2IMP25 Software Evolution

Software metrics

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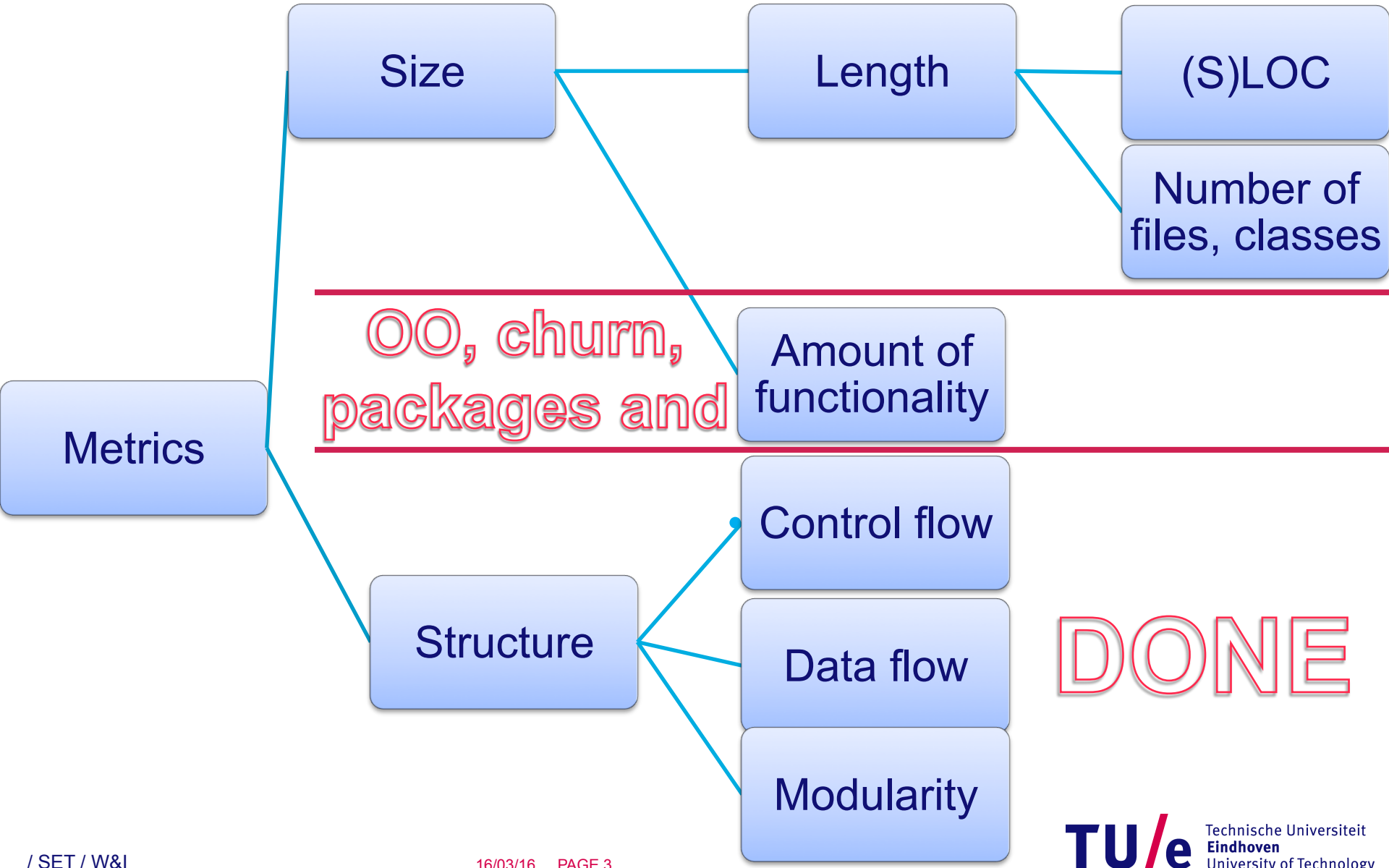
Where innovation starts

Assessement

- **Assignment 2: Thank you for submitting!**
  - **Median 7, mean 6.56**
  - **First feedback:** 3 5 4 5 1
    - **Like:** topic, tool chain, compilers, visual aspect
    - **Don't like:**
      - Building tools vs using tools
      - Rascal learning curve
      - Spelling
- **Assignment 3: March 30, 23:59**

Where are we now?



From imperative to OO

- All metrics so far were designed for imperative languages
  - Applicable for OO
    - On the method level
    - Also
      - Number of files → number of classes/packages
      - Fan-in → afferent coupling (C_a)
      - Fan-out → efferent coupling (C_e)
  - But do not reflect OO-specific complexity
    - Inheritance, class fields, abstractness, …
- Popular metric sets
  - Chidamber and Kemerer, Li and Henry, Lorenz and Kidd, Abreu, Martin

Chidamber and Kemerer

- WMC – weighted methods per class
  - Sum of metrics(m) for all methods m in class C
- DIT – depth of inheritance tree
  - java.lang.Object? Libraries?
- NOC – number of children
  - Direct descendents
- CBO – coupling between object classes
  - A is coupled to B if A uses methods/fields of B
  - CBO(A) = | {B|A is coupled to B} |
- RFC - #methods that can be executed in response to a message being received by an object of that class.

Modularity metrics: LCOM

- **LCOM – lack of cohesion of methods**

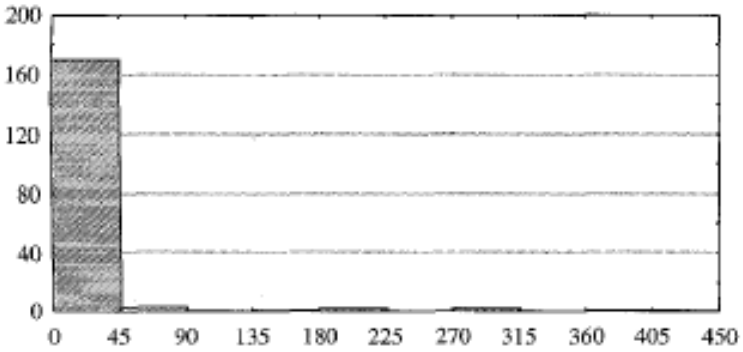
- **Chidamber Kemerer:**

$$LCOM(C) = \begin{cases} P - Q & \text{if } P > Q \\ 0 & \text{otherwise} \end{cases}$$

where

  - P = #pairs of distinct methods in C that do not share instance variables
  - Q = #pairs of distinct methods in C that share instance variables

- Do you remember what is an **instance variable**?



[BBM] 180 classes

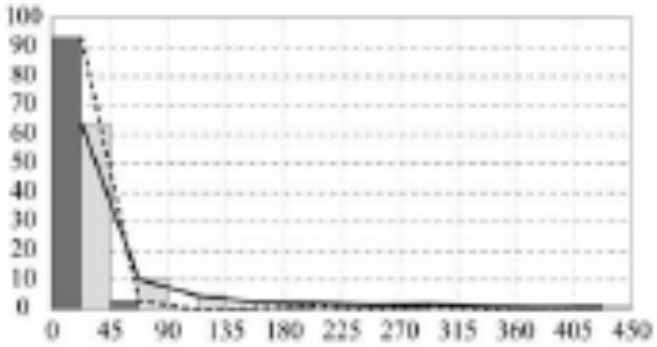
Discriminative ability is insufficient

What about methods that use get/set instead of direct access?

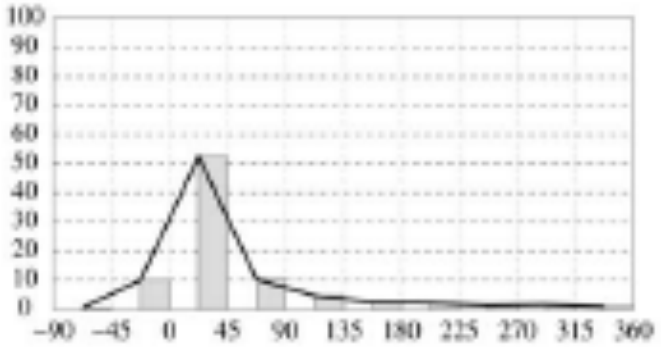
First solution: LCOMN

- **Defined similarly to LCOM but allows negative values**

$$LCOMN(C) = P - Q$$



LCOM



LCOMN

Henderson-Sellers, Constantine and Graham 1996

- m – number of methods
- v – number of variables (attrs)
- m(V_i) - #methods that access V_i

$$\frac{\left(\frac{1}{v}\sum_{i=1}^{v} m(V_i)\right) - m}{1 - m}$$

- Cohesion is maximal: all methods access all variables

  $m(V_i) = m$ and $LCOM = 0$

- No cohesion: every method accesses a unique variable

  $m(V_i) = 1$ and $LCOM = 1$

- Can LCOM exceed 1?

