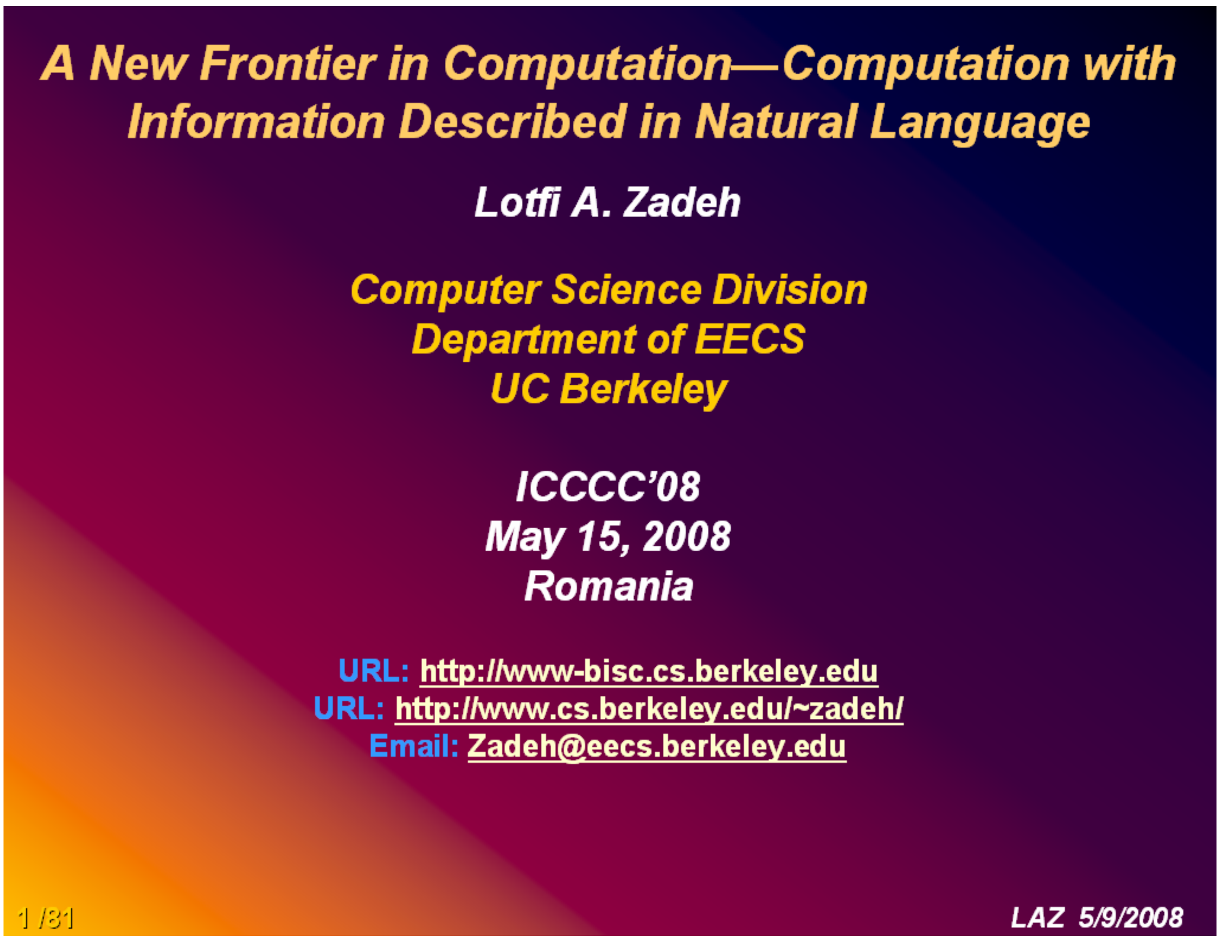
Zadeh L.A., Tufiş D., Filip F.G., Dziţac I.(Eds.),
From Natural Language to Soft Computing: New Paradigms in Artificial Intelligence,
Editing House of Romanian Academy, Bucharest, ISBN 978-973-27-1678-6, 2008, pp. 227-267

APPENDIX 1

Slides of PowerPoint Presentation of Workshop's Keynote Lecture




PREVIEW
2 /81
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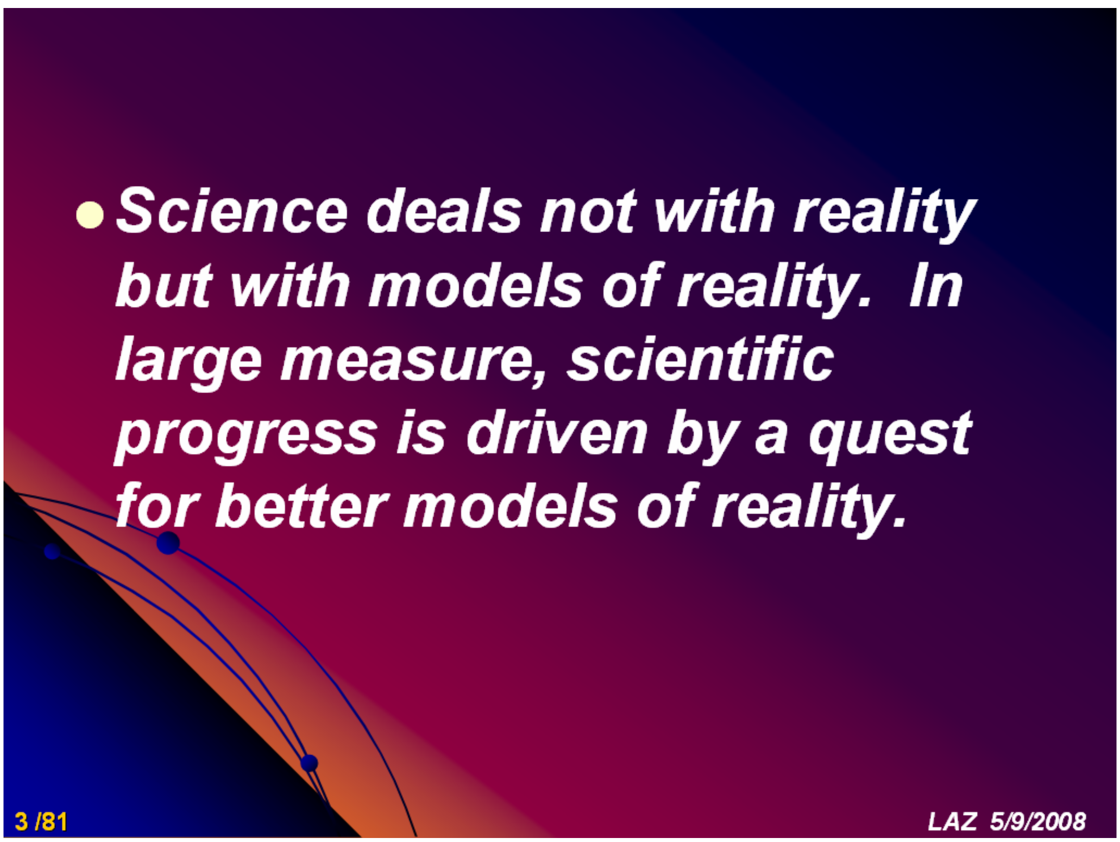
• Science deals not with reality but with models of reality. In large measure, scientific progress is driven by a quest for better models of reality.
3 /81
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- *The real world is pervaded with various forms of imprecision and uncertainty. To construct better models of reality it is essential to develop a better understanding of the remarkable human capability to converse, communicate and make rational decisions in an environment of imprecision, uncertainty, incompleteness of information, partiality of truth and partiality of possibility.*

- *Formalization/mechanization of this capability is the principal motivation for the development of NL-Computation—computation with information described in natural language. NL-Computation/Computing with Words opens the door to a wide-ranging enlargement of the role of natural languages in scientific theories, especially in the realms of economics, medicine, biology, law, psychology and political science.*

PREAMBLE

- *In conventional modes of computation, the objects of computation are values of variables. In computation with information described in natural language, or NL-Computation for short, the objects of computation are not values of variables but information about the values of variables, with the added assumption that information is described in natural language.*

6 /81 LAZ 5/9/2008

CONTINUED

- *The role model for NL-Computation is the remarkable human capability to converse, reason and make rational decisions in an environment of imprecision, uncertainty, incompleteness of information or partiality of truth.*

7 /81 LAZ 5/9/2008

MODALITIES OF VALUATION

valuation: assignment of a value to a variable

numerical: Vera is 48

linguistic: Vera is middle-aged

Computing with Words (CW): Vera is likely to be middle-aged

NL-Computation: Vera has a teenager son and a daughter in mid-twenties

world knowledge: child-bearing age ranges from about 16 to about 42.

