2IS55 Software Evolution

Software metrics (3)

Alexander Serebrenik

TU/e Technische Universiteit Eindhoven University of Technology

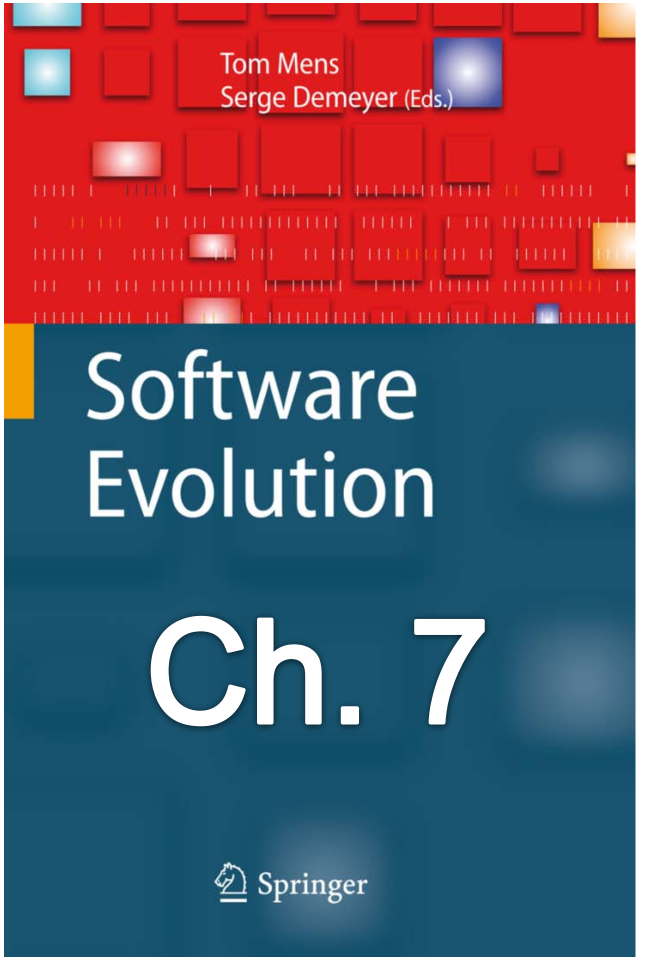
Where innovation starts

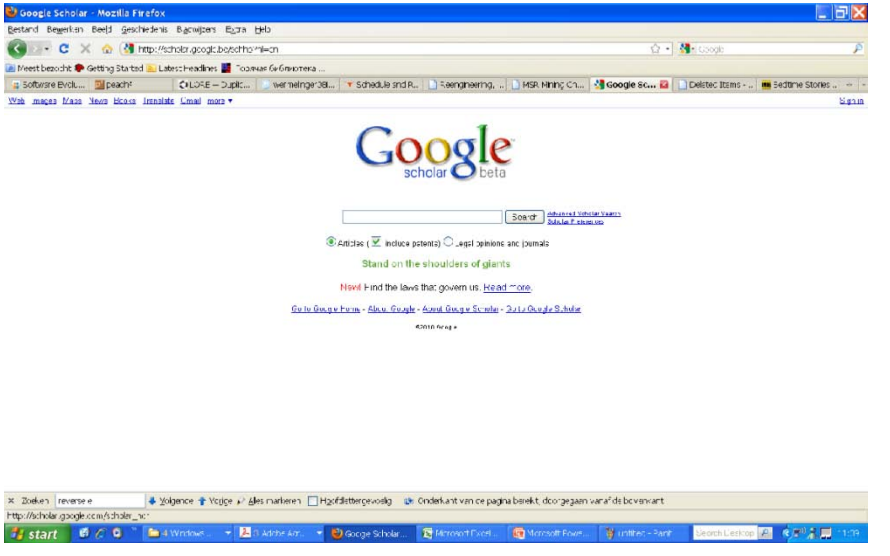
Assignments

- **Assignment 6:**
  - **Architects vs. developers (software metrics)**
  - **Deadline: May 10**
  - **3-4 students**

  - **Questions?**

Sources





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Recap: Software metrics

- So far
  - Metrics scales:
  - Size: LOCs, #files, functionality (function points, API)
  - Complexity: Halstead, McCabe, Henry-Kafura
  - OO:
    - Chidamber-Kemerer (WMC, DIT, etc.)
    - LCOM and variants

- Today
  - Package metrics
    - Aggregation of metrics values
  - Churn metrics

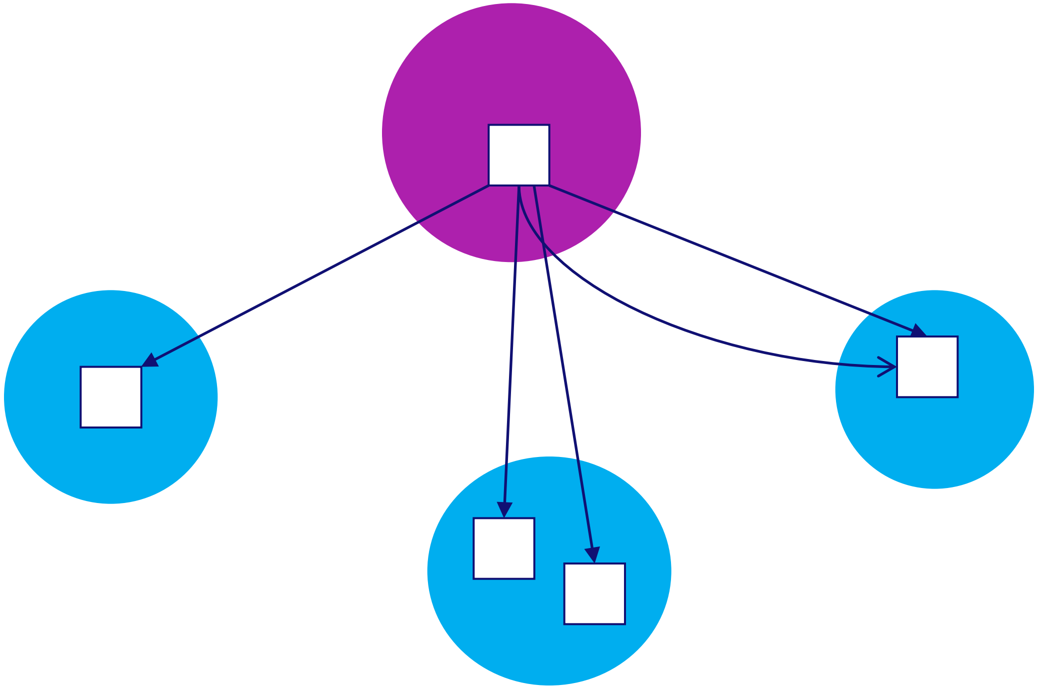
Package metrics

- **Size: number of classes**

- **Dependencies à la fan-in and fan-out**
  - **Marchesi's UML metrics**
  - **Martin's D_n: abstractness-instability balance or "the normalized distance from the main sequence"**
  - **PASTA**

- **Aggregations of class metrics**

"Fan-out"



PK_1: 5

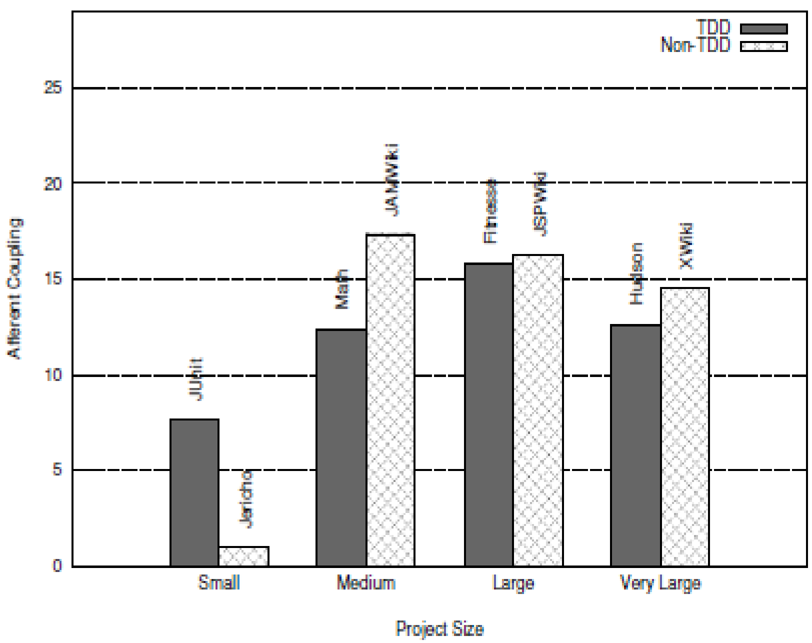
[Marchesi 1998]

C_e: 1 3 4

[Martin 1994] [JDepend] [Martin 2000]

Fan-in

- "Fan-in" similarly to the "Fan-out"
  - Afferent coupling (Martin)
  - PK_2 (Marchesi)



[Hilton 2009]

- Dark: TDD, light: no-TDD
- Test-driven development positively affects C_a
  - The lower C_a - the better.
- Exception: JUnit vs. Jerico
  - But Jericho is extremely small (2 packages)