LCOM > 1?

- **If some variables are not accessed at all, then**

$$m(V_i) = 0$$

and if no variables are accessed

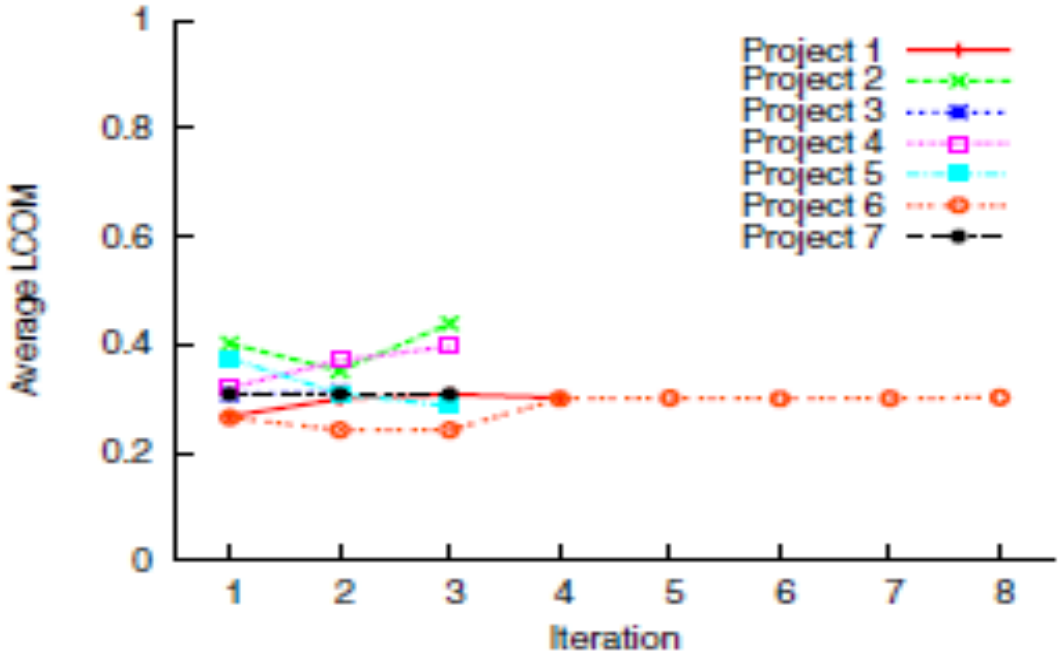
$$\frac{\left(\frac{1}{v}\sum_{i=1}^{v} m(V_i)\right) - m}{1-m} = \frac{-m}{1-m} = 1 + \frac{1}{m-1}$$

Hence

LCOM is undefined for m = 1

LCOM ≤ 2

Evolution of LCOM [Henderson-Sellers et al.]

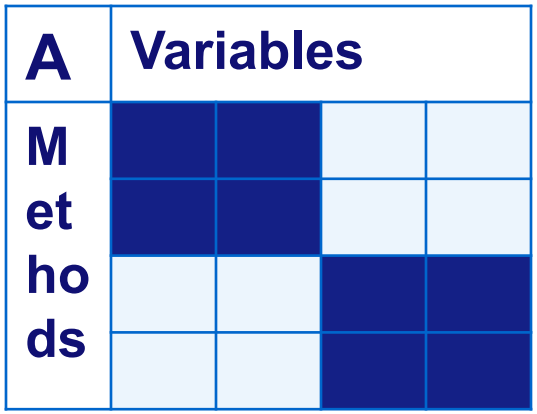


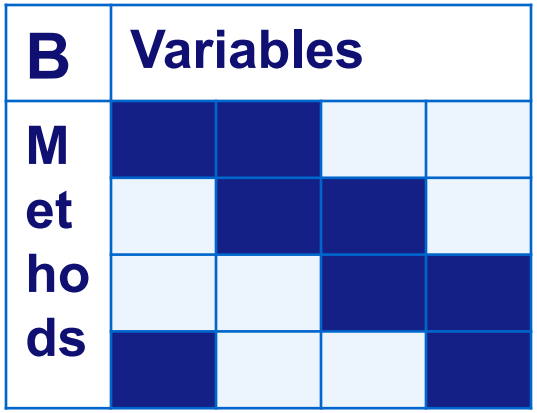
Sato, Goldman, Kon 2007

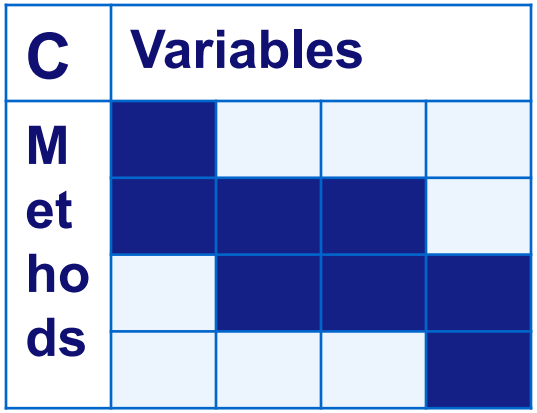
- **Project 6 (commercial human resource system) suggests stabilization, but no similar conclusion can be made for other projects**

Shortcomings of LCOM [Henderson-Sellers]

Due to [Fernández, Peña 2006]







- **Method-variable diagrams: dark spot = access**
- **LCOM(A) ? LCOM(B) ?LCOM(C) ?**

$$\frac{\left(\frac{1}{v}\sum_{i=1}^{v} m(V_i)\right) - m}{1 - m}$$

Shortcomings of LCOM [Henderson-Sellers]

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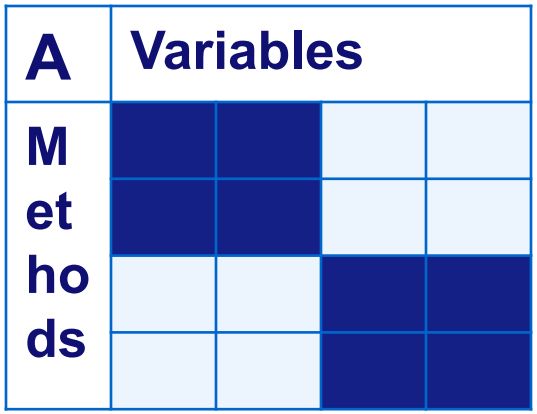

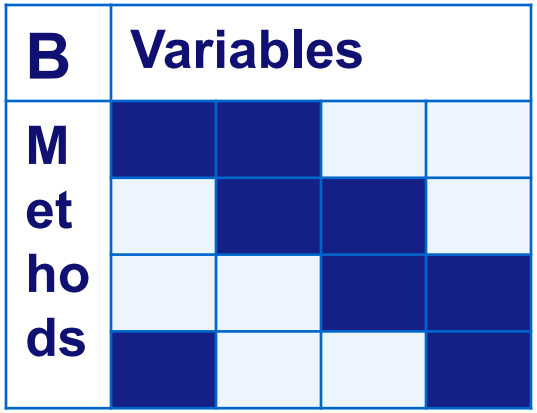

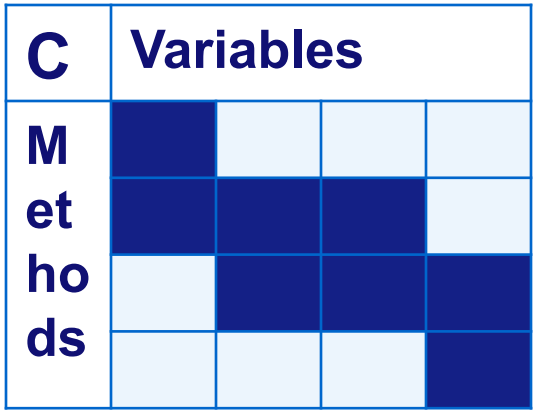

- All LCOM values are the same: 0.67
  - m=4, m(Vi) = 2 for all i
- A seems to be less cohesive than B and C!

$$\frac{\left(\frac{1}{v}\sum_{i=1}^{v} m(V_i)\right) - m}{1 - m}$$

Alternative [Hitz, Montazeri 1995]

- LCOM as the number of strongly connected components in the following graph
  - Vertices: methods
    - except for getters/setters
  - Edge between a and b, if
    - a and b access the same variable

- LCOM values
  - 0, no methods
  - 1, cohesive component
  - 2 or more, lack of cohesion

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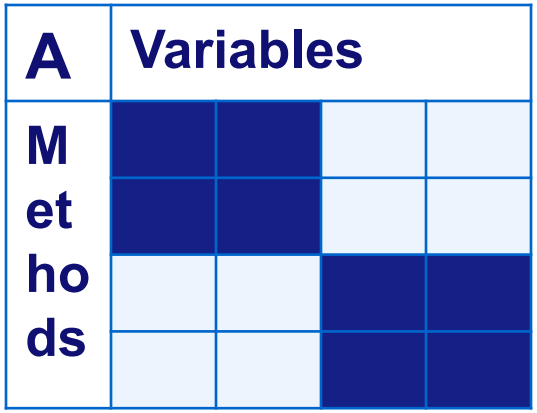
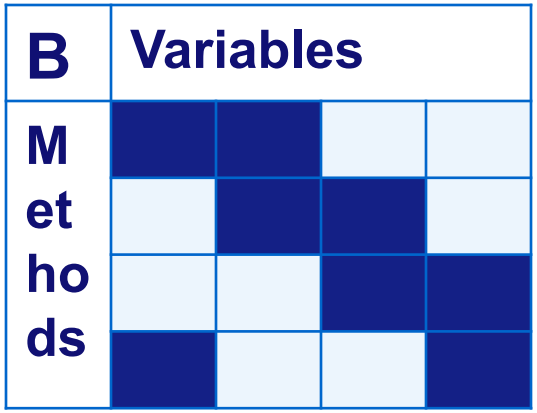
Question: LCOM?





