

# ***Fuzzy Analogy: A New Approach for Software Cost Estimation***

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# Summary

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- ⊙ Introduction
- ⊙ Software Cost Estimation Models
- ⊙ Estimation by Analogy
- ⊙ Fuzzy Logic
- ⊙ Linguistic Quantifiers
- ⊙ Fuzzy Analogy
- ⊙ Conclusions and Future Work

# Introduction

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- ⊙ Software cost estimation is one of the most critical activities in managing software projects
- ⊙ Estimation by Analogy is a promising technique to solve the software estimation problem
- ⊙ Critic : Estimation by Analogy cannot handle categorical data such as '**very low**', '**low**', '**high**'....
- ⊙ However, software projects are always described by categorical rather than numerical data:
  - ↪ **COCOMO'81**: 16 out of 17 attributes are categorical
  - ↪ **COCOMOII**: 22 out of 24
  - ↪ **Function Points** : Evaluation of the complexity for Inputs, Outputs, Files, Inquiries. Evaluation of the TCF

## ◎ Objective

A new approach for software cost estimation based on reasoning by **Analogy**, **Fuzzy Logic** and **Linguistic Quantifier**



# Software Cost Estimation Models

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## History

↪ 1975, Halstead

$$Effort = \frac{\mathbf{n}_1 N_2 \text{Log}(\mathbf{n}_1 + \mathbf{n}_2)}{2S\mathbf{m}_2}$$

↪ 1978, Putnam

$$CT = \left(\frac{DSI}{C}\right)^{\frac{9}{7}} D_0^{\frac{4}{7}}$$

↪ 1981, Boehm, COCOMO

# Software Cost Estimation Models

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## ◎ Classification

### ↪ Algorithmic Models

↪ Regression simple/multiple, Interpolation, Bayesian, PCA, etc.

#### ↪ Advantages

- Easy to use
- Easy to develop

#### ↪ Critics

- They make assumption about the form of the prediction function  $Effort = a \times size^b$
- They need to be adjusted or calibrated to local circumstances

# Software Cost Estimation Models

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## ◎ Classification

### ↪ Non-algorithmic Models

↪ NN, CBR, Rule Induction, Regression Trees

#### ↪ Advantages

- Capabilities to adequately model the complex set of relationship between factors
- Learning
- Their behavior is easy to understand

#### ↪ Critics

- They are not easy to develop
- They need software tools to automate their process

# *Estimation by Analogy*

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- ⊙ **Estimation by Analogy is based on the affirmation :**

*Similar software projects have similar costs*

- ⊙ **Estimation by analogy is composed by :**

- ↪ **Characterization of the projects by a set of attributes such as Reliability, Complexity, Analysts competence ...**
- ↪ **Evaluation of the similarity between the candidate project and each project in the database**
- ↪ **Adaptation**

- ⊙ **Related Works** : Vacninanza, **Sheppered**, Briand, Angelis,...



⊙ Shepperd et al. (1997)

$$d(P_1, P_2, V) = \frac{1}{\sum_{v_j} d_{v_j}(P_1, P_2)}$$

$$d_{v_j}(P_1, P_2) = \begin{cases} (V_j(P_1) - V_j(P_2))^2 & \\ 0 & \text{si } V_j(P_1) \neq V_j(P_2) \\ 1 & \text{si } V_j(P_1) = V_j(P_2) \end{cases}$$

Classical Logic

Fuzzy Logic

**Imprecise and Uncertain Data**  
**Low, High, Excellent ???**

↪ **Idri and Abran, 7<sup>th</sup> FT&T, Atlantic City, 2000**

The equality distance is not precise and can give great difference when estimating effort for two similar software projects described by Vagueness information

↪ **Idri and Abran, 6<sup>th</sup> MCSEAI, Morocco, 2000**

We have proposed a set of similarity measures based on fuzzy logic

↪ **Idri and Abran, 7<sup>th</sup> IEEE Metrics, London, 2001**

We have validated by means of an axiomatic approach the proposed similarity measures

↪ **Idri and Abran, 9<sup>th</sup> IFSA/20<sup>th</sup> NAFIPS, Vancouver, 2001**

We have improved the retained measures by using linguistic quantifier guided aggregations