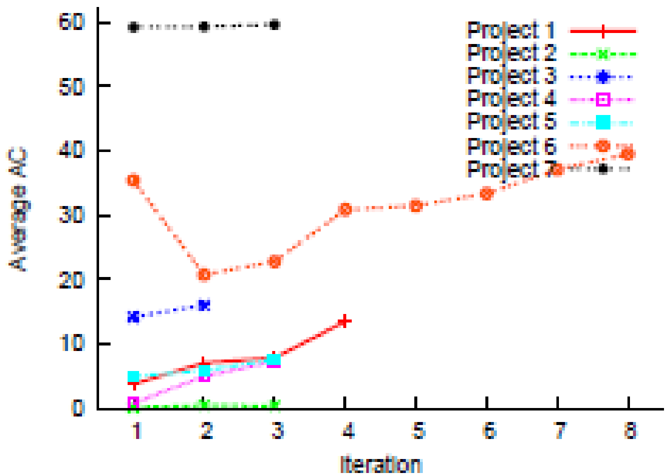
More fan-in and fan-out

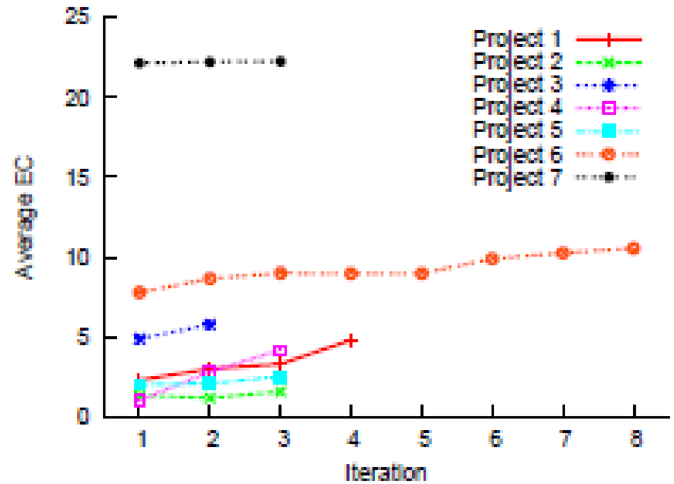
- "Fan-in" similarly to the "Fan-out"
  - Afferent coupling (Martin)
  - PK_2 (Marchesi)

Marchesi	Man-months	#Pack	avg(PK_1)
Railway simulator	13	6	8.7
Warehouse management	7	5	5.0
CASE tool	13	5	8.1

SAP (Herzig)	Correlation post-release defects
Afferent	0.091
Efferent [Martin 2000]	0.157
Class-in	0.084
Class-out	0.086
Fan-in	0.287
Fan-out	0.148

Evolution of afferent and efferent coupling





Sato, Goldman, Kon 2007

- Almost all systems show an increasing trend (Lehman's growing complexity)
- Project 7 (workflow system) is almost stable but very high!
  - Outsourced development
  - No automated tests
  - Severe maintainability problems

Package metrics: Stability

Stability is related to the amount of work required to make a change [Martin, 2000].

- **Stable** packages
  - Do not depend upon classes outside
  - Many dependents
  - <u>Should be</u> extensible via inheritance (*abstract*)
- **Instable** packages
  - Depend upon many classes outside
  - No dependents
  - <u>Should not be</u> extensible via inheritance (*concrete*)

What does balance mean?

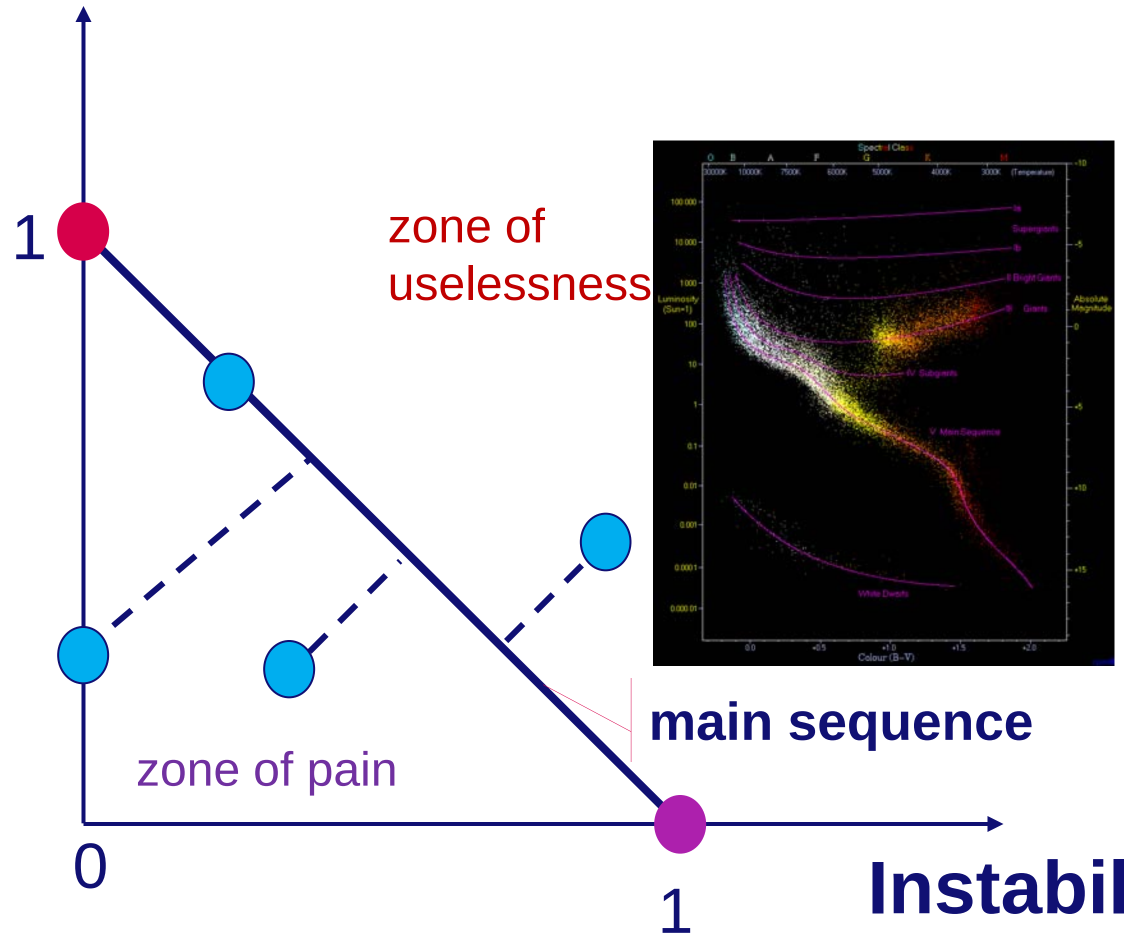
A good real-life package must be **instable** enough in order to be easily modified

It must be **generic** enough to be adaptable to evolving requirements, either without or with only minimal modifications

Hence: contradictory criteria

D_n – Distance from the main sequence

Abstractness = **#AbstrClasses/#Classes**



Instability = **$C_e/(C_e+C_a)$**

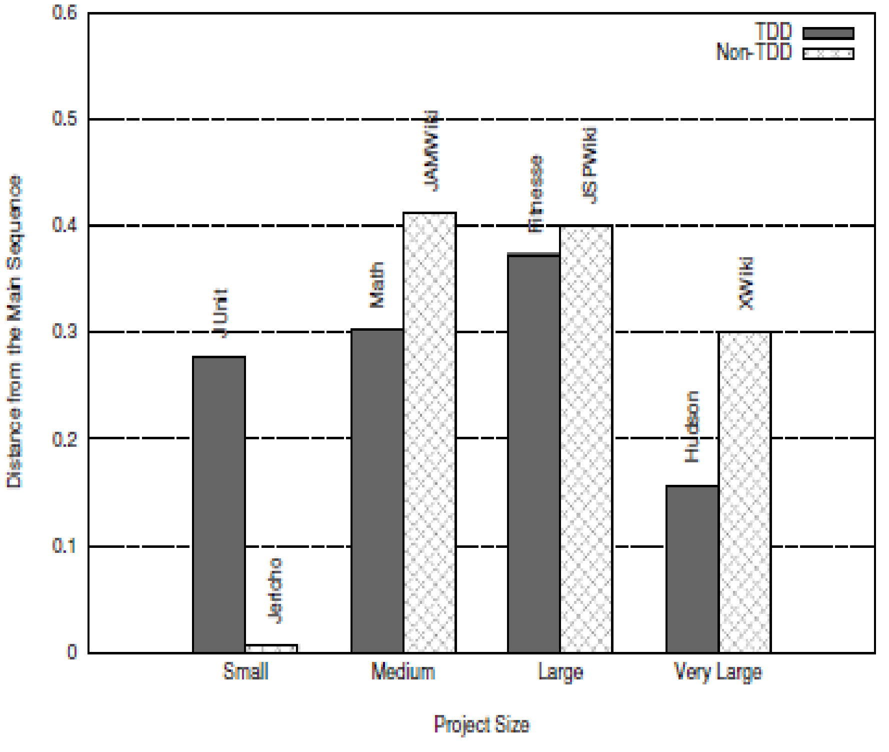
D_n =

| Abstractness +

Instability – 1 |

[R.Martin 1994]