granular

- *A concept which plays a key role in NL-Computation is that of precisiation*

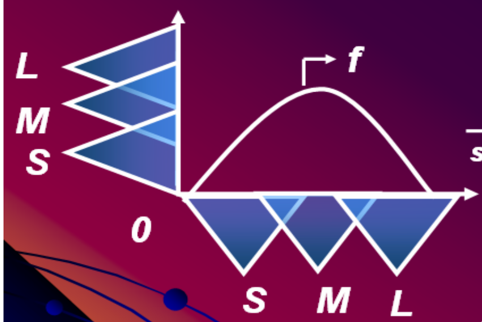
NL-COMPUTATION—BASIC IDEA

$$*Y = *f(*X)$$

- *given: *X, information about the value of X described in natural language*
- *given: *f, information about f described in natural language*
- *compute: *Y, information about the value of Y described in natural language*

EXAMPLE

Y=f(X)



summarization

*f

If X is small then Y is small
If X is medium then Y is large
If X is large then Y is small

S, M, L, are fuzzy sets

*X: usually X is medium

? *Y

10 /81 LAZ 5/9/2008

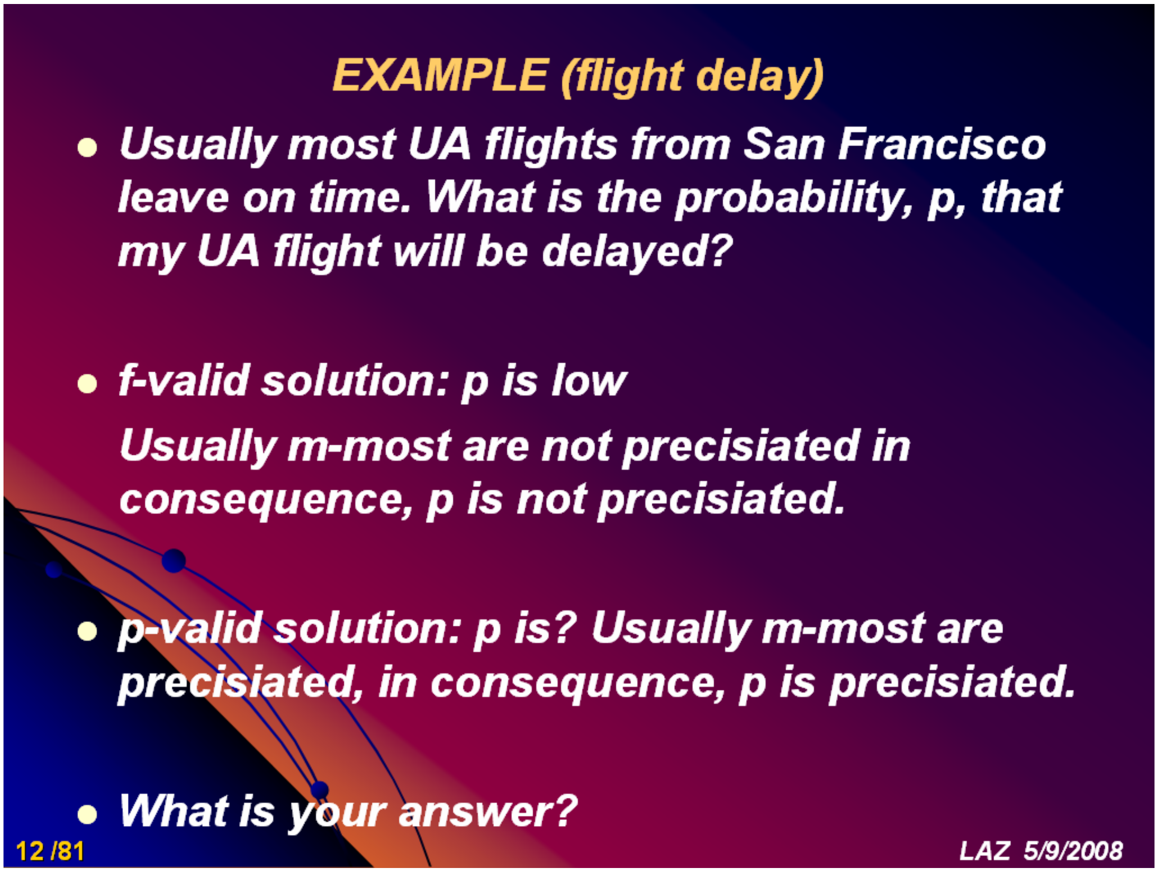
EXAMPLE (balls-in-box)

- A box contains about 20 black and white balls. Most are black. There are several times as many black balls as white balls. What is the number of white balls?

EXAMPLE (chaining)

- Overeating causes obesity
- Overeating and obesity cause high blood pressure
- I overeat. What is the probability that I will develop high blood pressure?

11 /81 LAZ 5/9/2008


EXAMPLE (flight delay)
Usually most UA flights from San Francisco leave on time. What is the probability, p, that my UA flight will be delayed?
f-valid solution: p is low
Usually m-most are not precisiated in consequence, p is not precisiated.
p-valid solution: p is? Usually m-most are precisiated, in consequence, p is precisiated.
What is your answer?
12 /81
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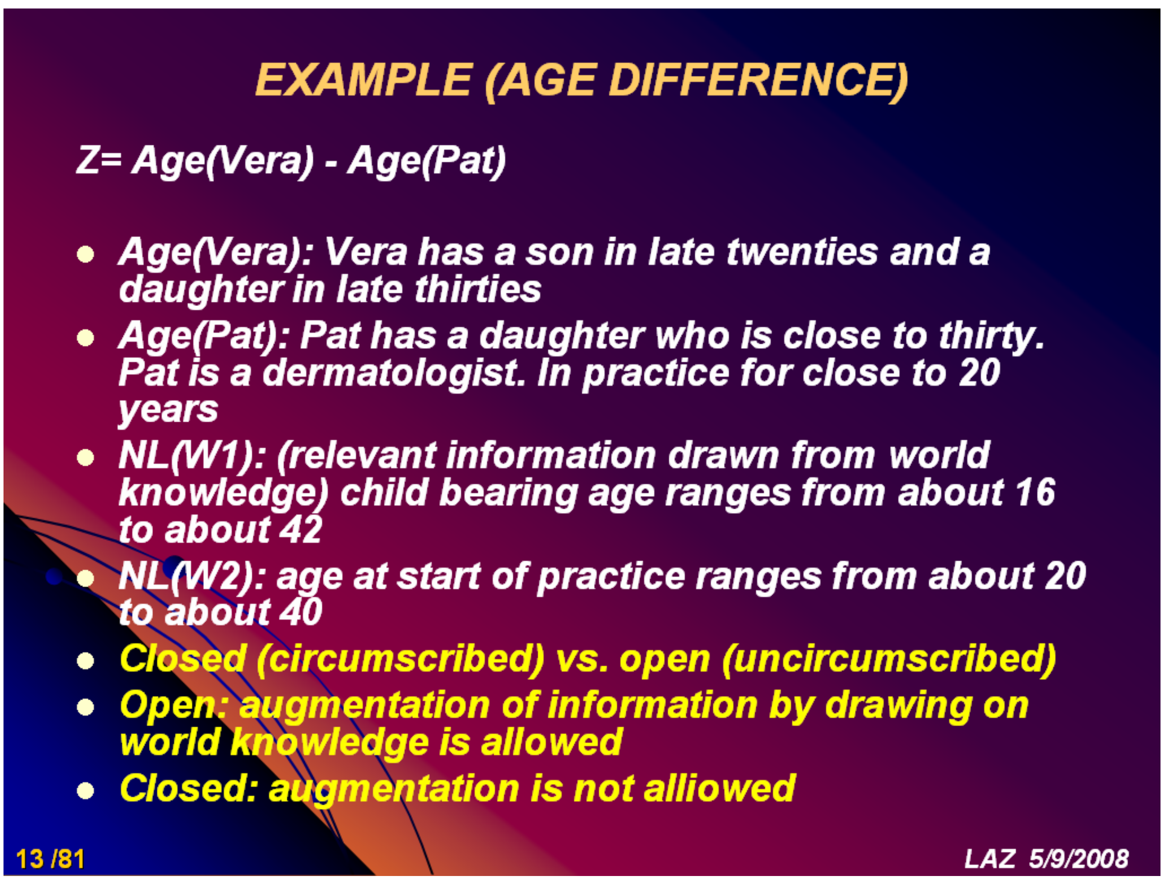

EXAMPLE (AGE DIFFERENCE)
Z= Age(Vera) - Age(Pat)
Age(Vera): Vera has a son in late twenties and a daughter in late thirties
Age(Pat): Pat has a daughter who is close to thirty. Pat is a dermatologist. In practice for close to 20 years
NL(W1): (relevant information drawn from world knowledge) child bearing age ranges from about 16 to about 42
NL(W2): age at start of practice ranges from about 20 to about 40
Closed (circumscribed) vs. open (uncircumscribed)
Open: augmentation of information by drawing on world knowledge is allowed
Closed: augmentation is not alliowed
13 /81
LAZ 5/9/2008

A SIMPLE EXAMPLE—A PREVIEW

- A small glass jar contains about 20 balls of various sizes. Most are small. A few are large. What is the average size of balls?

