Toward Human Level Machine Intelligence—Is it Achievable?
The Need for A Paradigm Shift

Lotfi A. Zadeh

Computer Science Division
Department of EECS
UC Berkeley

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Email: zadeh@eecs.berkeley.edu
Achievement of human level machine intelligence (HLMI) has long been one of the principal goals of AI. Since its inception in the early fifties of the last century, AI has scored important successes. But progress toward achievement of human level machine intelligence has been and continues to be slow.
The principal thesis of this lecture is that achievement of human level machine intelligence is beyond the reach of AI’s armamentarium—a collection of concepts, methods and techniques based in the main on bivalent logic and bivalent-logic-based probability theory.
Achievement of human level machine intelligence is a challenge that is hard to meet. In addition to advances in hardware and software what is needed is a paradigm shift—a shift from computation with numbers to computation with words and from manipulation of measurements to manipulation of perceptions. The centerpiece of the paradigm shift is the concept of precisiation.
Fundamentally, scientific progress is associated with progression from the use of words to manipulation of numbers. In the new paradigm, Computing with Words (CW), two capabilities are added: (a) a methodology centered on progression from unprecisiated words to precisiated words; and (b) a methodology centered on progression from numbers to precisiated words.
In large measure, scientific progress is associated with progression from perceptions to measurements.
PARADIGM SHIFT

**Traditional**

- Unprecisiated words → Progression → Numbers

**Nontraditional**

- NL: Unprecisiated words → Progression → Precisiated words

**Countertraditional**

- PNL: Numbers → Progression → Summarization → Precisiated words
Science deals not with reality but with models of reality. In large measure, scientific progress is driven by a quest for better models of reality.

The real world is pervaded with various forms of imprecision and uncertainty. To construct better models of reality it is essential to develop a better understanding of how to deal with imprecision and uncertainty. Such understanding is a prerequisite to achievement of human level machine intelligence.
Al can point with pride to important successes but progress in the realm of human level machine intelligence has been limited and slow. Anyone who had the painful experience of struggling with a dumb automated customer service system will readily agree that HLMl is not yet a reality. The Turing Test lies far beyond. Today, no machine can pass the Turing Test and none is likely to do so in the foreseeable future.
What is the problem? What is holding up progress toward achievement of HLMI? In an article entitled “A new direction in AI—toward a computational theory of perceptions,” AI Magazine, Vol. 22, No. 1, 73-84, 2001, I pointed out that humans have two remarkable capabilities. First, the capability to converse, summarize, reason and make rational decisions in an environment of imprecision, uncertainty, incompleteness of information, partiality of truth and partiality of possibility.
And second, the capability to perform a wide variety of physical and mental tasks, such as driving a car in city traffic, without any measurements and any computations. Underlying these capabilities is the human capability to reason with and act on perceptions rather than measurements. A natural language is basically a system for describing perceptions. Mechanization of this capability is a prerequisite to achievement of human level machine intelligence.
In my view, the lack of machinery for dealing with perceptions is the prime reason why progress toward achievement of HLMI has been limited and slow.

What is needed to develop a computational theory of perceptions? In the past, AI’s armamentarium consisted, in the main, of methods based on classical, Aristotelian, bivalent logic. The problem-solving capability of AI was significantly enhanced through the addition of probability theory to its armamentarium.
But the problem is that the development of a computational theory of perceptions is beyond the reach of bivalent logic and bivalent-logic-based probability theory. I have been arguing for some time that what AI has to do is to add to its armamentarium concepts and techniques drawn from other methodologies—especially from fuzzy logic. I believe that sooner or later this view will find acceptance because the inadequacy of existent tools will become too apparent to ignore.
My AAAI article contained a key idea. Specifically, the idea is to compute not with perceptions per se but with their descriptions in a natural language. In this way, computation with perceptions reduces to computation with information described in natural language, Computing with Words (CW) for short or, more generally, NL-Computation.
A prerequisite to computation with information described in natural language is mechanization of natural language understanding. What has not been widely recognized is that a prerequisite to mechanization of natural language understanding is precisiation of meaning.
A conclusion which follows is that progress toward achievement of human level machine intelligence requires a resolution of the problem of precisiation of meaning. To resolve this problem what is needed is a paradigm shift from computing with numbers to computing with words (CW). The centerpiece of CW is the concept of precisiation of meaning. An outline of the shift is presented in the following.
HLMI—PRINCIPAL COMPONENTS

