Evaluating Software Project Similarity by using Linguistic Quantifier Guided Aggregations

Ali IDRI, ENSIAS, Rabat, Morocco
Alain ABRAN, UQAM, Montreal, Canada

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Summary

- Software Project Similarity Measures: Background and Related Work
- Linguistic Quantifiers
- Limits of the Existing Similarity Measures
- Improvements by Using Linguistic Quantifiers
- Illustration with COCOMO'81 Dataset
- Conclusions and Future Work

Software Project similarity Measures

- **Software Project similarity is one of the most important process software attribute**
- **It is often used when estimating software development effort by analogy**
- **Intuitively, two software projects are not similar if the <u>differences</u> between their <u>sets of attributes</u> are <u>obvious</u>**
- **Analogy**

Human	Software Project
Size	Size
Color of skin	Complexity
Color of eyes	Reliability
Color of hair	Analysts competency
...	...

Related Work

Sheppered et al. (1997)

$$d(P_1,P_2,V) = \frac{1}{\sum_{v_j} d_{v_j}(P_1,P_2)} \quad d_{v_j}(P_1,P_2) = \begin{cases} (v_j(P_1) - v_j(P_2))^2 \\ \begin{cases} 0 & if \quad v_j(P_1) = v_j(P_2) \\ 1 & if \quad v_j(P_1) \neq v_j(P_2) \end{cases} \end{cases}$$

Idri and Abran, 7th 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, 6th MCSEAI, Morocco, 2000

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

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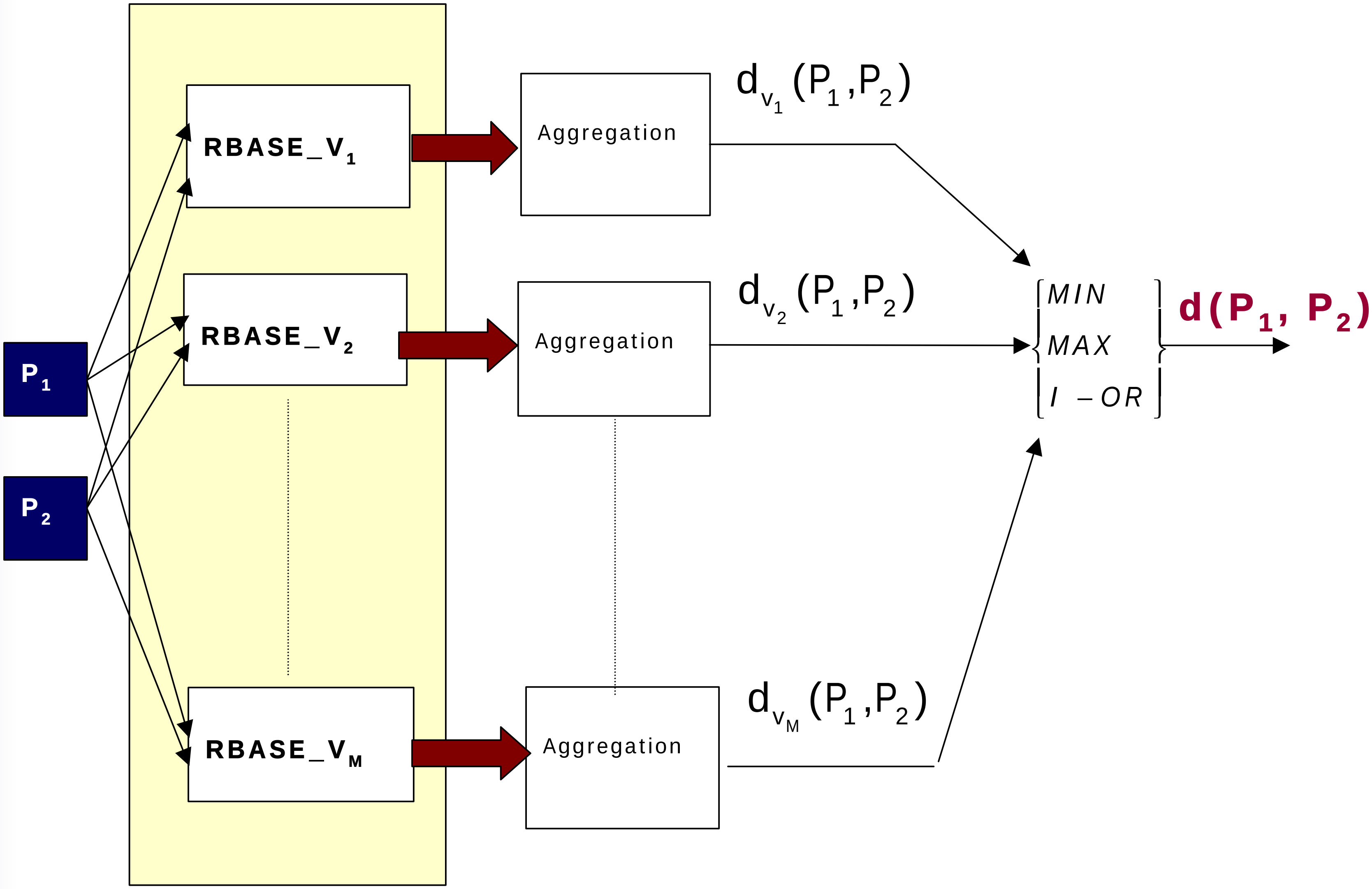
RBASE