Solution

Population= $(b_1, \ldots, b_N)$

d_i= diameter of b_i, $i=1, \ldots, N$

14 /81 LAZ 5/9/2008

CONTINUED

- A glass jar contains about 20 balls $\xrightarrow{\text{mm-precisiation}}$ N is *20
- Most are small $(\mu_{small}(d_1)+\ldots+\mu_{small}(d_N))/N$ is most $\xrightarrow{\text{mm-precisiation}}$
- A few are large $\mu_{large}(d_1)+\ldots+\mu_{large}(d_N)$ is few $\xrightarrow{\text{mm-precisiation}}$
- What is the average size of balls?
- $(d_1+\ldots+d_N)/N$ is ?A

15 /81 LAZ 5/9/2008

CONTINUED

*N is *20*

$(\mu_{small}(d_1)+\ldots+\mu_{small}(d_N))/N$ *is most*

$\mu_{large}(d_1)+\ldots+\mu_{large}(d_N)$ *is few*

- $(d_1+\ldots+d_N)/N$ *is ?A*
- ***Solution reduces to generalized constraint propagation***

16 /81 LAZ 5/9/2008

KEY OBSERVATIONS—COMPUTATION, PRECISIATION AND UNDERSTANDING

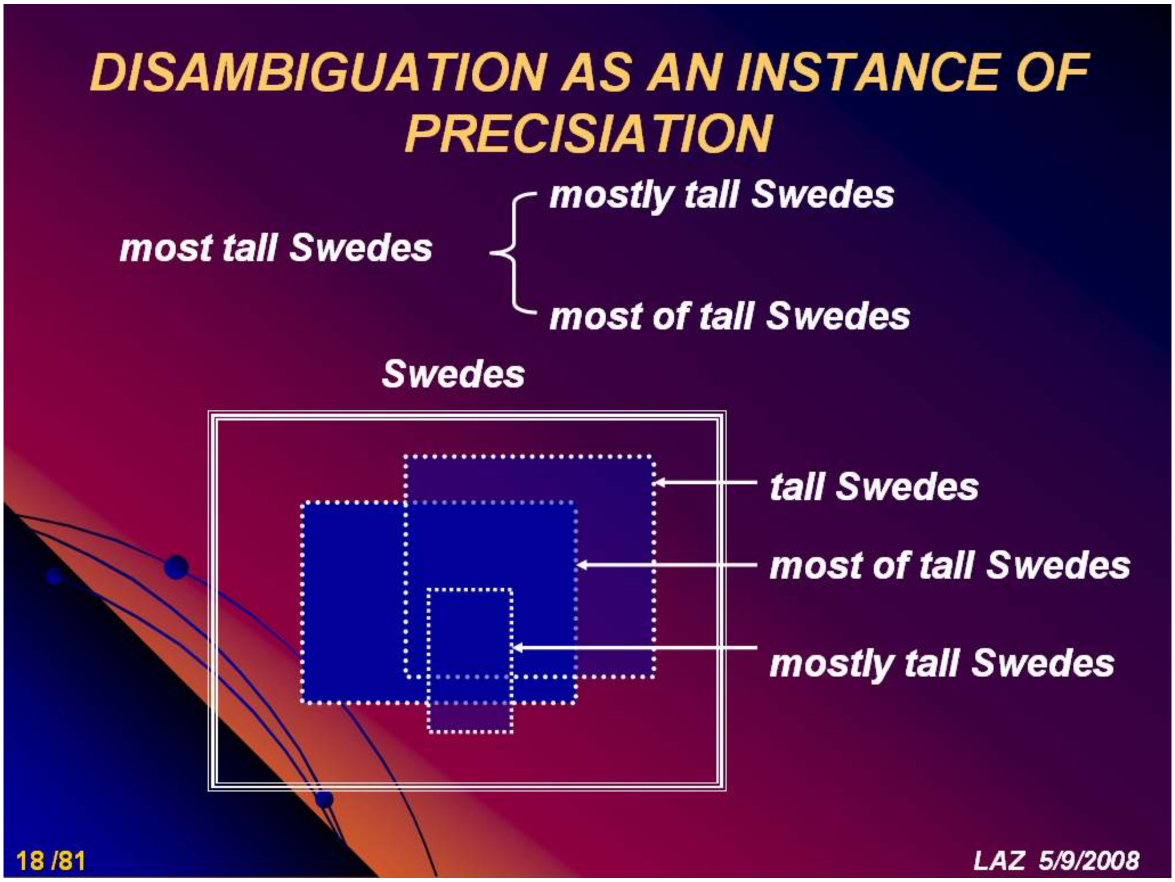
- ***As stated, the problems are not well posed. To make them well posed, what is needed is precisiation***
- ***Precisiation is a prerequisite to computation***
- ***Understanding is a prerequisite to precisiation***

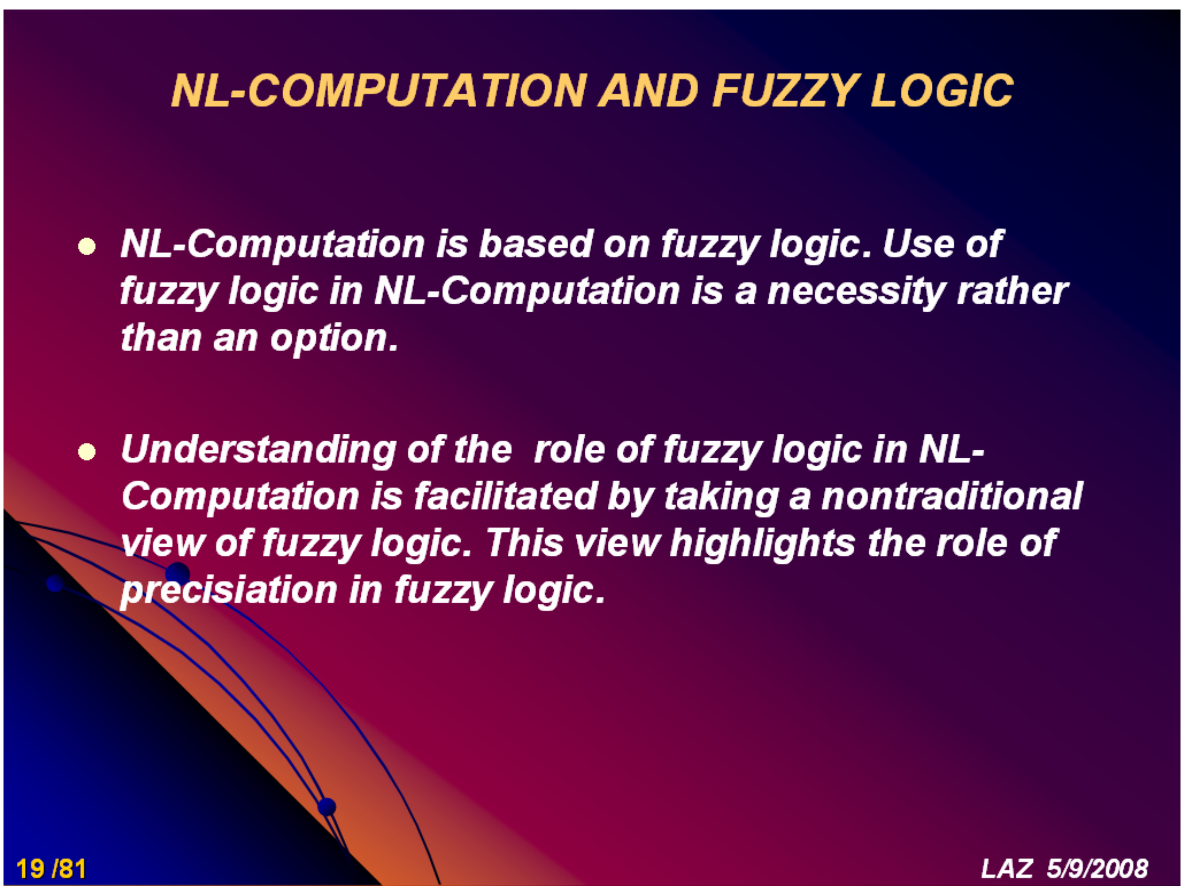
Example:

p: Use with adequate ventilation

I understand what you mean but can you be more precise?

