Effort Prediction Models for Interval Estimation

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Interval Estimation

- Confidence intervals for Point Estimations
  - Regression
  - Estimation by Analogy
  - Other statistical models
- Estimation of Probabilities of Predefined intervals
  - Ordinal Regression
  - BBNs
  - Machine learning methods

Advantages of interval estimation

- Safer to produce interval estimates, along with a probability distribution over the estimated intervals
- Relying blindly on point estimates may lead easily in wrong decisions
- An interval estimate can provide a point estimate for practical purposes
- Intervals give information about the reliability of the estimation process
- Intervals provide the basis for risk and what-if project analysis

Relevant research at PLaSE Lab

- Since 1999…
  - Statistical models for interval estimation
  - Comparisons of various models
  - Phd students
  - Master theses
  - Involved in two relevant funded research projects
  - Most recent project: Optimization of Telecommunication Software process development (DIERGASIA)

Confidence Intervals for Estimation by Analogy (EbA)

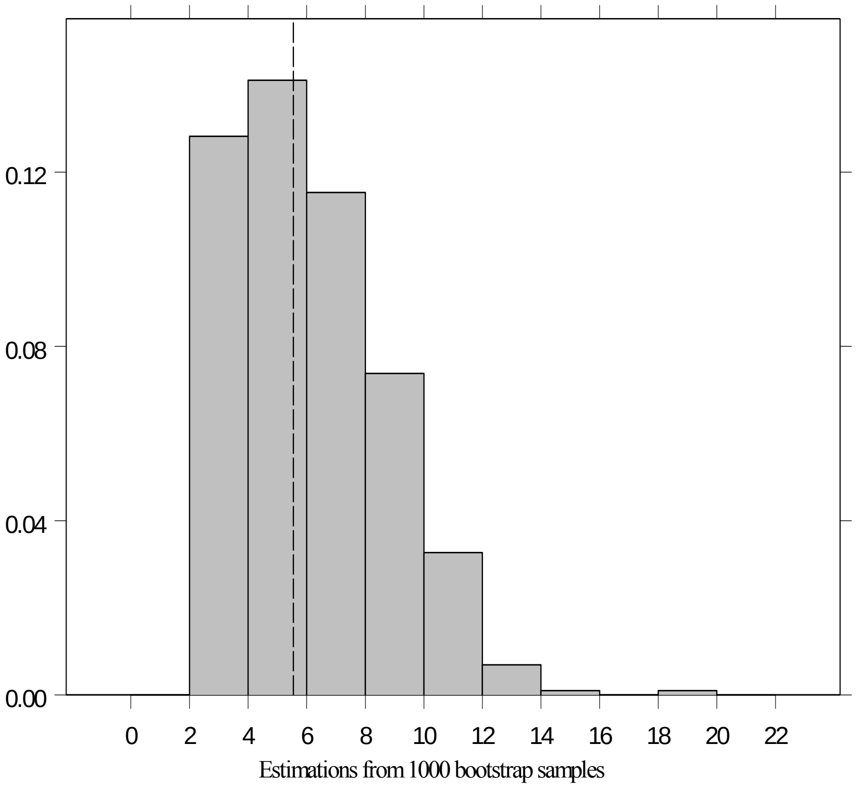
- Bootstrap resampling methods
  - Non-parametric bootstrap (draw samples with replacement from the original sample)
  - Parametric bootstrap (draw samples from a theoretical distribution fitting well to the sample)
- The same methods were used for calibration of EbA (number of analogies, distance metric, standardization, etc)

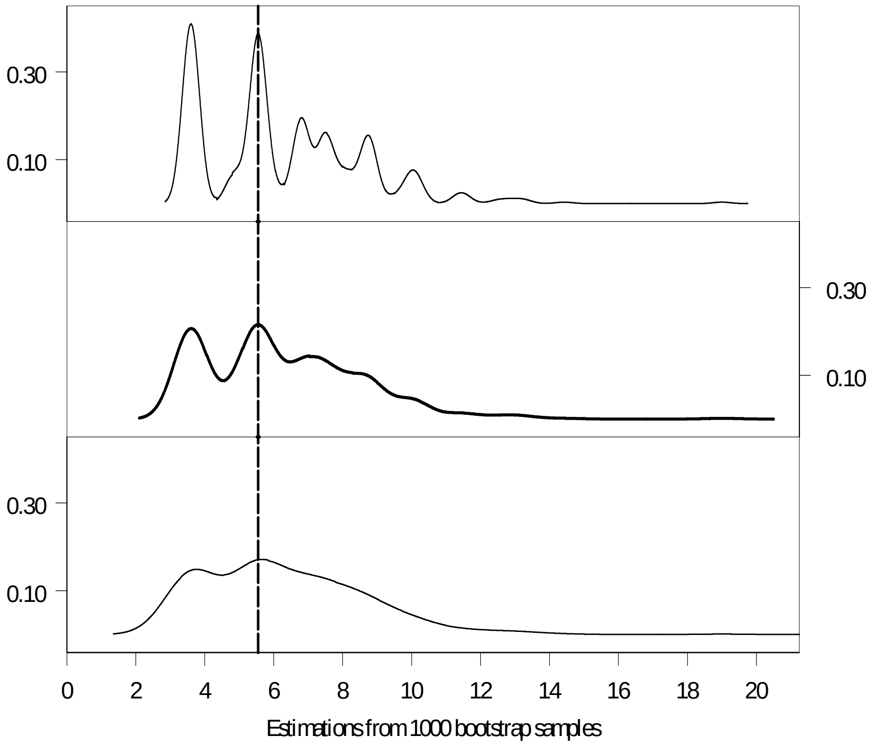
Example (Albrecht data set)

- Non-parametric bootstrap confidence interval
- Estimate the effort of a new hypothetical project:
- Predictors: IN = 27, OUT = 36, FILE = 20, INQ = 10.
- Point estimation based on 2 analogies = 5.55 man months
- *B* = 1000 bootstrap samples, estimation each time of the effort using 2 analogies exactly as for the point estimation
- Confidence intervals (using bootstrap distribution and kernel density smoother):