- Communication
- Reasoning
- Decision-making
- World knowledge
- Domain knowledge

Natural language understanding

Precisiation of meaning

Principal challenge: mechanization
ACHIEVEMENT OF HUMAN LEVEL MACHINE INTELLIGENCE

Objective:
- Human level machine intelligence

Prerequisite:
- Mechanization of natural language understanding
- Precisiation of meaning
PRECISIATION
OF MEANING
In one form or another, precisiation of meaning has always played an important role in science. Mathematics is a quintessential example of what may be called a meaning precisiation language system.

Note: A language system differs from a language in that in addition to descriptive capability it has a deductive capability. For example, probability theory may be viewed as a precisiation language system so is Prologue. A natural language is a language rather than a language system.
Precisiation of meaning has direct relevance to mechanization of natural language understanding. For this reason, precisiation of meaning is an issue that is certain to grow in visibility and importance as we move further into the age of machine intelligence and automated reasoning.
Semantic imprecision of natural languages is a very basic characteristic—a characteristic which is rooted in imprecision of perceptions. Basically, a natural language is a system for describing perceptions. Perceptions are imprecise. Imprecision of perceptions entails semantic imprecision of natural languages.
SEMANTIC IMPRECISION (EXPLICIT)

EXAMPLES

WORDS/CONCEPTS
- Recession
- Civil war
- Very slow
- Honesty
- Arthritis
- High blood pressure
- Cluster
- Hot

PROPOSITIONS
- It is likely to be warm tomorrow.
- It is very unlikely that there will be a significant decrease in the price of oil in the near future.
CONTINUED
EXAMPLES

COMMANDS

- Slow down
- Slow down if foggy
- Park the car
SEMANTIC IMPRECISION (IMPLICIT)

EXAMPLES

- Speed limit is 65 mph
- Checkout time is 1 pm
NECESSITY OF IMPRECISION

- Can you explain to me the meaning of "Speed limit is 65 mph?"
- No imprecise numbers and no probabilities are allowed
- Imprecise numbers are allowed. No probabilities are allowed.
- Imprecise numbers are allowed. Precise probabilities are allowed.
- Imprecise numbers are allowed. Imprecise probabilities are allowed.
NECESSITY OF IMPRECISION

- Can you precisiate the meaning of “arthritis”? 
- Can you precisiate the meaning of “recession”? 
- Can you precisiate the meaning of “beyond reasonable doubt”? 
- Can you precisiate the meaning of “causality”? 
- Can you precisiate the meaning of “near”? 
Imprecision of meaning = elasticity of meaning

Elasticity of meaning = fuzziness of meaning

Example: middle-aged
Traditional approaches to semantics of natural languages, among them truth-conditional semantics, possible-world semantics and Montague semantics, do not address the issue of semantic imprecision of natural languages. The issue is not addressed because the conceptual framework of traditional approaches is not the right framework for dealing with semantic imprecision. In traditional approaches, elasticity of meaning is not dealt with.
There is a need for new direction. It is this need that motivates generalized-constraint-based semantics of natural languages, or GCS for short. As an issue, semantic imprecision has a position of centrality in GCS.

The point of departure in GCS is the concept of precisiation of meaning—a concept which goes beyond the familiar concept of representation of meaning.
REPRESENTATION VS. PRECISIATION

semantics

meaning
representation

meaning
precisiation

r-semantics
traditional

p-semantics
nontraditional

Lily is young \rightarrow Age(Lily) is young

representation
presentation

\mu

young

0 1 Age
**REPRESENTATION VS. PRECISION**

- *most Swedes are tall* \(_{\text{representation}}\)
  \(\text{Count}(\text{tall}.\text{Swedes}/\text{Swedes})\) is most.
- \(\text{Count}(\text{tall}.\text{Swedes}/\text{Swedes})\) \(_{\text{precisiation}}\)

\[ \begin{align*}
\mu &\quad \text{tall} \\
1 &\quad 1 \\
0 &\quad 0 \\
\end{align*} \quad \begin{align*}
\mu &\quad \text{most} \\
1 &\quad 1 \\
0 &\quad 0 \\
\end{align*} \]
THE CONCEPTS OF PRECISIATION AND COINTENSIVE PRECISIATION
The concept of precision has a position of centrality in scientific theories. And yet, there are some important aspects of this concept which have not been adequately treated in the literature. One such aspect relates to the distinction between precision of value (v-precision) and precision of meaning (m-precision).

