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
HUMAN LEVEL MACHINE INTELLIGENCE (HLMI)

KEY POINTS

Informally

- Human level machine intelligence = Machine with a human brain

More concretely,

- A machine, M, has human level machine intelligence if M has human-like capabilities to
  - Understand
  - Converse
  - Learn
  - Reason
  - Answer questions
  - Remember
  - Organize
  - Recall
  - Summarize
Every day experience in the use of automated consumer service systems

The Turing Test (Turing 1950)

Machine IQ (MIQ) (Zadeh 1995)
IQ and MIQ are not comprovable

A machine may have superhuman intelligence in some respects and subhuman intelligence in other respects. Example: Google

MIQ of a machine is relative to MIQ of other machines in the same category, e.g., MIQ of Google should be compared with MIQ of other search engines.
PREAMBLE—HLMI AND REALITY

- The principal thesis of my lecture is that achievement of human level machine intelligence is beyond the reach of the armamentarium of AI—an armamentarium which is based in the main on classical, Aristotelian, bivalent logic and bivalent-logic-based probability theory.

- To achieve human level machine intelligence what is needed is a paradigm shift.

- Achievement of human level machine intelligence is a challenge that is hard to meet.
THE PARADIGM SHIFT

traditional

unprecisiated words \(\rightarrow\) progression \(\rightarrow\) numbers

nontraditional

Precisiated Natural Language

NL

unprecisiated words \(\rightarrow\) progression \(\rightarrow\) precisiated words

(a)

countertraditional

PNL

numbers \(\rightarrow\) progression summarization \(\rightarrow\) precisiated words

(b)
THE NEED FOR A PARADIGM SHIFT

objective

HLMI

BL+PT

measurement-based information

BL+PT+FL+FPT

perception-based information

paradigm shift
ROAD MAP TO HLMI—A PARADIGM SHIFT

HLMI

computation/deduction

precisiation

NL

perceptions

fuzzy logic

Computing with Words

from measurements to perceptions
In science and engineering there is a deep-seated tradition of according much more respect to numbers than to words. The essence of this tradition was stated succinctly by Lord Kelvin in 1883.
“In physical science the first essential step in the direction of learning any subject is to find principles of numerical reckoning and practicable methods for measuring some quality connected with it.
I often say that when you can measure what you are speaking about and express it in numbers, you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meager and unsatisfactory kind: it may be the beginning of knowledge but you have scarcely, in your thoughts, advanced to the state of science, whatever the matter may be.”
EXAMPLE—FROM NUMBERS TO WORDS

wine tasting

WINE → SOMELIER

chemical analysis of wine → machine somelier

excellent
HUMAN LEVEL MACHINE INTELLIGENCE

- Achievement of human level machine intelligence has long been one of the principal objectives of AI

- Progress toward achievement of human level machine intelligence has been and continues to be very slow

Why?
IS MACHINE INTELLIGENCE A REALITY?
Modern society is becoming increasingly infocentric. The Internet, Google and other vestiges of the information age are visible to all. But human level machine intelligence is not yet a reality. Why?

Officially, AI was born in 1956. Initially, there were many unrealistic expectations. It was widely believed that achievement of human level machine intelligence was only a few years away.
An article which appeared in the popular press was headlined “Electric Brain Capable of Translating Foreign Languages is Being Built.” Today, we have automatic translation software but nothing that comes close to the quality of human translation.

It should be noted that, today, there are prominent members of the AI community who predict that human level machine intelligence will be achieved in the not distant future.
"I've made the case that we will have both the hardware and the software to achieve human level artificial intelligence with the broad suppleness of human intelligence including our emotional intelligence by 2029." (Kurzweil 2008)
Humans have many remarkable capabilities. Among them there are two that stand out in importance. First, the capability to converse, reason and make rational decisions in an environment of imprecision, uncertainty, incompleteness of information and partiality of truth. 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 brain’s capability to process and reason with perception-based information. It should be noted that a natural language is basically a system for describing perceptions.