Normalized distance from the main sequence



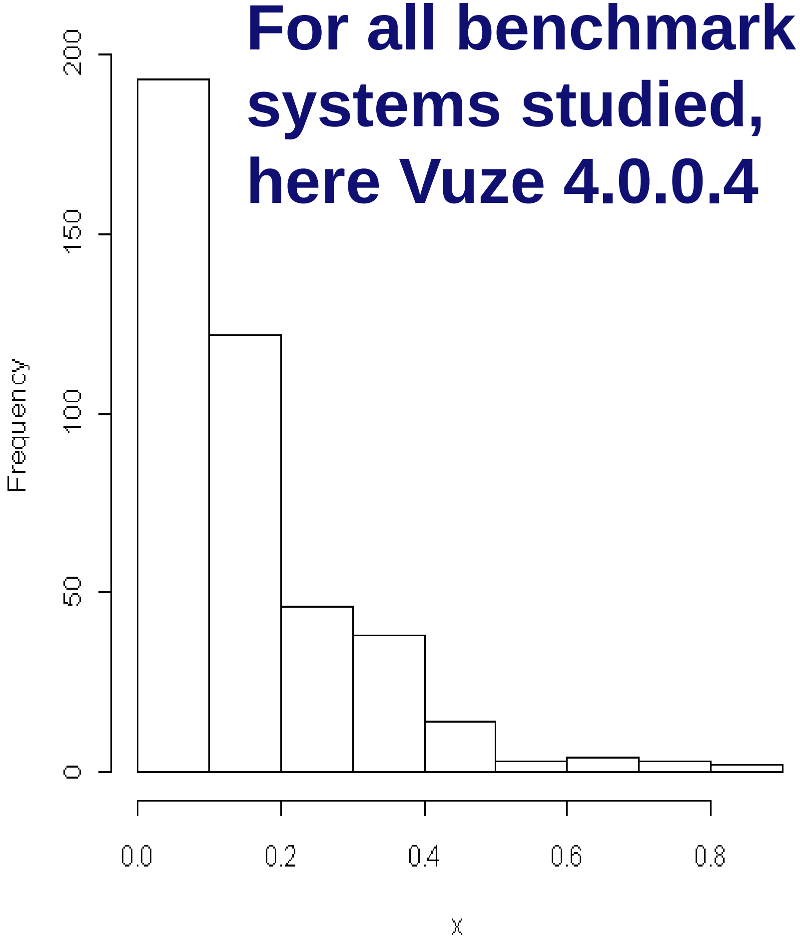
[Hilton 2009]

- Dark: TDD, light: no-TDD
- Test-driven development positively affects D_n
  - The lower D_n - the better.
- The same exception (Jericho vs. JUnit)

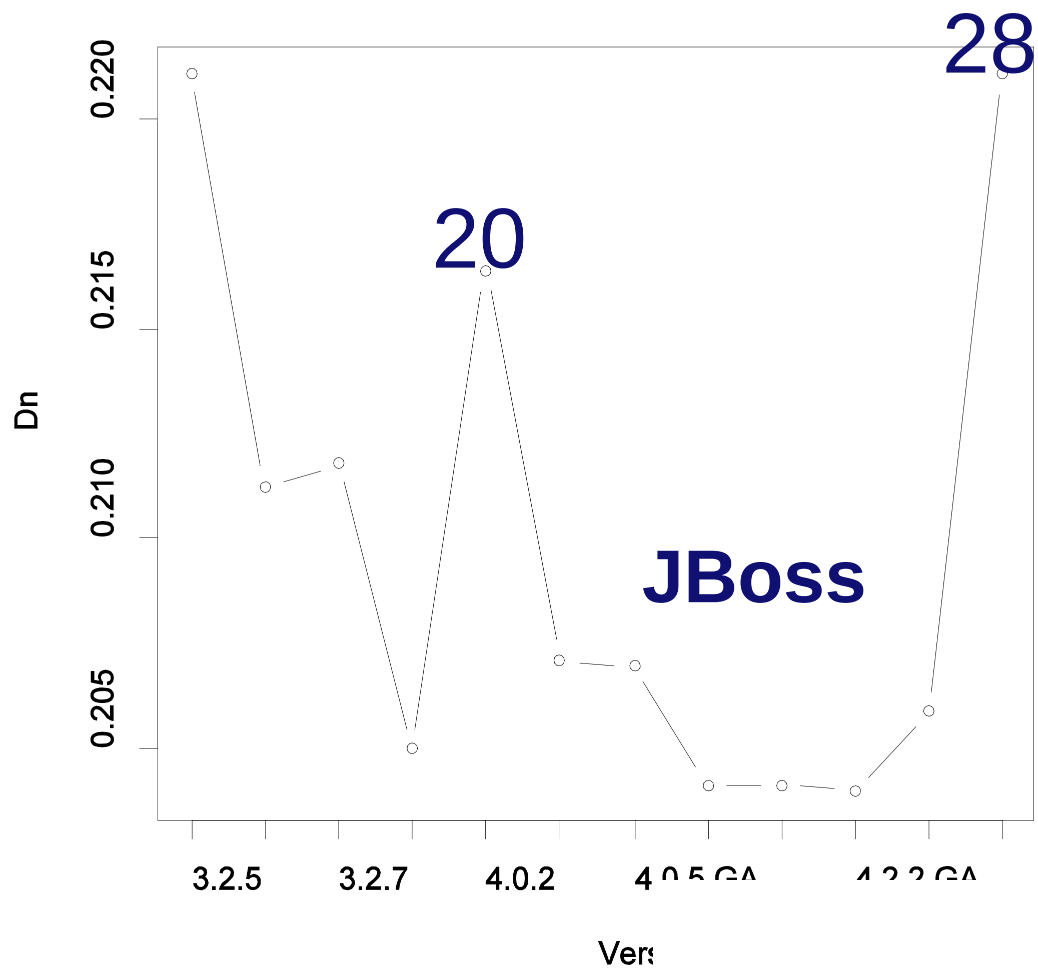
Distribution and evolution

Exponential distribution

For all benchmark systems studied, here Vuze 4.0.0.4



Peak: many feature requests (average Dn)

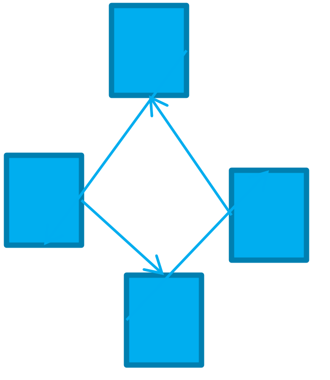


PASTA [Hautus 2002]

- PASTA – Package structure analysis tool

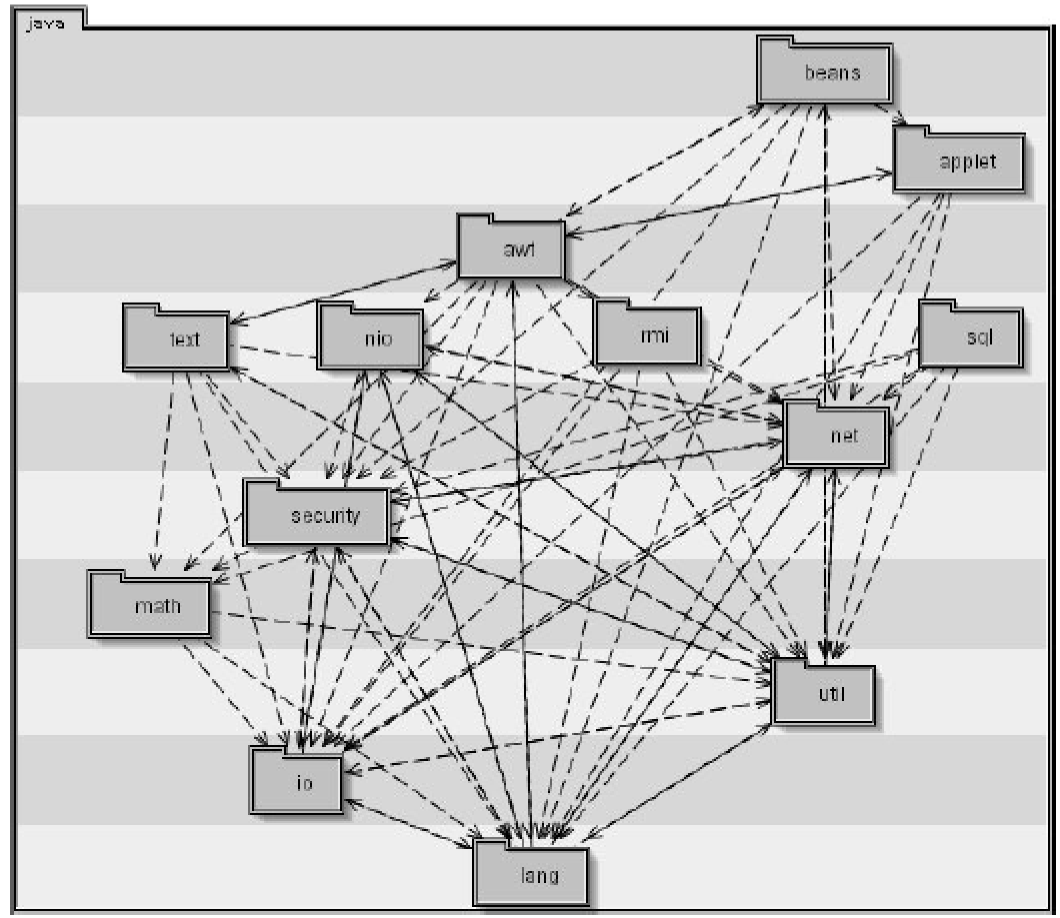
- Dependencies between subpackages

- Some dependencies are worse than others
  - What are the “bad dependencies”?
  - Cyclic dependencies, layering violations



PASTA [Hautus]

- **Idea: remove bad (cycle-causing) dependencies**
  - **Weight – number of references from one subpackage to another one.**
  - **Dependencies to be removed are such that**
    - **The result is acyclic**
    - **The total weight of the dependencies removed is minimal**
  - **Minimal effort required to resolve all the cycles**