17 /81 LAZ 5/9/2008


DISAMBIGUATION AS AN INSTANCE OF PRECISIATION
most tall Swedes
mostly tall Swedes
most of tall Swedes
Swedes
tall Swedes
most of tall Swedes
mostly tall Swedes
18 /81
LAZ 5/9/2008


NL-COMPUTATION AND FUZZY LOGIC
• NL-Computation is based on fuzzy logic. Use of fuzzy logic in NL-Computation is a necessity rather than an option.
• Understanding of the role of fuzzy logic in NL-Computation is facilitated by taking a nontraditional view of fuzzy logic. This view highlights the role of precisiation in fuzzy logic.
19 /81
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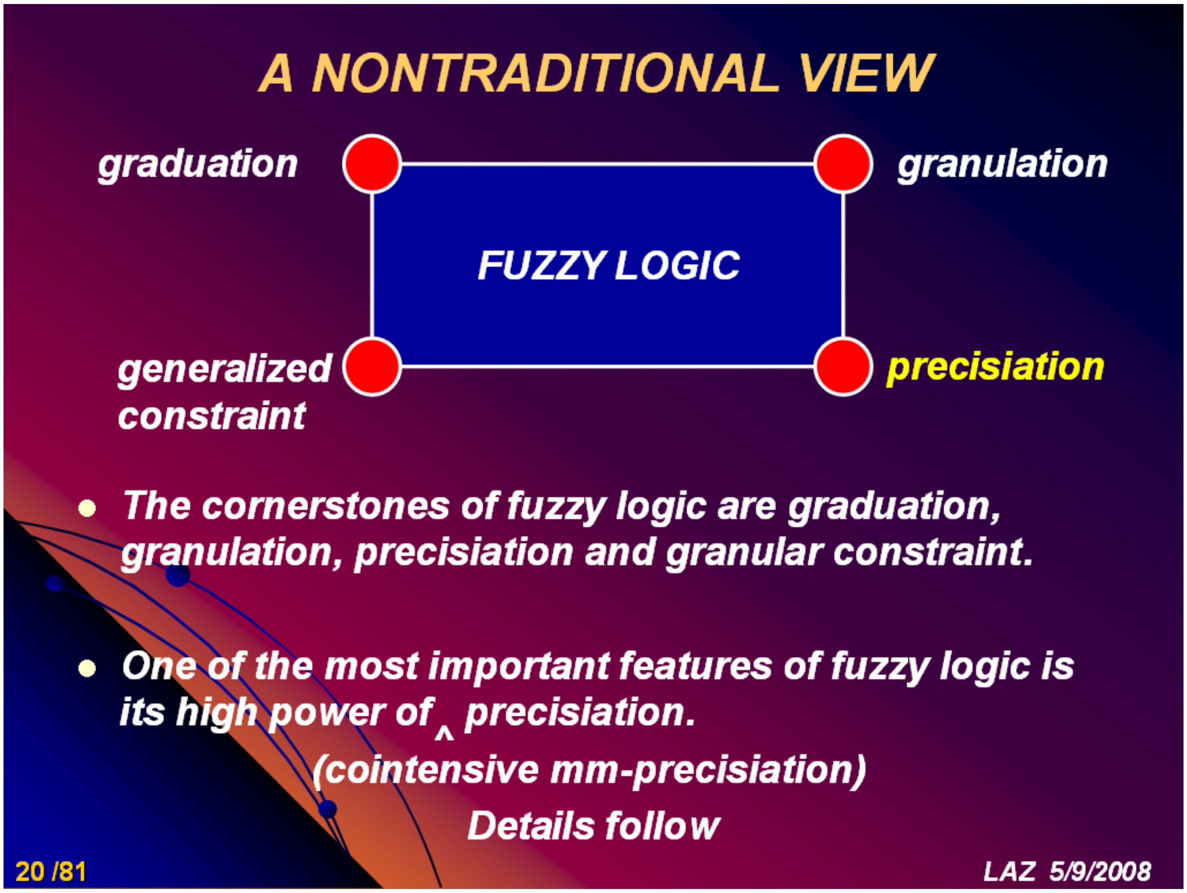
A NONTRADITIONAL VIEW
graduation
granulation
FUZZY LOGIC
generalized constraint
precisiation
• The cornerstones of fuzzy logic are graduation, granulation, precisiation and granular constraint.
• One of the most important features of fuzzy logic is its high power of ^ precisiation.
(cointensive mm-precisiation)
Details follow
20 /81
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THE CONCEPTS
OF PRECISIATION
AND COINTENSIVE
PRECISIATION
21 /81
LAZ 5/9/2008

PRECISION IN VALUE AND PRECISION IN MEANING

- ***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 in value (v-precision) and precision in meaning (m-precision).***
- ***The same distinction applies to imprecision, precisiation and imprecisiation.***

22 /81 LAZ 5/9/2008

CONTINUED

PRECISE

v-precise ← precise value

m-precise ← precise meaning

- *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 σ^2. m and σ^2 are precisely defined real numbers*
- *p is v-imprecise and m-precise*

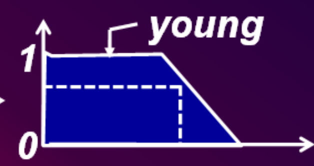
23 /81 LAZ 5/9/2008

PRECISIATION AND IMPRECISIATION

- A proposition, predicate, query or command may be precisiated or imprecisiated
- Definition is a form of m-precisiation

Example

young → **m-precisiation** →



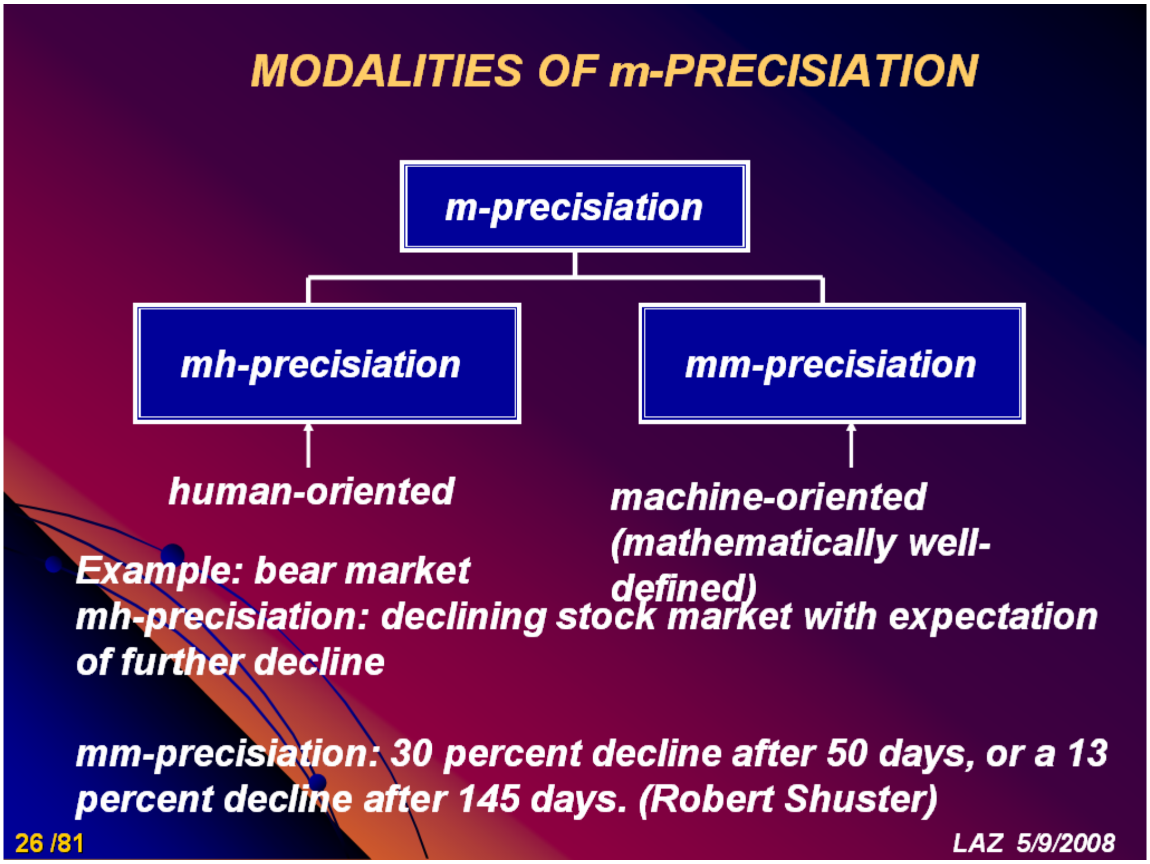
Lily is 25 → **v-imprecisiation m-imprecisiation** → Lily is young