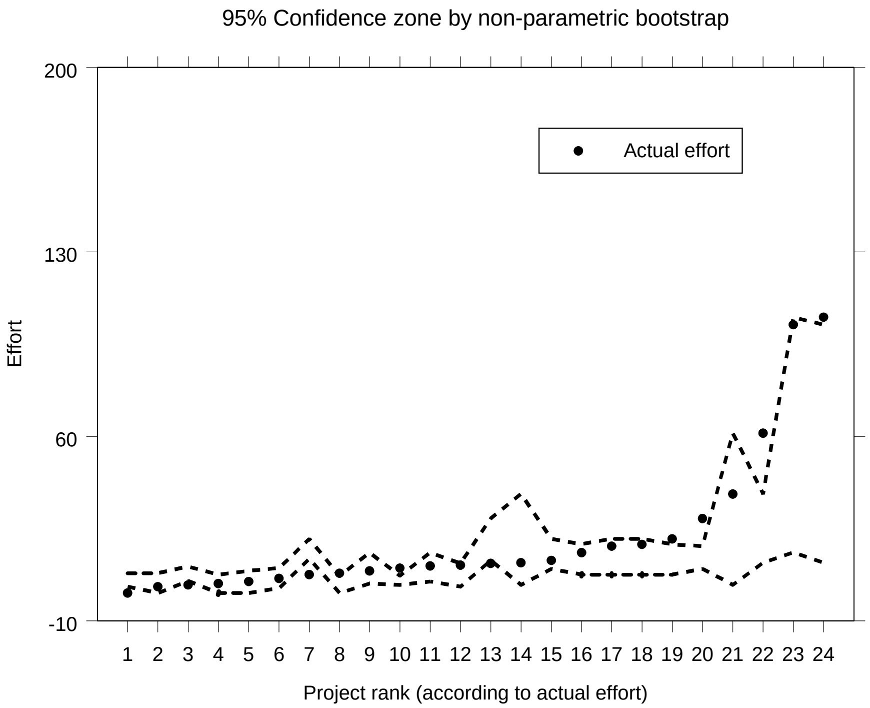
$$95\%\ CI_{boot} = [3.6, 11.45] \qquad 50\%\ CI_{boot} = [3.6, 7.5]$$

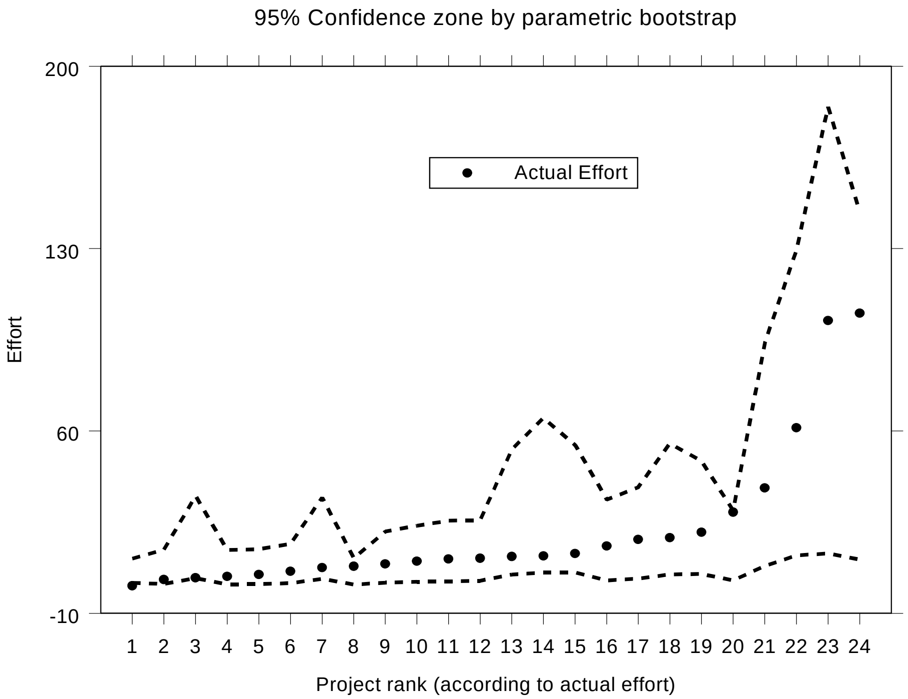
Example (cont.)



