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An Insight Into The Z-number Approach To CWW

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Abstract. The Z-number is a new fuzzy-theoretic concept, proposed by Zadeh in 2011. It extends the basic philosophy of Computing With Words (CWW) to include the perception of uncertainty of the information conveyed by a natural language statement. The Z-number thus, serves as a model of linguistic summarization of natural language statements, a technique to merge human-affective perspectives with CWW, and consequently can be envisaged to play a radical role in the domain of CWW-based system design and Natural Language Processing (NLP). This article presents a comprehensive investigation of the Z-number approach to CWW. We present here: a) an outline of our understanding of the generic architecture, algorithm and challenges underlying CWW in general; b) a detailed study of the Z-number methodology - where we propose an algorithm for CWW using Z-numbers, define a Z-number based operator for the evaluation of the level of requirement satisfaction, and describe simulation experiments of CWW utilizing Z-numbers; and c) analyse the strengths and the challenges of the Z-numbers, and suggest possible solution strategies. We believe that this article would inspire research on the need for inclusion of human-behavioural aspects into CWW, as well as the integration of CWW and NLP.

Keywords: Cognition, fuzzy sets, linguistics, machine learning, text-summarization, dialogue-based systems, affective computing, Natural Language Processing (NLP), perceptions, soft computing, natural computing

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1. Introduction

"In the coming years, computing with words is likely to evolve into a basic methodology in its own right with wide-ranging ramifications on both the basic and the applied levels."
- L. A. Zadeh, *Fuzzy Logic = Computing with words*, 1996

Nature, in its broadest sense, implies the physical world - the existing system of things; matter and mind; the universe. One of the principal objectives of computer science is to understand the information processing taking place in nature - the human brain being the ultimate inspiration.

The human brain, possesses an amazing decision-making ability, based on 'perceptions' encoded in the 'words' and 'phrases' in natural language sentences - giving rise to the "Computing with Words (CWW) [24]" paradigm. Coined by Zadeh in 1996, this paradigm aspires to 'teach' the computer to 'learn', 'think' and 'respond' to 'words', or rather 'word-perceptions' as well as human beings. A successful implementation of the paradigm would, nevertheless, symbolize a gigantic leap in the "Intelligent Systems Revolution [19], [25]".

The concepts of CWW are essentially rooted in [24], [21], [22] and [23], [27], where Zadeh equates the concepts of fuzzy logic to CWW, describes the rationale underlying fuzzy linguistics and information granulation, elucidates the concept of the test-score semantics that associates all natural language statements to degrees of constraint satisfaction, explains the precisiation of natural language, and illustrates the computational theory of perceptions, respectively. He further proceeds to define the 'levels' of CWW in [13] and [28], where 'level-1' seeks to quantify the perceptions of adjectives and adverbs (words and phrases) while, 'level-2' aims at precisiating natural language statements.

Since its coinage, the last decade has seen a surge in research on the concepts of CWW. Notable works include: [4] where the authors attempt to break away from the traditional rule-based approach to formulate an arithmetic-based technique based on fuzzy numbers; [11] describes the application of the mass assignment theory to fuzzy sets to provide semantic interpretations for membership functions; [18] illustrates the concept of a fuzzy Finite State Machine (FSM) to generate linguistic descriptions of complex phenomenon, which is further extended in [20] to simulate emotions in such a system; [12] explains the relevance of the Interval Type-2 Fuzzy Set (IT2-FS) in mapping the different levels of ambiguities in word perceptions - crucial to the intended human-like responses of a system based on CWW; [17] coalesces the concepts of fuzzy sets and ontology; while [8] and [9] formalize the Generalized Constraint Language (GCL) into a tool for CWW.

In 2011, Zadeh proposed the notion of the Z-number [29] - a technique to incorporate the concept of the reliability of information within CWW. The Z-number draws on the concepts in [24], [21], [22], [23] and [27], and is subtly inspired by [7]. In this article, we regard the novelty of the Z-number to be lying in the fact that it not only considers perceptions of individual words, but also the perception of an entire sentence. Consequently, the concept can be envisioned as capable of modelling the process of natural language comprehension by human beings - serving as a bridge between CWW, Natural Language Processting (NLP) and affective computing. The Z-number can thus be conceptualized as a formidable tool in the design of discourse-oriented decision-making systems, risk assessment, text-summarization or even semantic-based plagiarism detection systems. The Z-number is a manifestation of level-2 CWW. In the light of the possible potential of the Z-number in the arena of CWW, probing into its strengths as well as the challenges underlying its implementation is an absolute requirement.

This article is an elucidation on our investigations on the Z-number approach to CWW. Here, we begin with an elementary overview of the concepts of perceptions (Section 2.1) and CWW (Section 2.2). The latter includes an illustration of our visualization of the generic architecture and our algorithm for CWW, followed by an outline of the basic challenges in designing a system that computes on words. The article then proceeds to an introduction to the Z-numbers (Section 3); followed by our proposed methodology for CWW using the Z-number technique - which includes an algorithm for Z-number based CWW (Section 4.1), an operator to evaluate requirement satisfaction (Section 4.2) and experiments that depict the simulation of actual CWW by human beings (Section 4.3). The article concludes with a detailed analysis of the strengths (Section 5.1), the challenges and probable solution strategies (Section 5.2), underlying the implementation of the Z-numbers.

We believe CWW and NLP to be supplementary technologies, where through its different levels, CWW seeks to precisiate statements, while NLP seeks the same across any natural language sentence. Moreover, automated CWW cannot do without basic NLP methodologies like Part-Of-Speech tagging, anaphora resolution etc., as is revealed in the algorithms proposed in the following sections. This article is our attempt at a seamless integration of CWW and NLP.

Note: “Sentences are collections of words that make complete sense. The sense is not complete, unless something is being said about something [15]”

In this article, the word 'statement' implies a declarative sentence, while the word 'sentence' is used when we do not wish to highlight sentence-types.

2. Essential Concepts

This section presents an elementary discussion on the concepts of perceptions and CWW.

2.1. Perceptions

Perception is the process of cognition of the environment by the interpretation of the signals received by the sense organs. Perceptions vary between individuals, and depend on complex analytic functions of the nervous system. The process of cognition, however, appears to be effortless as the processing occurs beyond conscious awareness. Perceptions are continually shaped by learning (experience), memory and expectation, and thus change with age, work habits, environment, interests etc. The same situation, is often, perceived differently by different people.

The question that arises here is, “How do people communicate when they might perceive the same situation differently?” In [10] we find the answer to this. It says, “It is only when the individual perceptions, concerning a situation, overlap considerably, that people comprehend one another.” As for example, all people with normal colour vision are likely to identify the colour blue, but very few are able to spot the subtle difference between Tufts Blue and Cornflower Blue.

This brief discussion on perceptions prepares the base for all that a machine requires to accomplish when it computes on word-perceptions.

2.2. Computing With Words (CWW)

Computing, traditionally, stands for the manipulation of precise numbers or symbols. Computing with Words (CWW), however, refers to an entire “paradigm shift”, where the elements of manipulation are no longer numbers but 'words' and 'phrases' in natural language statements [24], [26]. CWW is inspired by the remarkable ability of the human brain to act on the basis of perceptions of events - summarized by 'words' or 'phrases'. [24] and [26] assert that CWW is imperative when:

(i) *Do not know rationale* - The available information is not sufficiently precise to be summarized in the form of numbers. E.g., the age of a person is often denoted by the word 'young' when the exact age is unknown.

(ii) *Do not need rationale* - The tolerance to imprecision may be exploited to formulate “tractable, robust and low cost solutions”. E.g., putting up a picture on the wall as per the directions of another person.

(iii) *Cannot solve rationale* - The problems cannot be solved via numerical computing processes. E.g., automation of driving in traffic.

(iv) *Cannot define rationale* - Words express more than numbers. E.g., a patient describing his illness.

Some examples of everyday CWW by human beings are as follows:

(i) “This diagram looks rather big. I think I'll scale it down a bit.” - An example of the 'do not need rationale'.

