An Experiment on the Design of RBF Networks for Software Cost Estimation

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Outline

- Motivations and Objectives
- Clustering techniques for RBF networks
- Experiment Design and Data Description
- Overview of Empirical Results
- Conclusions and Future Work

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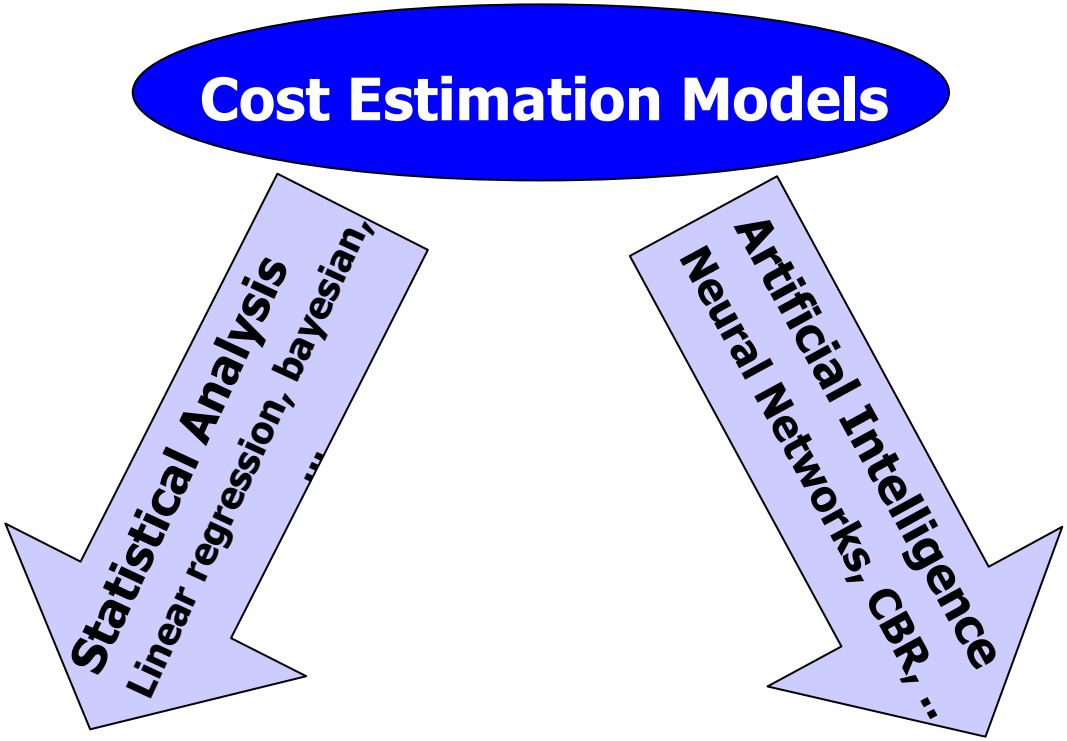
Motivations and Objectives

- **Software cost estimation is one of the most critical activities in managing software projects**



Algorithmic Models **Non-Algorithmic Models**

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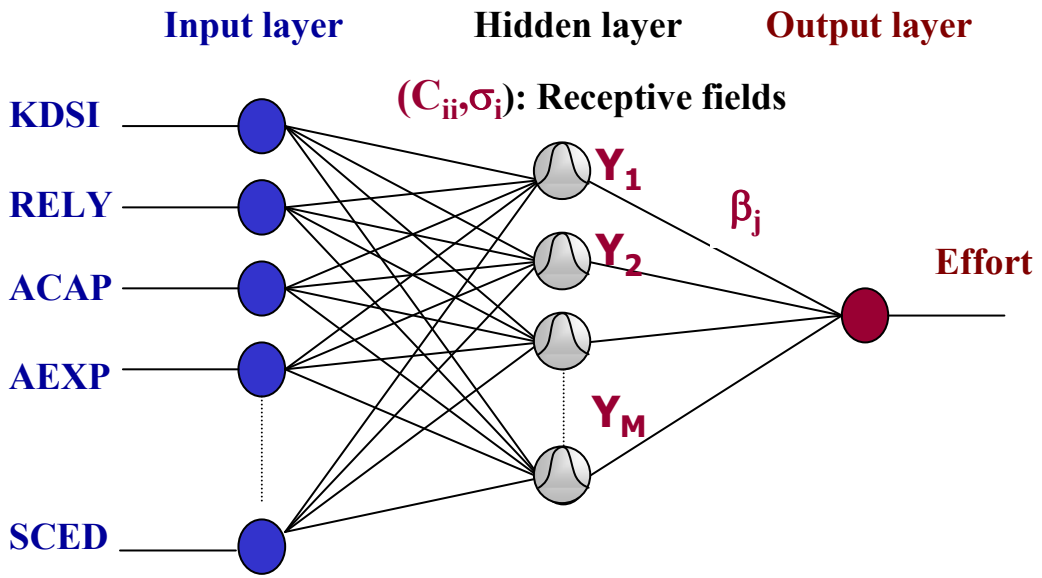
⊙ Estimation by ANN is a promising technique to solve the software cost estimation problem:

- ➢ It provides learning from historical projects data
- ➢ It can model a complex set of relationships between the dependent variable (cost, effort) and the independent variables (cost drivers)



$$Effort = \sum_{j=1}^{M} y_j \beta_j \qquad with \quad y_j = e^{\left(-\frac{\|x-c_j\|^2}{\sigma_j^2}\right)}$$

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⊙ The use of RBFN to estimate Software development effort requires the determination of the midde-layer parameters:

- Clustering techniques
- Empirical domain knowledge

⊙ Objectives

- To discuss the preprocessing phase of the design of RBFN using two clustering techniques : C-means and APC-III algorithms
- To validate the software cost estimation models based on RBFN

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Clustering Techniques for RBF Networks

- Clustering is one method to find most similar groups from given data, which means that data belonging to one cluster are the most similar; and data belonging to different clusters are the most dissimilar
- Clustering techniques may be grouped into major categories : Hierarchical and Partitional
- Partitional clustering algorithms suppose that the data set can be well represented by finite prototypes

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- **Clustering has been often exercised as a preprocessing phase used in the design of the RBF neural networks**
- **The primary aim of clustering is to set up an initial distribution of the receptive fields (hidden neurons) across the space of the input variables**
- **We use two clustering techniques :**
  - **APC-III**
  - **C-means**

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- **APC-III clustering algorithm (Hwang and Bang, 1997)**
  - **APC-III is a one-pass algorithm unlike C-means**
  - **It has a constant radius R_0**

$$R_0 = \alpha \frac{1}{N} \sum_{i=1}^{N} \min_{i \neq j} (\| P_i - P_j \|)$$

  - **The number of clusters depends on the α and the sequence presentation of the projects**

- **The C-means algorithm partitions a collection of N vectors into C clusters Ci, i=1,..,c to minimize**

$$J = \sum_{i=1}^{c} \sum_{x_k \in C_i} \| x_k - c_i \|^2$$

  - **C-means is a multip-pass algorithm**
  - **The number of clusters is fixed in the beginning**

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Experiment Design

- The experiment uses the COCOMO'81 dataset
- This dataset contains 263 historical software projects
  - Each project is described by 13 attributes
    - ✓ Software size measured in terms of KDSI
    - ✓ 12 attributes related to the software development environment such as software complexity, the method used in the development and the time and storage constraints imposed on the software
- Number of input neurons is the same as the number of cost drivers, say 13
- The number of hidden neurons is determined by the number of clusters (c) provided by the APC-III or the C-means algorithms

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- **In addition, the configuration of the RBFN depends also on the widths σi used by the hidden units**
- **In the literature, the widths were determined to cover the input space as uniformly as possible**
  - **Consequence : The RBFN will be able to generate an estimate for a new project even though it is not similar to any historical project**
  - **Preference: The RBFN does not provide any estimate than one it may easily lead to wrong managerial decisions**
- **Our strategy :**

$$\sigma_i = \begin{cases} \max\limits_{x_j \in C_i} d(x_j, c_i) & if\ card(C_i) > 1 \\ \max\limits_{k/card(C_k)>1} \sigma_k & if\ card(C_i) = 1 \end{cases}$$