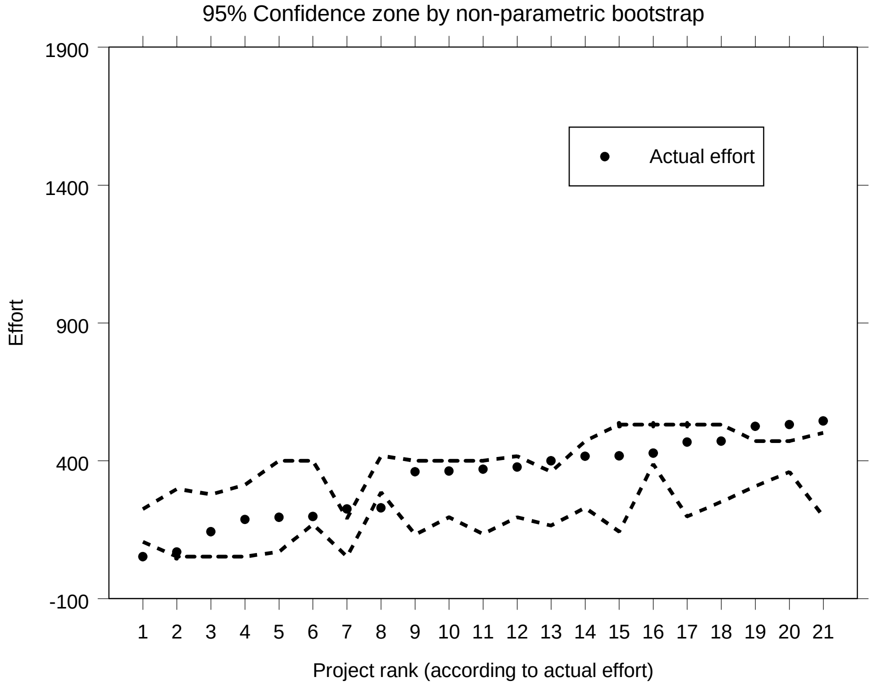


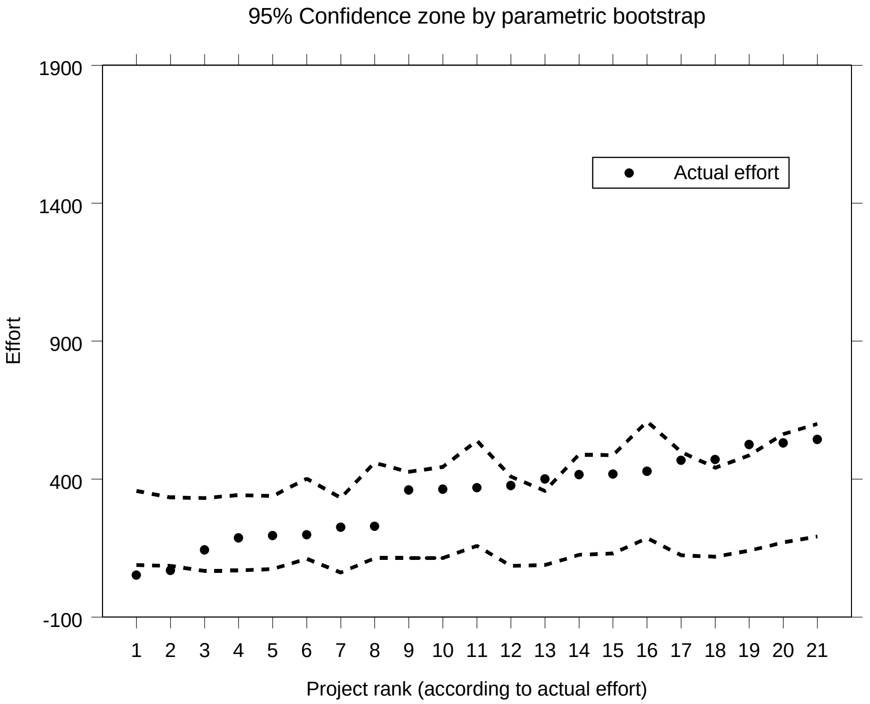
Confidence zones for EbA using bootstrap and jackknife (Albrecht data set)





Confidence zones for EbA using bootstrap and jackknife (Abran-Robillard data set)





BRACE (BootstRap Based Analogy Cost Estimation)

- Typical input/output functions and file management facilities
- Definition of attributes and project characterisation
- Project/attribute management (e.g. exclusion of projects/attributes from calculations)
- Choice of options to be considered for method calibration (with and without bootstrap)
- Determination of the best attribute set (the one providing the better accuracy results according to some criterion)
- Generation of estimations for a single project (with and without bootstrap)

A Case Study in Industrial Context

- Controlling the Cost of Software Development for Supply Chain Information Systems
- **Supply Chain ISBSG Project Subset**
  - 59 projects implementing information systems for manufacturing, logistics, warehouse management, …
  - characterised through effort, size, elapsed time, team size, project nature attributes
  - accurate project attribute measurement
  - average productivity ~ 190 FP/ 1000 mh
- **BRACE Application**
  - Various strategies were tried because of missing values
  - Best strategy pursued a trade-off between number of projects and attributes
  - Precision was measured through jackknife
  - Different treatment for elapsed time and max team size

Interval Estimation of the cost of a project portfolio

- Combination of :
  - EbA
  - non-parametric bootstrap
  - Stochastic Budget Simulation)

- The method allows risk analysis

Example

- Cost data set: Abran – Robillard
- 21 projects - 10 variables
- 16 projects considered completed
- 5 project considered new (portfolio)
- Estimation by analogy and 1000 bootstrap samples: empirical distributions of individual projects