In this example, the dimension of the diagram is described by the phrase 'rather big' - the perception of which, leads to the obvious decision of the need to “scale it down a bit”.

(ii) “It takes me *about an hour to reach Point A*, and *about another quarter of an hour to reach Point B from point A*. I shall be travelling during the *rush hour*. I think I need to *start at least an hour and a half in advance*.” - This example is a combination of the 'do not know' and the 'do not need' rationales.

Here, the events of time and travel conditions are illustrated in the italicized phrases. The perceptions of all these facts taken together result in the decision of “start at least an hour and a half in advance”.

CWW, evidently aims at capacitating the machine to 'compute' as do human beings, given the aforementioned situations. The penultimate goal of CWW-based system design can accordingly be summed up as “modelling human-responses to word-perceptions such that these systems may participate in a discourse with a human, translate between languages on the level of a human interpreter, assist individuals in subjective judgements and risk assessments, summarize texts or even prepare linguistic descriptions of intricate events”.

The following subsections reflect our vision of the generic architecture of such CWW-based systems, the algorithm underlying the operation of such systems and the basic challenges involved in the design.

2.2.1. The Generic Architecture for a System Based on CWW

A system based on CWW, takes as input a set of natural language sentences that describes an event, and presents as output the corresponding response in the natural language as well.

The generic architecture for a system that computes with words is hence, as is shown in Figure 1. The components of the architecture are:

(i) The *Encoder*, processes through the two levels of CWW to translate input sentences to the corresponding antecedent constraints, i.e., the inputs are precisiated into some symbolic form (S) as is processed by the system - reminiscent of Russell's concept of philosophical logic;

(ii) The *Rule Base* consists of the antecedent-consequent event relationships, typical to the context of discourse. The rule base may be in the form of an Explanatory Database (ED);

(iii) The *Inference Engine*, in conjunction with the rule base is instrumental in processing the antecedent constraints to arrive at the consequent results. These results are in the symbolic form S';

(iv) The *Decoder* translates S' into words that can be frame semantically correct natural language sentences.

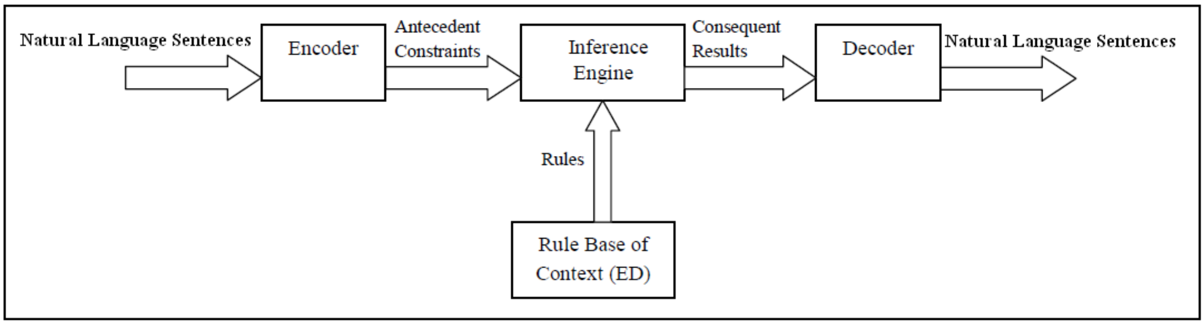

Figure 1. The generic architecture for a system based on CWW

2.2.2. The Generic Algorithm for CWW

Based on the above architecture, the algorithm underlying CWW can be intuitively outlined as is shown below. The algorithm demonstrates the union of CWW and NLP concepts. It takes as input natural language sentences, reduces them to their simple sentence components and converts them into some precisiated form which are processed to arrive at words that are then framed into sentences.

Algorithm 1
Input: Natural language sentence (I).

Output: Context-dependent response (O) to I.

Assumptions:

i. The system is capable of identifying irrelevant sentences.

ii. The system grasps the perception of a complex or a compound sentence (Y) by -

  a. Extracting the simple sentence components of Y.

  b. Comprehending each of these simple sentence components.

  c. Combining these component perceptions with respect to the conjunctions ('or', 'and' etc) in Y.

[*Note:* Assumption (ii) mirrors instinctive language cognition in human beings]

Steps:

1. If I is irrelevant
    Then
        Goto step 7
    Else
        Goto step 2
2. If I is a simple sentence
    Then
        Goto step 3
    Else
        a. Extract the simple sentence component set (I') of I
        b. Repeat steps 3 through 5 for each sentence in I'
        c. Goto step 6.
3. Convert I into the precisiated form (P)
4. Evaluate P to receive a set of words (W) in response
5. Assimilate W into simple sentences (S)
6. If step 5 results in more than one simple sentence
    Then
        If some or all the sentences in S can be compiled into a single sentence
        Then
            a. Assimilate all compatible simple sentences into a complex/compound sentence (S')
            b. If S' does not include all the sentences in S
                Then
                    b.1. $S'' = S - S'$
                    b.2. $O = S' \cup S''$
                Else
                    $O = S'$
        Else
            $O = S$
    Else
        $O = S$
7. Stop

Execution of steps 1 through 3 of Algorithm 1 fall under the jurisdiction of the encoder (Figure 1), implementation of step 4 requires the rule-base and the inference engine, while the decoder is responsible for the execution of steps 5 through 7.

2.2.3. The Challenges Inherent in CWW-Based System Design

Considering the richness and the inherent ambiguity of natural languages, and that machines yet lack in 'common-sense', it perhaps would be pragmatic to design systems that process words pertaining to a particular context. These individual systems may then be integrated into one that is adept at comprehending words across multiple contexts. The design of such context-sensitive CWW-based systems, is encumbered by the following challenges:

(i) Model the perceptions of words/phrases -

a. Model to accommodate multi-perception words - polysemes, homonyms, capitonyms.

b. Model the uncertainty of word perceptions, particularly of adjectives and adverbs, across human beings (inter-uncertainty) as well as the intrinsic uncertainty within a person (intra-uncertainty).

c. Model the change in perceptions, within a person, over time.

d. Model to accommodate synonyms.

(ii) Model the perception conveyed by the sentence -

a. Translate the input natural language sentence to some precisiated form - this requirement is in conjunction with Russell's philosophic logic and the need for the machine to be able to process the input.

b. Evaluate the relevance of the sentence - includes identification of paradoxes and rhetorical questions as irrelevant.

c. Model to be context-independent.

d. Model to accommodate simple, complex and compound sentences;

e. Model to accommodate declarative, interrogative, imperative, exclamatory and conditional sentences.

f. Model to depend on semantics and not only on the syntax of sentences - perceptions are often comprehensible despite syntactical errors.

g. Model to accommodate rhetorical figures of speech.

(iii) Prepare an antecedent-consequence rule-base for the context to guide the computation -

a. Allow rule-base to grow and evolve with time.

(iv) Design rules of computations with the word perceptions, such that the results lie within the context -

a. Rules of computation to be guided by the word-perception model, sentence-perception model and rule-base.

(v) Processing time requirements to be of the order of average human cognition [~150 - 300 ms].

(vi) Translate results of computation to sentences.

(vii) Allow the system vocabulary to grow and evolve with time.

(viii) Natural language comprehension is not only influenced by words but non-verbal affects (voice intonation, facial expressions, hand movements, eye-gaze, eye-brightness, response time) and word-sentiment valencies as well. Thus, the simulation of realistic language interpretation models requires the inclusion of components into the architecture of Figure 1 and Algorithm 1 that take into account these non-verbal sentence-meaning influencers. This would actually result in the integration of CWW, NLP and affective computing.

With this brief sketch of concepts that form the basis of our work, the paper now proceeds to an elaboration on our exploration of the Z-number approach to CWW. While Zadeh proposed the Z-number as a method of extracting the reliability of information conveyed in a statement, we envisage the concept to be capable of merging CWW, NLP and affective computing. This article focuses primarily on the assimilation of CWW and NLP techniques and provides subtle hints on the inclusion of human-behavioural elements.

In the following section (Section 3) we present an overview of the Z-number, as is visualized by Zadeh in [29], and then describe our proposed methodology for CWW using the Z-numbers (Section 4).