Lily is young → **v-precisiation m-precisiation** → Lily is 25

PRECISIATION VS. IMPRECISIATION

p ← precisiation — p*

p ← imprecisiation — *p


MODALITIES OF m-PRECISIATION
m-precisiation
mh-precisiation
mm-precisiation
human-oriented
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)
26 /81
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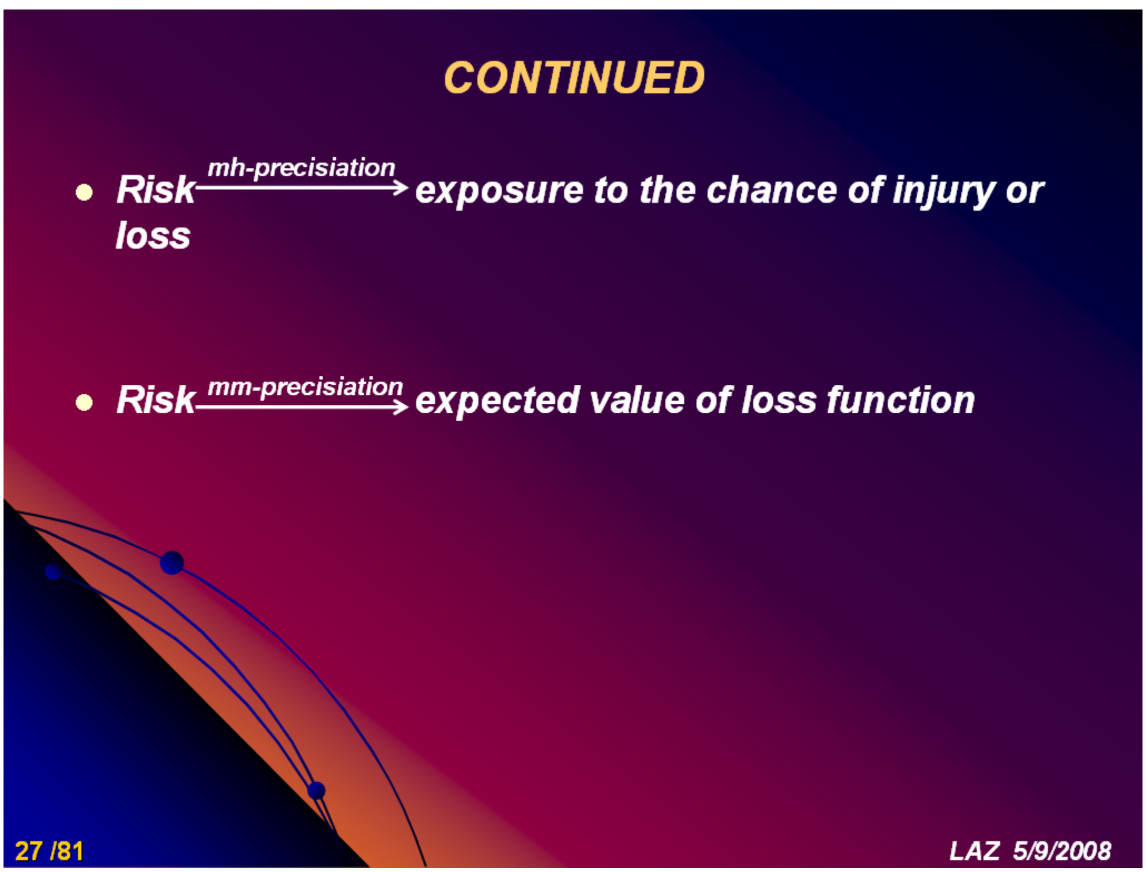
CONTINUED
Risk $\xrightarrow{\text{mh-precisiation}}$ exposure to the chance of injury or loss
Risk $\xrightarrow{\text{mm-precisiation}}$ expected value of loss function
27 /81
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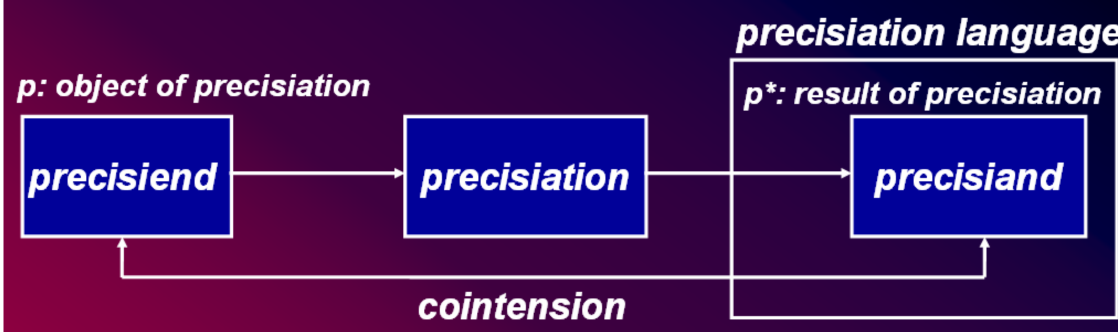
BASIC CONCEPTS



- precisiand = model of meaning
- intension = attribute-based meaning
- cointension = measure of closeness of meanings
  = measure of goodness of model
- A precisiend has many precisiands. Pres(p) denotes the set of precisiands of p

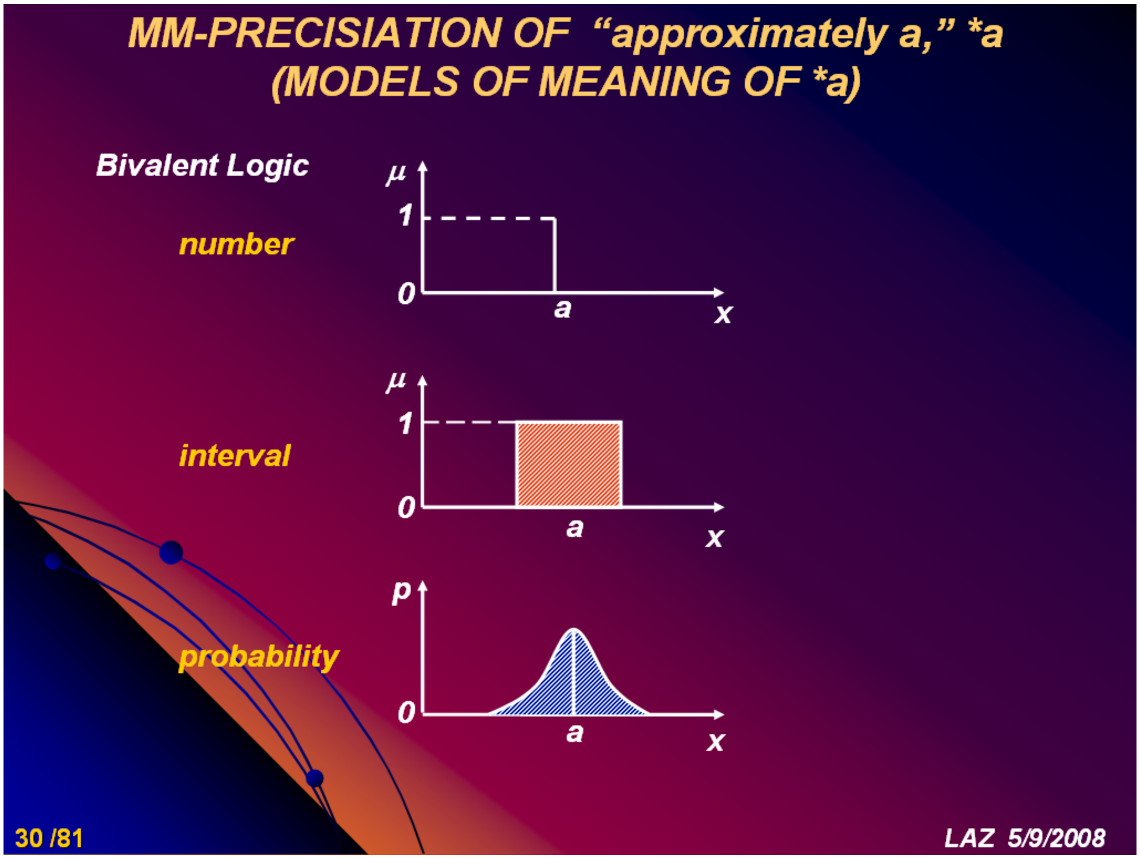
precisiation = translation into a precisiation language