The same distinction applies to imprecision, precisiation and imprecisiation.
precise value

- \( p: X \) is in the interval \([a, b]\). \( a \) and \( b \) are precisely defined real numbers
- \( p \) is \( v \)-imprecise and \( m \)-precise

precise meaning

- \( p: X \) is a Gaussian random variable with mean \( m \) and variance \( \sigma^2 \). \( m \) and \( \sigma^2 \) are precisely defined real numbers
- \( p \) is \( v \)-imprecise and \( m \)-precise
PRECISIATION AND IMPRECISIATION

- A proposition, predicate, query or command may be precisiated or imprecisiated

Examples

- Data compression and summarization are instances of imprecisiation
MODALITIES OF m-PRECISIATION

- **m-precisiation**
  - **mh-precisiation**: human-oriented
  - **mm-precisiation**: machine-oriented (mathematically well-defined)

**Example**: bear market

**mh-precisiation**: declining stock market with expectation of further decline

**mm-precisiation**: 30 percent decline after 50 days, or a 13 percent decline after 145 days. (Robert Shuster)
**BASIC CONCEPTS**

- **precisiend**: object of precisiation
- **precisiation**: precisiation language system
- **precisiation**: translation into a precisiation language system
- **precisiand**: result of precisiation
- **cointension**: measure of closeness of meanings = measure of closeness of model
- **precisiand = model of meaning**
- **precisiation ~ modelization**
- **intension = attribute-based meaning**
- **cointension = measure of closeness of meanings**

5/27/08
CONTINUED
MM-PRECISIATION OF “approximately a,” *a (MODELS OF MEANING OF *a)

Bivalent Logic

- number
- interval
- probability

It is a common practice to ignore imprecision, treating what is imprecise as if it were precise.

5/27/08
CONTINUED

Fuzzy Logic: Bivalent Logic + ...

fuzzy interval

fuzzy interval

fuzzy probability

Fuzzy logic has a much higher expressive power than bivalent logic.
GOODNESS OF MODEL OF MEANING

goodness of model = (cointension, computational complexity)

*a: approximately a

two numbers

one number

four numbers

cointension

computational complexity
Recession (mh-precisiand):
- A period of an economic contraction, sometimes limited in scope or duration.

Recession (mm-precisiand):
- A recession is a decline in a country's gross domestic product (GDP), or negative real economic growth, for two or more successive quarters of a year.
**PRECISIATION IN COMMUNICATION**

- **mm-precisiation is desirable but not mandatory**
  - Humans can understand unprecisiated natural language. Machines cannot.
- **mm-precisiation is mandatory**

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**communication**

- **HHC** (human-human communication)
  - *mm-precisiation is desirable but not mandatory*
  - *Humans can understand unprecisiated natural language. Machines cannot.*
- **HMC** (human-machine communication)
  - *mm-precisiation is mandatory*
Recipient: I understand what you sent, but could you precisiate what you mean, using … (restrictions)?

Sender: (a) I will be pleased to do so
(b) sorry, it is your problem
In mechanization of natural language understanding, the precisiator is the machine.