RBASE_V1
RBASE_V2
RBASE_VM
P1
P2
Aggregation
Aggregation
Aggregation
$d_{V_1}(P_1,P_2)$
$d_{V_2}(P_1,P_2)$
$d_{V_M}(P_1,P_2)$
$\begin{Bmatrix} MIN \\ MAX \\ I-OR \end{Bmatrix}$
$d(P_1, P_2)$

Idri and Abran, 7th IEEE Metrics, London, 2001

After an axiomatic validation, we have retained the following similarity measures :

$$d_{v_j}(P_1,P_2) = \mu_{\underset{\approx}{R}^{v_j}}(P_1,P_2) = \begin{cases} \max_k \min(\mu_{A_k}^{v_j}(P_1), \mu_{A_k}^{v_j}(P_2)) \\ \max-\min \;\; aggregation \\ ou \\ \sum_k \mu_{A_k}^{v_j}(P_1) \times \mu_{A_k}^{v_j}(P_2) \\ sum - product \;\; aggregation \end{cases}$$

$$d(P_1,P_2) = \begin{cases} \min(d_{v_1}(P_1,P_2),\ldots,d_{v_M}(P_1,P_2)) \\ \max(d_{v_1}(P_1,P_2),\ldots,d_{v_M}(P_1,P_2)) \\ i-or(d_{v_1}(P_1,P_2),\ldots,d_{v_M}(P_1,P_2)) = \begin{cases} 0 \quad \exists k,h / d_{v_k}(P_1,P_2) = 1 \text{ and } d_{v_h}(P_1,P_2) \\ \dfrac{\prod_{j=1}^{M} d_{v_j}(P_1,P_2)}{\prod_{j=1}^{M}(1-d_{v_j}(P_1,P_2)) + \prod_{j=1}^{M} d_{v_j}(P_1,P_2)} \quad \text{otherwise} \end{cases} \end{cases}$$

Objective

To improve our similarity measures by using a **soft aggregation** of the individuals similarities

Similarity measures will be easily calibrated and adapted to the needs and the characteristics of each organization

Linguistic quantifiers

- **Human discourse uses a large number of linguistic quantifiers**
- **Zadeh distinguishes between two classes:**
  - Absolute linguistic quantifiers
  - 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**)

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Limits of the existing similarity measures

- **In the previous work, we have used only two RIM quantifiers '<u>all</u>' and '<u>there exists</u>' to combine the individual distances**

- **Critics:**
  - The **'all'** and the **'there exists'** quantifiers are not always a good combination:

$$d_{v_{j0}}(P_1, P_2) = 0 \text{ (or 1)}, \quad d_{v_j}(P_1, P_2) = 1 \text{ (or 0) for } j \neq j_0$$

When we use a *min* (or *max*) operator, the overall distance $d(P_1, P_2)$ is null (or equal to 1), while a suitable combination would seem to give a value in the vicinity of 1 (or 0);

- In many situations, other linguistic quantifiers can be useful such that **'most'**, **'many'**, and **'at least a'**

- We must take into account the importance of the variables describing the software projects because often the influence of some variables is greater than of others

- The **i-or** operator?