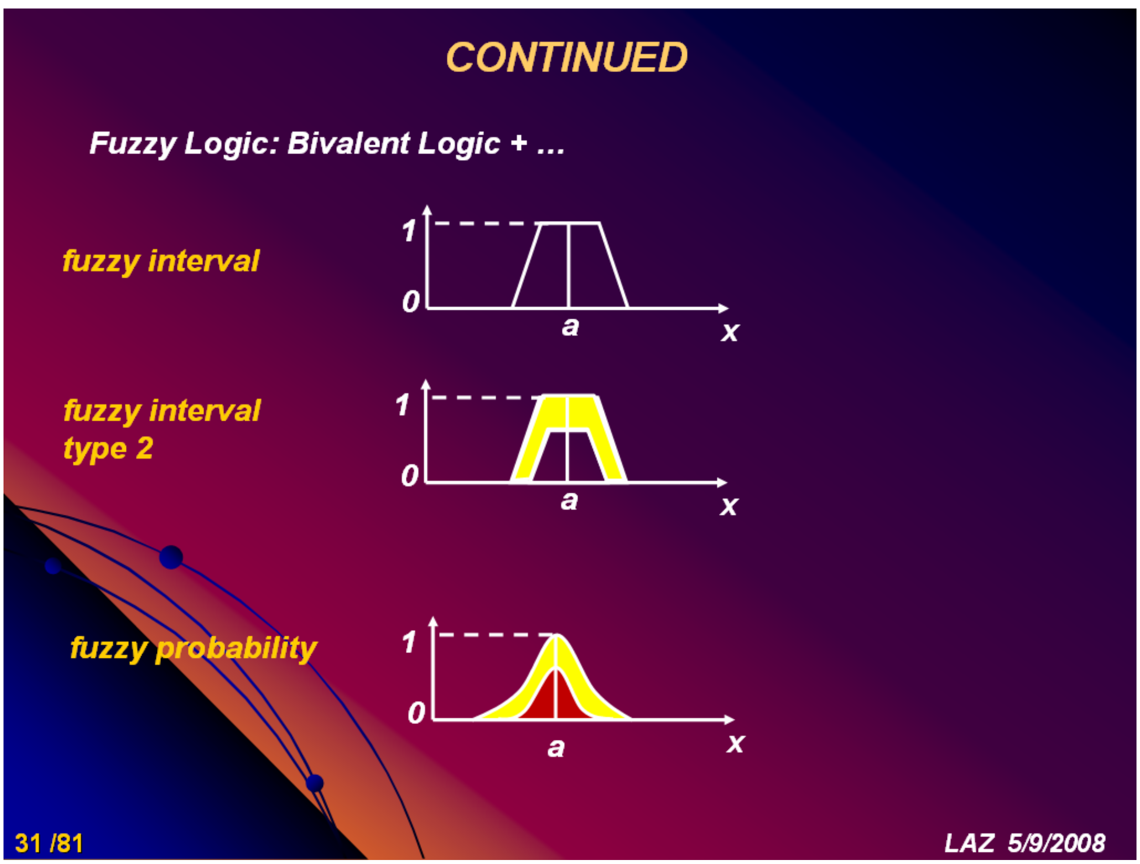
28 /81 LAZ 5/9/2008

PRECISIATION AND MODELING

- mm-precisiand = mathematical model
- mm-precisiation = construction of a mathematical model
- Unless stated to the contrary, precisiation should be interpreted as mm-precisiation

29 /81 LAZ 5/9/2008


MM-PRECISIATION OF "approximately a," *a
(MODELS OF MEANING OF *a)
Bivalent Logic
number
interval
probability
μ
1
0
a
x
p
30 /81
LAZ 5/9/2008


CONTINUED
Fuzzy Logic: Bivalent Logic + ...
fuzzy interval
fuzzy interval
type 2
fuzzy probability
1
0
a
x
31 /81
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v-IMPRECISIATION

v-imprecisiation

Imperative (forced) | Intentional (deliberate)

imperative: value is not known precisely

intentional: value need not be known precisely

- v-imprecisiation principle: Precision carries a cost. If there is a tolerance for imprecision, exploit it by employing v-imprecisiation to achieve lower cost, robustness, tractability, decision-relevance and higher level of confidence. Employ mm-precisiation to achieve computability.
- data compression and summarization are instances of v-imprecisiation

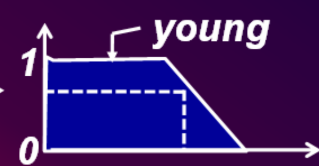
32 /81 LAZ 5/9/2008

THE FUZZY LOGIC GAMBIT

p → v-imprecisiation → mm-precisiation →

reduction in cost ↑ (v-imprecisiation) achievement of computability ↑ (mm-precisiation)

Lily is 25 → Lily is young →



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

33 /81 LAZ 5/9/2008

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

34 /81 LAZ 5/9/2008

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?*

35 /81 LAZ 5/9/2008

mm-PRECISIATION

Basic questions

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

b) How can mm-precisiand of p be treated as an object of computation/deduction?

- In NL-Computation these questions are addressed through the use of fuzzy-logic-based computational semantics of natural languages.

FUZZY-LOGIC-BASED COMPUTATIONAL SEMANTICS OF NATURAL LANGUAGES

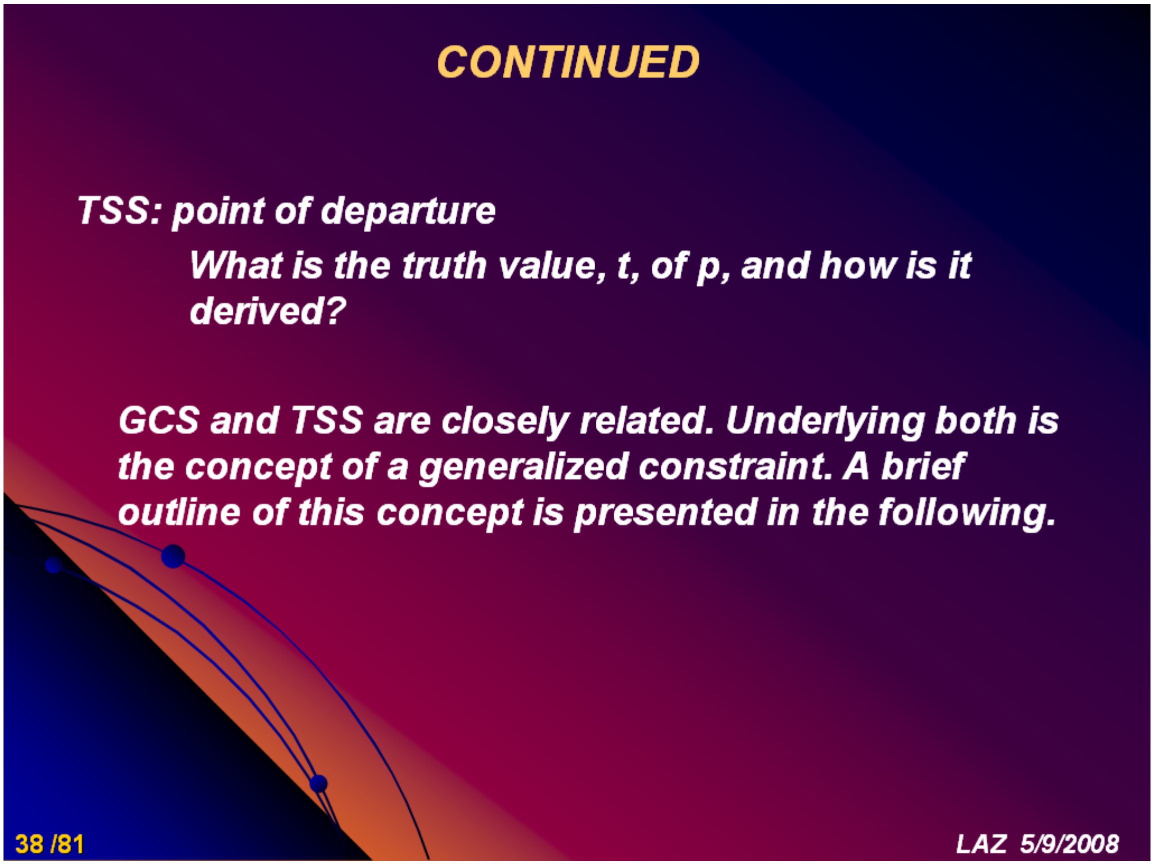
GCS	TCS
generalized-constraint-based semantics (Zadeh 2006)	test-score semantics (Zadeh 1982)