Natural languages are nondeterministic
In a paper entitled “A new direction in AI—toward a computational theory of perceptions,” AI Magazine, 2001. I argued that the principal reason for the slowness of progress toward human level machine intelligence was, and remains, AI’s failure to (a) recognize the essentiality of the role of perceptions in human cognition; and (b) to develop a machinery for reasoning and decision-making with perception-based information.
There is an explanation for AI’s failure to develop a machinery for dealing with perception-based information. Perceptions are intrinsically imprecise, reflecting the bounded ability of human sensory organs, and ultimately the brain, to resolve detail and store information. In large measure, AI’s armamentarium is based on bivalent logic. Bivalent logic is intolerant of imprecision and partiality of truth. So is bivalent-logic-based probability theory.
The armamentarium of AI is not the right armamentarium for dealing with perception-based information. In my 2001 paper, I suggested a computational approach to dealing with perception-based information. A key idea in this approach is that of computing not with perceptions per se, but with their descriptions in a natural language. In this way, computation with perceptions is reduced to computation with information described in a natural language.
The Computational Theory of Perceptions (CTP) which was outlined in my article opens the door to a wide-ranging enlargement of the role of perception-based information in scientific theories.

Computational Theory of Perceptions falls within the province of cognitive informatics.
Perceptions are intrinsically imprecise. A natural language is basically a system for describing perceptions. Imprecision of perceptions is passed on to natural languages. Semantic imprecision of natural languages cannot be dealt with effectively through the use of bivalent logic and bivalent-logic-based probability theory. What is needed for this purpose is the methodology of Computing with Words (CW) (Zadeh 1999).
In CW, the objects of computation are words, predicates, propositions and other semantic entities drawn from a natural language.

A prerequisite to computation with words is precisiation of meaning.

Computing with Words is based on fuzzy logic. A brief summary of the pertinent concepts and techniques of fuzzy logic is presented in the following section.
FUZZY LOGIC (FL)
AND
COMPUTING
WITH WORDS (CW)
There are many misconceptions about fuzzy logic. Fuzzy logic is not fuzzy. In essence, fuzzy logic is a precise logic of imprecision.

The point of departure in fuzzy logic—the nucleus of fuzzy logic, FL, is the concept of a fuzzy set.
Informally, a fuzzy set, A, in a universe of discourse, U, is a class with a fuzzy boundary.
A set, $A$, in $U$ is a class with a crisp boundary.

A set is precisiated through association with a characteristic function $c_A : U \rightarrow \{0, 1\}$

A fuzzy set is precisiated through graduation, that is, through association with a membership function $\mu_A : U \rightarrow [0, 1]$, with $\mu_A(u)$, $u \in U$, representing the grade of membership of $u$ in $A$.

Membership in $A$ is a matter of degree.

In fuzzy logic everything is or is allowed to be a matter of degree.
EXAMPLE—MIDDLE-AGE

- Imprecision of meaning = elasticity of meaning
- Elasticity of meaning = fuzziness of meaning

\[ \mu \\
\]

\[ \begin{array}{ccc}
40 & 43 & 55 \\
0.8 & & \\
0 & 40 & 60 \\
\end{array} \]

\[
\text{definitely not middle-age}
\]

\[
\text{definitely middle-age}
\]

\[
\text{core of middle-age}
\]

\[
middle-age
\]
EXAMPLE—HUMAN BODY PARTS: HAND

- **Drawing the boundary**
  1. ballpoint pen (bivalent logic)
  2. chisel pen (bivalent logic)
  3. spray pen with adjustable pattern (fuzzy logic)

Which is most realistic?
From the point of departure in fuzzy logic, the concept of a fuzzy set, we can move in various directions, leading to various facets of fuzzy logic.
The concept of FL-generalization of a theory, T, relates to introduction into T of the concept of a fuzzy set, with the concept of a fuzzy set serving as a point of entry into T as possibly other concepts and techniques drawn from fuzzy logic. FL-generalized T is labeled fuzzy T (T⁺). Examples: fuzzy topology, fuzzy measure theory, fuzzy control, etc.
A facet of FL consists of a FL-generalization of a theory or a FL-generalization of a collection of related theories.