Experimental evaluation of LCOM variants

Cox, Etzkorn and Hughes 2006	Correlation with expert assessment	
	Group 1	Group 2
Chidamber Kemerer	-0.43 (p = 0.12)	-0.57 (p = 0.08)
Henderson-Sellers	-0.44 (p = 0.12)	-0.46 (p = 0.18)
Hitz, Montazeri	-0.47 (p = 0.06)	-0.53 (p = 0.08)

Etzkorn, Gholston, Fortune, Stein, Utley, Farrington, Cox	Correlation with expert assessment	
	Group 1	Group 2
Chidamber Kemerer	-0.46 (rating 5/8)	-0.73 (rating 1.5/8)
Henderson-Sellers	-0.44 (rating 7/8)	-0.45 (rating 7/8)
Hitz, Montazeri	-0.51 (rating 2/8)	-0.54 (rating 5/8)

LCC and TCC [Bieman, Kang 1994]

- Recall: LCOM HM "a and b access the same variable"
- What if a calls a', b calls b', and a' and b' access the same variable?
- Metrics
  - NDP – number of pairs of methods directly accessing the same variable
  - NIP – number of pairs of methods directly or indirectly accessing the same variable
  - NP – number of pairs of methods: n(n-1)/2
- Tight class cohesion TCC = NDP/NP
- Loose class cohesion LCC = NIP/NP
- NB: Constructors and destructors are excluded

Experimental evaluation of LCC/TCC

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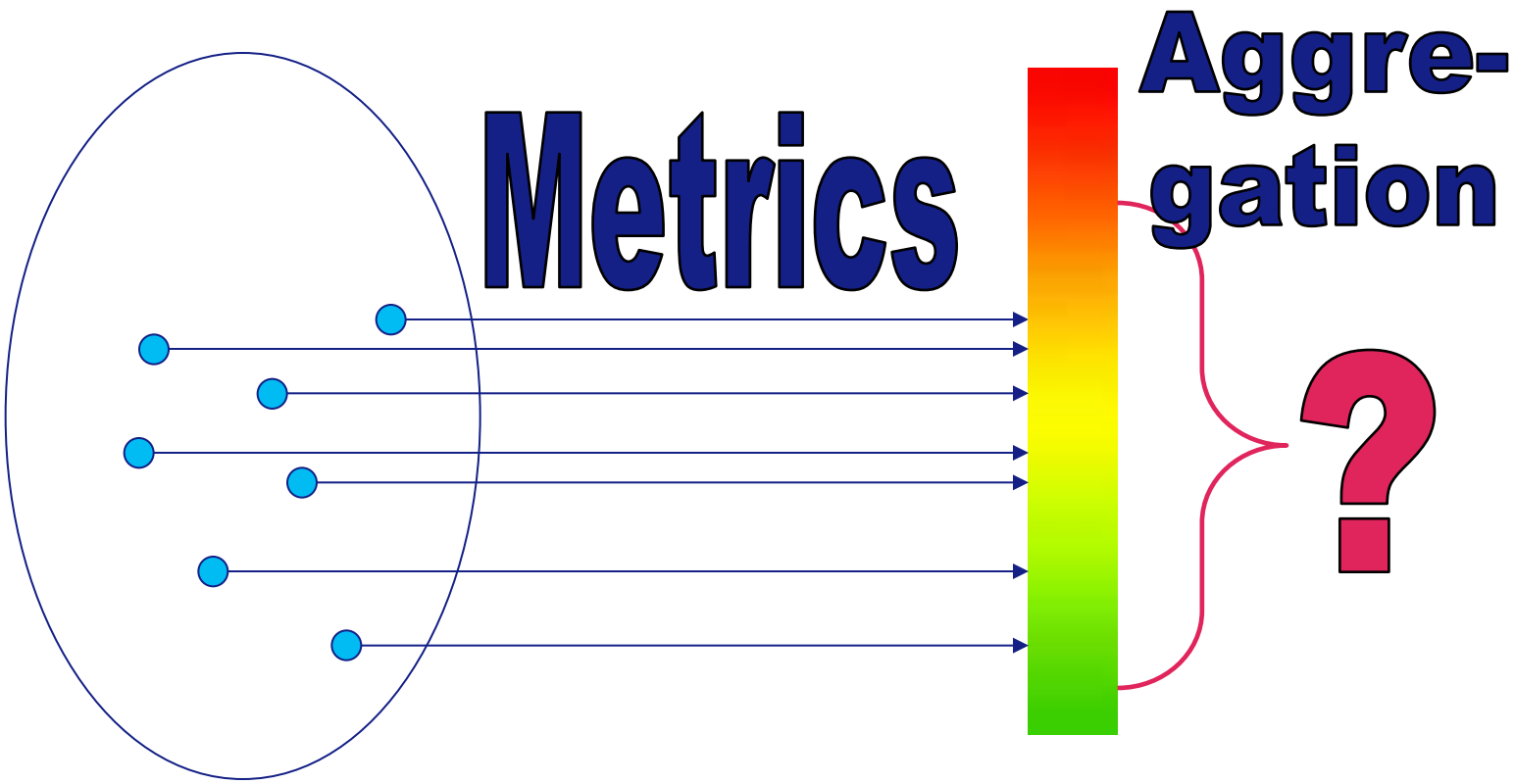
Hitz, Montazeri	-0.51 (rating 2/8)	-0.54 (rating 5/8)
TCC	-0.22 (rating 8/8)	-0.057 (rating 8/8)
LCC	-0.54 (rating 1/8)	-0.73 (rating 1.5/8)

Metrics so far…

Level	Metrics
Method	LOC, McCabe
Class	WMC, NOC, DIT, LCOM (and variants), LCC/TCC
Packages	???