Histogram of the 1000 bootstrap estimates for each one of the individual efforts

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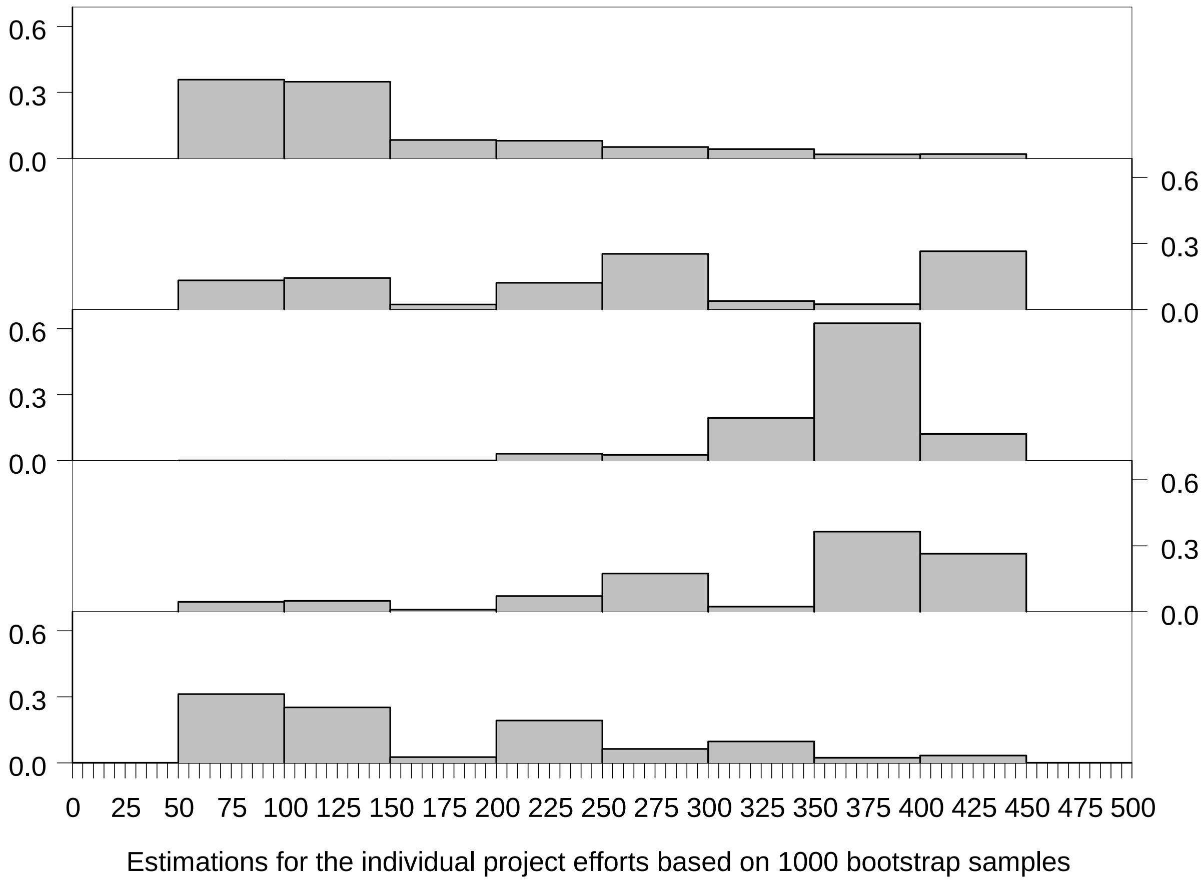
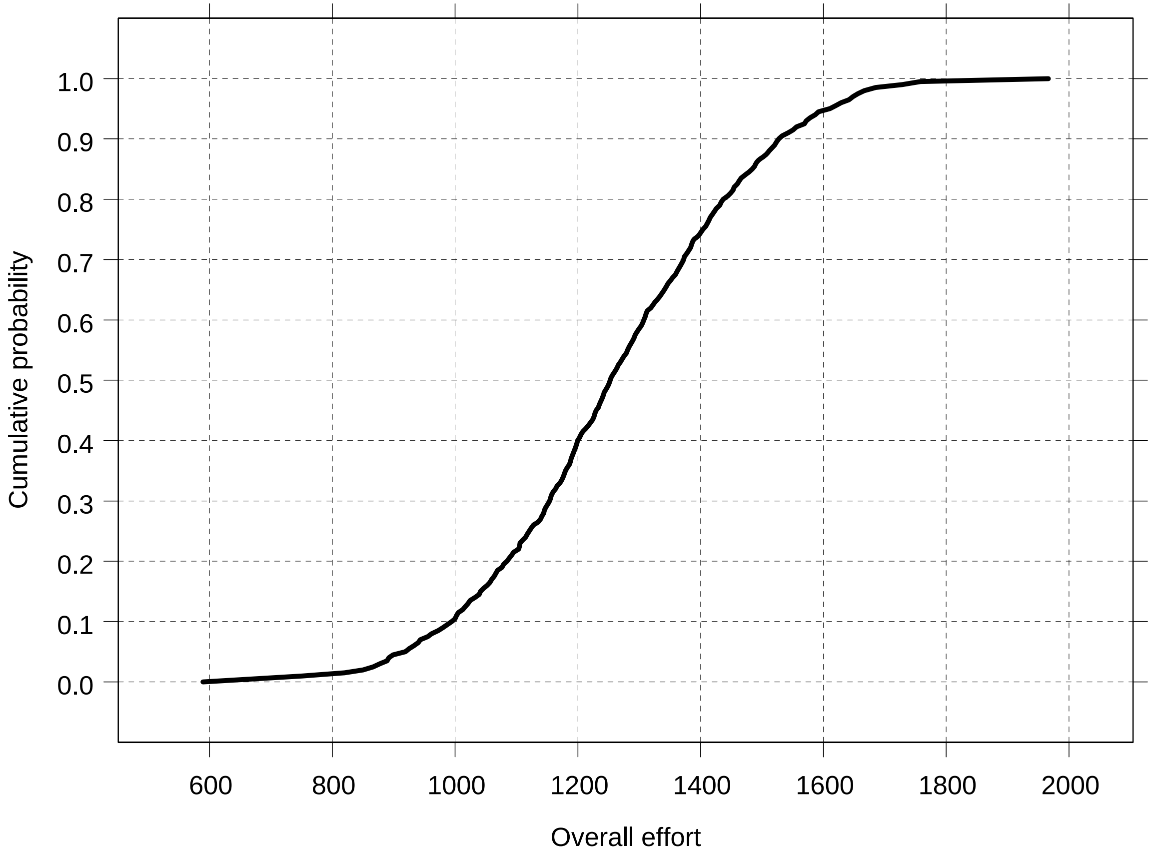


Using the empirical distribution for simulation

- Fitting of a known theoretical distribution or a smoothing procedure like *kernel density estimation*
- Stochastic simulation sampling from fitted distributions a large number of times, adding each time the individual effort values to get the overall effort
- The entire set of the overall effort values from simulation produces the cumulative density function (useful for computing probabilities of various effort intervals)

Cumulative distribution function of the overall effort obtained by Stochastic Budget Simulation



Confidence intervals for project portfolios costs

99% Confidence intervals for the overall effort for project portfolios

Portfolio number	Portfolio projects	Actual effort	99% CI (BS-ED method)	99% CI (BS-SBS method)
1	17, 20, 21, 5, 7	1147	533–2026	664–1771
2	6, 9, 10, 15, 17	1276	782–2013	890–1725
3	9, 12, 13, 18, 20	1341	920–2014	1035–1942
4	4, 7, 8, 13, 15	1414	1040–2027	1148–1791
5	12, 15, 16, 21, 2	1417	1089–2002	1136–1851
6	18, 21, 1, 6, 8	1439	1116–2011	1221–1984
7	15, 18, 19, 3, 5	1444	834–1945	899–1832
8	21, 3, 4, 9, 11	1519	841–2021	932–1786
9	7, 10, 11, 16, 18	1608	609–1639	770–1541
10	19, 1, 2, 7, 9	1617	712–1931	854–1829
11	20, 2, 3, 8, 10	1621	957–2147	1075–2119
12	8, 11, 12, 17, 19	1623	1135–2102	1313–2063
13	11, 14, 15, 20, 1	1625	1038–1990	1047–1977
14	10, 13, 14, 19, 21	1722	979–1865	999–1866
15	13, 16, 17, 1, 3	1742	693–1554	715–1550
16	5, 8, 9, 14, 16	1787	957–1830	1086–1888
17	14, 17, 18, 2, 4	1928	1166–2039	1211–2014
18	16, 19, 20, 4, 6	2014	1119–1804	1138–1799
19	3, 6, 7, 12, 14	2082	956–2022	1241–1994
20	1, 4, 5, 10, 12	2217	727–1987	1107–1976
21	2, 5, 6, 11, 13	2257	1008–2280	1200–2129