1. **It has no clear natural interpretation**

$$\frac{ab}{(1-a)(1-b)+ab} = w_1 a + w_2 b \quad with \quad \begin{cases} w_1, w_2 \in [0,1] \\ w_1 + w_2 = 1 \end{cases}$$

2. **Suppose that we have**

$$d_{v_{j0}}(P_1, P_2) = 1, \quad d_{v_j}(P_1, P_2) - \approx 0 \text{ for } j \neq j_0$$

When applying the I-or operator, the overall distance $d(P_1,P_2)$ is equal to 1, while a suitable combination seems to give a result other than 1.

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Improvements by using Linguistic Quantifiers

Solution

Evaluation of the $d(P_m,P_n)$ by aggregating the individual distances using RIM linguistic quantifiers

$$d(P_m,P_n) = \begin{cases} all \;\; of \;\; d_{v_j}(P_m,P_n) \\ most \;\; of \;\; d_{v_j}(P_m,P_n) \\ many \;\; of \;\; d_{v_j}(P_m,P_n) \\ at \;\; least \;\; four \;\; of \;\; d_{v_j}(P_m,P_n) \\ \ldots \\ there \;\; exists \;\; of \;\; d_{v_j}(P_m,P_n) \end{cases}$$

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RIM linguistic quantifiers is implemented by OWA operators

- We must provide the appropriate linguistic quantifier to be used in an organization, **Q**
- The linguistic quantifier, **Q**, is used to generate an OWA weighting vector **W (w_1, w_2, …, w_M)**
- We calculate the overall similarity by :

$$d(P_1, P_2) = \sum_{j=1}^{M} w_j d_{v_j}(P_1, P_2)$$

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

Illustration with COCOMO'81 dataset

- **COCOMO'81 dataset is composed of 63 software projects**

- **Each project is described by 17 attributes:**

  - Software size measured in **KDSI**

  - Project Mode is defined as **Organic**, **Semi-detached** or **Embedded**

  - 15 cost drivers related to the software environment

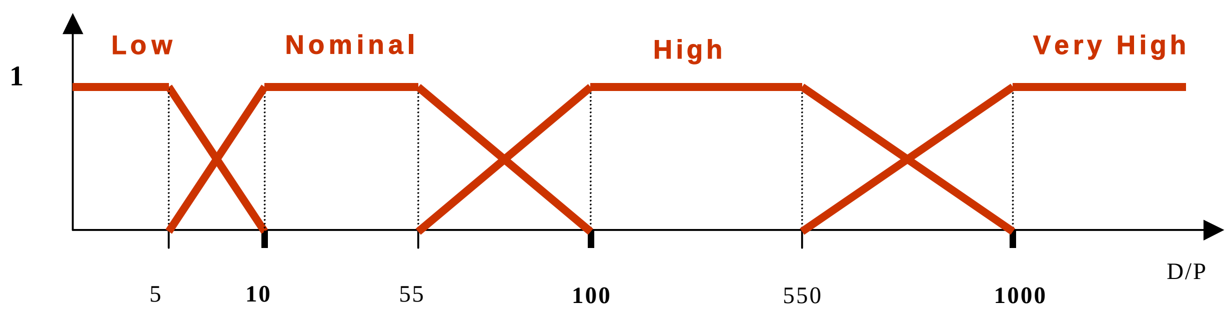
    Very low, Low, Nominal, High, Very high, Extra-high

Example: DATA cost driver

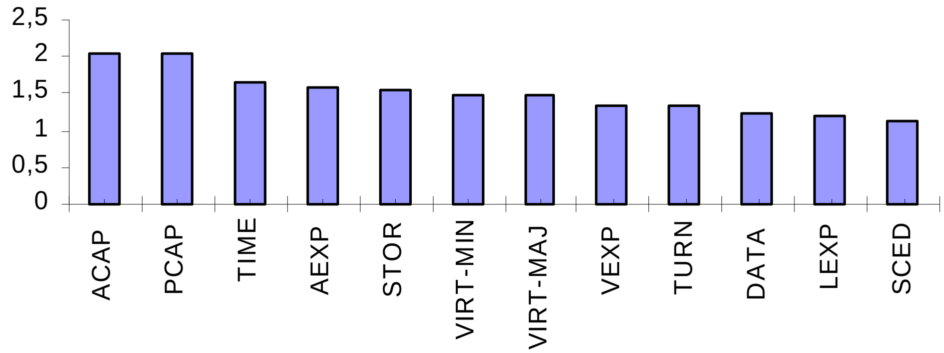
$$\frac{D}{P} = \frac{\text{Database size in bytes or characters}}{\text{Program size in DSI}}$$