3. An Overview of the Z-number

All our voluntary actions are the result of decision-making processes. Decisions depend on information. Thus, greater the reliability of the information, stronger is the decision made. The Z-numbers aims at capturing the reliability or the confidence in the information conveyed by natural language statements.

Given a natural language statement, Y, the 'Z-number' of Y is a 2-tuple $Z = \langle A, B\rangle$, where A is the restriction (constraint) on the values of X (a real-valued uncertain variable, interpreted as the subject of Y) and B is a measure of the reliability (certainty) of A. Typically, A and B are expressed as words or clauses, and are both fuzzy numbers.

Examples:

(i) Y_1 = This water is decidedly cold.
Therefore, X = Temperature of water, and Z = $\langle$cold, decidedly$\rangle$.

(ii) Y_2 = It takes me about half an hour to reach point A.
Therefore, X = Time to reach point A, and Z = $\langle$about half an hour, usually$\rangle$.

Understandably, A is context-dependent while B is perceived from the statement. The value of B could be explicitly quoted in the statement (as in example (i)) or it could be implicit (as is example(ii), and in most natural language statements).

The ordered 3-tuple $\langle X, A, B\rangle$ is referred to as a 'Z-valuation'. A Z-valuation is equivalent to an assignment statement 'X is $\langle A, B\rangle$'. As for example:

(i) The Z-valuation of Y_1 is $\langle$Temperature of water, cold, decidedly$\rangle$.
Implication: [Temperature of water] is $\langle$cold, decidedly$\rangle$.

(ii) The Z-valuation of Y_2 is $\langle$Time to reach point A, about half an hour, usually$\rangle$.
Implication: [Time to reach point A] is $\langle$about half an hour, usually$\rangle$.

A collection of Z-valuations is referred to as 'Z-information'. The Z-information is the stimulus to a decision-making process.

Preliminary rules of computation [29] using the Z-numbers are as follows:

(i) For the purpose of computation, the values of A and B need to be precisiated through association with membership functions, μ_A, μ_B respectively.

(ii) X and A together define a random event in R, and the probability of this event, p, may be expressed as:

$$p = \int_R \mu_A(u) p_X(u) du \tag{1}$$

where, u is a real valued generic value of X and p_X is the underlying (hidden) probability density of X.

(iii) The Z-valuation $\langle X, A, B \rangle$ is viewed as a generalized constraint on X, and is defined by:

$$Probability\ (X\ is\ A)\ is\ B$$

or,

$$p = \int_R \mu_A(u) p_X(u) du\ is\ B \tag{2}$$

(iv) (2) is mathematically equivalent to the expression:

$$\mu_B(\int_R \mu_A(u) p_X(u) du) \tag{3}$$

Subject to:

$$\int_R p_X(u) du\ =\ 1 \tag{4}$$

(v) Computation using the Z-numbers is based on the 'Principle of Extension'. As for example, Considering a problem statement of the form:

"It is probable that Mr. Smith is old. What is the probability that he is not?"

Let, X = Mr. Smith's age, A = old, B = probable, C = not old, D = degree of certainty;
μ_A, μ_B, μ_C, μ_D are the membership functions associated with A, B, C and D respectively;
p_X is the underlying (hidden) probability density of X;
u is a real valued generic value of X.

Therefore, we have: (X is A) is B; and
We need to evaluate: (X is C) is ? D.

Thus, using the Principle of Extension and (2), (3) and (4):

$$\frac{\langle X, A, B \rangle}{\langle X, C,\ ?D \rangle} = \frac{Prob\ (X\ is\ A)\ is\ B}{Prob\ (X\ is\ C)\ is\ ?D} = \frac{\mu_B(\int_R \mu_A(u) p_X(u) du)}{\int_R \mu_C(u) p_X(u) du\ is\ ?D}$$

this implies,

$$\mu_D(w) \;=\; sup_{p_X}(\mu_B(\int_R \mu_A(u)p_X(u)du)) \tag{5}$$

subject to:

$$w \;=\; \int_R \mu_C(u)p_X(u)du;\; \int_R p_X(u)du \;=\; 1 \tag{6}$$

4. Proposed Methodology for CWW Using the Z-number Approach

This section focuses on our study of CWW from the Z-number perspective. Here, we present an algorithm for CWW using Z-numbers and an operator that uses the Z-number to evaluate requirement satisfaction. This is followed by a description of our experiments - attempts at the simulation of real-life CWW, using the Z-number technique. Our approach incorporates basic NLP strategies to extend the Z-number to work with any sentence type.

4.1. Algorithm for CWW Using Z-numbers

Modifying Algorithm 1 so as to incorporate the Z-number methodology, the algorithm for CWW utilizing the Z-number concept is:

Algorithm 2
Input: Natural language sentence (I).

Output: Context-dependent response (O) to I.

Assumptions:
- i. The system is capable of identifying irrelevant sentences.
- ii. The system grasps the perception of a complex or a compound sentence (Y) by -
  - a. Extracting the simple sentence components of Y.
  - b. Comprehending each of these simple sentence components.
  - c. Combining these component perceptions with respect to the conjunctions ('or', 'and' etc) in Y.

Steps:
1. If I is irrelevant
   Then
      Goto step 10
   Else
      Goto step 2
2. If I is a simple sentence
   Then
      Goto step 3
   Else
      a. Extract the simple sentence component set (I') of I
      b. Repeat steps 3 through 4 for each sentence in I'
      c. Goto step 5.
3. Extract the values of X, A and B in I to evaluate the Z-valuation (Z_I)

4. Convert Z_I into equivalent mathematical expression (Z_E) (following (3) and (4))
5. Assemble all Z_E to form the logical expression (E) guided by the conjunctions in I
6. Convert E to the mathematical expression (M)
7. Evaluate M to receive a set of Z-valuations (Z_O) in response
8. Translate Z_O into simple sentences (S)
9. If step 8 results in more than one simple sentence
   Then
      If some or all the sentences in S can be compiled into a single sentence
      Then
         a. Assimilate all compatible simple sentences into a complex/compound sentence (S')
         b. If S' does not include all the sentences in S
            Then
               b.1. S'' = $S - S$'
               b.2. O = S' ∪ S''
            Else
               O = S'
      Else
         O = S
   Else
      O = S
10. Stop

4.2. Z-number Based Operator: Intersection of Perceptions $(\cap_p)$ to Evaluate Requirement Satisfaction

Let S_1 and S_2 be two natural language statements, where S_1 defines a requirement and S_2 describes some event from the perspective of S_1, i.e., $Z_1 = \langle X_1, A_1, B_1\rangle$ and $Z_2 = \langle X_2, A_2, B_2\rangle$ are the Z-valuations of S_1 and S_2 respectively, X_1 and X_2 are synonymous and $(A_1 = A_2) \neq \emptyset$.

We define the *Intersection of Perceptions* $(Z_1 \cap_p Z_2)$ as:

$$(Z_1 \cap_p Z_2) = \langle X_1, A_1, B_2\rangle \tag{7}$$

which describes the certainty with which Z_2 complies with Z_1, which in turn is a measure of the certainty with which S_2 satisfies S_1.

As for example:

(i) Requirement: S_1 = I would like my book to be a Miss Marple mystery; Z_1 = ⟨detective, Marple, expectedly⟩
Statement in a mystery book: S_2 = Miss Marple was asking questions; Z_2 = ⟨questioner, Marple, certainly⟩
Thus, $(Z_1 \cap_p Z_2)$ = ⟨detective, Marple, certainly⟩ implies that my book is certainly a Miss Marple mystery.

(ii) Requirement: S_1 = I would like the soup to be piping hot; Z_1 = ⟨temperature, piping hot, expectedly⟩
Situation: S_2 = The soup that I have been served is lukewarm; Z_2 = ⟨temperature, piping hot, false⟩

[lukewarm = not piping hot]

Thus, $(Z_1 \cap_p Z_2) = \langle$temperature, piping hot, false$\rangle$ implies that my soup is not piping hot.