The principal facets of FL are: logical, FL1; fuzzy set theoretic, FLs; epistemic, FLe; and relational, FLr.
NOTE—SPECIALIZATION VS. GENERALIZATION

- Consider a concatenation of two words, $MX$, with the prefix, $M$, playing the role of a modifier of the suffix, $X$, e.g., small box.
- Usually $M$ specializes $X$, as in convex set.
- Unusually, $M$ generalizes $X$. The prefix fuzzy falls into this category. Thus, fuzzy set generalizes the concept of a set. The same applies to fuzzy topology, fuzzy measure theory, fuzzy control, etc. Many misconceptions about fuzzy logic are rooted in misinterpretation of fuzzy as a specializer rather than a generalizer.
The cornerstones of fuzzy logic are: graduation, granulation, precisiation and the concept of a generalized constraint.
THE CONCEPT OF GRADUATION

- Graduation of a fuzzy concept or a fuzzy set, A, serves as a means of precisiation of A.

Examples

- Graduation of middle-age
- Graduation of the concept of earthquake via the Richter Scale
- Graduation of recession?
- Graduation of civil war?
- Graduation of mountain?
THE CONCEPT OF GRANULATION

- The concept of granulation is unique to fuzzy logic and plays a pivotal role in its applications. The concept of granulation is inspired by the way in which humans deal with imprecision, uncertainty and complexity.

- Granulation serves as a means of imprecisiation.
In fuzzy logic everything is or is allowed to be granulated. Granulation involves partitioning of an object, A, into granules. More generally, granulation involves an association with A of a system of granules. Informally, a granule is a clump of elements drawn together by indistinguishability, equivalence, similarity, proximity or functionality. Example: body parts

A granule, G, is precisiated through association with G of a generalized constraint.
GRANULATION / PARTITION

- Graduated granulation = fuzzy granulation
Graduated granulation = fuzzy granulation
EXAMPLE: GRANULATION OF AGE

Partition

- Age: young + middle-aged + old

System (Linguistic Variable)

- Age: young + middle-aged + old + very young + not very old + quite young + not very young and not very old + ...
SINGULAR AND GRANULAR VALUES

A

granular value of X

singular value of X

universe of discourse

<table>
<thead>
<tr>
<th>singular</th>
<th>granular</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.3%</td>
<td>high</td>
</tr>
<tr>
<td>.8</td>
<td>high</td>
</tr>
<tr>
<td>160/80</td>
<td>high</td>
</tr>
</tbody>
</table>

unemployment

probability

blood pressure
Granulation may be applied to objects of arbitrarily complexity, in particular to variables, functions, relations, probability distributions, dynamical systems, etc.

Quantization is a special case of granulation.
GRANULATION

- Forced: singular values of variables are not known.
- Deliberate: singular values of variables are known. There is a tolerance for imprecision. Precision carries a cost. Granular values are employed to reduce cost.
Granulation may be viewed as a form of summarization/information compression.

Humans employ graduated granulation to deal with imprecision, uncertainty and complexity.

A linguistic variable is a granular variable with linguistic labels.
GRANULATION OF A FUNCTION
GRANULATION = SUMMARIZATION

if $X$ is small then $Y$ is small
if $X$ is medium then $Y$ is large
if $X$ is large then $Y$ is small
GRANULAR VS. GRANULE-VALUED DISTRIBUTIONS

$g(u):$ probability density of $X$

Possibility distribution of probability distributions

Probability distribution of possibility distributions

Granules
FUZZY LOGIC GAMBIT

- Fuzzy Logic Gambit = deliberate granulation followed by graduation

- The Fuzzy Logic Gambit is employed in most of the applications of fuzzy logic in the realm of consumer products
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)
Computing with Words relates to computation with information described in a natural language. More concretely, in CW the objects of computation are words, predicates or propositions drawn from a natural language. The importance of computing with words derives from the fact that much of human knowledge and especially world knowledge is described in natural language.
The point of departure in CW is the concept of an information set, I, described in natural language (NL).

- **I/NL**: information set
- **q/NL**: question
- **ans(q/I)**

I/NL: $p_1, p_n, p_{wk}$

$p$'s are given propositions

$p_{wk}$ is information drawn from world knowledge
EXAMPLE

- $X$ is Vera’s age

$p_1$: Vera has a son in mid-twenties

$p_2$: Vera has a daughter in mid-thirties

$p_{\text{wk}}$: mother’s age at birth of her child is usually between approximately 20 and approximately 30

$q$: what is Vera’s age?
EXAMPLE

- X is a real-valued variable
  I: X is much larger than approximately a
  q: What is the probability that X is smaller than approximately b?