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



Aggregation techniques

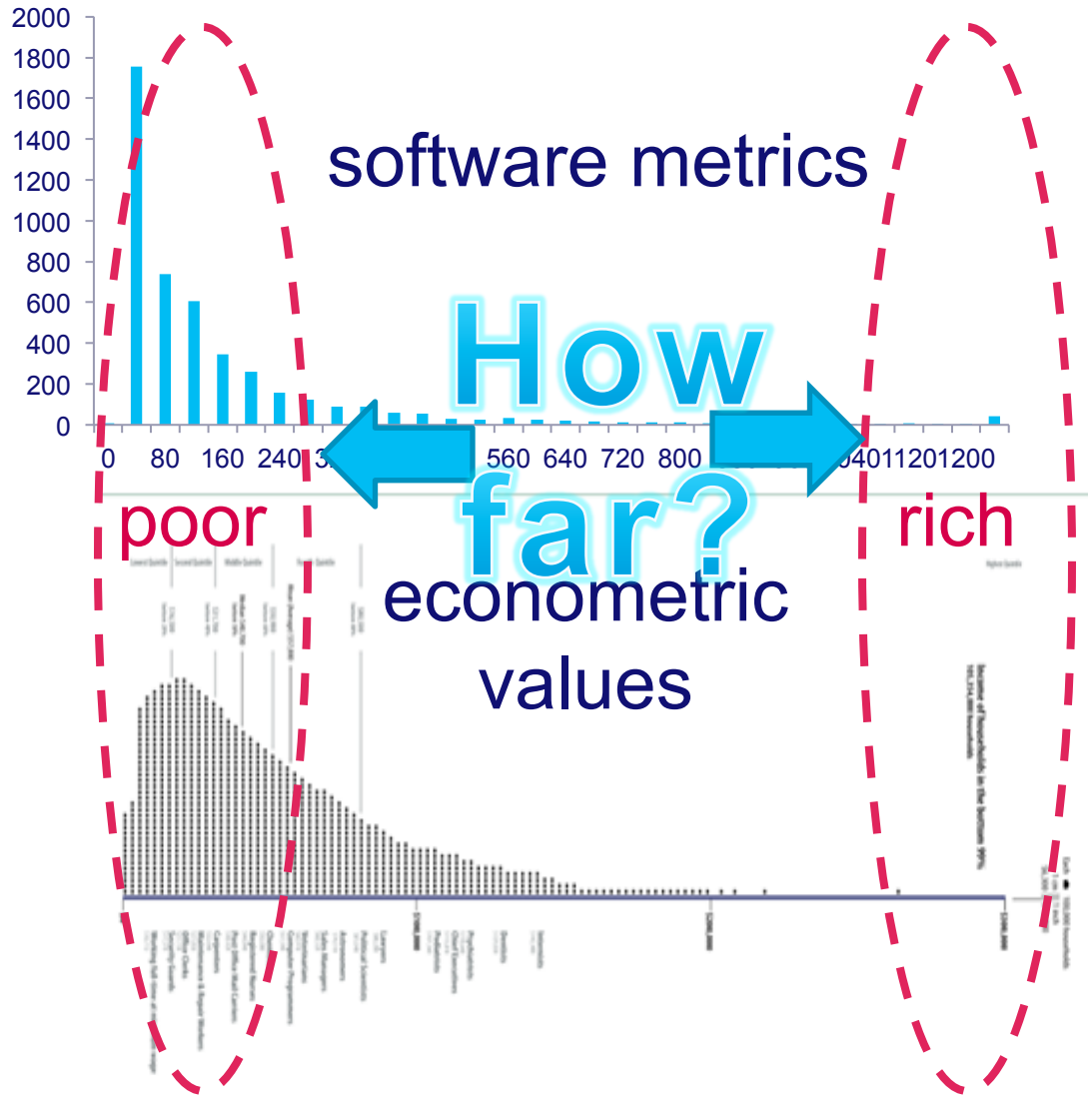
- **Metrics-independent**
  - **Applicable for any metrics to be aggregated**
    - **Traditional: mean, median...**
      - **“By no means”**
    - **Econometric: inequality indices**