The perception-intersection operator defined above could predictably come of use in scenarios where it is imperative to verify the confidence with which the current situation satisfies a given requirement. The Z-number-simulation experiments described in the following section utilize the $\cap_p$ operator to arrive at results that coincide with the intuitive response of human beings.

4.3. Experiments

Our experiments here relate to the simulation, of two real-life CWW-based subjective-judgement processes, using the Z-number approach.

***Generic Intuitive Algorithm for Subjective Judgements* -** The following algorithm attempts to conceptualize generic intuitive subjective judgement making by a human being:

Algorithm 3

Input:

i. S is a set of antecedent constraints that summarize the current situation.

ii. Event set (E) of n ($n \geq 1$) event summaries $\{E_1, E_2, ..., E_n\}$ $[E = \cup_{i=1}^{n} E_i]$, typical to the context. Each E_i is described as set of antecedent-consequent constraints. E implies the event summaries gained through experience and knowledge.

iii. Rule set (R) defining rules to resolve confusions.

Output: Decision corresponding to S.

Steps:

1. For every E_i in E
   Repeat step 2
2. If $|E_i \cap S| \geq 1$
   Then
      Assign E_i a membership value (> 0), indicating the degree of similarity between S and E_i
   Else
      Membership of E_i = 0
3. Sort all E_i in the descending order of memberships of similarity
4. If every E_i is assigned a unique membership of selection
   Then
      a. Select E_i with the highest membership as the event selected
      b. Use the decision (D) taken in E_i as that for S
   Else
      a. Select all E_i with the highest membership
      b. Use R to resolve confusion and identify a decision (D) for S
5. $E = E \cup (S \rightarrow D)$ [E is updated to include the new experience gathered from S]
6. Stop

Note: Each event, in sets S and E, is essentially implied by 'keywords' - the basis for the process of CWW by the human brain.

In the following experiments, Algorithm 3 is modified to fit the real-life situations of text-selection and conversation-based-differential diagnosis. Both these situations involve intense CWW by human beings and are thus our experiment subjects.

4.3.1. Text Selection

This experiment is an attempt at simulating the process of selecting a book at a store, based on the text-summary on the book jacket. Such processes employ 'computing' on 'genre-specific words'; the Z-number approach to CWW clearly replicates the process of intuitive reasoning by human beings in such situations.

A. Intuitive Algorithm Underlying 'Text Selection'

Drawing from Algorithm 3, the intuitive process of text-selection, given a genre and content-preference, follows the algorithm outlined below:

Algorithm 4
Input:
i. The summary set (S) of a set of n ($n \geq 1$) books (B), where $S = \{S_1, S_2, , ..., S_n\}, B = \{B_1, B_2, ..., B_n\}$ and S_i is the summary on the jacket of B_i.
ii. Event set (E) of the reader's expectation of literary events in the book to be purchased.
iii. Lower threshold (T) indicating the minimum number of events, out of E, that need to exist in the S_i of the selected B_i.
iv. Additional selection criteria (R).

Output: Book selected.

Steps:
1. For every B_i in B
    Repeat steps 2 though 4
2. Read S_i
3. Extract event set E_S in S_i
4. If $|E \cap E_S| \geq T$
    Then
        Assign B_i a membership of selection (> 0)
    Else
        Membership of selection of B_i = 0
5. Sort B_i in the descending order of memberships of selection
6. If there is at least one B_i with membership > 0
    Then
        If every B_i is assigned a unique membership of selection
        Then
            Select B_i with the highest membership as the book to be purchased

Else
a. Select all B_i with the highest membership
b. Identify the B_i that satisfies most of R as the book to be purchased
Else
'No book is purchased'
7.Stop

Note:

(i) Besides the summary of the book, the following are natural contributing factors to the selection process and are elements of R:
a. The book being read or in the possession of the reader.
b. Cost of the book.
c. Condition of the book - brittleness, ink marks, crumpled pages, pages missing.
d. Presence and quality of pictures.
e. Font type and font size.
f. Rarity of the book.

(ii) In this experiment, the selection process is entirely platonic - devoid of any emotions occurring in real-life situations that lead to the selection of a book devoid of the expected features.

(iii) The process of identification of new words and phrases, and the subsequent updation of the vocabulary has not been considered, for simplicity.

B. Algorithm for 'Text Selection' Using Z-numbers

Combining elements of Algorithm 2 and Algorithm 4, the algorithm for the book selection process using the Z-number Technique can consequently be formulated as follows:

Algorithm 5
Input:
i. The summary set (S) of a set of n ($n \geq 1$) books (B), where $S = \{S_1, S_2, ..., S_n\}, B = \{B_1, B_2, ..., B_n\}$ and S_i is the summary on the jacket of B_i.
ii. Event set (E), in the form of Z-valuation expressions (i.e., Z-valuations joined by appropriate conjunctions), of the reader's expectation of literary events in the book to be purchased.
iii. Lower threshold (T) indicating the minimum number of events, out of E, that need to exist in the S_i of the selected B_i.
iv. Additional selection criteria (R).

Output: Book selected.

Assumptions:
i. A sentence is considered relevant if it contains at least one word from E.
ii. Any word (W) in S_i that is a synonym of a word (W') in E, is treated as W'.
iii. The system comprehends the perception of a complex or a compound sentence (Y) by -
a. Extracting the simple sentence components of Y.

b. Comprehending the meaning of each of these simple sentence components.
c. Combining these component perceptions with respect to the conjunctions used in Y.

iv. The memberships of selection are assigned on the basis of the Principle of Extension, explained in Section 3.

v. The reader does not read the summary of a book he/she has read before.

vi. The Machine is the reader.

Steps:

1. For every B_i in B
   Repeat steps 2 though 10
2. Initialize E_S = $\emptyset$ [E_S = Z-valuations for the event set of the current B_i]
3. For every sentence (I) in S_i
   Repeat steps 4 through 7
4. If I is irrelevant
   Then
      a. Discard I
      b. Goto next I
   Else
      Goto step 5
5. If I is a simple sentence
   Then
      Goto step 6
   Else
      a. Extract the simple sentence component set (I') of (I)
      b. Repeat step 6 for each sentence in I'
      c. Goto step 7
6. Extract the values of X, A and B in the sentence to evaluate the Z-valuation (Z_I)
7. Assemble all Z_I to form a single Z-valuation expression (E') guided by the conjunctions in I
8. $E_S = E_S \cup E'$
9. If $|E \cap_p E_S| \geq T$
   Then
      a. Convert the results of $(E \cap_p E_S)$ to the Z-valuation expression $E^{\sim}$
      b. Convert E and $E^{\sim}$ to the mathematical expressions M and $M^{\sim}$ respectively
      c. Evaluate the membership of selection of B_i by applying the Principle of Extension on M and $M^{\sim}$
   Else
      Membership of selection of B_i = 0
10. Sort B_i in the descending order of memberships of selection
11. If there is at least one B_i with membership > 0
   Then
      If every B_i is assigned a unique membership of selection
      Then
         Select B_i, with the highest membership, as the book to be purchased

Else
a. Select all B_i with the highest membership
b. Identify the B_i, that satisfies most of R, as the book to be purchased
Else
'No book is purchased'
13. Stop

C. Simulation

Assumptions -

(i) The machine (**Mc**) is capable of -
a. Annotating the words in a given text sample into the correct parts of speech.
b. Resolving all anaphoric and cataphoric dependencies.
c. Identifying the category of the sentence (simple, complex, compound, declarative, imperative, interrogative, conditional, exclamatory) under consideration.

(ii) **Mc** has read thirty works of fiction under the genre 'Mystery'.

(iii) **Mc**'s vocabulary consists of one hundred and sixty five words (X) which it has found to be commonly occurring in the summary of the books it has read. Each of these words is assigned a probability of occurrence (p_X), based on the number of books the words are found in.