# Fuzzy Logic

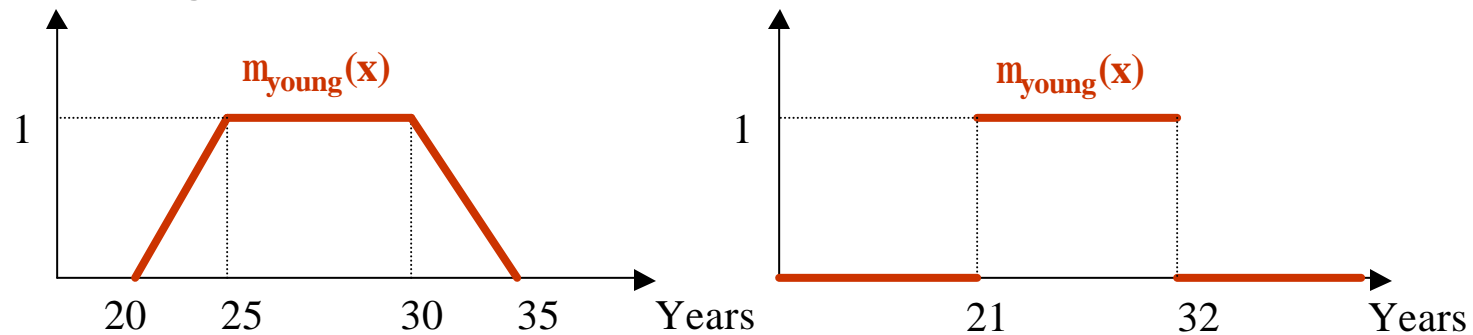
- ◉ Values between 'TRUE' and 'FALSE' ?

'The main motivation of fuzzy logic is the desire to build up a formal, quantitative framework that captures the vagueness of human knowledge via natural languages' Dubois and Prade 1991

- ◉ 1965, Zadeh : Fuzzy Set

- ◉ 1994, Zadeh : Fuzzy Logic = Fuzzy Set Theory

- ◉ **Fuzzy Set:** set with a membership function which takes values in the unit interval  $[0, 1]$  rather than in the  $\{0, 1\}$  as in the classical logic



# Linguistic quantifiers

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- ⊙ Human discourse uses a large number of linguistic quantifiers
- ⊙ Zadeh distinguishes between two classes:
  - ↳ Absolute linguistic quantifiers '**approximately 10**'
  - ↳ Proportional linguistic quantifiers (**most, few, at least, at most,...**)
- ⊙ Yager has distinguished three categories of proportional quantifiers:
  - ↳ RIM quantifiers (**most, at least a,...**)
  - ↳ RDM quantifiers (**few, at most a,...**)
  - ↳ RUN quantifiers (**about a**)

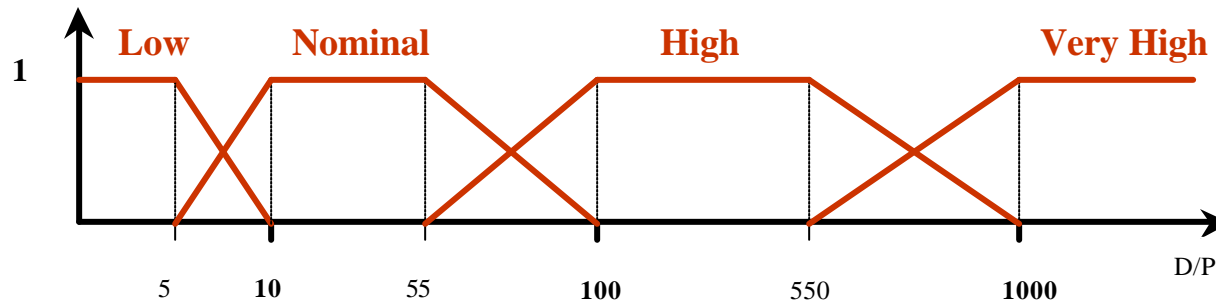
# *Fuzzy Analogy for Cost Estimation*

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- ⊙ **Fuzzy Analogy is a fuzzification of the classical analogy procedure**
- ⊙ **Fuzzy Analogy is composed of three steps:**
  - ↪ Identification of software projects
  - ↪ Evaluation of similarity between projects
  - ↪ Adaptation
- ⊙ **Identification Step:**
  - ↪ The aim is to describe the software projects by a set of attributes that are:
    - ↪ **Relevant**
    - ↪ **Independent**
    - ↪ **Comprehensive**
    - ↪ **Operational**