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

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…**

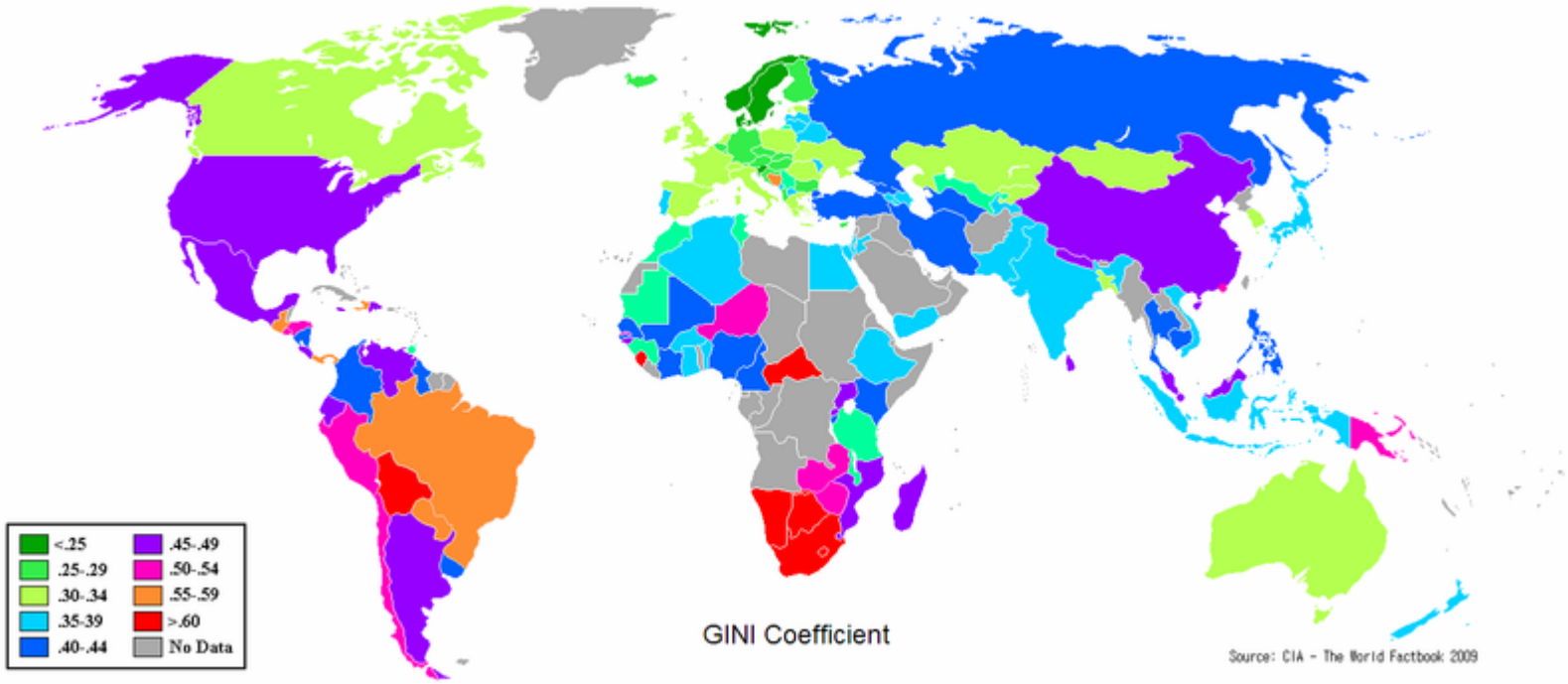
Metrics are like money



- prog. lang.
- domain
- …

- region
- education
- gender
- …

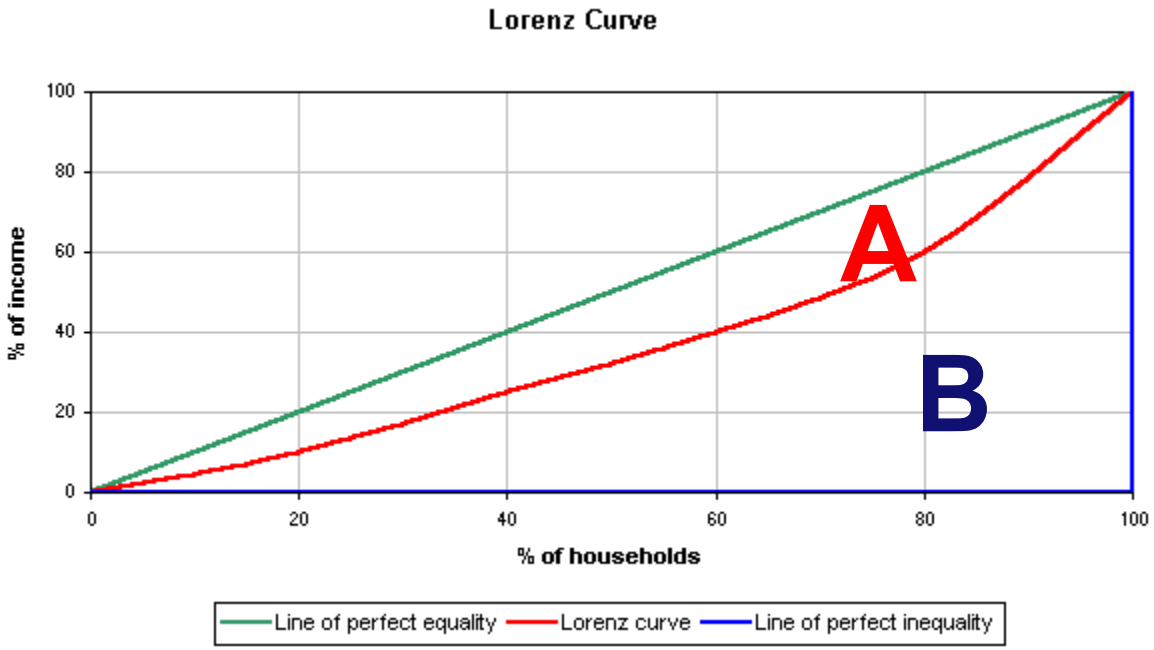
Popular technique: Gini coefficient



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

Gini coefficient: Formally

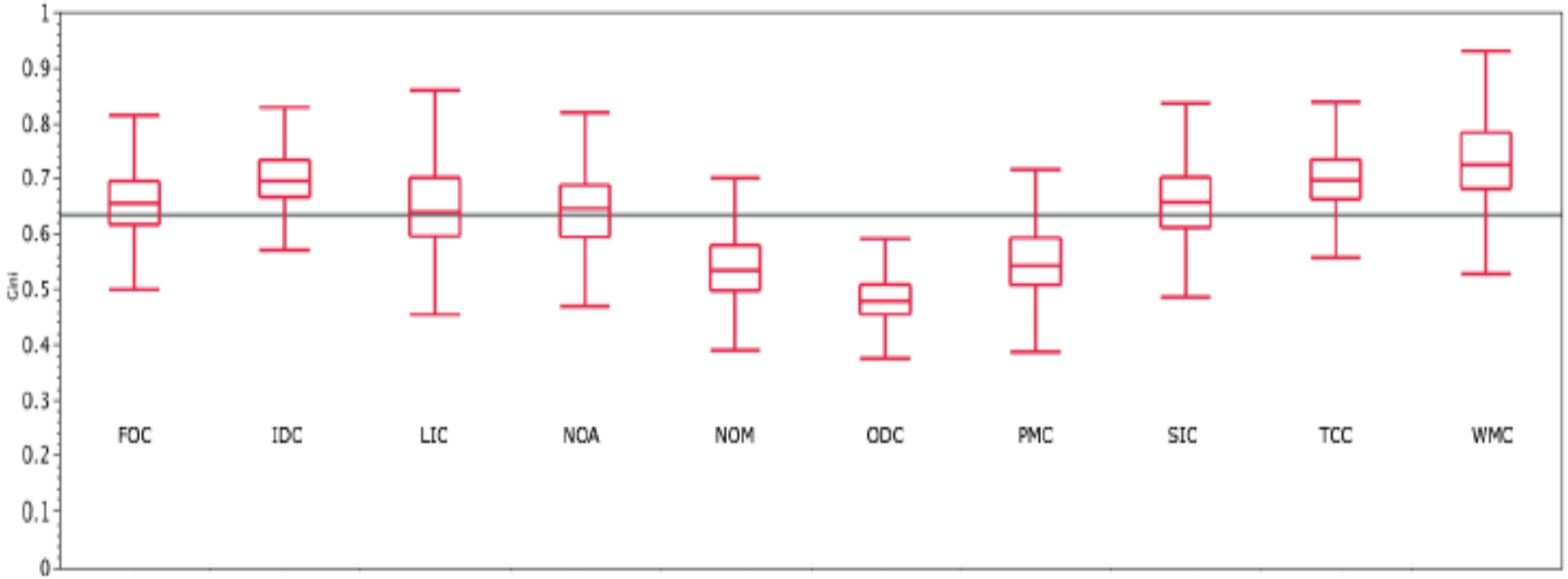
- **Lorenz curve:**
  - **% of income shared by the lower % of the population**



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

  Gini = 2A

Gini and software metrics [Vasa et al. 2009]

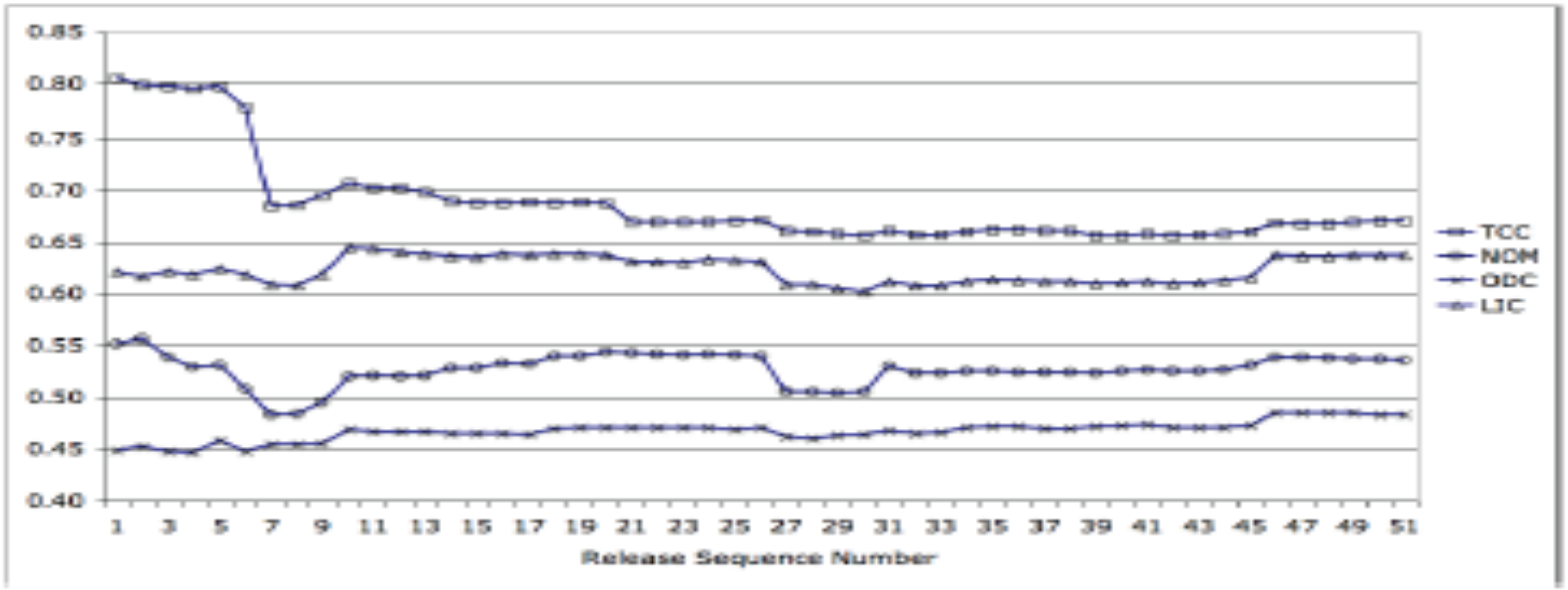


- For most of the metrics on the benchmark systems: 0.45 ≤ Gini ≤ 0.75
- Higher Gini/WMC: presence of generated code or code, structured in a way similar to the generated code (parsers)

Gini and metrics: Exceptions

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.

Gini and evolution: Spring



- **Rather stable: programmers accumulate competence and tend to solve similar problems by similar means**
- **Similar for other econometric techniques: Theil, Hoover, Atkinson, ...**

Aggregation techniques

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

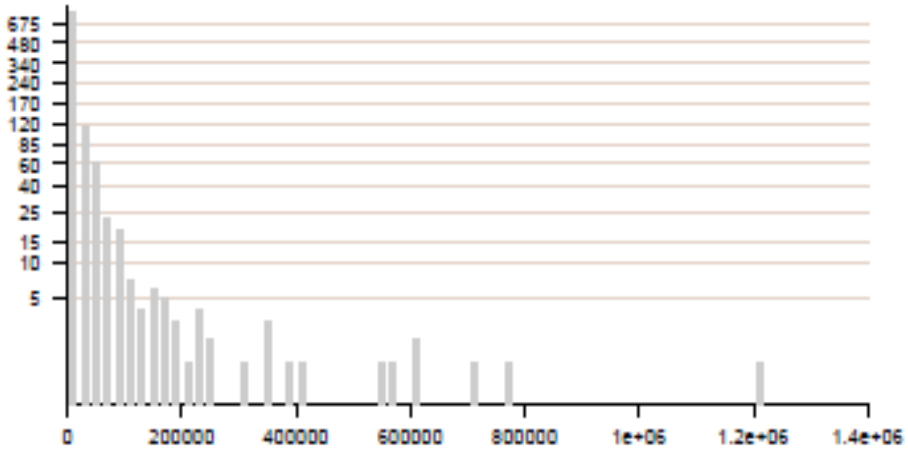
- **Metrics-dependent**
  - **Produces more precise results**
  - **BUT: needs to be redone for any new metrics**
  - **Based on fitting probability distributions**

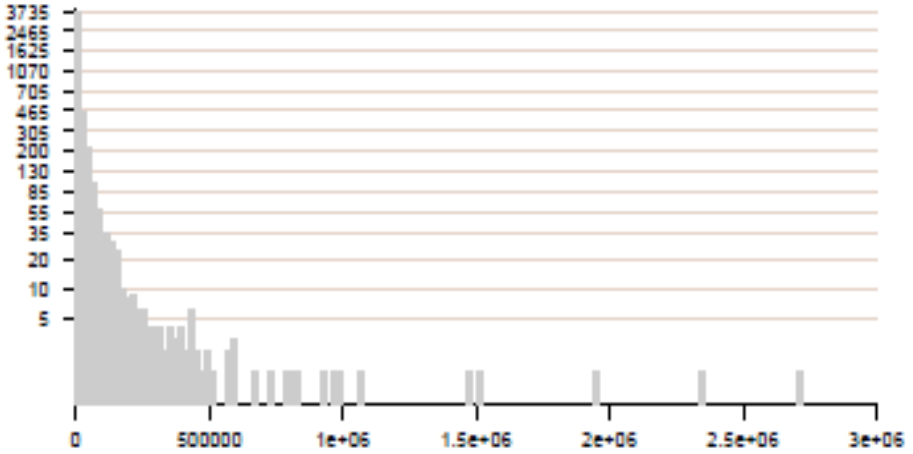
Metrics-dependent aggregation: Statistical fitting