- This example is intended to demonstrate that probability and possibility are distinct concepts.
Phase 1: Precisiation (prerequisite to computation)

\[ p_1 \leftrightarrow p_{1*} \]
\[ \cdots \]
\[ p_n \leftrightarrow p_{n*} \]
\[ p_{wk} \leftrightarrow p_{wk*} \]

\( p_i^* \) is a generalized constraint
CW-BASED APPROACH

Phase 2: Computation/Deduction

\[ \text{generalized constraint propagation} \]

\[ p_1^*, \ldots, p_n^*, p_{wk}^* \rightarrow \text{ans}(q/l) \]
PHASE 1
The Concepts of Precisiation and Cointensive Precisiation
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, a language system has a deductive capability. For example, probability theory may be viewed as a precisiation language system; so is Prolog. A natural language is a language rather than a language system.

PNL is a language system.
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
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”? 

9/10/08
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.
- \( p: X \) is in the interval \([a, b]\). \( a \) and \( b \) are precisely defined real numbers
- \( p \) is \( v \)-imprecise and \( m \)-precise

- \( p: X \) 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
A proposition, predicate, query or command may be precisiated or imprecisiated

Examples

- Data compression and summarization are instances of imprecisiation

\[ m\text{-precisiation} \]

\[ v\text{-imprecisiation} \]

Lily is 25 → Lily is young
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**

- **precisiand** = model of meaning
- **precisiation** ≈ modelization
- **intension** = attribute-based meaning
- **cointension** = measure of proximity of meanings
  = measure of proximity of the model and the object of modelization

**precisiation** = translation into a precisiation language system
Precisiation is a form of modelization.

$mh$-precisiand $\approx h$-model

$mm$-precisiand $\approx m$-model

Nondeterminism of natural languages implies that a semantic entity, e.g., a proposition or a predicate has a multiplicity of models.
It is a common practice to ignore imprecision, treating what is imprecise as if it were precise.
Fuzzy Logic: Bivalent Logic + ...

Fuzzy interval

Fuzzy interval type 2

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

\[ \mu \]

\[ 0 \quad a \quad 1 \]

\[ x \]

\[ \mu \]

\[ 0 \quad a \quad 1 \]

\[ x \]

\[ \mu \]

\[ 0 \quad a \quad 1 \]

\[ x \]

best compromise

cointension

computational complexity
PRECISIATION IN COMMUNICATION

Human-human communication

- mm-precisiation is desirable but not mandatory

Human-machine communication

- mm-precisiation is mandatory

Humans can understand unprecisiated natural language. Machines cannot.

Scientific progress

mh-precisiation \rightarrow mm-precisiation
Recipient: I understand what you sent, but could you precisiate what you mean, using ... (restrictions)?

Sender: (a) (s-precisiation) I will be pleased to do so
(b) (r-precisiation) 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.
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)
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

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 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
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
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 bivalent-logic-based 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

- **open** \( GC(X) \): \( X \) is free (\( GC(X) \) is a predicate)
- **closed** \( GC(X) \): \( X \) is instantiated (\( GC(X) \) is a proposition)

\[ r: \in | = | \leq | \geq | \subset | \ldots | \text{blank} | p | v | u | rs | fg | ps | \ldots \]
GENERALIZED CONSTRAINT—MODALITY $r$

$X isr R$

- $r: =$ equality constraint: $X = R$ is abbreviation of $X is = R$
- $r: \leq$ inequality constraint: $X \leq R$
- $r: \subset$ subsethood constraint: $X \subset R$
- $r: \text{blank}$ possibilistic constraint; $X is R; R$ is the possibility distribution of $X$
- $r: v$ veristic constraint; $X isv R; R$ is the verity distribution of $X$
- $r: p$ probabilistic constraint; $X isp R; R$ is the probability distribution of $X$

Standard constraints: bivalent possibilistic, bivalent veristic and probabilistic
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
  - $X/\text{Age(Monika)}$ is $R/\text{young}$ (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
THE CONCEPT OF GENERALIZED CONSTRAINT AS A BASIS FOR PRECISIATION OF MEANING