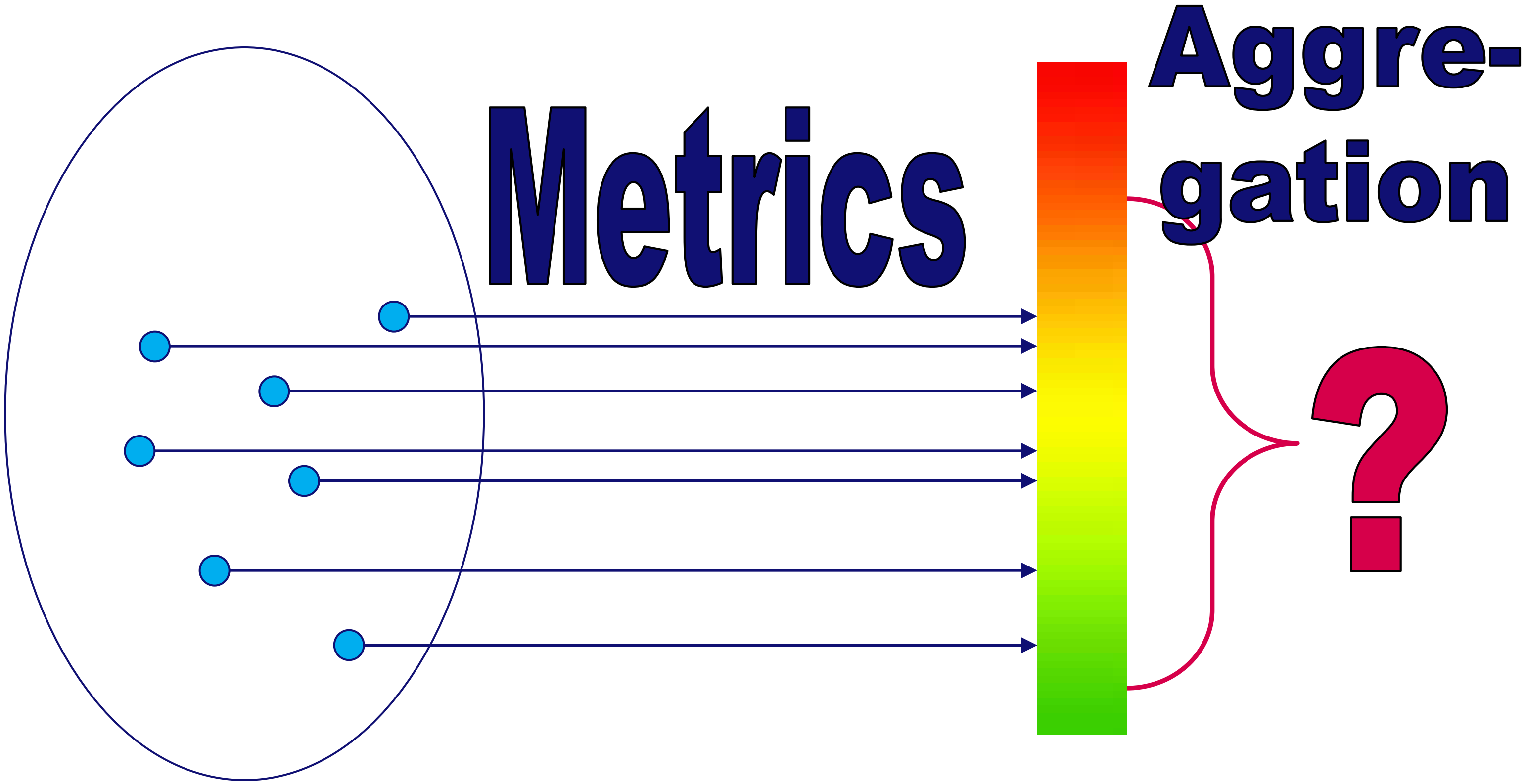
Upwards dependencies should be removed

From dependencies to metrics

- **PASTA(P) = Total weight of the dependencies to be removed / total weight of the dependencies**
- **No empirical validation of the metrics**
- **No studies of the metrics evolution**

Package	PASTA Metric
junit	0%
org.apache.batik	0%
org.apache.tools.ant	1%
java	5%
org.apache.jmeter	6%
javax.swing	10%
org.jboss	11%
org.gjt.sp.jedit	18%
java.awt	20%

Metrics for higher-level objects as aggregation of metrics for low-level objects



Aggregation techniques

- Metrics-independent
  - Applicable for any metrics to be aggregated
  - Are the results also metrics-independent?
  - Based on econometrics

- Metrics-dependent
  - Produces more precise results
  - BUT: needs to be redone for any new metrics
  - Based on fitting probability distributions

Examples of aggregation functions so far

- Sum
  - WMC is a class-level metrics defined as the sum of metrics for its lower-level elements (methods)
  - McCabe's complexity of a file is the sum of McCabe's complexities of its functions
    - Effort to test all functions of the file
  - Not all metrics are additive (DIT? LCOM???)

- Average
  - Maintainability index
  - Central tendency is insufficient for assessment
  - Unreliable for skewed distribution

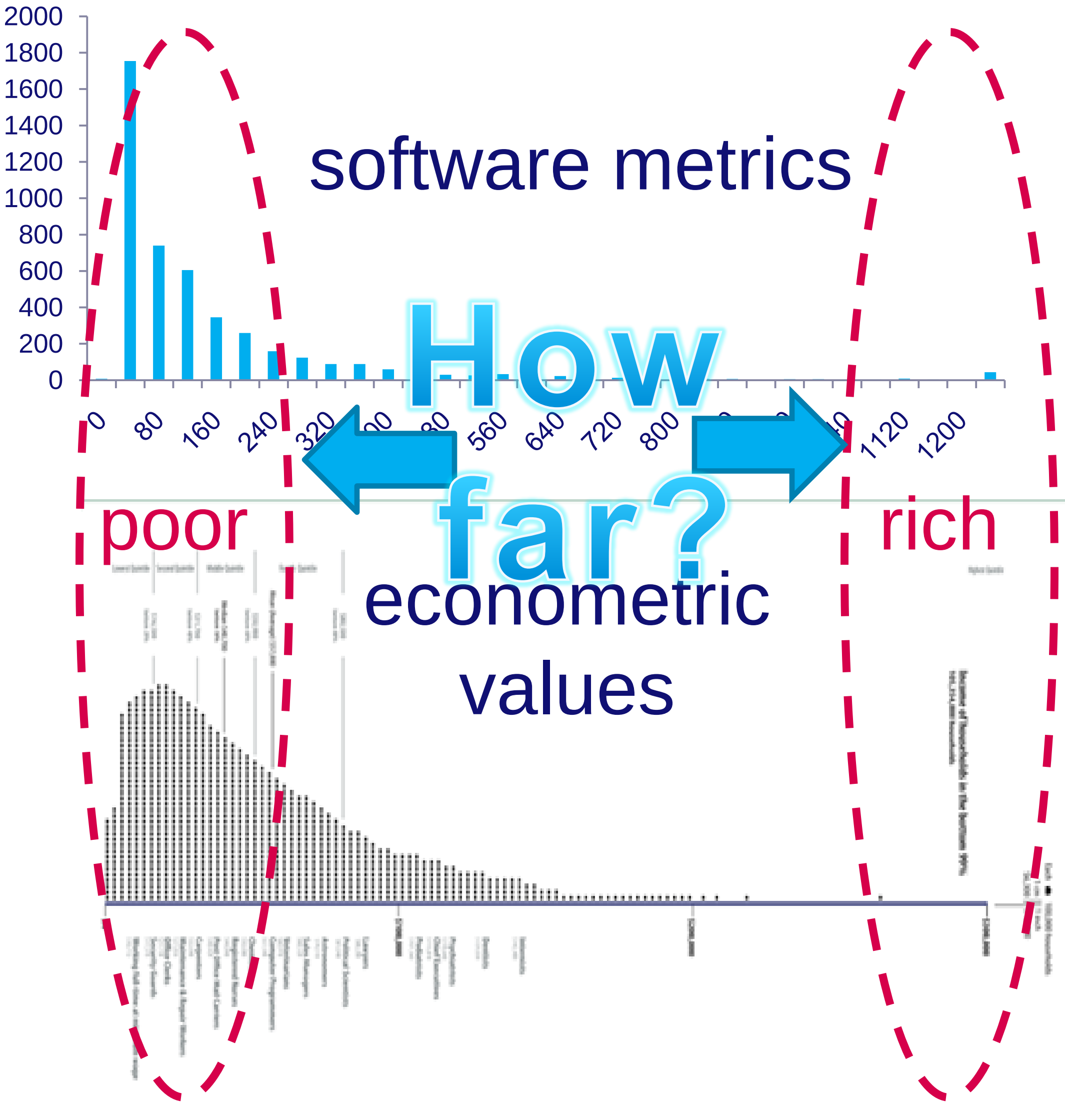
Metrics independent: Coefficient of variation

- Coefficient of variation: $C = \sigma/\mu$

  - Allows to compare distributions with different means

  - Sometimes used to assess stability of the metrics
    - Metrics is stable for $C < 0.3$
    - Unreliable for small samples
    - Evolution should be studied…