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

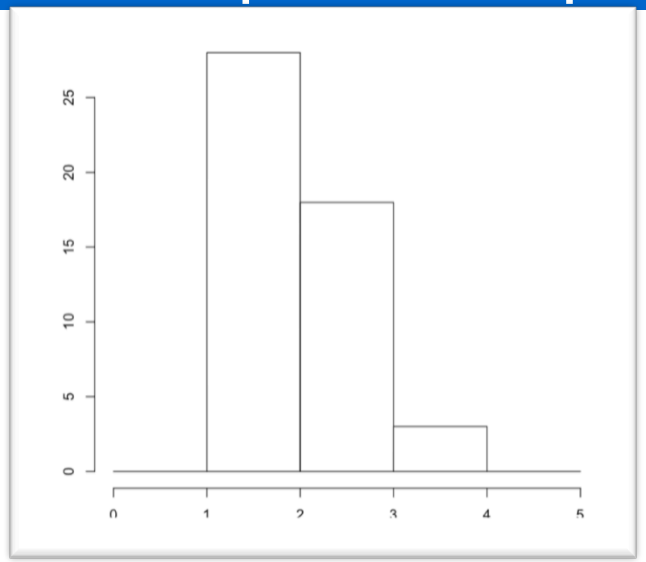
- **We have seen quite a number of them already!**

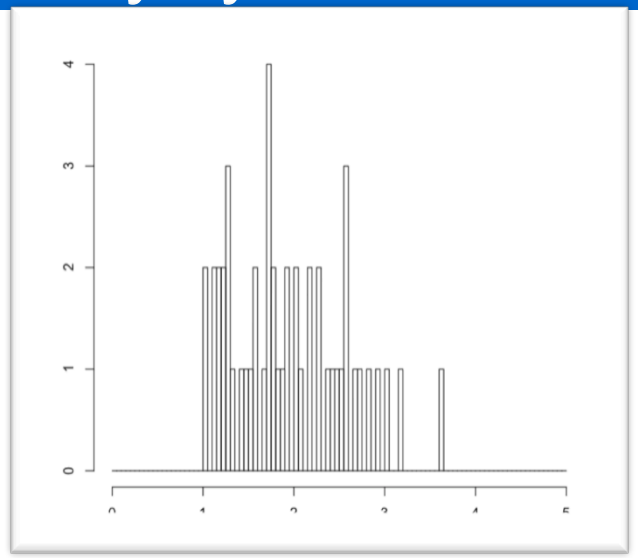


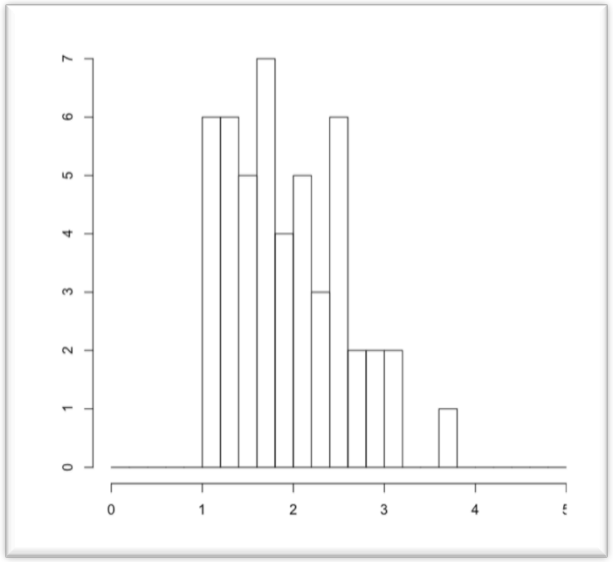


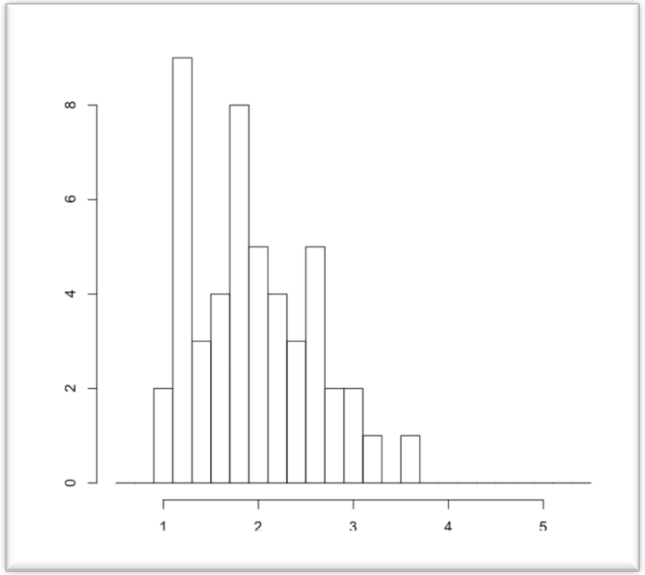
Robles et al. 2006: LOC in Debian 2.0 (left) and 3.0 (right)

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

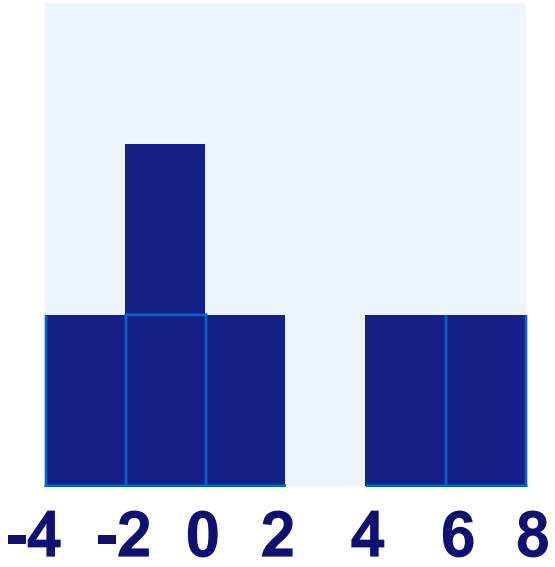
Kernel density estimators

- **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

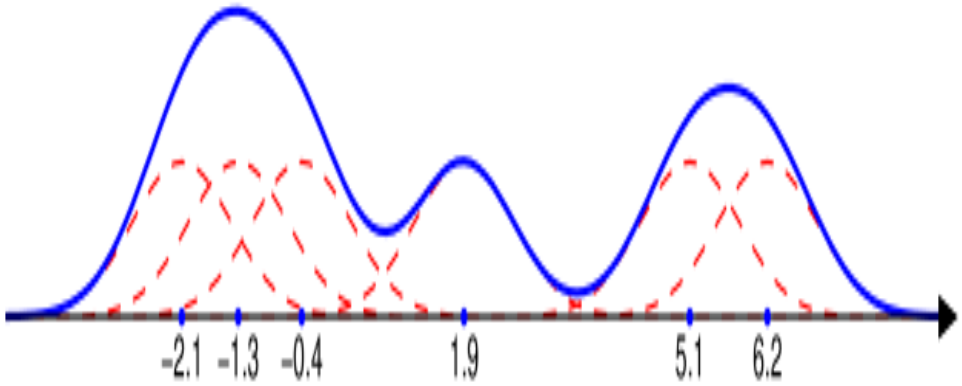
- Data: -2.1, -1.3, -0.4, 1.9, 5.1, 6.2



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?