Estimation of predefined intervals – Ordinal Regression

- For ordinal dependent variables (the cost intervals)
- General form of the OR prediction equations :

$$l(c_j) = \theta_j - \sum_{i=1}^{k} \beta_i x_i$$

- c_j the cumulative probability for the -th category,
- $l(\,)$ *link function* (usually one of the following):
  - Logit function: $\log\left(\frac{c}{1-c}\right)$
  - Complementary log-log function: $\log(-\log(1-c))$
  - Negative log-log function: $-\log(-\log(c))$
  - Probit function: $\Phi^{-1}(c)$
  - Cauchit function: $\tan(\pi(c-0.5))$

Application of OR to three data sets (4 categories)

- Maxwell
- COCOMO81
- ISBSG 7

$$l(c_j) = \theta_j - 2.144 * \delta(apl\_2) + 2.433 * \delta(br\_2) - d_{dbm\_3} * dbm\_3 + 1.707 * \delta(lg\_2) + 4.260 * \delta(org\_2) - 1.045 * year$$

for $j = 1, 2, 3, 4.$

where $\delta(x) = \begin{cases} 1 & \text{if } x = 1 \\ 0 & \text{if } x = 2 \end{cases}$ and $\theta_j = \begin{cases} 2078.154 & \text{if } j = 1 \\ 2080.423 & \text{if } j = 2 \\ 2086.031 & \text{if } j = 3 \\ 0 & \text{if } j = 4 \end{cases}$

$$d_{dbm\_3} = \begin{cases} 3.386 & \text{if } dbm\_3 = 1 \\ 2.311 & \text{if } dbm\_3 = 2 \\ 0 & \text{if } dbm\_3 = 3 \end{cases}$$

Machine Learning methods for predefined intervals

Machine Learning (ML) methods

- Association Rules
- Classification and Regression Trees
- Bayesian Belief Networks

Predefined intervals in combination with ML

- Estimation of an interval
- Probabilities
- Combination of information from past historical data with expert knowledge
- Justification of the estimation

Estimation Process for ML

- Initial discretization of productivity value
- Application of the methods, estimation models
- Transformation of the interval estimate into a numeric estimate using the mean or the median point of the interval
- Calculation of MMRE, pred(25), hitrate

Estimation example

- ISBSG data set release 7
  - Data split in 3 sets according to their application type. Models predicting the productivity values of Management Information Systems (MIS), Transaction Production systems and the rest of the projects
  - Variables used:
    - Function points, time size, language type, primary programming language, organization type, database, development platform, use of methodology, business area type, implemntation date.
  - Methods applied AR, CART, AR+CART (combination)
  - Example: Estimation models of MIS projects
  - Training data set: 128 projects Test data: 7 projects

Association Rules

- Probabilistic statements about the co-occurence of certain events in a database.

IF A1=X AND A2=Y THEN A3=Z

- **A1=X AND A2=Y :** rule body
- **A3=Z** : rule head
- **Confidence:** p(A3=Z|A1=X,A2=Y)
- **Support** : expresses the frequency of the rule in the whole data set.

AR for ISBSG

MIS projects				
no	support	confidence	rule body	rule head
1.	3.1	100.0	BAT = OTHER and PPL in {APG, 4GL, VB, SQL, TELON, OTHER}	$0.137 < P \le 0.273$
2.	9.4	92.3	PPL= ACCESS	$0.274 < P \le 5.353$
3.	3.1	80.0	DP = MF and $286 < FP \le 629$ and DT in {New=development, Re- development}	$0.066 < P \le 0.136$
4.	3.1	80.0	LT= 4GL and DP= PC and OT= ProfessionalServices and BAT in {Engineering, Personnel, Research&Development}	$0.274 < P \le 0.590$
5.	8.6	78.5	DBMS= IMS and BAT in {Banking, Accounting, Logistics, Manufacturing, Sales& Marketing}	$0.015 < P \le 0.065$
6.	7.8	76.9	PPL= COBOL and BAT in {Banking, Accounting, Logistics, Manufacturing, Sales&Marketing}	$0.032 < P \le 0.065$
7.	4.0	71.4	LT=3GL and DBMS=ORACLE	$0.066 < P \le 0.136$
8.	3.1	66.7	BAT=Engineering andPPLin{ACCESS,NATURAL}	$0.274 < P \le 0.590$
9.	2.4	58.3	DT=Enhancement and PPL=SQL	$0.015 < P \le 0.065$
10.	3.9	45.5	LT=4GL and DBMS=ACCESS	$0.591 < P \le 5.353$

AR ISBSG data set

- Support and confidence threshold 3,125% (4 projects) and 45.5 % correspondingly.
- Frequent appearing attributes are Business Area Type (*BAT*) and Development Type (*DT*).
- Rules for high productivity values were very few.