- **Meaning postulate**

\[ p \xrightarrow{\text{mm-precisiation}} X \text{ isr } R \]

Equivalently, mm-precisiation of \( p \) may be realized through translation of \( p \) into GCL.
EXAMPLES: POSSIBILISTIC

- **Lily is young** → **Age (Lily) is young**
  - \( X \)
  - \( R \)

- **most Swedes are tall** → **Count (tall.Swedes/Swedes) is most**
  - \( X \)
  - \( R \)

annotation
PHASE 2
Computation with Precisiated Information
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 extension 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 $\mu_A(v), \quad v \in V$.

- $g$ 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 $B$?
If \( f(X) \) is \( A \) and \( g(X) \) is \( B \), subject to
\[
\mu_B(w) = \sup_u \mu_A(f(u))
\]
subject to
\[
w = g(u)
\]
where \( \mu_A \) and \( \mu_B \) are the membership functions of \( A \) and \( B \), respectively.
STRUCTURE OF THE EXTENSION PRINCIPLE

$U$

$f^{-1}(A)$

$\mu_A(f(u))$

$V$

$f(u)$

$A$

$W$

$w$

$g(f^{-1}(A))$

counterpropagation

propagation
- \( p: \) most Swedes are tall
  - \( p^*: \Sigma \text{Count(tall.Swedes/Swedes)} \) is most

- \( q: \) How many are short?
  - further precisiation

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

\[
\int_{a}^{b} X(h) \, dh = 1
\]
fraction of tall Swedes: \[ \int_{a}^{b} X(h) \mu_{\text{tall}}(h) \, dh \]

constraint on \( X(h) \)

\[ \int_{a}^{b} X(h) \mu_{\text{tall}}(h) \, dh \text{ is most } \mu_{\text{most}}(\int_{a}^{b} X(h) \mu_{\text{tall}}(h) \, dh) \]
deduction:

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

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

solution:

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

subject to

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

\[
\int_a^b X(h) \, dh = 1
\]
In a general setting, computation/deduction is governed by the Deduction Principle.

- Point of departure: question, q
- Information set: \( I = (X_1/u_1, \ldots, X_n/u_n) \)
- \( u_i \) is a generic value of \( X_i \)
- \( \text{ans}(q/I) \): answer to \( q/I \)
If we knew the values of the $X_i$, $u_1$, ..., $u_n$, we could express $\text{ans}(q/I)$ as a function of the $u_i$

$$\text{ans}(q/I) = g(u_1, ..., u_n) \quad u = (u_1, ..., u_n)$$

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

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

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

subject to

\[ v = g(u) \]
EXAMPLE

I: 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

$g_i =$ height of $S_i$ , $g = (g_1, \ldots, g_n)$

$h_j =$ height of $I_j$ , $h = (h_1, \ldots, h_n)$

$\mu_{ij} = \mu_{\text{much.taller}}(g_i, h_j)$ = degree to which $S_i$ is much taller than $I_j$
Relative \( \Sigma \) Count of Italians in relation to whom \( S_i \) is much taller

\[
\begin{align*}
  r_i &= \frac{1}{n} \sum_j \mu_{ij} \\
  t_i &= \mu_{\text{most}}(r_i) = \text{degree to which } S_i \text{ is much taller than most Italians} \\
  v &= \frac{1}{m} \sum t_i = \text{Relative } \Sigma \text{ Count of Swedes who are much taller than most Italians} \\
  ts(g, h) &= \mu_{\text{most}}(v)
\end{align*}
\]

generalized constraint on \( S \) and \( I \)

\[
q: \quad d = \frac{1}{m} \sum_i g_i - \frac{1}{n} \sum_j h_j
\]
Step 2. Deduction via extension principle

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

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.


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.


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.


v-IMPRECISIATION

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

v-imprecisiation → mm-precisiation

Reduction in cost

Achievement of computability

Lily is 25 → Lily is young

Fuzzy logic gambit = v-imprecisiation followed by mm-precisiation
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.
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
Count of papers containing the word “fuzzy” in title, as cited in INSPEC and MATH.SCI.NET databases. Compiled on July 17, 2008.

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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
12. Fuzzy Information Engineering