Metrics are like money



- prog. lang.
- domain
- …

- region
- education
- gender
- …

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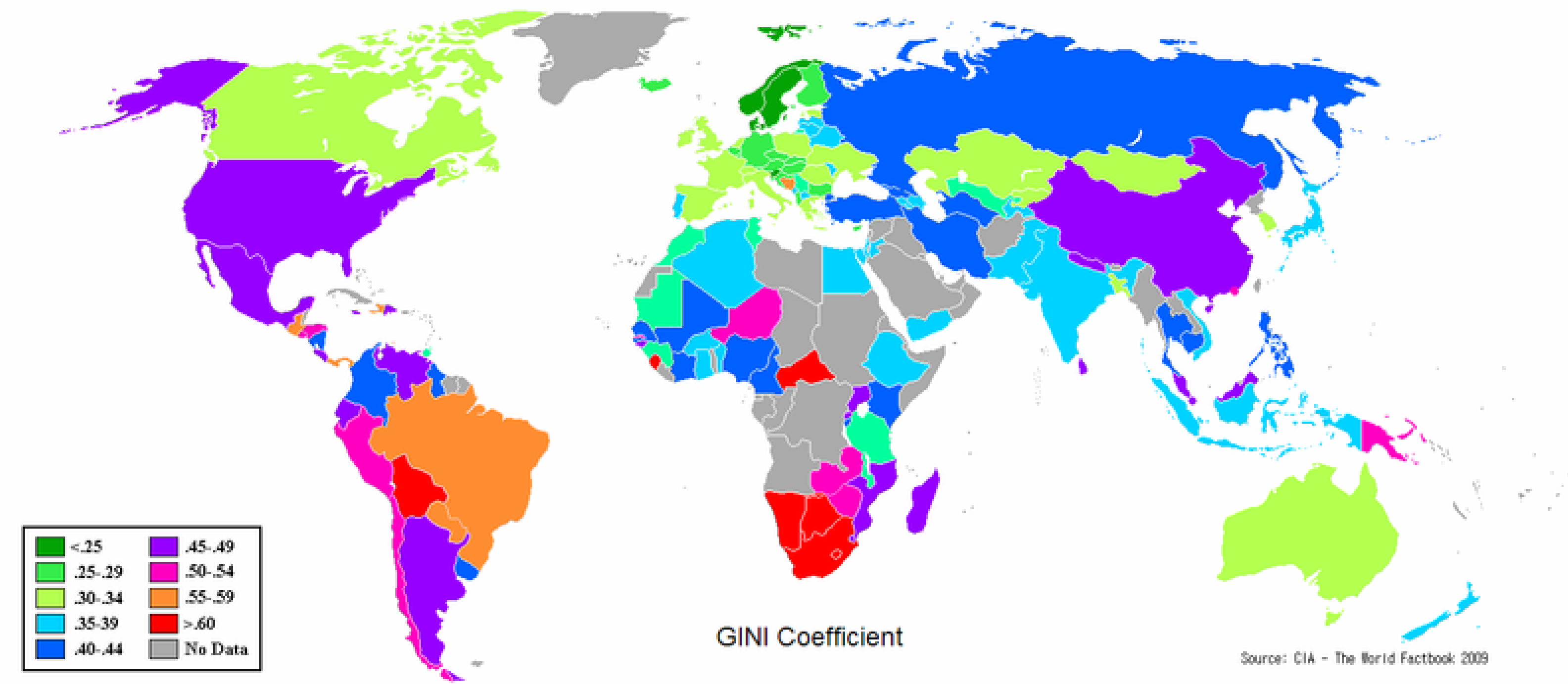
Popular technique: Gini coefficient



- **Gini coefficient measure of economic inequality**
- **Ranges on [0; 1]**
- **High values indicate high inequality**

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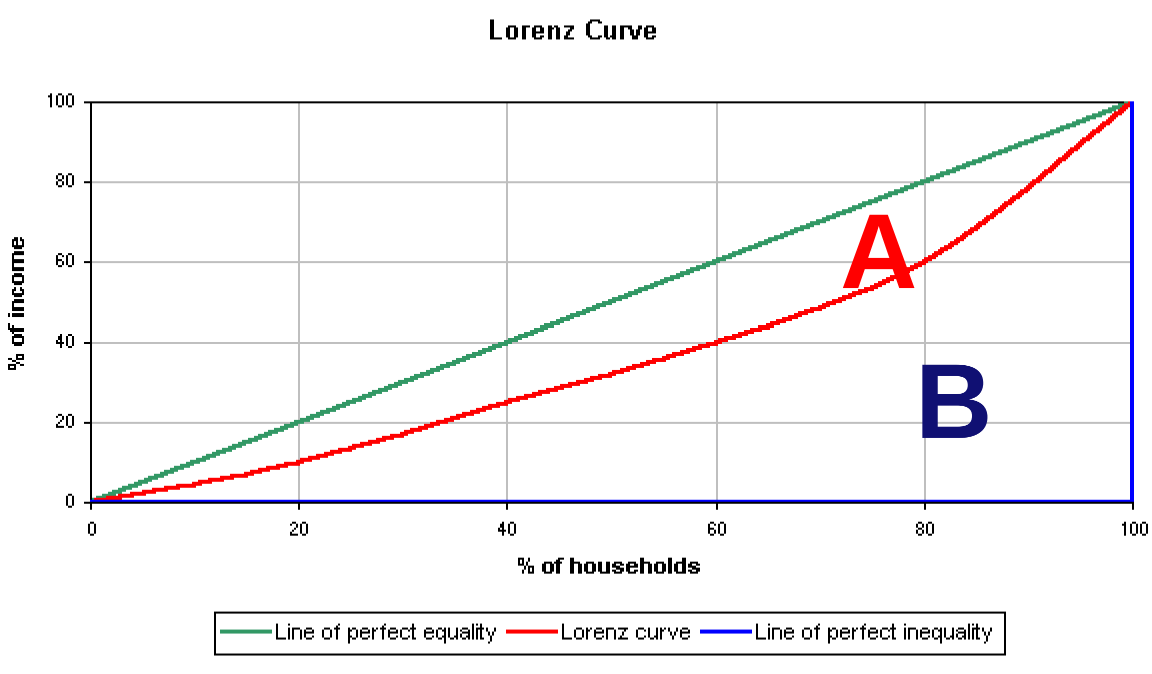
Gini coefficient: Formally

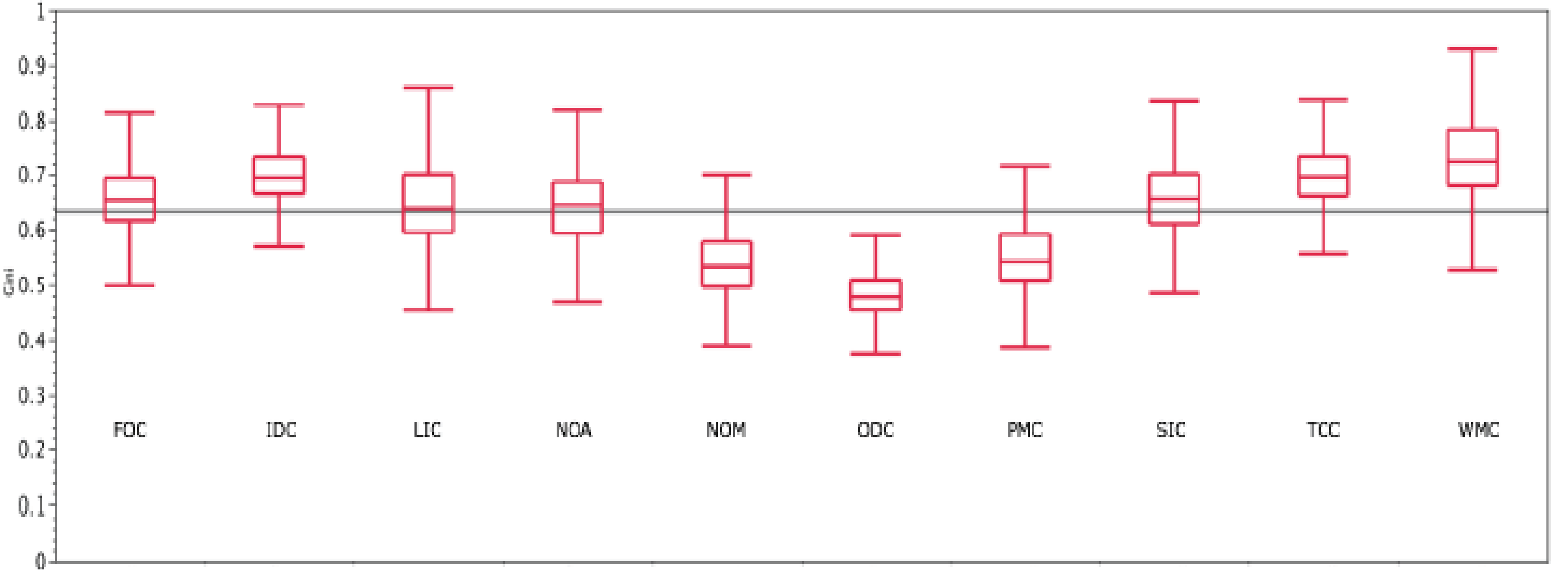
- **Lorenz curve:**
  - **% of income shared by the lower % of the population**