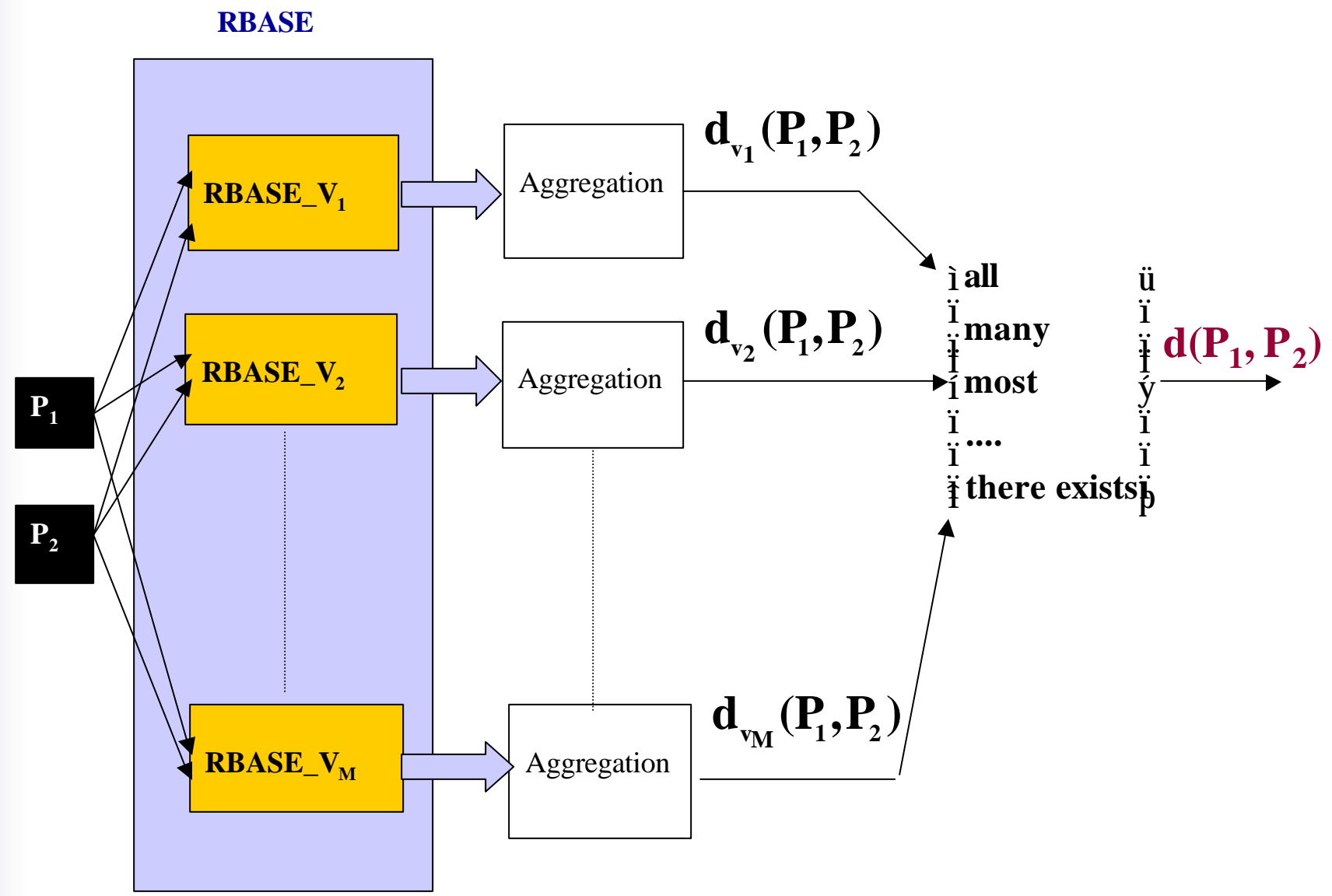
- ↪ Each selected attribute is measured either by numerical or categorical data
- ↪ Categorical data are represented by fuzzy sets rather than classical set
- ↪ **Example:** The factor **DATA** of the COCOMO model

Low	Nominal	High	Very high
$D/P < 10$	$10 \leq D/P < 100$	$100 \leq D/P < 1000$	$D/P \geq 1000$



- ↪ Each selected attribute has a weight expressing its importance,  $U_k$

# ○ Evaluation of software projects similarity



## ⊙ Individual similarities

$$d_{v_j}(P_1, P_2) = \begin{cases} \hat{=} \max_k \min(m_{A_k}^{v_j}(P_1), m_{A_k}^{v_j}(P_2)) \\ \hat{=} \text{max- min aggregation} \\ \text{ou} \\ \hat{=} \hat{=} m_{A_k}^{v_j}(P_1) \cdot m_{A_k}^{v_j}(P_2) \\ \hat{=} \text{sum - product aggregation} \end{cases}$$

