$.

However, these transformations do not by themselves explain the relationships among Fuzzy Set Theory, Fuzzy Logic, and Probability Theory. The key issue is how membership functions and probabilities are interpreted and used in operations on . Since fuzzy sets are only one component of fuzzy set theory, comparisons among these theories should not be based on that concept alone. In probability theory, intersection and union operations (∩ and ∪) are context-dependent: $P(x \cap y) = f(P(x), P(y|x)) = P(x)P(y|x)$, where the conditional probability $P(y|x)$ captures the dependence between x and y. By contrast, operations in Fuzzy Set Theory and Fuzzy Logic are context-free: $m(x\&y) = f(m(x), m(y))$, so they do not capture conditional properties or dependencies. In this sense, Fuzzy Logic and Fuzzy Set Theory may be viewed as special cases of Probability Theory, since t-norms form a subset of copulas, which represent multidimensional probability distributions.

B.How Membership Functions Relate to Probability

The membership function of a crisp set is neither a probability density function nor a probability distribution, because it only indicates whether an element belongs to the set. Although a membership function is generally not a pdf or probability distribution, the comparison need not rely on one-to-one mapping. The relationship can instead be one-to-many, similar to how a set of linear functions can represent a piecewise linear function. In this sense, a set of pdfs can represent the membership function of a crisp or fuzzy set. Let $f(x) = 1$ be the membership function of the interval $[a, b]$. For each x, define the event pair $\{e_1(x), e_2(x)\}$ = {x belongs to $[a, b]$, x does not belong to $[a, b]$}, with $P_x(e_1(x)) = 1$ if x belongs to $[a, b]$ and $P_x(e_2(x)) = 0$ otherwise. Thus, $P_x(e_1(x)) = f(x)$ =1, $P_x(e_2(x)) = 0$, and $P_x(e_1(x)) + P_x(e_2(x)) = 1$. This gives the simplest probability space satisfying Kolmogorov's axioms. The full set of such pdfs, $P = \{P_x\}$ for all x in $[a, b]$, is therefore equivalent to the membership function of the crisp set. For a fuzzy set with a membership function f(x) we have probabilities $P_x(e_1(x)) = f(x), P_x(e_2(x)) = 1 - f(x)$ that satisfy all Kolmogorov's axioms of probability, where again a set of these pdfs $P = \{P_x\}$ for all x from $[a, b]$ is equivalent to MF of the fuzzy set $\langle [a, b], f \rangle$.

Zadeh objects to equating a grade of membership and a truth value to probability but equates a grade of membership and a truth value as obvious. He states that "equating grade of membership to probability, is not meaningful", and that "consensus-based definitions may be formulated without the use of probabilities". To support this statement, he provided an example of a grade of membership 0.7 that Radha is middle-aged if she is 38. Below we explicate and analyze his statement for this example that is reproduced as follows. Grade of Membership that Radha is middle-aged being 38:

GradeMembership (Radha is middle-aged| Age = 38) = 0.7,--------- (1)

Truth value for Age=38 to be middle-aged,

Truth Value (Age=38 is middle-aged) =0.7.-----------(2)

Possibility that Radha is middle-aged for the Age = 38,

$Pos(Age = 38 \mid\ Radha\ is\ middle\ aged)\ =\ 0.7$-------------(3)

Probability that Radha is middle-aged for the Age = 38,

$P(Radha\ is\ middle - aged \mid Age\ =\ 38)\ =\ 0.7$-------------(4)

In other words, Zadeh treats (1), (2), and (3) as equivalent, while rejecting their equivalence to (4) as unnecessary and not meaningful. However, a crisp voting model can give the grade of membership a meaningful probabilistic interpretation. In this model, each respondent classifies the statement "Radha is middle-aged" as either true or false, and the membership grade is defined as the average of these votes. A flexible voting model extends this idea by allowing each voter to assign a membership grade between 0 and 1, interpreted as that voter's subjective or declarative probability. With multiple voters, the consensus-based membership grade is then the average of their subjective probabilities. Thus, a simple and long-standing probabilistic interpretation of membership grades is available.

IX. Conclusion

This paper clarifies the relationship between probability and possibility theory under extreme natural-language uncertainty. It challenges Zadeh's claim that such tasks belong only to fuzzy logic and possibility theory by showing that probabilistic methods can also be suitable. Using specialized Kolmogorov-measure probability spaces, it offers a constructive framework for explaining links between the two theories and identifying directions for a more rigorous possibility theory and future research.

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