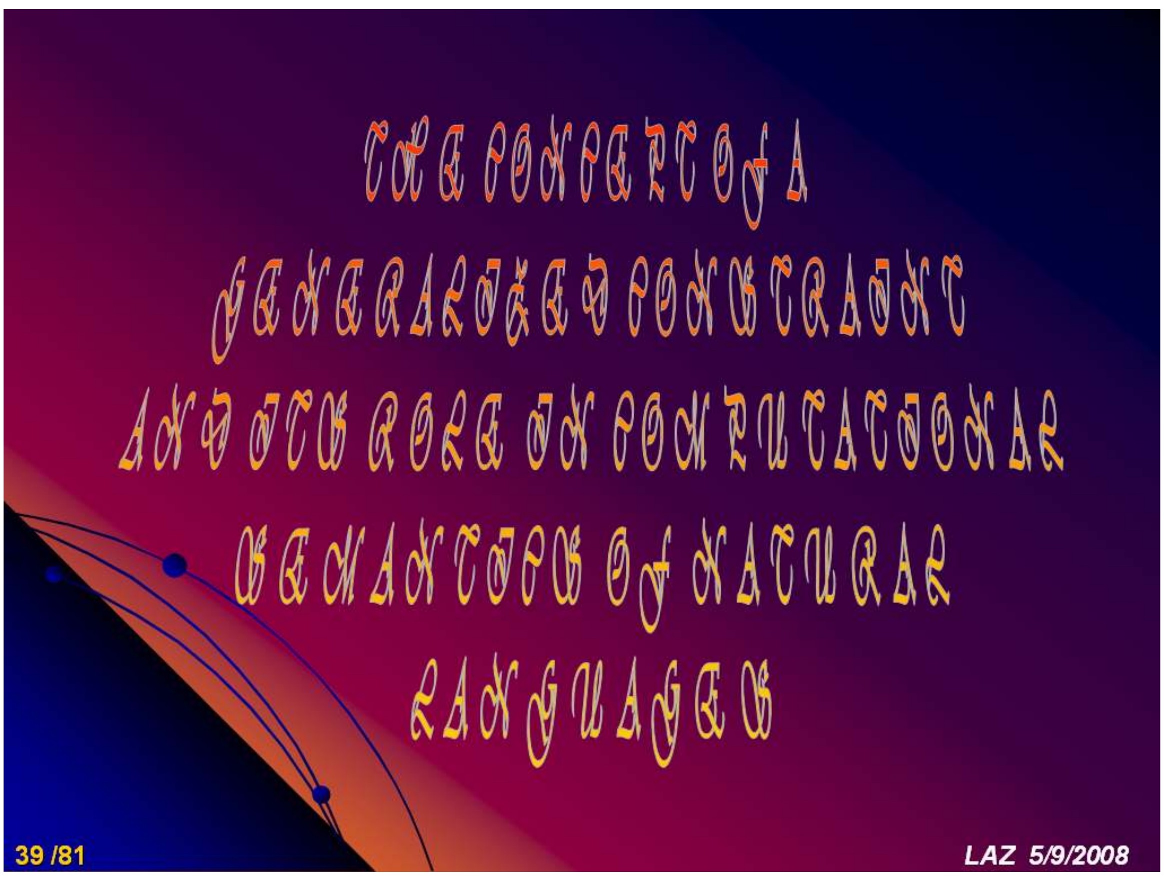
GCS: point of departure

p is a proposition

X is a variable which is explicit or implicit in p

p is interpreted as an answer to the question: What is the value of X and how is it derived?


CONTINUED
TSS: point of departure
What is the truth value, t, of p, and how is it derived?
GCS and TSS are closely related. Underlying both is the concept of a generalized constraint. A brief outline of this concept is presented in the following.
38 /81
LAZ 5/9/2008


THE CONCEPT OF A GENERALIZED CONSTRAINT AND ITS ROLE IN COMPUTATIONAL SEMANTICS OF NATURAL LANGUAGES
39 /81
LAZ 5/9/2008

PREAMBLE

- *The concept of a generalized constraint is the centerpiece of generalized-constraint-based semantics. An outline of this concept if presented in the following.*
- *In scientific theories, representation of constraints is generally oversimplified. Oversimplification of constraints is a necessity because existing constrained definition languages have a very limited expressive power.*

CONTINUED

- *The concept of a generalized constraint is intended to provide a basis for construction of a maximally expressive constraint definition language which can also serve as a meaning representation/precisiation language for natural languages.*

GENERALIZED CONSTRAINT (Zadeh 1986)

- Bivalent constraint (hard, inelastic, categorical:)

$X \varepsilon C$ — constraining bivalent relation

- Generalized constraint on X: GC(X)

$\boxed{GC(X): X \text{ isr } R}$

R — constraining non-bivalent (fuzzy) relation

r — index of modality (defines semantics)

X — constrained variable

r: $\underbrace{\varepsilon \mid = \mid \leq \mid \geq \mid \subset \mid \ldots}_{\text{bivalent}}$ | blank | p | v | u | rs | fg | ps |…

primary: blank, p, v

- 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

$\boxed{X \text{ isr } R}$

r: =	equality constraint: X=R is abbreviation of X is=R
r: ≤	inequality constraint: X ≤ R
r:⊂	subsethood constraint: X ⊂ R
r: 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

CONTINUED

r: bm bimodal constraint; X is a random variable; R is a bimodal distribution

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

EXAMPLES: POSSIBILISTIC

- *Monika is young* $\longrightarrow$ $\underbrace{\textit{Age (Monika)}}_{X}$ *is* $\underbrace{\textit{young}}_{R}$

- *Monika is much younger than Maria* $\longrightarrow$
  $\underbrace{\textit{(Age (Monika), Age (Maria))}}_{X}$ *is* $\underbrace{\textit{much younger}}_{R}$

- *most Swedes are tall*
  $\longrightarrow$ *Count* $\underbrace{\textit{(tall.Swedes/Swedes)}}_{X}$ *is* $\underbrace{\textit{most}}_{R}$

46 /81 LAZ 5/9/2008

EXAMPLES: PROBABILISITIC

- *X is a normally distributed random variable with mean m and variance* σ^2 $\longrightarrow$
  X *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* $\longrightarrow$

  X *isp* $(p_1\backslash u_1 + p_2\backslash u_2 + p_3\backslash u_3)$

47 /81 LAZ 5/9/2008

EXAMPLES: VERISTIC

- Robert is half German, quarter French and quarter Italian

  Ethnicity (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]

STANDARD CONSTRAINTS

- Bivalent possibilistic: $X \varepsilon C$ (crisp set)
- Bivalent veristic: Ver(p) is true or false
- Probabilistic: X 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 generated by combination, qualification, propagation and counterpropagation of generalized constraints*
- *examples of elements of GCL*
  - *(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*

CLARIFICATION
LANGUAGE VS. LANGUAGE SYSTEM

- *Language= (description system)*
- *Description system= (syntax, semantics)*
- *Language system= (description system, computation/deduction system)*

Examples: Java is a language; Prologue is a language system; probability theory is al language system; fuzzy logic is a system of language systems.

- *Generalized Constraint Language (GCL) is a language system.*
- *The rules of deduction in GCL are the rules which govern propagation and counterpropagation of generalized constraints.*

EXTENSION PRINCIPLE

- *The principal rule of deduction in NL-Computation is the Extension Principle (Zadeh 1965, 1975).*

$$\frac{f(X) \text{ is } A}{g(X) \text{ is } B}$$

$$\mu_B(v) = sup_u\, \mu_A(f(u))$$

subject to

$$v = g(u)$$

PROTOFORMAL DEDUCTION RULE

- *Syllogism*

$$\frac{\begin{array}{l} Q_1\ A\text{'s are } B\text{'s} \\ Q_2\ (A\&B)\text{'s are } C\text{'s} \end{array}}{Q_1Q_2 A\text{'s are } (B\&C)\text{'s}}$$

Example

- *Overeating causes obesity* $\xrightarrow{\text{precisiation}}$ *most of those who overeat become obese*
- *Overeating and obesity cause high blood pressure* $\xrightarrow{\text{precisiation}}$ *most of those who overeat and are obese have high blood pressure*
- *I overeat and am obese. The probability that I will develop high blood pressure is most*^{2}

PROTOFORMAL DEDUCTION RULE

$$\frac{1/n\Sigma Count(G[H \text{ is } R]) \text{ is } Q}{1/n\Sigma Count(G[H \text{ is } S]) \text{ is } T}$$

$$\frac{\Sigma_i \mu_R(h_i) \text{ is } Q}{\Sigma_i \mu_S(h_i) \text{ is } T}$$

$$\boxed{\begin{array}{l} \mu_T(v) = sup_{h_1, \ldots, h_n}(\mu_Q(\Sigma_i \mu_R(h_i)) \\ \text{subject to} \\ v = \Sigma_i \mu_S(h_i) \end{array}}$$

values of H: $h_1, \ldots, h_n$

54 /81 LAZ 5/9/2008

GENERALIZED-CONSTRAINT-BASED SEMANTICS

- *Generalized-constraint-based semantics suggests a novel, powerful approach to semantics of natural languages. It is generalized-constraint-based semantics that opens the door to computation with information described in natural language.*
- *The point of departure in generalized-constraint-based semantics is the fundamental thesis of fuzzy logic.*

Information = generalized constraint

Basically, what this means is that information about a variable, X, may be viewed as a constraint on the values which X can take.