The words in **Mc**'s vocabulary are: abduct, accomplice, advocate, agent, alibi, allegation, ammunition, anonymous, arms, assistant, awkward, baffle, blood, blunder, bury, case, catch, chief, chilling consequence, clue, cold-blooded, conspiracy, constable, convict, corpse, crime, criminologist, crooked, curious, danger, death, deceive, deduce, desperate, detective, discover, doctor, drug, duplicate, eavesdrop, enemy, evidence, evil, exhume, fake, fatal, fear, figure-out, find-out, fingerprint, follow, forbidden, forget, foul play, gang, gore, graveyard, gray cells, guilty, headquarters, hidden, hoax, homicide, how, illegal, illegitimate, illicit, impersonate, ingenuity, innocence, inquest, inspector, instinct, intrigue, investigate, jewels, judge, juvenile, kidnap, kill, lawyer, letters, locate, loot, macabre, Marple, mask, missing, mistake, motive, murder, mystery, nab, notorious, overhear, peculiar, plan, plot, plunder, Poirot, poison, police, post mortem, practical joke, prison, problem, proof, prosecution, psychology, puzzle, quarrel, question, racket, ransack, ransom, realize, red-handed, remember, remorse, remorseless, replicate, revenge, robber, sabotage, scandal, scheme, Scotland Yard, secret, sentence, shocking, shoot, sinister, soldier, solve, spy, stab, stolen, strange, suicide, superintendent, surprise, suspect, suspicious, symbols, terror, thief, tragic, trap, trial, trouble, underground, unknown, vengeance, verdict, victim, vile, violence, warning, weapons, what, when, where, who, whom, why, witness.

Mc is aware of synonyms like: (kill, murder), (problem, puzzle), (deduce, find-out, figure-out), (anonymous, unknown), (suspicious, curious), (verdict, sentence), (plot, scheme).

Mc is aware of the multiple senses (polysemes, homonyms, capitonyms) and syntactic forms of certain words like: (puzzle (noun, verb), puzzled, puzzling), (judge (noun, verb)), (mystery, mysterious), (murder (noun, verb), murderer).

(iv) The words in X are subdivided into categories like: mystery-category, detective-name, events, verdicts, and so on where each such generic value is mapped to a real number - following the definition of the Z-number.

The words are further clustered into semantic nets or groups of words that occur together or are semantically linked e.g. Murder-net: <murder, motive, quarrel, post mortem, police, exhume, fatal, clue, revenge>.

Inputs -

(i) **Mc** wants to buy a new book with the requirements as is shown in Table 1. Thus, E can be

Table 1. Requirement set of **Mc**

Requirements - Event Set (E)	
Natural Language Sentences	**Z-valuations**
1. The book needs to be a Mystery story	Z_1 = <Book Genre, mystery, certainly>; A = mystery, u_1 = book genre
2. Preferably a murder mystery and solved by Miss Marple	Z_{21} = <Mystery category, murder, ideally>; A = murder, u_2 = mystery category Z_{22} = <Detective, Marple, ideally>; A = Marple, u_3 = detective
3. A mystery involving a grand robbery and solved by Marple or Poirot would be okay	Z_{31} = <Mystery category, robbery, possibly>; A = robbery, u_2 = mystery category Z_{32} = <Detective, Marple, probably>; A = Marple, u_3 = detective Z_{33} = <Detective, Poirot, probably>; A = Poirot, u_3 = detective
Requirements - Others (R)	
Price $\leq$ Rs. 300/-; New - no crumpled pages or ink marks; **Mc** should not have read the book	

summarized by the logical expression:

$$E = [Z_1 \wedge ((Z_{21} \wedge Z_{22}) \vee (Z_{31} \wedge (Z_{32} \vee Z_{33}))] \tag{8}$$

and following (2), (3) and (4), as discussed in Section 3, (8) may be rewritten as:

$$\begin{aligned} M = \mu_{certainly}(\int_R \mu_{mystery}(u_1)p_X(u_1)du_1) \wedge [\{\mu_{ideally}(\int_R \mu_{murder}(u_2)p_X(u_2)du_2)\wedge \\ \mu_{ideally}(\int_R \mu_{Marple}(u_3)p_X(u_3)du_3)\} \vee [\mu_{possibly}(\int_R \mu_{robbery}(u_2)p_X(u_2)du_2) \wedge \\ \{\mu_{probably}(\int_R \mu_{Marple}(u_3)p_X(u_3)du_3) \vee \mu_{probably}(\int_R \mu_{Poirot}(u_3)p_X(u_3)du_3)\}]] \end{aligned} \tag{9}$$

where,

$$\int_R p_X(u_1)du_1 = 1; \int_R p_X(u_2)du_2 = 1; \int_R p_X(u_3)du_3 = 1 \tag{10}$$

(ii) T = 2

(iii) The texts of some new books in the book store are summarized as follows:

(a) **Summary:** Lymstock is a town with more than its share of secrets - a town where even a sudden outbreak of anonymous hate-mail causes only a minor stir. But all that changes when one of its recipients, Mrs. Symmington, commits suicide. Her final note said, “I can't go on.” Only Miss Marple questions the coroner's verdict of suicide. Was this work of a poison-pen? Or of a poisoner? - The Moving Finger (Agatha Christie)

Other Properties: Price = Rs. 150/-; New book; Not read

(b) **Summary:** “The Curious Case of the Maiden Eggesford Horror.” When the doctor advises Bertie to live the quiet life, he and Jeeves head for the pure air and peace of Maiden Eggesford. However, they hadn't reckoned on Bertie's irrepressible but decidedly scheming Aunt Dahlia, around whom an imbroglio of impressive proportions develops involving 'The Cat Which Kept Popping Up When Least Expected'. As Bertie observes, whatever aunts are, they are not gentlemen. - Aunts Aren't Gentlemen (P. G. Wodehouse)

Other Properties: Price = Rs. 250/-; New book; Not read

(c) **Summary:** Gerry Wade had proved himself to be a champion sleeper; so the other house guests decided to play a practical joke on him. Eight alarm clocks were set to go off, starting at 6:30 a.m. But when morning arrived, one clock was missing and the prank had backfired with tragic consequences. Gerry never woke up. Was he murdered? - The Seven Dials Mystery (Agatha Christie)

Other Properties: Price = Rs. 150/-; New book; Not read

Execution -

Following the summarization of Book 1 (Table 2), we have:

(i) $E_{S1} = (Z_{11} \wedge Z_{12} \wedge Z_{13}) \wedge Z_2 \wedge (Z_{31} \wedge Z_{32}) \wedge (Z_4 \vee Z_5)$

(ii) By virtue of Z_{32} and Z_5 in the summary of Book 1; and the fact that quite a large number of words in the summary fall under the vocabulary of **Mc**, the book certainly pertains to the genre 'Mystery'. Therefore,

$$|E \cap_p E_{S1}| = 3 > T$$

and consequently, from (7),

$$(E \cap_p E_{S1}) = [\langle \text{Book genre, mystery, certainly} \rangle \wedge \langle \text{Detective, Marple, probably} \rangle \wedge \langle \text{Mystery category, murder, expectedly} \rangle]$$

Table 2. Summarization of Book 1

Relevant Sentence from Summary	**Relevant Simple Sentence Components**	**Z-valuations**
1. Lymstock is a town with more than its share of secrets - a town where even a sudden outbreak of anonymous hate-mail causes only a minor stir.	a. Lymstock is a town with secrets. b. There is a sudden outbreak of anonymous hate-mail.	Z_{11} = <Location, Lymstock, supposedly> Z_{12} = <Location property, has secrets, supposedly> Z_{13} = <Event, anonymous letters, probably> [hate-mail = letters]
2. But all that changes when one of its recipients, Mrs. Symmington, commits suicide.	Recipient Mrs. Symmington commits suicide.	Z_2 = <Letter event, recipient commits suicide, probably>
3. Only Miss Marple questions the coroners verdict of suicide.	a. Coroner's verdict is suicide. b. Miss Marple questions verdict.	Z_{31} = <Coroner verdict, suicide, probably> Z_{32} = <Verdict event. Marple questions, probably>
4. Was this work of a poison-pen?	- A simple sentence -	Z_4 = <Suspect, poison-pen, expectedly>
5. Or of a poisoner?	- A simple sentence -	Z_5 = <Suspect, murderer, expectedly> [poisoner = murderer]

(iii) Using (9), we arrive at,

$$M^{\sim} = \mu_{certainly}(\int_R \mu_{mystery}(u_1)p_X(u_1)du_1)\wedge \\ \{\mu_{probably}(\int_R \mu_{Marple}(u_3)p_X(u_3)du_3) \wedge \mu_{expectedly}(\int_R \mu_{murder}(u_2)p_X(u_2)du_2)\} \tag{11}$$

where,

$$\int_R p_X(u_1)du_1 = 1; \int_R p_X(u_2)du_2 = 1; \int_R p_X(u_3)du_3 = 1 \tag{12}$$

The membership of selection for Book 1 is evaluated on the basis of the application of the Principle of Extension to (9) and (11), and considering the degree of overlap, the membership of selection should ideally approximate 1.