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Empirical Results

- The calculations were made using two software prototypes developed with C language under a Microsoft Windows PC environment.
  - The first software prototype implements the APC-III and the C-means clustering algorithms, providing both the clusters and their centers from the COCOMO'81 dataset.
  - The second software prototype implements a cost estimation model based on an RBFN architecture in which the middle-layer parameters are determined by means of the first software prototype
- We have conducted several experiments with both the C-means and the APC-III to decide on the number of hidden units

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- **Choosing the 'best' classification to be used in the RBFN depends on the following two criteria:**
  - **It improves the accuracy of the RBFN**
  - **It provides coherent clusters, i.e. the software projects of a given cluster have satisfactory degrees of similarity**
- **The accuracy of the estimates is evaluated by :**
  - **MMRE**

$$MMRE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Effort_{actual,i} - Effort_{estimated,i}}{Effort_{actual,i}}\right| \times 100$$

  - **Pred (0.25)**

$$Pred(p) = \frac{k}{N}$$

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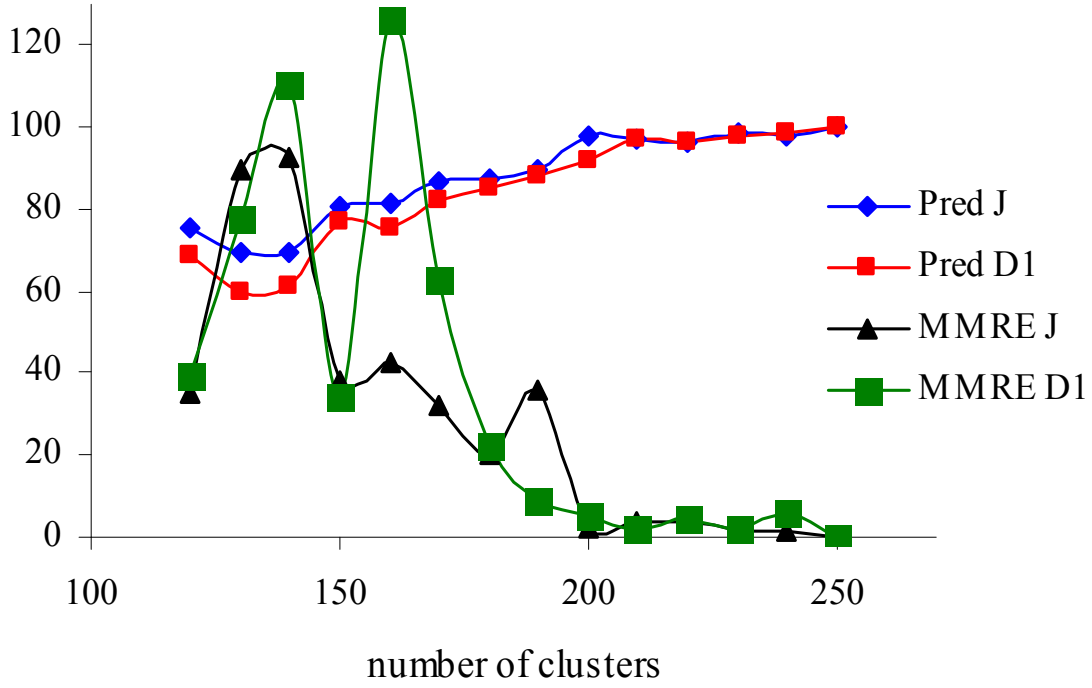
Accuracy of an RBFN with C-means

- The coherence of clusters is measured by the means of two criteria: the objective function J or the Dunn's validity index defined by the following formula:

$$D_1 = \min_{1 \le i \le c} \left(\min_{i+1 \le j \le c-1} \left(\frac{d(C_i, C_j)}{\max_{1 \le k \le c}(d(C_k))} \right) \right)$$