In most applications of fuzzy logic, the precisiator is the human. In this case, context-dependence is not a problem. As a consequence, precisiation is a much simpler function.
HONDA FUZZY LOGIC TRANSMISSION

Fuzzy Set

Control Rules:
1. If (speed is low) and (shift is high) then (-3)
2. If (speed is high) and (shift is low) then (+3)
3. If (throt is low) and (speed is high) then (+3)
4. If (throt is low) and (speed is low) then (+1)
5. If (throt is high) and (speed is high) then (-1)
6. If (throt is high) and (speed is low) then (-3)
HUMAN-HUMAN COMMUNICATION (HHC)

- mm-precisiation is desirable but not mandatory.
- mm-precisiation in HHC is a major application area for generalized-constraint-based deductive semantics.
- Reformulation of bivalent-logic-based definitions of scientific concepts, associating Richter-like scales with concepts which are traditionally defined as bivalent concepts but in reality are fuzzy concepts.
- Examples: recession, civil war, stability, arthritis, boldness, etc.
v-IMPRECISIATION

- Imperative (forced)
- Intentional (deliberate)

imperative: value is not known precisely
intentional: value need not be known precisely

- data compression and summarization are instances of v-imprecisiation
THE FUZZY LOGIC GAMBIT

Fuzzy logic gambit = v-imprecisiation followed by mm-precisiation

Lily is 25 → Lily is young

p

v-imprecisiation

mm-precisiation

reduction in cost

achievement of computability

young
Most applications of fuzzy logic in the realm of consumer products employ the fuzzy logic gambit. Basically, the fuzzy logic gambit exploits a tolerance for imprecision to achieve reduction in cost.
THE CONCEPT OF COINTENSIVE PRECISIATION

\*m*-precisiation of a concept or proposition, p, is cointensive if \( p^* \) is cointensive with p.

Example: bear market

We classify a bear market as a 30 percent decline after 50 days, or a 13 percent decline after 145 days. (Robert Shuster)

This definition is clearly not cointensive
EXAMPLE: IMPACT FACTOR

- \( A = \) citations in 1992 to articles published in 1987-91
- \( B = \) articles published in 1987-91
- \( C = A/B = \) five-year impact factor

- Is the definition of impact factor cointensive?
Basic question

- Given a proposition, \( p \), how can \( p \) be cointesively mm-precisiated?

Key idea

- In generalized-constraint-based semantics, mm-precisiation is carried out through the use of the concept of a generalized constraint.

- What is a generalized constraint?
THE CONCEPT OF A GENERALIZED CONSTRAINT

A BRIEF INTRODUCTION
PREAMBLE

- The concept of a generalized constraint is the centerpiece of generalized-constraint-based semantics.

- In scientific theories, representation of constraints is generally oversimplified. Oversimplification of constraints is a necessity because existing constraint definition languages have a very limited expressive power.
The concept of a generalized constraint is intended to provide a basis for construction of a maximally expressive meaning precisiation language for natural languages.

- Generalized constraints have elasticity.
- Elasticity of generalized constraints is a reflection of elasticity of meaning of words in a natural language.
GENERALIZED CONSTRAINT (Zadeh 1986)

- **Bivalent constraint (hard, inelastic, categorical):**
  \[ X \in C \]
  constraining bivalent relation

- **Generalized constraint on X: GC(X) (elastic)**

  \[ GC(X): X \text{ isr } R \]
  constraining non-bivalent (fuzzy) relation
  index of modality (defines semantics)
  constrained variable

  \[ r: \epsilon | = | \leq | \geq | \subset | ... | \text{blank} | p | v | u | rs | fg | ps | ... \]
  bivalent
  primary

- **open GC(X): X is free (GC(X) is a predicate)**
- **closed GC(X): X is instantiated (GC(X) is a proposition)**
GENERALIZED CONSTRAINT—MODALITY $r$

$X \text{ isr } R$

$r: =$ equality constraint: $X = R$ is abbreviation of $X \text{ is } = R$

$r: \leq$ inequality constraint: $X \leq R$

$r: \subset$ subsethood constraint: $X \subset R$

$r: \text{ blank}$ possibilistic constraint; $X \text{ is } R$; $R$ is the possibility distribution of $X$

$r: v$ veristic constraint; $X \text{ isv } R$; $R$ is the verity distribution of $X$

$r: p$ probabilistic constraint; $X \text{ isp } R$; $R$ is the probability distribution of $X$

Standard constraints: bivalent possibilistic, bivalent veristic and probabilistic
CONTINUED

\( r: rs \) random set constraint; \( X \) isrs \( R \); \( R \) is the set-valued probability distribution of \( X \)