Now, from the summarization of Book 2 (Table 3), we have:

(i) $E_{S2} = (Z_1 \wedge Z_{21} \wedge Z_{22} \wedge Z_{31} \wedge Z_{32})$

Table 3. Summarization of Book 2

Relevant Sentence from Summary	Relevant Simple Sentence Components	Z-valuations
1. 'The Curious Case of the Maiden Eggesford Horror.'	- A simple sentence -	Z_1 = <Case, Maiden Eggesford Horror, supposedly>
2. However, they hadn't reckoned on Bertie's irrepressible but decidedly scheming Aunt Dahlia, around whom an imbroglio of impressive proportions develops involving 'The Cat Which Kept Popping Up When Least Expected'.	Aunt Dahlia is decidedly scheming	Z_{21} = <Character, Aunt Dahlia, certainly> Z_{22} = <Character nature, scheming, decisively>
3. As Bertie observes, whatever aunts are, they are not gentlemen.	Bertie observes that aunts aren't gentlemen.	Z_{31} = <Character, Bertie, certainly> Z_{32} = <Character action, observation decisively>

(ii) Considering the fact that some words in the summary of Book 2 fall under the vocabulary of **Mc**, the book 'probably' pertains to the genre 'Mystery'. Therefore,

$$|E \cap_p E_{S2}| = 1 < T$$

Thus, Book 2 is assigned a membership of selection = 0.

Table 4 illustrates the summary of Book 3, and we have:

(i) $E_{S3} = (Z_1 \wedge Z_{21} \wedge Z_{22} \wedge Z_{23} \wedge Z_{24} \wedge Z_3)$

(ii) By virtue of Z_3 in the summary of Book 3; and the fact that quite a large number of words in the summary fall under the vocabulary of **Mc**, the book certainly pertains to the genre 'Mystery'. Therefore,

$$|E \cap_p E_{S3}| = 2 = T$$

and consequently, using (7)

$$(E \cap E_{S3}) = [\langle \text{Book genre, mystery, certainly} > \wedge < \text{Mystery category, murder, expectedly} \rangle]$$

(iii) Using (9),

$$M^{\sim} = \mu_{certainly}(\int_R \mu_{mystery}(u_1) p_X(u_1) du_1) \wedge \mu_{expectedly}(\int_R \mu_{murder}(u_2) p_X(u_2) du_2) \quad (13)$$

Table 4. Summarization of Book 3

Relevant Sentence from Summary	**Relevant Simple Sentence Components**	**Z-valuations**
1. Gerry wade had proved himself to be a champion sleeper; so the other house guests decided to play a practical joke on him.	The house guests played a practical joke on Gerry.	Z_1 = <Event, practical joke, supposedly>
2. But when morning arrived, one clock was missing and the prank had backfired with tragic consequences.	a. One clock was missing. b. Prank had backfired. c. Consequences were tragic.	Z_{21} = <Event, clock missing, supposedly> Z_{22} = <Event, practical joke, supposedly> [prank = practical joke] Z_{23} = <Practical joke event, backfire, supposedly> Z_{24} = <Practical joke event, tragic consequence, supposedly>
3. Was he murdered?	- A simple sentence -	Z_3 = <Event, murder, expectedly>

where,

$$\int_R p_X(u_1)du_1 = 1; \int_R p_X(u_2)du_2 = 1; \int_R p_X(u_3)du_3 = 1 \qquad (14)$$

The membership of selection for Book 3 is evaluated on the basis of the application of the Principle of Extension to (9) and (13), and considering the degree of overlap, the membership of selection should lie in the range (0, 1) and should be less than that of Book 1.

Thus, on the basis of the interpretations of (11) and (13), **Mc** evidently selects Book 1 - “The Moving Finger” by Agatha Christie. This decision by **Mc** coincides exactly with the judgement a human being would make, given the scenario.

4.3.2. Differential Diagnosis

This experiment is an attempt at simulating the process of differential diagnosis on the basis of symptom descriptions obtained from the patient. The 'Symptom Checker' [1] application under the St. Mary's Hospital, London, is the inspiration behind this experiment. The 'Symptom Checker' enquires patient symptoms through a rigid questionnaire. Our aim lies in replacing such questionnaires by an interactive-dialogue based system where patients could describe their problems, as they would to a human doctor.

A machine can never substitute a human doctor or offer complete medical care, but such systems could undoubtedly help patients (or people around them) identify the probable disease, contact the appropriate specialist and even offer preliminary medical advice - especially during an emergency. Moreover, the results by the system would assist the doctor in differential diagnosis. Such systems very strongly depend on CWW.

The Z-number element attaches the 'human' element to such systems stirring an attempt at the amalgamation of behavioural computing and basic CWW.
Differential diagnosis, we believe, is the best example of CWW being used in pattern recognition.

A. Intuitive Algorithm Underlying 'Differential Diagnosis'

Drawing from Algorithm 3, the intuitive process of differential diagnosis follows the algorithm outlined below:

Algorithm 6
Input:
i. The summary set (S) of a patient's symptom description.
ii. Summary set (E) of n ($n \geq 1$) diseases, $E = \{E_1, E_2, ..., E_n\}$ where E_i is the symptom set of $disease_i$.
iii. Rules to resolve confusions in diagnosis (R).

Output: Disease that the patient is suffering from.

Steps:
1. For every E_i in E
   Repeat steps 2 though 4
2. If $|E_i \cap S| \geq 1$
   Then
      Assign E_i a membership (> 0), reflecting the confidence that S implies $disease_i$
   Else
      Membership of E_i = 0
3. Sort E_i in the descending order of memberships
4. If every Ei is assigned a unique membership of selection
   Then
      Select $disease_i$ with the highest membership as the patient-symptom diagnosis result
   Else
      a. Select all E_i with the highest membership
      b. Use R to resolve confusion and arrive at some decision ($disease_j$)
5. Stop

Note:

(i) Some rules in R could be those requesting pathological tests.

(ii) The human process of clinical diagnosis includes traits of the general health of the patient perceived by the doctor (these symptoms are usually not included in the patient's description of his problems), as for instance - dull, swollen or red eyes, roughness of the skin, pulse rate etc. Thus simulation of clinical diagnosis must include methods of extraction of the observable characteristics of a patient, in addition to CWW on the patient's description.

(iii) The doctor's gain in experience with respect to handling the diagnosed disease has not been considered, for simplicity.

B. Algorithm for 'Differential Diagnosis' Using Z-numbers

Combining elements of Algorithm 2 and Algorithm 6, the algorithm for the process of differential diagnosis using the Z-number Technique can consequently be formulated as follows:

Algorithm 7

Input:

i. The summary set (S) of the patient's symptoms.

ii. Summary set (E) - in the form of Z-valuation expressions (i.e., Z-valuations joined by appropriate conjunctions) - of n ($n \geq 1$) diseases, $E = E_1, E_2, ..., E_n$ where Ei is the Z-valuation expression of the symptom set of $disease_i$.

iii. Rules (R) to resolve confusion in diagnosis.

Output: Disease that the patient is suffering from.

Assumptions:

i. A sentence is considered relevant if it contains at least one word from E.

ii. Any word (W) in the S that is a synonym of a word (W') in E, is treated as W'.

iii. The system comprehends the perception of a complex or a compound sentence (Y) by -

a. Extracting the simple sentence components of Y.

b. Comprehending the meaning of each of these simple sentence components.

c.Combining these component perceptions with respect to the conjunctions used in Y.

iv. The memberships of selection are assigned on the basis of the Principle of Extension, explained in Section 3.