AR-ISBSG data set

- Estimate the project with the following values use the previous table

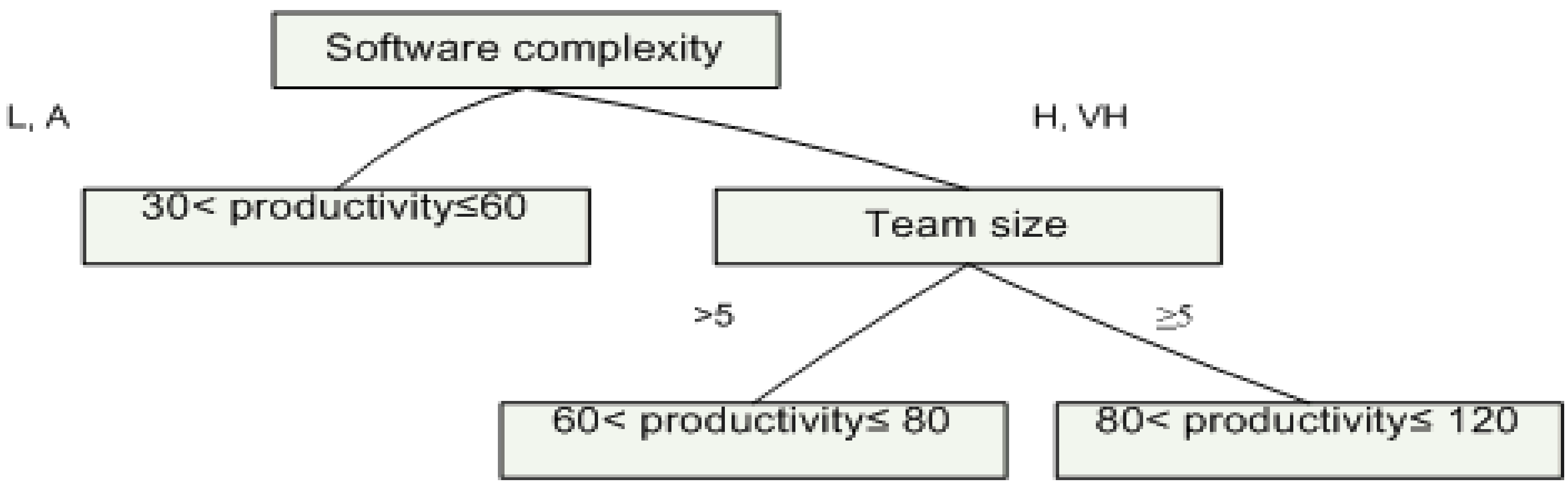
“AT_MIS” “BAT_Engineering” “DBMS_ACCESS” “DT_New Development” “FP_3” “PPL_ACCESS”“LT_4GL” “MTS_3” “OT_ElectricityGasWater” “DP_PC”

- The first two rules that provide estimation for the project are the following:

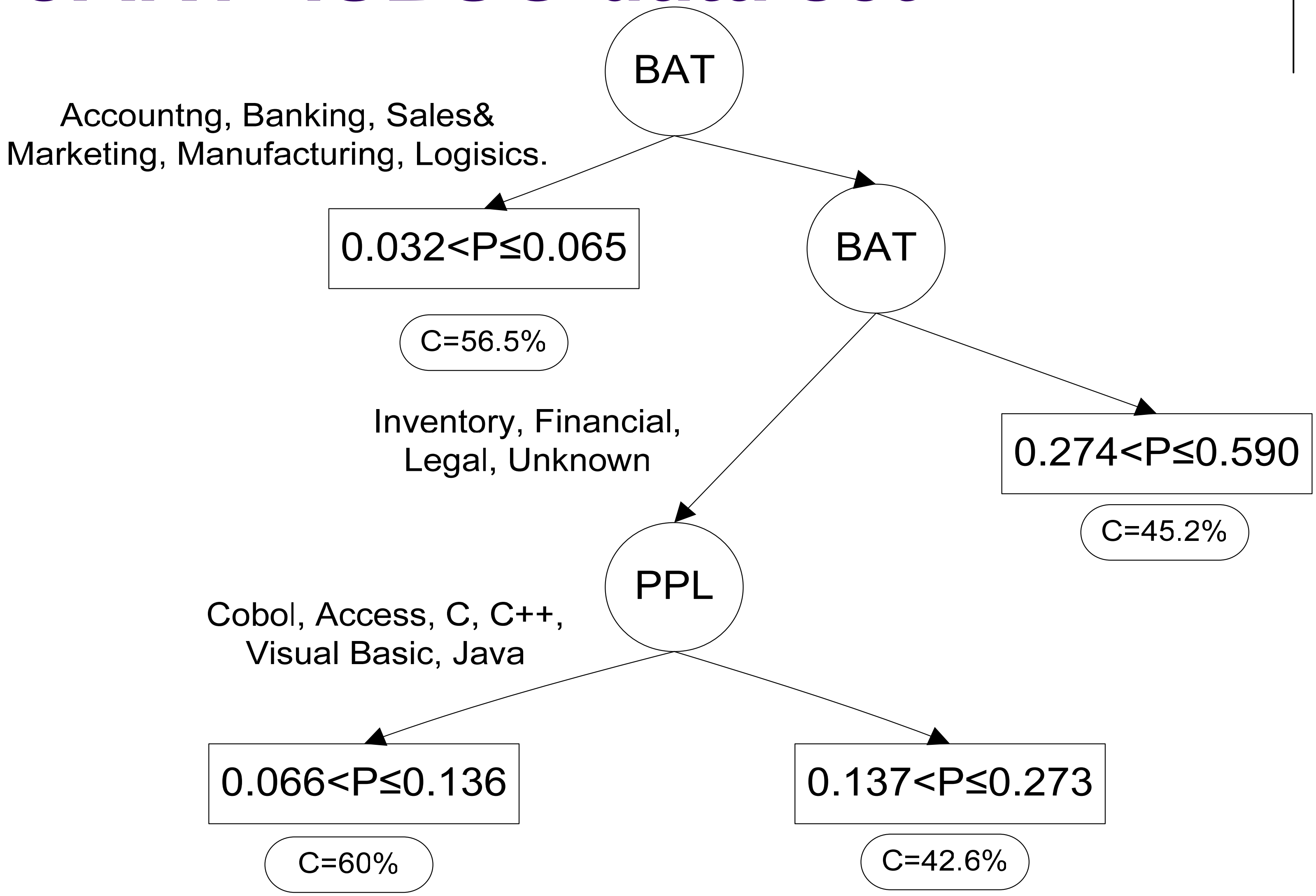
no	support	confidence	rule head	rule body
2.	9.4	92.3	PPL_ACCESS	0.274< P ≤5.353
8.	3.1	66.7	BAT_Engineering+PPL in{ACCESS, NATURAL}	0.274< P ≤0.590

CART

- CART tree model consists of an hierarchy of:
  - Univariate binary decisions.
  - Classifies all possible cases.
  - Example: simple CART estimating productivity measured in Lines of code per hour



CART- ISBSG data set



CART- ISBSG data set

- The CART can be explained as following:
  - If the business area type is Accounting, Banking, Manufacturing, Sales&Marketing, Logistics then there is 56,5% probablitiy that the productivity will be between 0.032 and 0.065 fp/ hour
  - Else if the business area type is Inventory, Financial, Legal or Unknown then if :
    - the language used is C, C++, Cobol, Access, Visual Basic or Java then there is 60% probability that the productivity will be between 0.066 and 0.136 fp/ hour
    - otherwise there is 60% probability that the productivity will be between 0.066 and 0.136 fp/ hour
  - If none of the previous is true then there is 45,2% probability that productivity will be between 0,274 and 0,590 fp/h.