- **Gini = A/(A+B)**
- **Since A+B = 0.5**

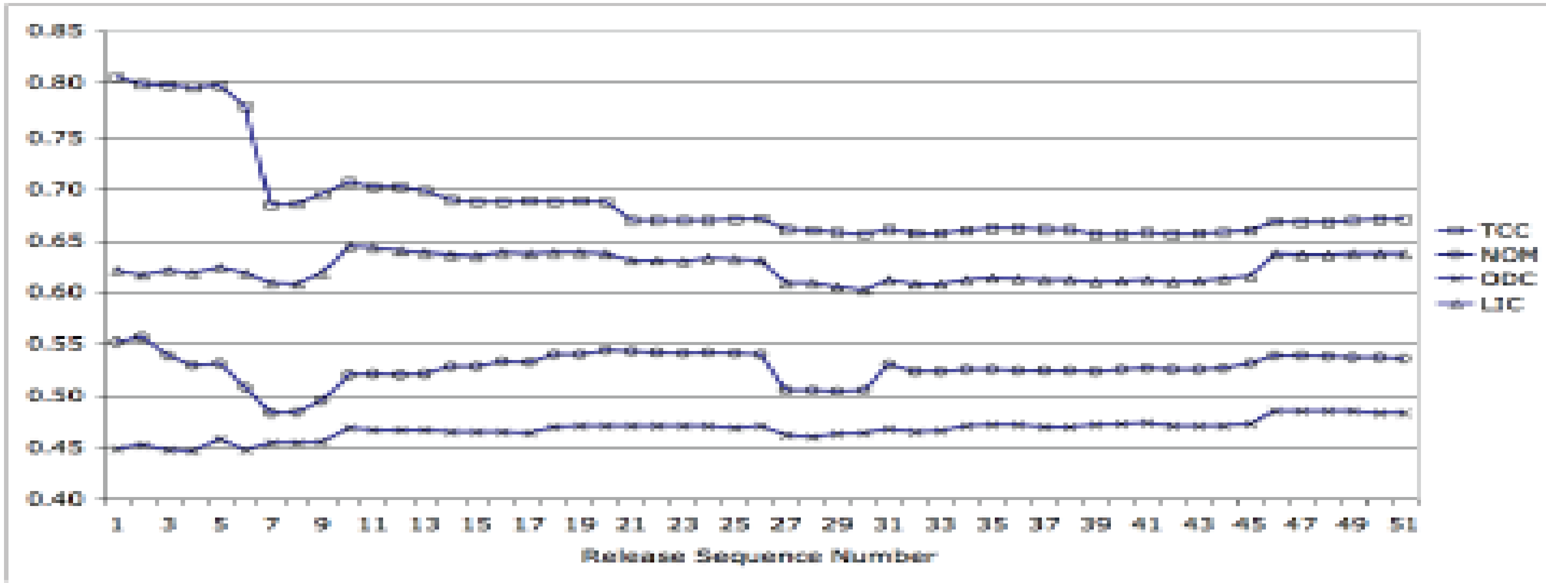
  Gini = 2A

Gini and software metrics [Vasa et al. 2009]



- For most of the metrics on the benchmark systems: 0.45 ≤ Gini ≤ 0.75
- Higher Gini/WMC: presence of generated code or code, structured in a way similar to the generated code (parsers)

Gini and evolution: Spring



- **Normally rather stable: programmers accumulate competence and tend to solve similar problems by similar means**

Exceptions are meaningful!

System	Metrics	Increase		Explanation
JabRef	WMC	0.75	0.91	Machine generated parser introduced
Checkstyle	Fan-in (classes)	0.44	0.80	Plug-in based architecture introduced.
Jasper-Reports	#Public methods	0.58	0.69	Introduction of a set of new base classes.
WebWork	Fan-out	0.51	0.62	A large utility class and multiple cases of copy-and paste introduced.

Aggregation techniques

- Metrics-independent
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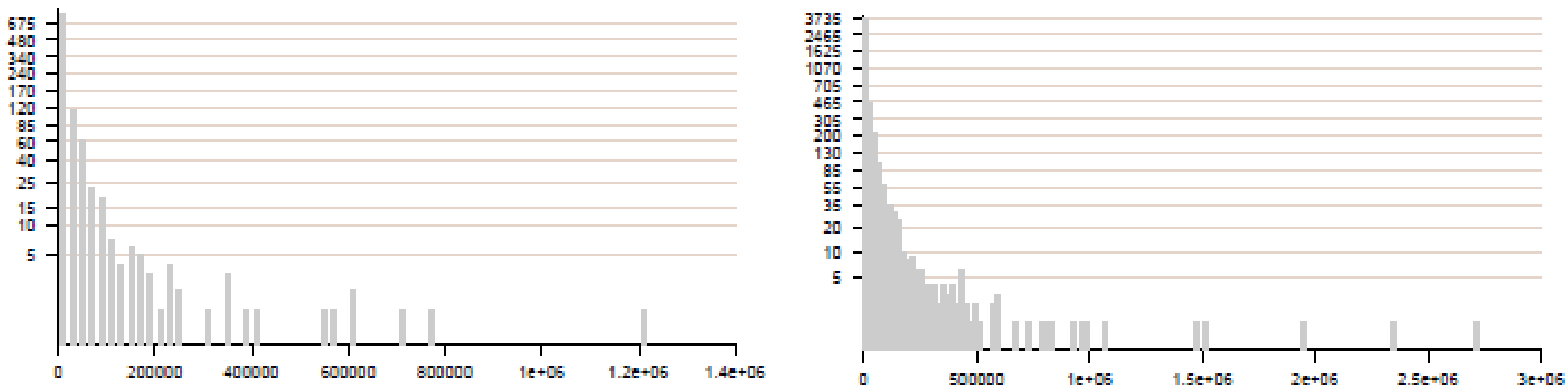
Metrics-dependent aggregation: Statistical fitting

1. Collect the metrics values for the lower-level elements
2. Present a histogram
3. Fit a (theoretical) probability distribution to describe the sample distribution
   a) Select a family of theoretical distributions
   b) Fit the parameters of the probability distribution
   c) Assess the goodness of fit

4. If a theoretical distribution can be fitted, use the fitted parameters as the aggregated value

Step 1: Histograms

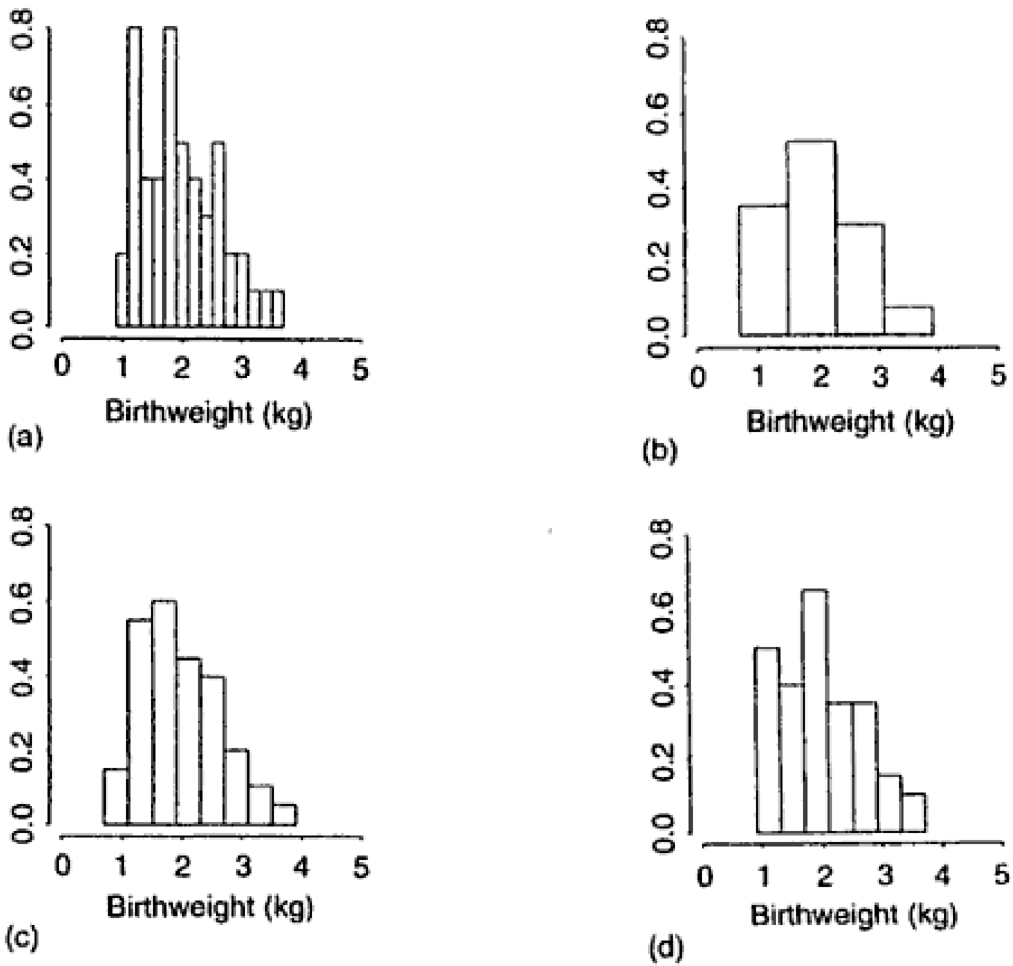
- **We have seen quite a number of them already!**



Robles et al. 2006: LOC in Debian 2.0 (left) and 3.0 (right)

Histograms are not without problems

- **Data: 50 birth weights of children with a severe idiopathic respiratory syndrome**



- **The same data leads to four different "distributions"**
- **What can affect the way histogram looks like?**
  - **Bin width**
  - **Position of the bin's edges**