Steps:

1. Initialize $E_S = \emptyset$ [E_S = Set of Z-valuations for S]
2. For every sentence (I) in S
   Repeat steps 3 through 7
3. If I is irrelevant
   Then
      a. Discard I
      b. Goto next I
   Else
      Goto step 4
4. If I is a simple sentence
   Then
      Goto step 5
   Else
      a. Extract the simple sentence component set (I') of I

b. Repeat steps 5 through 6 for each sentence in I'
c. Goto step 7
5. Extract the values of X, A and B in the sentence to evaluate the Z-valuation (Z_I)
6. Combine all (Z_I) to the Z-valuation expression (E') guided by the conjunctions in I
7. $E_S = E_S \cup E$'
8. For every E_i in E
Repeat step 9
9. If $|E_i \cap_p E_S| \geq T$
Then
a. Convert the results of $(E_i \cap_p E_S)$ to the Z-valuation expression $E^{\sim}$
b. Convert E and $E^{\sim}$ to mathematical expression M and $M^{\sim}$ respectively
c. Evaluate the membership of occurrence of E_i by applying the principle of extension on M and $M^{\sim}$
Else
Membership of E_i = 0
10. Sort E_i in the descending order of memberships of occurrence
11. If every E_i is assigned a unique membership of selection
Then
Select E_i with the highest membership as the diagnosis result
Else
a. Select all E_i with the highest membership
b. Use R to resolve confusion
12. Stop

C. Simulation In this experiment, we try to simulate the process of differential diagnosis by acquiring patient symptoms through the process of conversation, as in a real-life scenario. We consider here, a sample discourse (Table 5) between a doctor (D) and patient (P) as the basis of the simulation.

Assumptions -

(i) The Machine (**Mc**) is aware of the probability distribution of the symptoms and symptom details per disease.

(ii) **Mc** can identify the part of speech of every word, and resolve anaphoric and cataphoric dependencies.

(iii) **Mc** can categorize symptom descriptions into information granules like 'fever-presence-symptom', 'fever-fall-symptom'.

Execution -

Mc should ideally be behaving like the doctor (**D**) in the conversation shown in Table 5.
Thus, on the basis of the Z-information in the example, assuming the probability distributions of the

Table 5. Sample conversation between a doctor (**D**) and a patient (**P**), and the corresponding Z-valuations

Natural Language Statement	**Equivalent Z-valuations**
D: What is your problem?	Z = <Problem, exists, expectedly>
P: It's been two days that I have been suffering from high fever.	Z_1 = <Problems, high fever, certainly> Z_2 = <Duration, 2 days, probably>
D: Does the fever fluctuate, does it come at specific times, is it accompanied by other problems?	Z = <Fever details, exists, expectedly>
P: The fever comes at fixed times in the morning and in the evening and ranges around 102 - 104 degrees. It is accompanied by intense shivering, headache and muscle-ache. I have at times felt nauseous. The temperature falls after I have a bout of sweating.	Z_{31} = <Fever occurrence, fixed time, certainly> Z_{32} = <Fever occurrence, morning, certainly> Z_{33} = <Fever occurrence, evening, certainly> Z_4 = <Fever temperature, 102 104 oF, certainly> Z_{51} = <Fever presence symptom, intense shivering or chills, certainly> Z_{52} = <Fever presence symptom, headache, certainly> Z_{53} = <Fever presence symptom, muscle-ache, certainly> Z_{54} = <Fever presence symptom, nausea, occasionally> Z_{55} = <Fever fall symptom, sweating, certainly>

symptoms of diseases, the memberships of the symptoms with respect to the patient and the memberships of the level of certainty are available, the system ideally evaluates the membership of the probable diseases with respect to the expression:

$$(Z_1 \wedge Z_2 \wedge Z_{31} \wedge Z_{32} \wedge Z_{33} \wedge Z_4 \wedge Z_{51} \wedge Z_{52} \wedge Z_{53} \wedge Z_{54} \wedge Z_{55}), \tag{15}$$

to arrive at:

<Disease, malaria, most likely> and <Blood test, required, definitely>.

The two experiments described, visibly highlight the probable strengths and the challenges that underlie the implementation of the Z-number approach to CWW. The following section presents a detailed analysis of these features, unearthed during our investigation of the Z-numbers.

5. Analysis of the Strengths and the Challenges Underlying the Z-numbers

5.1. Strengths of the Z-number

The potential of the Z-numbers is best illustrated through the experiments described in Section 4

Evidently, the identifiable strengths of the Z-number are:

(i) Though traditionally a model for the precisiation of natural language statements, the Z-number methodology can be extended to precisiate any natural language sentence.

(ii) The Z-number captures the perception of a single natural language statement, while the Z-information does the same for a group of statements. The concept can consequently form the basis of discourse-based systems.

(iii) The Z-number operation is applicable on simple sentences only. Thus, if a complex or a compound sentence (S) were reduced into its component simple sentences, combining the Z-number of each of these component sentences would lead to the Z-information equivalent of S.

(iv) The Z-number supports the identification of the context (e.g., 'fever-occurrence', 'fever-presence' etc. with respect to Table 5) of a statement in the universe of discourse.

(v) The Z-information allows grouping statements into context-sensitive granules of information. This mimics the natural data-compression and subsequent data-comprehension by the human brain, and could thus be used to extract 'knowledge' from a sentence.

(vi) The Z-number takes into account the inherent uncertainty associated with human behaviour. If the architecture in Figure 1 were to incorporate sensors that capture the non-verbal behaviour of the persons participating in a conversation, the encoder would convert these sensor-values to the value of parameter B. The resultant Z-number consequentially integrates affective computing and CWW, thereby adding a new dimension or 'level' to CWW.

(vii) By virtue of points (i) though (vi), the Z-number is visibly in agreement with the intuitive process of reasoning in human beings.

(viii) The parameters of the Z-numbers are context-independent.

(ix) Translation from the Z-numbers to simple sentences is straightforward.

The strengths depict the probable areas of CWW that the Z-number contributes to.

5.2. Challenges in the Implementation of the Z-numbers

The irrefutable number of pros associated with the Z-numbers inspires an attempt at the implementation of the methodology. However, the implementation of the Z-number is wrought with challenges that need to be overcome before the technique is put into practice. This section highlights some of the challenges we have recognized, and the keynotes associated with the challenges hint at possible solution strategies.

This section is divided into the following categories -

(i) *Implicit Issues*: Dealing with the implementation issues associated with the definition of the Z-number.

(ii) *Explicit Issues*: Dealing with the implementation issues highlighted with respect to the steps of Algorithms 2, 5 and 7.

(iii) *Other Issues*: The implementation issues related to the realization of some of the potential areas of application.

5.2.1. Implicit Issues

With respect to the definition of the Z-numbers, given an input sentence (S) lying in the context of discourse:

a) A is an element of the set of linguistic values of the linguistic variable - the subject (X) of the input statement;
b) B defines the level of certainty involved; and
c) A and B are both fuzzy numbers.

For the purpose of computation, the Z-numbers require the probability distribution of the words that imply events and form values of A, and the membership functions of A and B.

A and B have different interpretations and thus may need different fuzzy set models. The Z-numbers do not dictate the fuzzy set model that is best aligned to support the word-perceptions. Thus, CWW-system designers are free to use the fuzzy set model that is most appropriate.

The identification of the probability distribution of the words in A, the membership functions for A and B, and creation of the system rule-base require knowledge of the words and phrases commonly used in connection with the context under consideration.