AR+CART

- The method exploits the advantages of AR
  - pertinent relationships among the project attributes and the development
  - AR is a method for descriptive modeling
  - representation form of AR, is transparent
- CART method on the other hand
  - as a predictive modeling method
  - provides a complete estimation framework
  - constructs a model that classifies *all* projects
  - CART also avoids overfitting of the model to the historical data information
- The combination of the methods provides:
  - Improved estimation results
  - Better understanding of the problem
  - Deals with the problem of AR to provide an estimation of all possible projects
  - Deals with the problem of CART that are often very inaccurate

AR+CART

- Estimation process
  - Identify ARs describing the influence of certain project attributes on the software development productivity
  - Build a CART model that will be able to classify *all* possible projects to a productivity
  - If the new project can be estimated by the AR model with a stronger confidence value than the CART model then use that estimate
  - Otherwise use the CART estimate
  - AR+CART results in 10-15% accuracy improvement w.r.t. AR alone

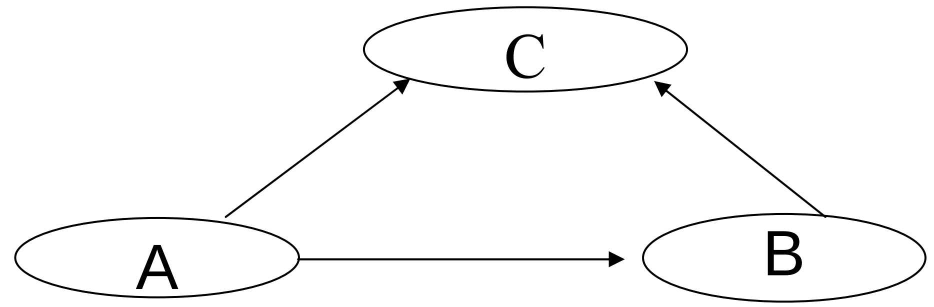
Bayesian Belief Networks

- Directed Acyclic Graphs (DAGs)
- Express cause-effect relationships
- Nodes represent variables, arcs represent relationships
- Node Probability table (conditional dependencies)
- Bayes' Rule:

$$P(A \mid B) = \frac{P(B \mid A) P(A)}{P(B)}$$

A-node	
T	0.6
F	0.4

a)



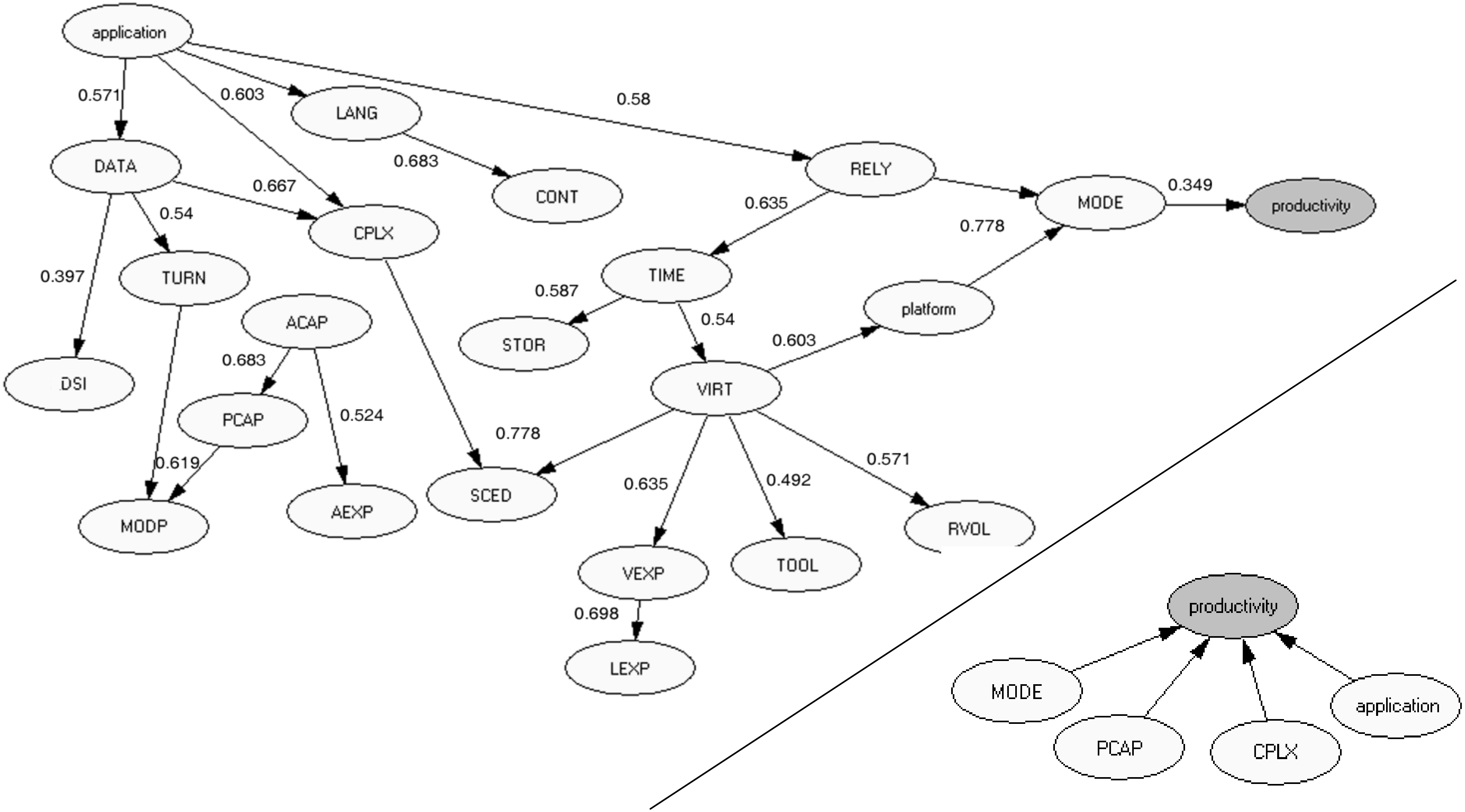
A-node / B-node	T	F
LOW	0.3	0.6
MED	0.5	0.25
HIGH	0.2	0.15

b)