\( r: fg \) fuzzy graph constraint; \( X \) isfg \( R \); \( X \) is a function and \( R \) is its fuzzy graph

\( r: u \) usuality constraint; \( X \) isu \( R \) means usually \( (X \) is \( R) \)

\( r: g \) group constraint; \( X \) isg \( R \) means that \( R \) constrains the attribute-values of the group
PRIMARY GENERALIZED CONSTRAINTS

- Possibilistic: $X$ is $R$
- Probabilistic: $X$ isp $R$
- Veristic: $X$ isv $R$

Primary constraints are formalizations of three basic perceptions: (a) perception of possibility; (b) perception of likelihood; and (c) perception of truth.

In this perspective, probability may be viewed as an attribute of perception of likelihood.
STANDARD CONSTRAINTS

- Bivalent possibilistic: $X \in C$ (crisp set)
- Bivalent veristic: $\text{Ver}(p)$ is true or false
- Probabilistic: $X \text{isp } R$
- Standard constraints are instances of generalized constraints which underlie methods based on bivalent logic and probability theory
GENERALIZED CONSTRAINT LANGUAGE (GCL)

- GCL is an abstract language
- GCL is generated by combination, qualification, propagation and counterpropagation of generalized constraints
- examples of elements of GCL
  - X/Age(Monika) is R/young (annotated element)
  - (X isp R) and (X,Y) is S)
  - (X isr R) is unlikely) and (X iss S) is likely
  - If X is A then Y is B
- the language of fuzzy if-then rules is a sublanguage of GCL

- deduction = generalized constraint propagation and counterpropagation
CLARIFICATION

LANGUAGE VS. LANGUAGE SYSTEM

- Language = (description system)
- Description system = (syntax, semantics)
- Language system = (description system, computation/deduction system)
- GCL is a language system
THE CONCEPT OF GENERALIZED CONSTRAINT AS A BASIS FOR PRECISIATION OF MEANING

- Meaning postulate

Equivalently, mm-precisiation of $p$ may be realized through translation of $p$ into GCL.
MEANING POSTULATE—A RATIONALE

- A proposition, \( p \), may be viewed as an answer to a question, \( q \).
- A question can be expressed as: What is the value of \( X \)? Where \( X \) is explicit or implicit in \( p \).
- A generalized constraint may be interpreted as an answer to a question. From this it follows that the answer to \( q \) may be expressed as a generalized constraint.

\[ X \text{ isr } R \]

- In general \( X \) and \( R \) are implicit in \( p \). In this sense, the meaning of \( p \) may be expressed as a generalized constraint in which \( X \) and \( R \) are defined procedurally.
- Note that \( X \) is a variable that is focused on but is not uniquely determined by \( X \). For this reason, \( X \) is referred to as a focal variable.
EXAMPLES: POSSIBILISTIC

annotation

- **Lily is young** → **Age (Lily) is young**
  \[ \downarrow_X \quad \downarrow_R \]

- **most Swedes are tall**
  \[ \downarrow_X \quad \downarrow_R \]
EXAMPLES: PROBABILITY

- $X$ is a normally distributed random variable with mean $m$ and variance $\sigma^2$.
  \[ X \text{ isp } N(m, \sigma^2) \]

- $X$ is a random variable taking the values $u_1, u_2, u_3$ with probabilities $p_1, p_2$ and $p_3$, respectively.
  \[ X \text{ isp } (p_1u_1 + p_2u_2 + p_3u_3) \]
EXAMPLES: VERISTIC

- Robert is half German, quarter French and quarter Italian

  Ethnicty (Robert) isv (0.5|German + 0.25|French + 0.25|Italian)

- Robert resided in London from 1985 to 1990

  Reside (Robert, London) isv [1985, 1990]
THE CONCEPT OF A PROTOFORM

- Protoform of p, Pro(p): abstracted summary of p

```
most Swedes are tall

most balls are large

QA’s are B’s

Count(B/A) is Q
```

protoform

protoform
PROTOFORMAL DEDUCTION

question/proposition

protoformal transformation

Pro(q/Pro(p))

deduction

ans(Pro(q/Pro(p)))

ans(q/p)

linguistic transformation
**EXAMPLE**

- **p**: most Swedes are tall
- **q**: how many are not tall?

\[
\text{Count(tall.Swedes/Swedes) is most} \\
\text{Count(not.tall.Swedes)/tall.Swedes is } R
\]

- **q is (1-most)**
- **R is (1-most)**
Precisiation and Computation

- Representation of the meaning of words, concepts and propositions as generalized constraints opens the door to Computing with Words (CW) or more generally, to computation with information described in natural language, or NL-Computation for short.