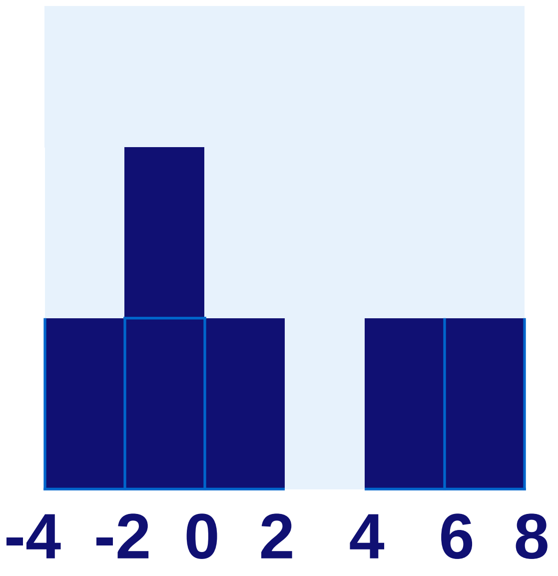
Kernel density estimators

- **Advantages**
  - **Statistically more sound (no dependency on the end-points of the bins)**
  - **Produces smooth curves**

- **Disadvantages**
  - **Statistically more complex**
  - **Parameter tuning might be a challenge**

Kernel density estimates: Intuition

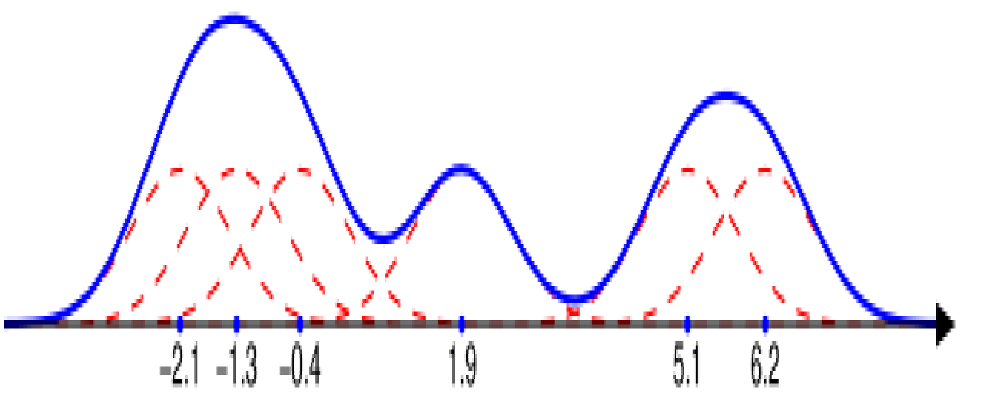
- **Data: -2.1, -1.3, -0.4, 1.9, 5.1, 6.2**



Histogram: every value is a rectangle.

Shape is a "sum" of the rectangles.

What if each value will be a "bump" that can be added together to create a smooth curve?

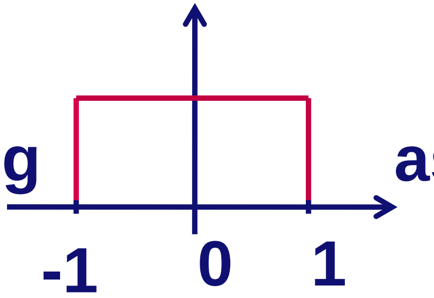


Kernel density estimation: Formally

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h} \right)$$

Where

- n – number of observations
- h – a smoothing parameter, the "bandwidth"
- K – a weighting function, the "kernel"

Histogram can be obtained using  as K

Once K is chosen one can determine the optimal h.

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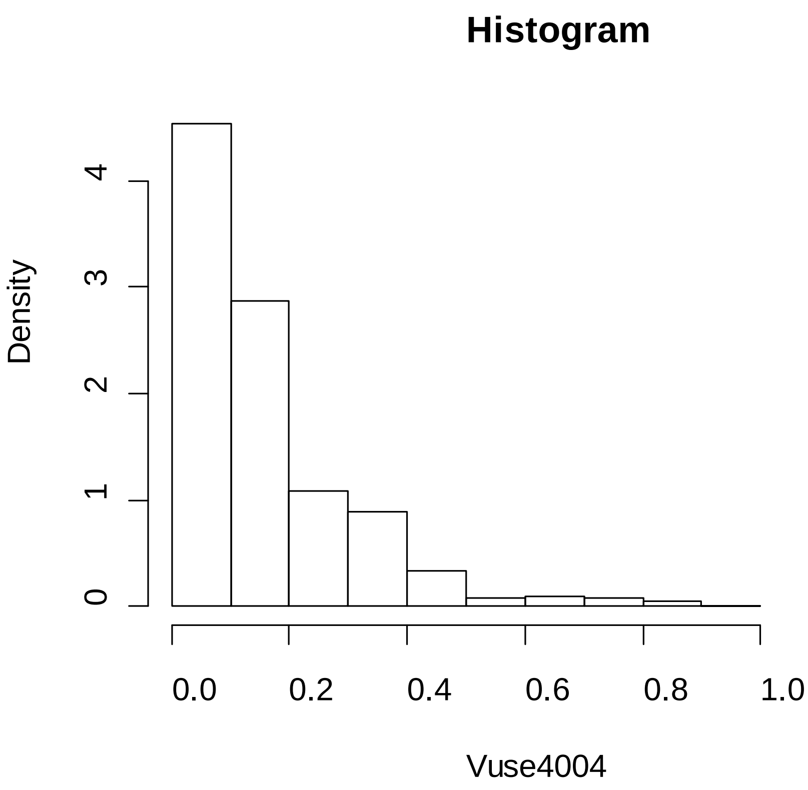
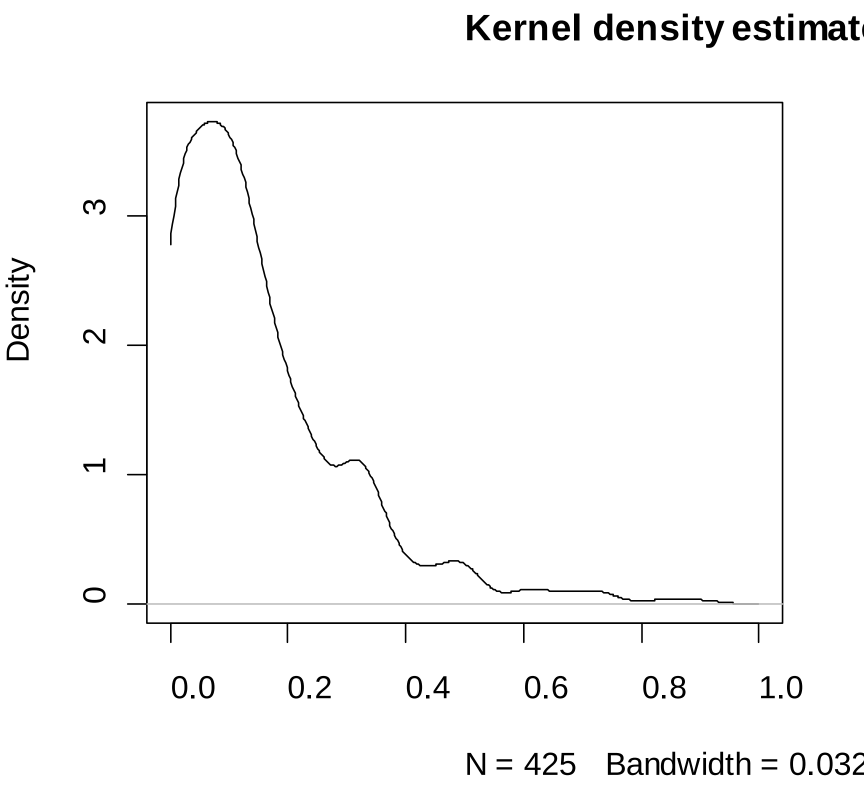
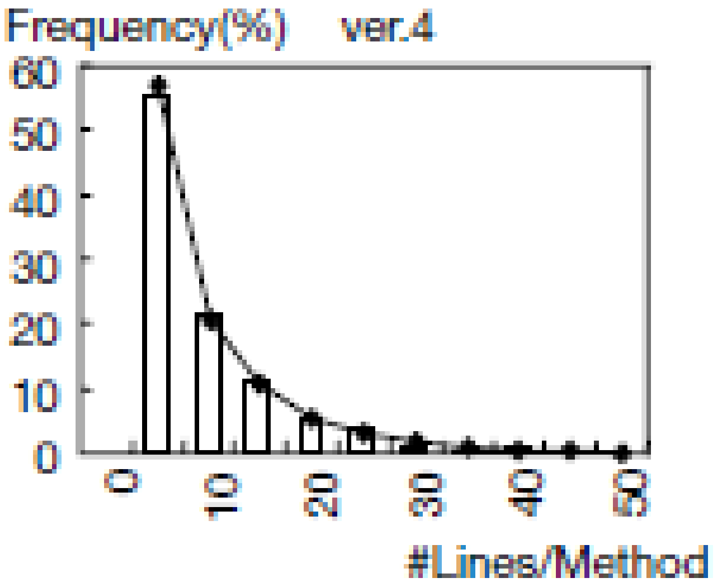
Histogram vs. Kernel density estimate





Step 2: fitting a distribution



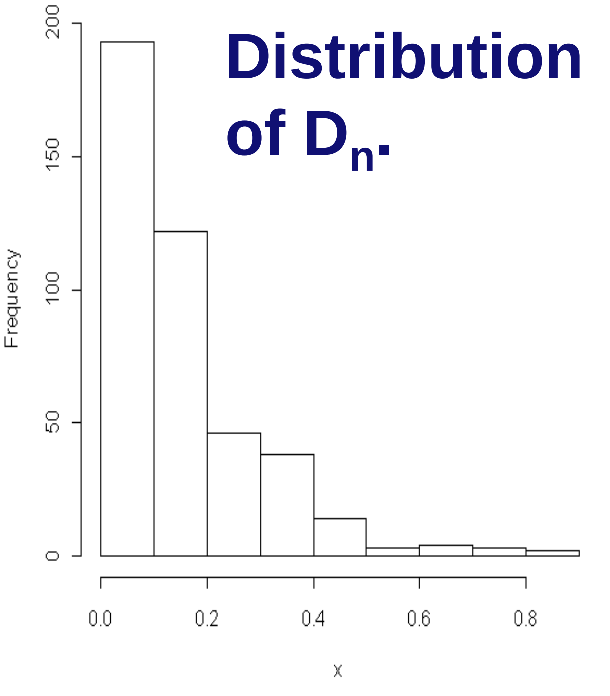
Tamai, Nakatani. Negative binomial distribution

- **Family of distributions is chosen based on shape**
- **If the parameters fitting is not good enough try a different one!**

Sometimes well-known distributions do not really seem to match

- **Exponential distribution:**

$$f(x) = \lambda e^{-\lambda x}$$



Distribution of D_n.