The rule-base and the word-perception model form the basis of the formulation of the rules of computation.
The pre-implementation issues associated with the implementation of the Z-numbers can thus be summarized as:

1.1 Preparation of a context-dependent dynamic text corpus - words and phrases that lie within the context.

1.2 Division of words and phrases into semantic nets and synonym clusters.

1.3 Categorization of words and phrases into categories - the categories define the generic value of X.

1.4 Identification of an appropriate fuzzy set model for the perceptions of words in A.

1.5 Identification of an appropriate fuzzy set model for the perceptions of words in B.

1.6 Identification of the probability distribution of the events defined by the words in A.

1.7 A and B need to evolve with time.

1.8 Creation of a dynamic rule-base or an explanatory database.

1.9 Formulation of the rules of computation

Keynotes:

(i) A text corpus is a large and structured set of texts (in our case, words and phrases in common use) on a specific subject and is used for statistical linguistic analysis. A text corpus could provide the basis for the generic values of X, words in A, probability distribution of the events defined by the words in A and help form the rule-base (Z-rule base) of the system.

The text corpus needs to evolve and grow to include new subjects that might develop within the context, while A and B need to accommodate new vocabulary and associated word perceptions.

(ii) The 'FrameNet' [3], 'WordNet' [14, 5] and 'ConceptNet' [6] projects could come to the aide of the creation of the semantic nets, synonym clusters and common-sense semantic nets, respectively.

The FrameNet project, under the International Computer Science Institute (Berkeley, California), works on the formation of semantic frames - a 2-tuple <script, concept>, used to describe an object, state or event. The FrameNet lexical database contains 10,000 lexical units (<word, meaning>); polysemous words are represented by several lexical units, 800 semantic frames and over 120000 example sentences.

The WordNet project, under the Cognitive Science Laboratory (Princeton University), works on the production of synonym sets - providing brief descriptions and semantic relations between the words in the nets.

The ConceptNet project under the Common Sense Computing Initiative (MIT Media Lab), aims at imparting common-sense knowledge - the kind of information that human beings know but do not mention explicitly - to the computer.

(iii) Words in A need to be categorized where each category defines the generic value of X. These categories need to be mapped to real numbers - following the definition of the Z-number.

(iv) The IT2-FS [12] has gained immense importance as one of the best fuzzy set models of word perceptions. The model captures the inter-uncertainty and the intra-uncertainty of perceptions.

The Spectral Fuzzy Set (Sp-FS) [16] allows multiple membership values for a term.

(v) With respect to the example of differential diagnosis in Section 4.3.2 of the clinical diagnosis, computation using the Z-numbers requires a measure of the probability distribution of the various symptoms associated with fever-related diseases like malaria, influenza etc. across at least 100 patients per disease. Values of the probability distribution may be received from medical journals, and the system certainly needs to update these values.

The questions that arise here are, is it possible to evaluate the probability distribution for all events in a context, and how can the probability distributions be updated? Could the probability distribution be replaced by better statistical parameters?

5.2.2. Explicit Issues

(i) A system capable of CWW is required to be able to handle sentences irrespective of them being simple, complex or compound. Given the definition of Z-numbers, input natural language statements require to be simple sentences.

Thus, the issues in this regard are:
2.1 Identification of the category of the input statement - simple, complex or compound.

2.2 Extraction of the simple sentence components if the input statement be complex or compound.

2.3 Extraction of the conjunctions (or, and etc) used in the sentence.

Note:
All sentences are evaluated with respect to their literal sense, ignoring any ulterior meanings a characteristic of natural human speech.

Keynote:

(a) Analysis of the parts of speech of the words and types of clauses of the sentences could be a possible solution technique. This calls for the use of standard NLP text annotation techniques.

(ii) In a given text sample, not all sentences may be relevant to the context under consideration. The system needs to be able to differentiate between the relevant and the irrelevant statements, such that appropriate subjective decisions can be made. Moreover, irrelevant statements need not be processed, thus saving the overall processing time.

The issue that needs to be resolved here is:
3.1 Evaluation of the relevance of the sentence with respect to the text corpus - Rhetorical questions and paradoxes are to be considered irrelevant.

Keynotes:

(a) Paradoxes are often analysed by creating 'metalanguages' [2] to separate statements into different levels on which truth and falsity can be assessed independently. Bertrand Russell noted that, The man who says, “I am telling a lie of order n” is telling a lie, but a lie of order (n + 1) [2].

(b) An investigation of the measures for intra-relevance and inter-relevance of a sentence with respect to the context is essential.

Intra-relevance - This indicates if the words in a given sentence fall within the context. The intra-relevance thus signifies if the sentence under observation falls within the universe of discourse and helps identify the sub-context of the statement. As for instance, the statements in Table 5 can be classified under the sub-contexts 'fever-presence', 'fever-occurrence', and 'fever-fall'.

Inter-relevance - This indicates the degree of relevance within a group of statements. The inter-relevance brings about the re-ordering of the sentences in a group into granules of sub-contexts, as well as, re-ordering the statements on the basis of the order of occurrence of the events described.

(iii) Given a sentence, the equivalent Z-valuation requires extraction of the subject (X), its value (A) and the associated level of certainty (B).

The points of concern here are:
4.1 Identification of X - X may be clearly stated or implied in the sentence.

4.2 Identification of A.

4.3 Identification of B - B may be explicitly or implicitly stated in the sentence.

Keynotes:

(a) Analysis of the parts of speech of the words and resolution of anaphoric and cataphoric dependencies in the sentences, could help in the identification of X, A and B (if B is explicit).

(b) The value of B is best identified from the non-verbal behaviour of the speaker. However, in the situation where the behavioural elements cannot be captured, identification of the type of sentence (declarative, interrogative, imperative, exclamatory) could indicate a default value for B. Suggested default values are shown in Table 6.

Table 6. Depiction of the suggested default value for B, with respect to the type of sentence

Sentence Type	**Remarks**	**Default Value for B**
Declarative		Probably, Supposedly
Exclamatory	Convey explicit emotion	Certainly, Definitely, Surely
Imperative	Expect a definite course of action	Definitely, Certainly, Surely
Interrogative	Expect an answer (Table 5 shows examples)	Expectedly

(iv) Following the extraction of the Z-information for the input sentence(s), the Z-information requires to be converted to the equivalent logical and corresponding mathematical expression.

The associated issues in this regard are:
5.1 Formulation of the logical expression based on the conjunctions linking the Z-valuations in the input sentence.

5.2 Conversion of the logical expression to the mathematical expression as is required by the application.

(v) After the computation process is over, the translation of the resultant Z-valuations to the required result(s) in the natural language requires handling the following issues:

6.1 Translation of the components of Z-valuations into a simple sentence.

6.2 Test if multiple resultant simple sentences can be connected to form one meaningful sentence and connect accordingly.

5.2.3. Other Relevant Issues

7.1 Designing algorithms to form information granules based on the sub-contexts, expressed through the parameter X of the Z-valuations of the input sentences - this could lead to the formation of reduced logical/mathematical expressions.

7.2 Formulation of algorithms to use the Z-numbers to extract 'knowledge'from the input sentences - resulting in the updation of the text corpus.

7.3 Devising techniques that enable the machine to identify new words, learn their meanings, and associate these words to synonyms in the existing vocabulary.

7.4 Formulation of methods to summarize human behaviour - this falls under the purview of behavioural or affective computing.

6. Conclusions

This article is an embodiment of our research on the Z-numbers - not only as an approach to CWW, but also as a means of integrating CWW, NLP and affective computing. It presents algorithms that we have devised for CWW in general as well as that including the Z-number approach, followed by our definition of a Z-number based operator that allows the evaluation of requirement satisfaction. Experiments that simulate two real-life situations of CWW have also been described. The paper ends with an analysis of the strengths, the challenges and possible solution strategies, associated with the implementation of the Z-numbers.

Our studies depict the Z-number to be capable of modelling sentence-perceptions, forming information-granules and precisiating human behaviour. However, implementation of the approach calls for research on a number of areas, namely: the development of algorithms - that enable extraction of the Z-number elements and convert them into computable expressions and natural language statements; identification of appropriate fuzzy set models for word-perceptions; creation and maintenance of the text corpus; text annotation; event-based probability-distribution measurements and formulation of the rules of computation.

We strongly believe the Z-number to be an indispensable concept in the realm of CWW and NLP. The concept now requires a practical application to test its actual functional competence and associated algorithmic complexity, and this is where our future research aspirations lie.

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