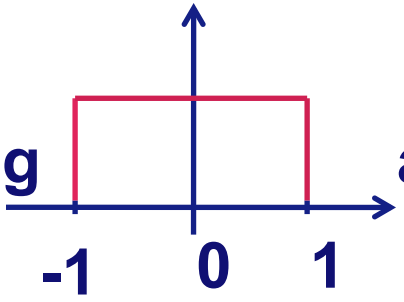


Kernel density estimation: Formally

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

Where

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

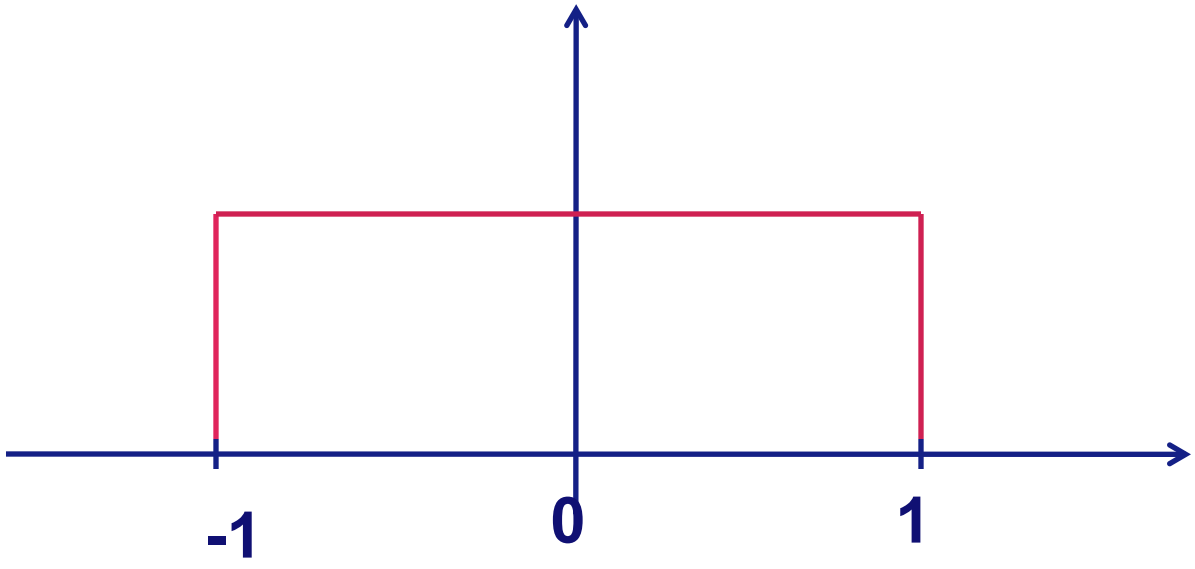
Histogram can be obtained using 

as K

Once K is chosen one can determine the optimal h.

Histogram as a kern density estimate

- h is the bin width
- x and x_i are in the same bin if $-1 \leq \frac{x - x_i}{h} \leq 1$



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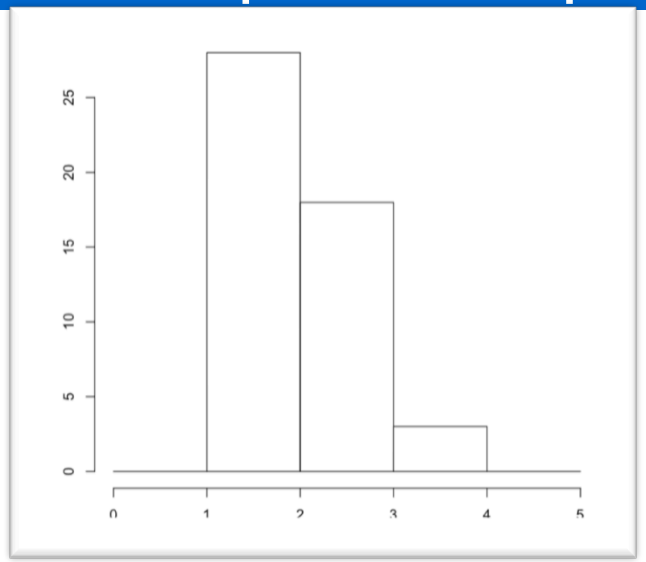
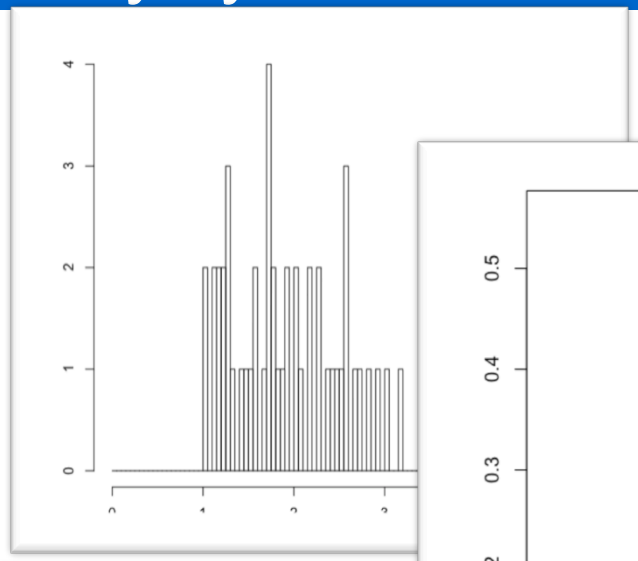
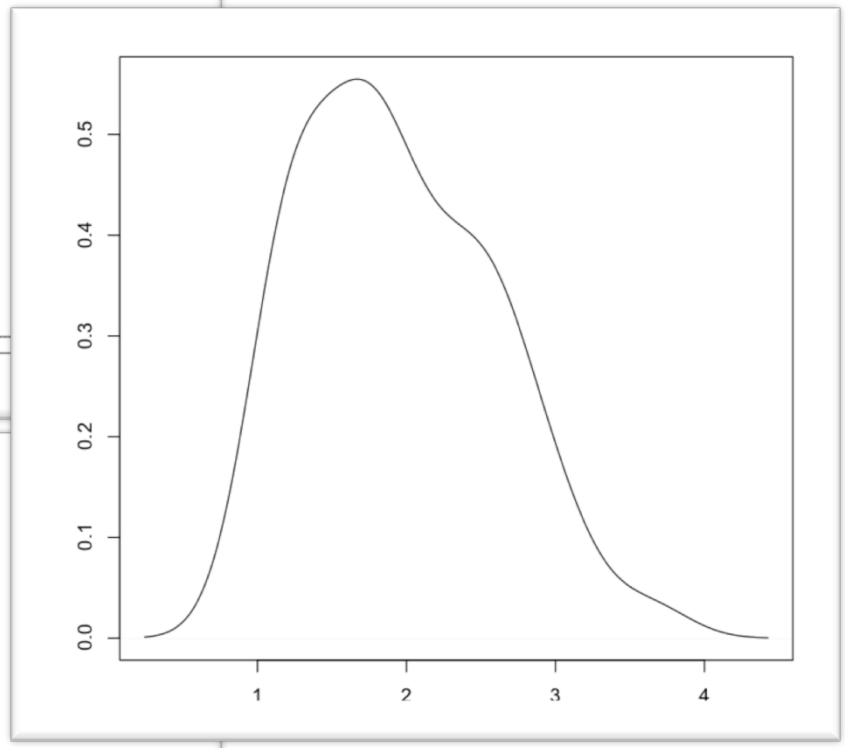
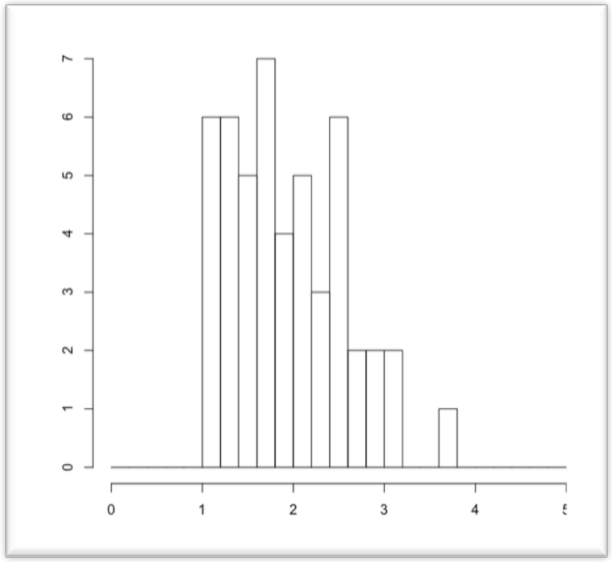
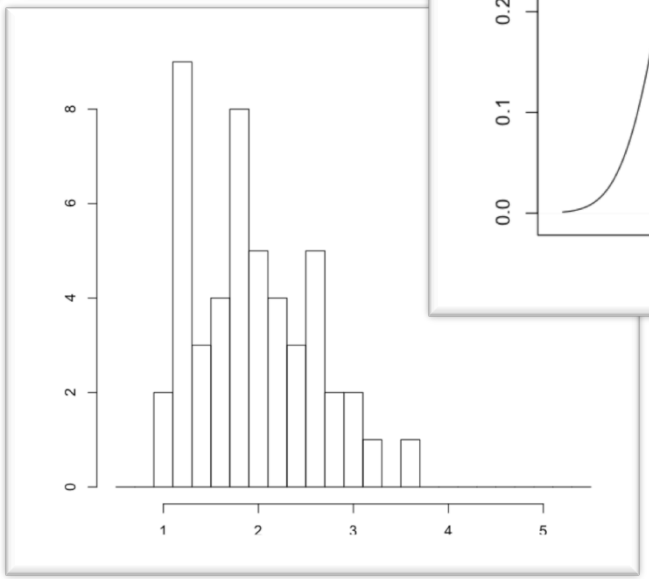