Low	Nominal	High	Very high
D/P<10	10<=D/P<100	100<=D/P<1000	D/P>=1000

- It is more general
- It mimics the way in which humans interpret linguistic values
- The transition from one linguistic value to a contiguous linguistic value is **gradual** rather than **abrupt**



- For simplification purpose, we calculate only the similarity between the first project and the first five projects of the dataset
- Our measures are computationally intensive; so we have developed a software prototype with VB and MS-access
- The prototype allows us to try various RIM linguistic quantifiers **Q** to the COCOMO'81 dataset
- The weights U_k is calculated by means of the project's productivity ratio :



- **In this illustration, we use RIM linguistic quantifiers defined by :**

$$Q(r) = r^{\alpha} \quad (\alpha > 0)$$

- **We use only the max-min aggregation to calculate the individual similarities:**

  - If all the fuzzy sets associated to software project attributes are **normal**, **convex** and form a **fuzzy partition** then max-min and sum-product aggregations give approximately the same results

  - The sum-product aggregation does not respect all axioms

$$d(P_i, P) \leq d(P, P) \; ?$$

		Max-min aggregation $d_{v_j}(P_1, P_n)$					
		d(P_1, P_n)					
			P_1	**P_2**	**P_3**	**P_4**	**P_5**
P_1	**a**	Max	**1**	**1**	**1**	**1**	**0,84096**
		1/100	0.99824	0.98529	0.97938	0.99095	0.82482
		1/30	0.99416	0.95189	0.93298	0.97018	0.78841
		1/20	0.99128	0.92879	0.90124	0.95564	0.76343
		1/15	0.98842	0.90629	0.87061	0.94134	0.73927
		1/10	0.98275	0.86304	0.81253	0.91344	0.69331
		1/7	0.97559	0.81069	0.74370	0.87890	0.63855
		1/5	0.96625	0.74617	0.66117	0.83505	0.57245
		1/3	0.94533	0.61618	0.50335	0.74178	0.44446
		1	0.85691	0.24612	0.132939	0.417857	0.13026
		3	0.69875	2.0948E-02	2.9783E-03	8.4882E-02	4.4606E-03
		5	0.62337	2.3918E-03	7.4220E-05	1.9233E-02	2.0768E-04
		7	0.58426	3.2462E-04	1.8898E-06	4.6167E-03	1.1676E-05
		10	0.55523	1.8895E-05	7.7274E-09	5.7808E-04	1.8904E-07
		15	0.53637	1.8861E-07	8.0929E-13	2.0205E-05	2.3544E-10
		20	0.52940	1.9602E-09	8.4763E-17	7.9559E-07	3.0742E-13
		30	0.52445	2.1614E-13	9.2985E-25	1.7490E-09	5.3075E-19
		100	0.52145	4.4160E-41	1.7777E-80	1.1339E-26	2.4419E-59
		Min	**0.52144**	**0**	**0**	**0**	**0**

Conclusions and Future work

- **We have improved a set of similarity measures by using linguistic quantifier guided aggregation.**
- **These measures are also applicable when the variables are numeric (no uncertainty)**
- **The advantages of using RIM linguistic quantifiers to combine the individual similarities are:**
  - The aggregation is **soft** rather than **hard**, so we can tolerate some restrictions in the decision making
  - The measures can be easily adapted to the needs of each organization

- **The empirical validation of estimation effort by analogy must be achieved:**
  - For the individual distance, we use the two retained measures
  - For the overall distance, we use RIM linguistic quantifiers
- **Can I use our measures for prediction of Size, Reliability, Maintainability,…?**
- **Building prediction systems by analogy that satisfy Soft Computing:**
  - Tolerance of imprecision (Fuzzy Logic)
  - Learning (Neural Networks)
  - Uncertainty (Belief networks, genetic algorithms,…)