## ↪ Overall similarity

$$d(P_1, P_2) = \begin{cases} \text{all of } d_{v_j}(P_1, P_2) \\ \text{most of } d_{v_j}(P_1, P_2) \\ \text{many of } d_{v_j}(P_1, P_2) \\ \text{at least four of } d_{v_j}(P_1, P_2) \\ \dots \\ \text{there exists of } d_{v_j}(P_1, P_2) \end{cases}$$



$$d(P_1, P_2) = \hat{=} \hat{=} w_j d_{v_j}(P_1, P_2) \quad j=1$$

$$w_j(P_1, P_2) = Q\left(\frac{\sum_{k=1}^j u_k}{T}\right) - Q\left(\frac{\sum_{k=1}^{j-1} u_k}{T}\right)$$



## ⊙ Adaptation

### ⊙ Two questions

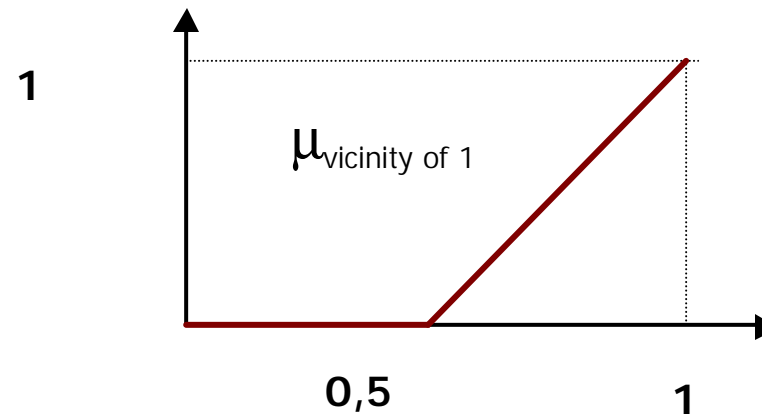
- ⊙ 1- How many similar projects will be used in the adaptation?
- ⊙ 2- How to adapt the chosen analogies in order to generate an estimate for the new project?

### ⊙ In the literature, there is no clear rule to guide the choice of the number of similar projects, **K**

- ⊙ In general **K=2**
- ⊙ Suppose that the first three similar projects to the new project P have the following distances: **3.00**, **4.00** and **4.01**
- ⊙ When **K=2**, we consider only the two first projects
- ⊙ Why we have not take into account the third projects?

## ⊙ Solution

- ⊙ What is 'P<sub>i</sub> is closely similar to P'?
- ⊙ The d(P<sub>i</sub>, P) is in the vicinity of 1



## ⊙ Adaptation formula:

$$\text{Effort}(P) = \frac{\sum_{i=1}^N \mu_{\text{vicinity of 1}}(d(P, P_i)) \times \text{Effort}(P_i)}{\sum_{i=1}^N \mu_{\text{vicinity of 1}}(d(P, P_i))} \quad (3)$$

If  $\mu_{\text{vicinity of 1}}(x) = x$  then (3) is exactly the ordinary weighted average

## ***Conclusions and Future work***

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- ⊙ **We have propose a new approach for software cost estimation: Fuzzy Analogy when software projects are described by categorical data**
- ⊙ **Fuzzy Analogy is also applicable when the variables are numeric (no uncertainty)**
- ⊙ **Advantages of Fuzzy Analogy**
  - ↪ It can handle correctly the imprecision and the uncertainty when describing software project
  - ↪ It can be easily adapted to the needs of each organization (RIM linguistic quantifiers, Vicinity of 1, ...)

- ⊙ **Empirical validation of Fuzzy Analogy is based on**

- ↪ COCOMO'81 dataset

- ↪ **F\_ANGEL**: A Software prototype based on Fuzzy Analogy

- ( To be submitted at 8<sup>th</sup> IEEE Metrics, June, Ottawa, Canada)

- ⊙ **Building prediction systems by analogy that satisfy Soft Computing:**

- ↪ Tolerance of imprecision (Fuzzy Logic)

- ↪ Learning (Neural Networks)

- ↪ Uncertainty (Belief networks, genetic algorithms,...)