Simple examples:

- Most Swedes are tall. What is the average height of Swedes?
- A box contains about 20 balls of various sizes. Most are small. There are many more small balls than large balls. What is the number of balls which are neither small nor large?
- Usually most UA flights leave on time. What is the probability that my flight will be delayed?
Representing the meaning of a proposition as a generalized constraint reduces the problem of computation with information described in natural language to the problem of computation with generalized constraints. In large measure, computation with generalized constraints involves the use of rules which govern propagation and counterpropagation of generalized constraints. Among such rules, the principal rule is the deduction principle (Zadeh 1965, 1975).
EXTENSION PRINCIPLE (POSSIBILISTIC)

- X is a variable which takes values in U, and f is a function from U to V. The point of departure is a possibilistic constraint on f(X) expressed as f(X) is A where A is a fuzzy relation in V which is defined by its membership function $\mu_A(v)$, $v \in V$.

- g is a function from U to W. The possibilistic constraint on f(X) induces a possibilistic constraint on g(X) which may be expressed as g(X) is B where B is a fuzzy relation. The question is: What is B?
Continued

\[
f(X) \text{ is } A
\]
\[
g(X) \text{ is } B
\]

\[
\mu_B(w) = \sup_u \mu_A(f(u))
\]

subject to

\[
w = g(u)
\]

\(\mu_A\) and \(\mu_B\) are the membership functions of A and B, respectively.
STRUCTURE OF THE EXTENSION PRINCIPLE

\[ f^{-1}(A) \]

\[ \mu_A(f(u)) \]

\[ f^{-1}(A) \rightarrow f(u) \]

\[ g(f^{-1}(A)) \]

\[ g \]

\[ f \]

\[ f^{-1} \]

\[ U \]

\[ V \]

\[ W \]
PRECISIATION AND COMPUTATION/DEDUCTION—EXAMPLE

- $p$: most Swedes are tall
  - $p^*$: $\Sigma$Count(tall.Swedes/Swedes) is most

- $q$: How many are short?
  - further precisiation

- $X(h)$: height density function (not known)
- $X(h)du$: fraction of Swedes whose height is in $[h, h+du]$, $a \leq h \leq b$

$$\int_{a}^{b} X(h)du = 1$$
CONTINUED

- fraction of tall Swedes: \( \int_a^b X(h) \mu_{\text{tall}}(h) \, dh \)
- constraint on \( X(h) \)

\[
\pi(X) = \mu_{\text{most}}(\int_a^b X(h) \mu_{\text{tall}}(h) \, dh)
\]
CONTINUED

deduction:

\[ \int_a^b X(h) \mu_{\text{tall}}(h) \, dh \] is most given

\[ \int_a^b X(h) \mu_{\text{short}}(h) \, dh \] is ? Q needed

solution:

\[ \mu_Q(v) = \sup X(\mu_{\text{most}}(\int_a^b X(h) \mu_{\text{tall}}(h) \, dh)) \]

subject to

\[ v = \int_a^b X(h) \mu_{\text{short}}(h) \, dh \]

\[ \int_a^b X(h) \, dh = 1 \]
**DEDUCTION PRINCIPLE**

- In a general setting, computation/deduction is governed by the Deduction Principle.