A-node	T			F		
B-node / C-node	LOW	MED	HIGH	LOW	MED	HIGH
ON	0.7	0.65	0.4	0.45	0.23	0.07
OFF	0.3	0.35	0.6	0.55	0.77	0.93

c)

BBN + COCOMO81 data set



BBN + COCOMO81 data set

- Variable that directly affects productivity is mode and can classify correct 34,9% of the data.
- For improved estimation results we empirically added 3 nodes as parents of productivity, PCAP,CPLX and application type.
- In the BBN we can observe the relationships among the projects attributes as well.
- The number that accompanies each arc is the estimation hitrate that each nodes classifies its child node.
- Evaluation results, Jackknife method

Interval Estimation papers

- ANGELIS L., I. STAMELOS (2000). A simulation tool for efficient analogy based cost estimation. *Empirical Software Engineering, 5, pp. 35-68*.
- STAMELOS I., L. ANGELIS (2001). Managing uncertainty in project portfolio cost estimation. *Information and Software Technology, 43, pp. 759-768* .
- STAMELOS I., L. ANGELIS, P. DIMOU, E. SAKELLARIS (2003). On the use of Bayesian belief networks for the prediction of software development productivity. *Information and Software Technology, 45, 1, pp. 51-60.*
- STAMELOS I., L. ANGELIS, M. MORISIO, G. BLERIS, E. SAKELLARIS (2003). Estimating the development cost of custom software. *Information & Management, 40, pp. 729-741.*
- BIBI S., I. STAMELOS, L. ANGELIS, (2003) Bayesian Belief Networks as a Software Productivity Estimation Tool, Proceedings of the 1st Balkan Conference in Informatics, pp. 585-596, Thessaloniki, November 2003.
- BIBI S., I. STAMELOS, (2004) Software Process modeling with Bayesian Belief Networks, Online Proceedings of the 10th IEEE International Conference on Software METRICS , Chicago.
- BIBI S., I. STAMELOS, L. ANGELIS, (2004) Software Productivity estimation based on Association Rules, Proceedings of the 1st European Software Process Improvement Conference, pp. 13 A.6, Trondheim.
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- SENTAS P., L. ANGELIS, I. STAMELOS, G. BLERIS (2005). Software productivity and effort prediction with ordinal regression. *Information and Software Technology, Volume 47, Issue 1, 17-29.*
- BIBI S., I. STAMELOS (2006). Selecting the Appropriate Machine Learning Tecnhiques for the Prediction of Software Development Costs, Proceedings of the 3rd IFIP Conference on Artificial Intelligence Applications & Innovations, pp 533-540, Athens.

Aristotle University

Teletel S.A.

DIERGASIA

Optimization of Telecommunication Software PROCESS development

Funded by the Greek Secretariat
for Research and Technology, a PAVET grant

Target of the project

- *Design, development and application of models describing software process development for telecommunication systems software.*
  - Definition of measurements
  - Definition of the appropriate observation points.
  - Selection and implementation of statistical models and software.
    - Cost estimation
    - Quality estimation
  - Specification of new improved processes.
  - Preparation for CMM-I assesment

W.P.1 – Research on software metrics and statistical methods for data processing

- **D1- Guide for measurement and statistical analysis**
- Identification of measurements and metrics for gathering quantitative data.
- Identification of statistical and data mining methods for qualitative analysis of data
  - Regression models, analogy based estimation, CART, Association Rules, Bayes Networks.
- Research on requirements specification process

W.P.2 – Measurement and data collection and transformation

- **D2.1 – Company data base of measurements**
  - Placement of the appropriate audits and metric pointers at particular development points.
  - Measurement completion and result recording.
  - Data collection from measurements.
  - Data collection from SAFIRE tool.
- **D2.2 – Quality report for measurements**
  - Initial application, mining, comparison and evaluation of models – emphasis on interval models
  - Data selection
  - Pre-Processing
  - Transformation
  - Statistical analysis

W.P.3 – Modeling company's process

- **D3.1 – Mathematical models for estimation of company’s process.**
- Statistical processing of data
  - Define analysis methods
  - Apply statistical analysis
  - Interpret results
  - Discuss results
- Models development
  - Software cost estimation
  - Software quality estimation
  - Reusable code assets
  - Requirements collection

W.P.4 – A model for SDL Systems Quality Evaluation

- **D4.1 – Quality model evaluation for SDL**
  - Specification of a model for quality evaluation
  - Development of a quality rule set SDL
- **D4.2 – Tool for automated quality evaluation for SDL**
  - Development of static metrics that implement SDL rules
  - Specification of quality intervals for each metric
  - Quality evaluation based on mathematical equations
  - Project evaluation based on the quality model.

W.P.5 – Specification of the company's processes- evaluation of the models

- **D5.1 – Company's process quality guide**
  - Models application
  - Models evaluation
  - Result comparison
  - Quality models specification
  - Models modification

W.P.6 – Software Process Improvement Certification

- **D6.1 – Software process improvement certification**
- Software Process Improvement Certification by major clients of Teletel (Alcatel).
- Process maturity estimation based on the standards of CMM/I.
- Training for CMM/I.

D1.1 – Guide for measurements and statistical analysis

Part A- Software metrics.

- Introduction
- Product metrics
  - Size metrics (LOC, FP)
  - Complexity metrics (Cyclomatic complexity, nodes)
  - Halstead Metrics (vocabulary, length, volume)
  - Quality metrics (Fault metrics, reliability, maintainability)
- Process metrics
  - Software cost/ effort/ productivity estimation
- Telecommunication systems metrics
  - SAFIRE metrics

D1.1 – Guide for measurements and statistical analysis

Part B - Statistical analysis methods

- Analogy based estimation
- Regression models
- Machine learning models
  - Rules
  - CART
  - Bayes Networks

Part C- Requirements model for telecommunication systems