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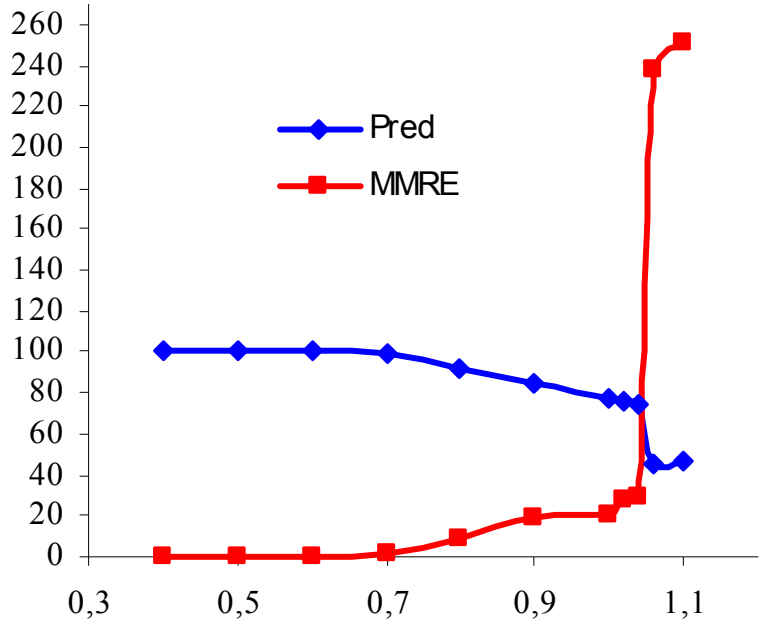
- **Accuracy of an RBFN with APC-III is better when α is lower than 1.04 (MMRE<30 and Pred (25)>70)**

α	Number of clusters
0.4|0.5|0.6|0.7|0.8	251|244|234|216/200
0.9|1.0|1.02|1.04	189|170|162|161
1.06|1.08|1.1	155|151|150



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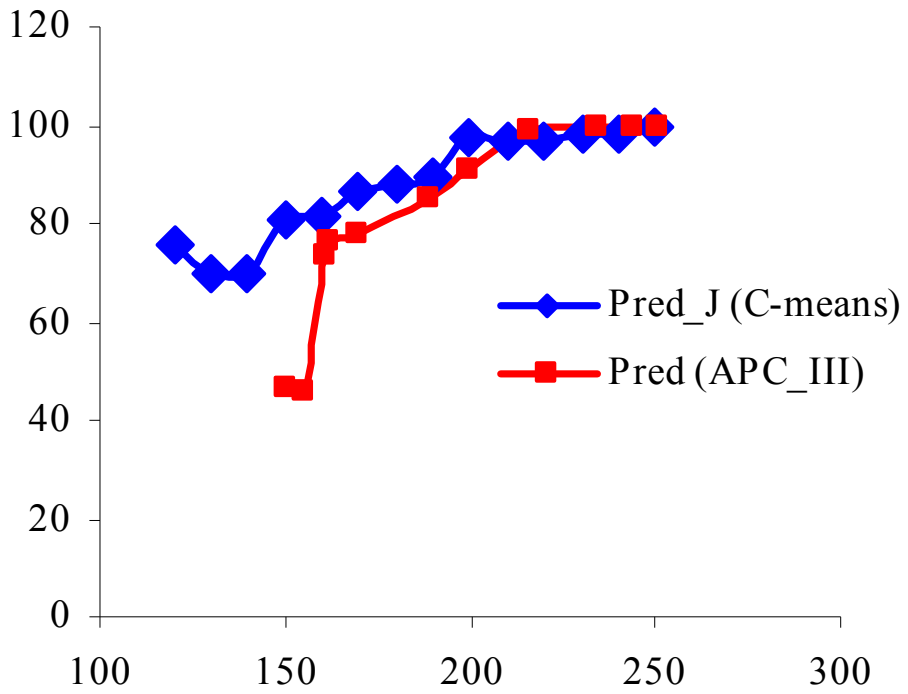
Comparing the accuracy of RBFN using C-means vs APC-III



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Conclusion and Future Work

- We have studied the use of two clustering techniques when designing an RBFN for software cost estimation
- The two used clustering techniques are C-means and APC-III
- The RBFN designed with C-means performs better, in terms of cost estimates accuracy, than the RBFN designed with the APC-III algorithm
- Further work :
  - Applying an RBFN construction based C-means on other historical software projects datasets.
  - Using different datasets for training and testing an RBFN in software cost estimation

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