55 /81 LAZ 5/9/2008

CONTINUED

- A proposition, p, is a carrier of information.
- A consequence of the fundamental thesis is the meaning postulate.

  meaning of p = generalized constraint
- In NL-Computation, the meaning of p is equated with its mm-precisiand. More specifically

proposition → mm-precisiation → X is R (closed)
↑—— instantiated

predicate → mm-precisiation → X is R (open)
↑—— free

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 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 procedurely.
- 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.

PRECISIATION AND DEDUCTION

- What should be stressed is that mm-precisiation is not the final goal. It is a preliminary to computation/deduction. The roles of mm-precisiation and computation/deduction are illustrated in the following.

58 /81 LAZ 5/9/2008

PRECISIATION AND COMPUTATION/DEDUCTION—EXAMPLE

- p: most Swedes are tall

  p*: ΣCount(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], $a \le h \le b$

$$\int_a^b X(h)du = 1$$

59 /81 LAZ 5/9/2008

CONTINUED

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

$\int_a^b X(h)\mu_{tall}(h)dh$ is most

granular value

$$\pi(X) = \mu_{most}\left(\int_a^b X(h)\mu_{tall}(h)dh\right)$$

CONTINUED

deduction:

$$\frac{\int_a^b X(h)\mu_{tall}(h)dh \text{ is most} \longleftarrow \text{given}}{\int_a^b X(h)\mu_{short}(h)dh \text{ is ? Q} \longleftarrow \text{needed}}$$

solution:

$$\mu_Q(v) = \sup_X\left(\mu_{most}\left(\int_a^b X(h)\mu_{tall}(h)dh\right)\right)$$

subject to

$$v = \int_a^b X(h)\mu_{short}(h)dh$$

$$\int_a^b X(h)dh = 1$$

DEDUCTION PRINCIPLE

- *In a general setting, computation/deduction is governed by the Deduction Principle.*
- *Point of departure: question, q*
- *Data: $D = (X_1/u_1, \ldots, X_n/u_n)$*

  u_i is a generic value of X_i

- *Ans(q): answer to q*

CONTINUED

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

  $$Ans(q)=g(u_1, \ldots, u_n) \qquad u=(u_1, \ldots, u_n)$$

- *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*

  $$f(u)=f(u_1, \ldots, u_n)$$

CONTINUED

- Use the extension principle

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

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 = height of S_i , $g = (g_1, \ldots, g_n)$
h_j = height of I_j , $h = (h_1, \ldots, h_n)$
$\mu_{ij} = \mu_{much.taller}(g_i, h_j)$= degree to which S_i is much taller than I_j

CONTINUED

$r_i = \frac{1}{n}\Sigma_j \mu_{ij}$ = Relative ΣCount of Italians in relation to whom S_i is much taller

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

$v = \frac{1}{m}\Sigma t_i$ = Relative ΣCount of Swedes who are much taller than most Italians

$ts(g, h) = \mu_{most}(v)$

$p \longrightarrow$ generalized constraint on S and I

q: $d = \frac{1}{m}\Sigma_i g_i - \frac{1}{n}\Sigma_j h_j$

66 /81 LAZ 5/9/2008

CONTINUED

Step 2. Deduction via Extension Principle

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

subject to

$$d = \frac{1}{m}\Sigma_i g_i - \frac{1}{n}\Sigma_j h_j$$

67 /81 LAZ 5/9/2008

EPILOGUE

THE NEED FOR PRECISIATION OF NATURAL LANGUAGE

- *Natural languages are intrinsically imprecise. A prerequisite to computation with information described in natural language is mm-precisiation of meaning. Mm-precisiation of meaning is the first step in NL-Computation. The concept of generalized-constraint plays a key role in both precisiation and computation/deduction.*

LAZ 5/9/2008

NL-INCAPABILITY

- NL-capability = capability to operate on information described in natural language
- Existing scientific theories are based for the most part on bivalent logic and bivalent-logic-based probability theory
- Bivalent logic and bivalent-logic-based probability theory do not have NL-capability
- For the most part, existing scientific theories do not have NL-capability

NL-CAPABILITY

- NL-Computation serves to add NL-capability to existing scientific theories and thereby opens the door to a wide ranging enlargement of the role of natural languages in scientific theories, especially in human-centric theories such as economics, linguistics, law and psychology.
- An important application of NL-Computation relates to computation with imprecise probabilities and probability distributions described in natural language.
- Generally, real-world probabilities and probability distributions are not known precisely.

A KEY OBSERVATION

- *The concept of a set has a position of centrality in mathematics. A set is a special set of a fuzzy set. Generalization of the concept of a set is the point of departure in fuzzy logic and underlies its generality and power. More generally, the concept of a fuzzy set opens the door to generalization of many branches of mathematics, among them topology, algebra, functional analysis and theory of relations.*

CONTINUED

- *More over, it serves as a basis for upgrading or, more concretely, FL enhancement, of bivalent-logic-based scientific theories through addition of concepts and techniques drawn from fuzzy logic. In the limit, FL enhancement leads to a shift in the foundations of a scientific theory from bivalent logic to fuzzy logic.*

CONTINUED

- A shift from bivalent logic to fuzzy logic results in a theory which has an enhanced capability to model reality. The enhanced capability to model reality is one of the main contributions of fuzzy logic.

74 /81 LAZ 5/9/2008

RELATED PAPERS BY L.A.Z IN REVERSE CHRONOLOGICAL ORDER

- Is there a need for fuzzy logic? Information Sciences, Vol. 178, No. 13, 2751-2779, 2008.
- Generalized theory of uncertainty (GTU)—principal concepts and ideas, Computational Statistics and Data Analysis 51, 15-46, 2006.
- Precisiated natural language (PNL), AI Magazine, Vol. 25, No. 3, 74-91, 2004.
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- A new direction in AI—toward a computational theory of perceptions, AI Magazine, Vol. 22, No. 1, 73-84, 2001.

75 /81 LAZ 5/9/2008

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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.
- Some reflections on soft computing, granular computing and their roles in the conception, design and utilization of information/intelligent systems, Soft Computing 2, 23-25, 1998.
- Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic, Fuzzy Sets and Systems 90, 111-127, 1997.

76 /81 LAZ 5/9/2008

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- Outline of a computational approach to meaning and knowledge representation based on the concept of a generalized assignment statement, Proceedings of the International Seminar on Artificial Intelligence and Man-Machine Systems, M. Thoma and A. Wyner (eds.), 198-211. Heidelberg: Springer-Verlag, 1986.
- Precisiation of meaning via translation into PRUF, Cognitive Constraints on Communication, L. Vaina and J. Hintikka, (eds.), 373-402. Dordrecht: Reidel, 1984.
- Fuzzy sets and information granularity, Advances in Fuzzy Set Theory and Applications, M. Gupta, R. Ragade and R. Yager (eds.), 3-18. Amsterdam: North-Holland Publishing Co., 1979.

77 /81 LAZ 5/9/2008

APPENDIX

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***

PUBLICATIONS

Count of papers containing the word “fuzzy” in title, as cited in INSPEC and MATH.SCI.NET databases. Compiled by Camille Wanat, Head, Engineering Library, UC Berkeley, March 13, 2007.

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

INSPEC - "fuzzy" in title	MathSciNet - "fuzzy" in title
1970-1979: 569	1970-1979: 443
1980-1989: 2,403	1980-1989: 2,465
1990-1999: 23,214	1990-1999: 5,487
2000-present: 24,910	2000-present: 6,217
Total: 51,096	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
7. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems
8. Journal of Japan Society for Fuzzy Theory and Systems
9. International Journal of Fuzzy Systems
10. International Review of Fuzzy Mathematics
11. Fuzzy Systems and Soft Computing

Zadeh L.A., Tufiş D., Filip F.G., Dziţac I.(Eds.),
From Natural Language to Soft Computing: New Paradigms in Artificial Intelligence,
Editing House of Romanian Academy, Bucharest, ISBN 978-973-27-1678-6, 2008, pp. 268-268

APPENDIX 2

PICTURES FROM EWNLC 2008

Picture 1. Lotfi A. Zadeh

Picture 2. Dan Tufiş

Picture 3. Florin Gheorghe Filip

Picture 4. Ioan Dziţac

Picture 5. Dan Tufiş, Ioan Dziţac, Lotfi A. Zadeh, Mişu-Jan Manolescu, Florin Gheorghe Filip

Picture 6. Lotfi A. Zadeh presenting workshop's keynote lecture