- **However, support is [0;1] rather than [0;∞)!**
  - **Since** $\int_0^1 f(x)dx = 1 - e^{-\lambda}$
  - **we normalize:** $g(x) = \dfrac{f(x)}{\int_0^1 f(x)dx}$

- **And use to find λ**

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Step 3c. Goodness of fit: Pearson χ^2 test

- **The test statistic** $$X^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$$

where

- **O – observed frequency of the result i**
- **E – expected frequency of the result i**

- **Compare X^2 with the theoretical χ^2 distribution for the given number of degrees of freedom: $P(\chi^2 > X^2)$**
  - **Degrees of freedom = number of observations – number of fitted parameters**
  - **Comparison is done based on table values**
  - **If the $P(\chi^2 > X^2)$ < threshold – the fit is good**
  - **Common thresholds are 0.1, 0.05 and 0.01**

Recapitulation: Statistical fitting

1. Collect the metrics values for the lower-level elements
2. Present a histogram
3. Fit a (theoretical) probability distribution to describe the sample distribution
   a) Select a family of theoretical distributions
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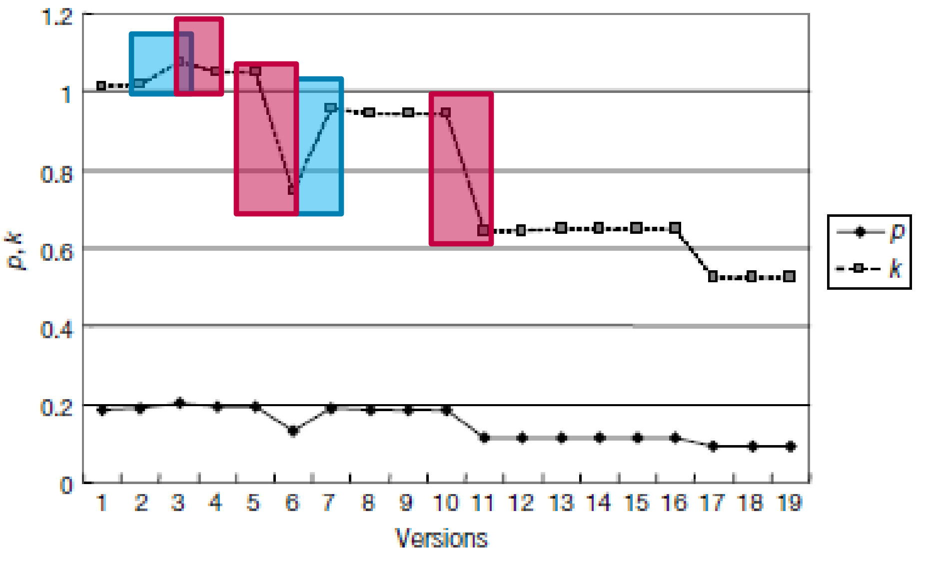
What about the evolution of the aggregated values?

- Geometry library: Jun, subsystem “Geometry”
- Tamai, Nakatani: Negative binomial distribution

$$f(x) = \binom{x-1}{k-1} p^k (1-p)^{x-k}$$



- p, k – distribution parameters
- $\binom{x-1}{k-1}$ - binomial coefficient extended to the reals

- Increase – functionality enhancement
- Decrease – refactoring

Reminder: package metrics

- Size: number of classes

- Dependencies à la fan-in and fan-out
  - Marchesi's UML metrics
  - Martin's D_n: abstractness-instability balance or "the normalized distance from the main sequence"
  - PASTA

- Aggregations of class metrics
  - Metrics independent: average, sum, Gini coefficient
  - Metrics dependent: Distribution fitting

Measuring change: Churn metrics

- **Why? Past evolution to predict future evolution**

- **Code Churn [Lehman, Belady 1985]:**
  - **Amount of code change taking place within a software unit over time**

- **Code Churn metrics [Nagappan, Bell 2005]:**

Absolute:
Total LOC, Churned LOC, Deleted LOC, File Count, Weeks of Churn, Churn Count, Files Churned

Relative:

M1: Churned LOC / Total LOC
M2: Deleted LOC / Total LOC
M3: Files churned / File count
M4: Churn count / Files churned
M5: Weeks of churn/ File count
M6: Lines worked on / Weeks of churn
M7: Churned LOC / Deleted LOC
M8: Lines worked on / Churn count

Case Study: Windows Server 2003

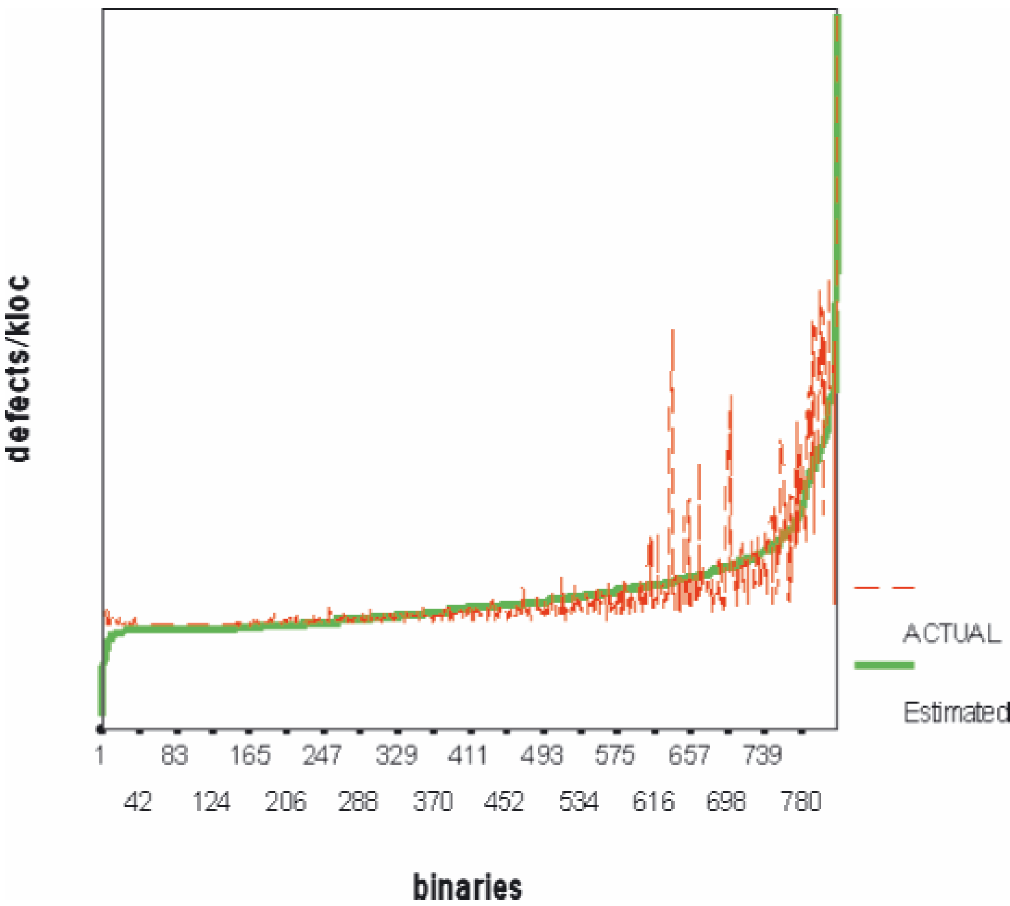
- **Analyze Code Churn between WS2003 and WS2003-SP1 to predict defect density in WS2003-SP1**
  - **40 million LOC, 2000 binaries**
  - **Use absolute and relative churn measures**

- **Conclusion 1: Absolute measures are no good**
  - **$R^2 < 0.05$**

- **Conclusion 2: Relative measures are good!**
  - **An increase in relative code churn measures is accompanied by an increase in system defect density**
  - **$R^2 \approx 0.8$**

Case Study: Windows Server 2003

- **Construct a statistical model**
  - **Training set: 2/3 of the Windows Set binaries**
- **Check the quality of the prediction**
  - **Test set: remaining binaries**
- **Three models**
  - **Right: all relative churn metrics are taken into account**



Open issues

- To predict bugs from history, but we need a history filled with bugs to do so
  - Ideally, we don't have such a history

- We would like to learn from previous projects:
  - Can we make predictions without history?
  - How can we leverage knowledge between projects?
  - Are there universal properties?
- Not just code properties but also properties of the entire software process

Conclusions

- **Package metrics**
  - **Directly defined: D_n, Marchesi metrics, PASTA**
  - **Aggregation based**
    - **Metrics-independent: average, sum, Gini coefficient**
    - **Metrics-dependent: fitted distributions**

- **Churn metrics**