- **Point of departure:** question, q

- **Data:** \( D = \left( X_1/u_1, \ldots, X_n/u_n \right) \)

  - \( u_i \) is a generic value of \( X_i \)

- **Ans(q):** answer to q
If we knew the values of the $X_i$, $u_1$, $\ldots$, $u_n$, we could express $\text{Ans}(q)$ as a function of the $u_i$

$$\text{Ans}(q) = g(u_1, \ldots, u_n) \quad u = (u_1, \ldots, u_n)$$

Our information about the $u_i$, $I(u_1, \ldots, u_n)$ is a generalized constraint on the $u_i$. The constraint is defined by its test-score function

$$f(u) = f(u_1, \ldots, u_n)$$
Use the extension principle

\[ \mu_{\text{Ans}(q)}(v) = \sup_u (ts(u)) \]

subject to

\[ v = g(u) \]
EXAMPLE

$p$: Most Swedes are much taller than most Italians
$q$: What is the difference in the average height of Swedes and Italians?

Solution

Step 1. precisiation: translation of $p$ into GCL

$S = \{S_1, \ldots, S_n\}$: population of Swedes
$I = \{I_1, \ldots, I_n\}$: population of Italians
$g_i = \text{height of } S_i$, $g = (g_1, \ldots, g_n)$
$h_j = \text{height of } I_j$, $h = (h_1, \ldots, h_n)$
$\mu_{ij} = \mu_{\text{much.taller}}(g_i, h_j) = \text{degree to which } S_i \text{ is much taller than } I_j$
\[ r_i = \frac{1}{n} \sum_{j} \mu_{ij} = \text{Relative } \sum \text{Count of Italians in relation to whom } S_i \text{ is much taller} \]

\[ t_i = \mu_{\text{most}} (r_i) = \text{degree to which } S_i \text{ is much taller than most Italians} \]

\[ v = \frac{1}{m} \sum t_i = \text{Relative } \sum \text{Count of Swedes who are much taller than most Italians} \]

\[ t_{s}(g, h) = \mu_{\text{most}}(v) \]

\[ p \rightarrow \text{generalized constraint on } S \text{ and } I \]

\[ q: d = \frac{1}{m} \sum_{i} g_i - \frac{1}{n} \sum_{j} h_j \]
Step 2. Deduction via extension principle

\[ \mu_q(d) = \sup_{g,h} \text{ts}(g,h) \]

subject to

\[ d = \frac{1}{m} \sum_i g_i - \frac{1}{n} \sum_j h_j \]
SUMMATION

- Achievement of human level machine intelligence has profound implications for our info-centric society. It has an important role to play in enhancement of quality of life but it is a challenge that is hard to meet.

- A view which is articulated in our presentation is that human level machine intelligence cannot be achieved through the use of theories based on classical, Aristotelian, bivalent logic. It is argued that to achieve human level machine intelligence what is needed is a paradigm shift—a shift from computing with numbers to computing with words.
In particular, a critical problem which has to be addressed is that of precisiation of meaning.

Resolution of this problem requires the use of concepts and techniques drawn from fuzzy logic.


CONTINUED

- From computing with numbers to computing with words --from manipulation of measurements to manipulation of perceptions, IEEE Transactions on Circuits and Systems 45, 105-119, 1999.


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- From computing with numbers to computing with words --from manipulation of measurements to manipulation of perceptions, IEEE Transactions on Circuits and Systems 45, 105-119, 1999.


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Factual Information About the Impact of Fuzzy Logic

**PATENTS**

- Number of fuzzy-logic-related patents applied for in Japan: 17,740
- Number of fuzzy-logic-related patents issued in Japan: 4,801
- Number of fuzzy-logic-related patents issued in the US: around 1,700

Number of papers in INSPEC and MathSciNet which have "fuzzy" in title:

INSPEC - "fuzzy" in title
1970-1979: 569
1980-1989: 2,403
1990-1999: 23,214
2000-present: 24,910
Total: 51,096

MathSciNet - "fuzzy" in title
1970-1979: 443
1980-1989: 2,465
1990-1999: 5,487
2000-present: 6,217
Total: 14,612
JOURNALS  (“fuzzy” in title)
1. Fuzzy in title
2. Fuzzy Sets and Systems
3. IEEE Transactions on Fuzzy Systems
4. Fuzzy Optimization and Decision Making
5. Journal of Intelligent & Fuzzy Systems
6. Fuzzy Economic Review
10. International Review of Fuzzy Mathematics
11. Fuzzy Systems and Soft Computing