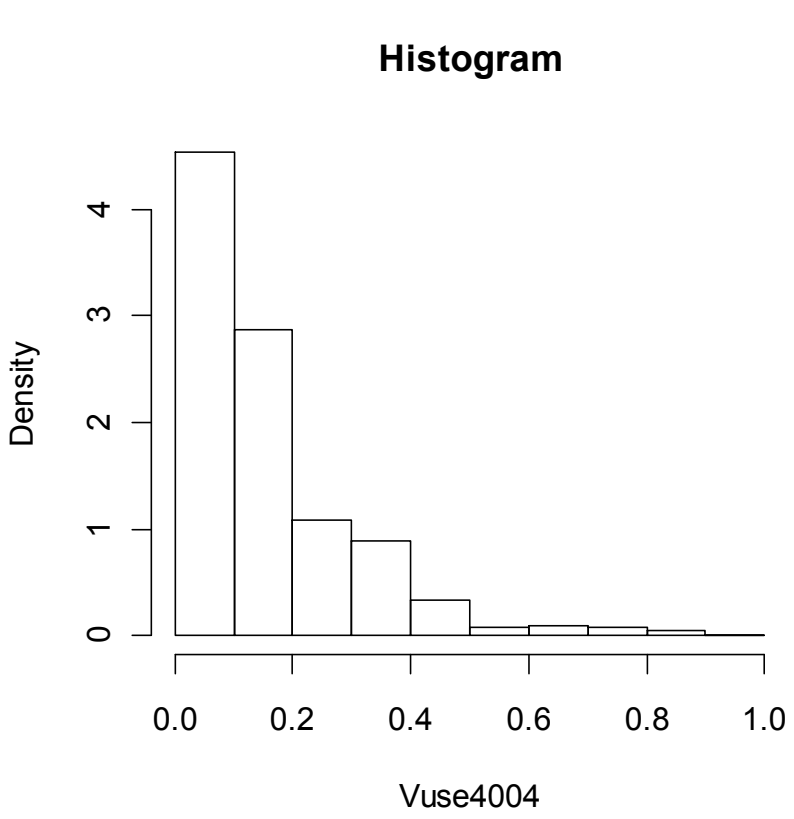


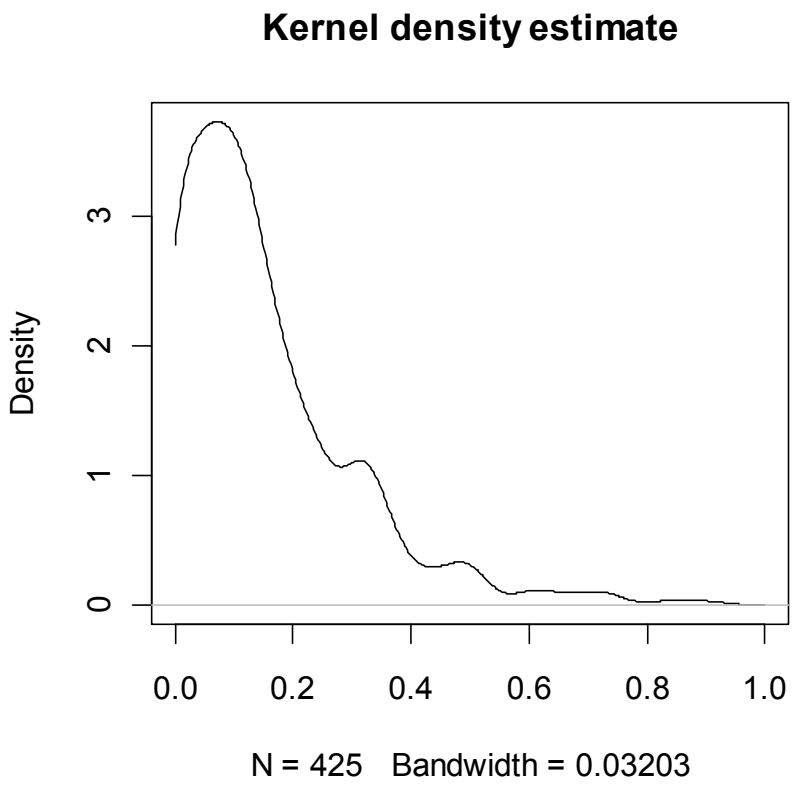




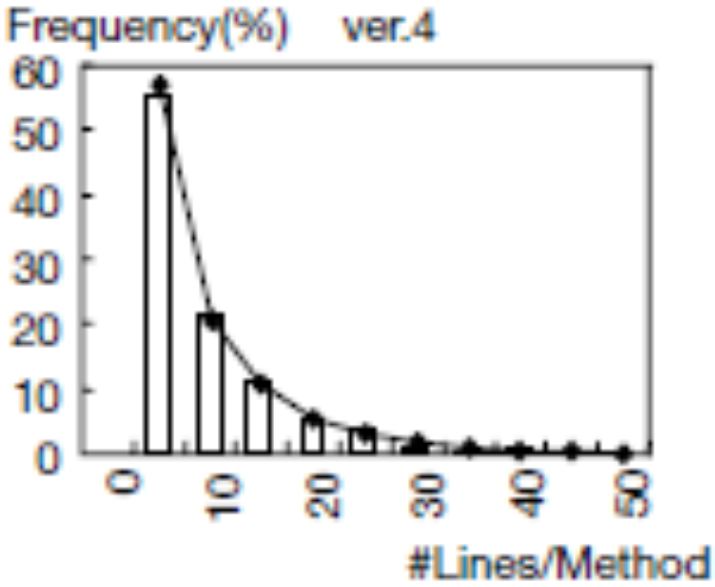


Histogram vs. Kernel density estimate

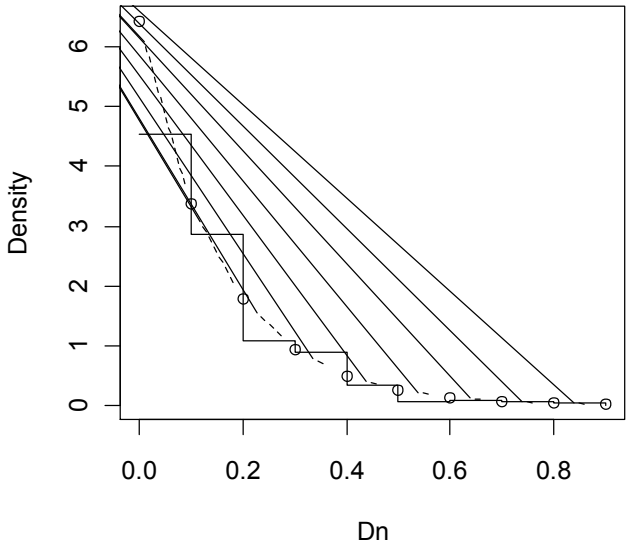




Step 2: fitting a distribution



Tamai, Nakatani.
Negative binomial distribution



S, Roubtsov, vd Brand
"Exponential" distribution

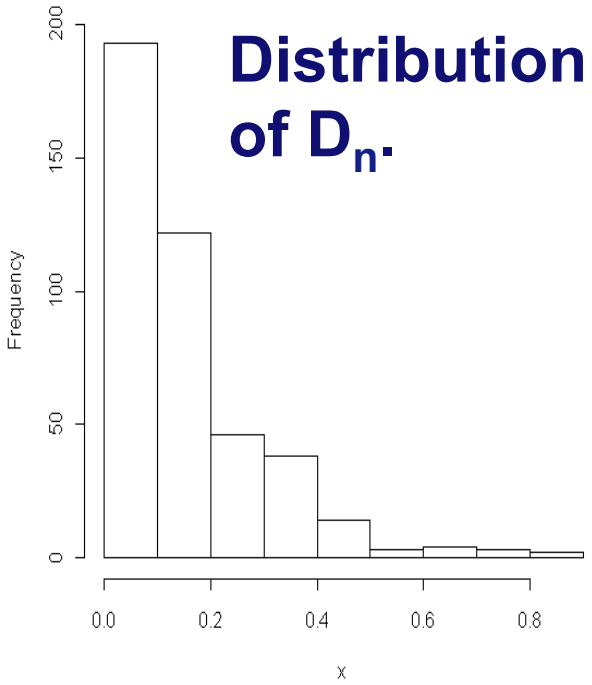
- Family of distributions is chosen based on shape
- If the parameters fitting is not good enough try a different one!

Sometimes well-known distributions do not really seem to match

- **Exponential distribution:**

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

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



Distribution of D_n.

- **And use *max-likelihood fitting* to find λ**

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**
  - **Degrees of freedom = number of observations – number of fitted parameters**
  - **Comparison is done based on table values**
  - **If the X^2 < table value – the fit is good**

Recapitulation: Statistical fitting

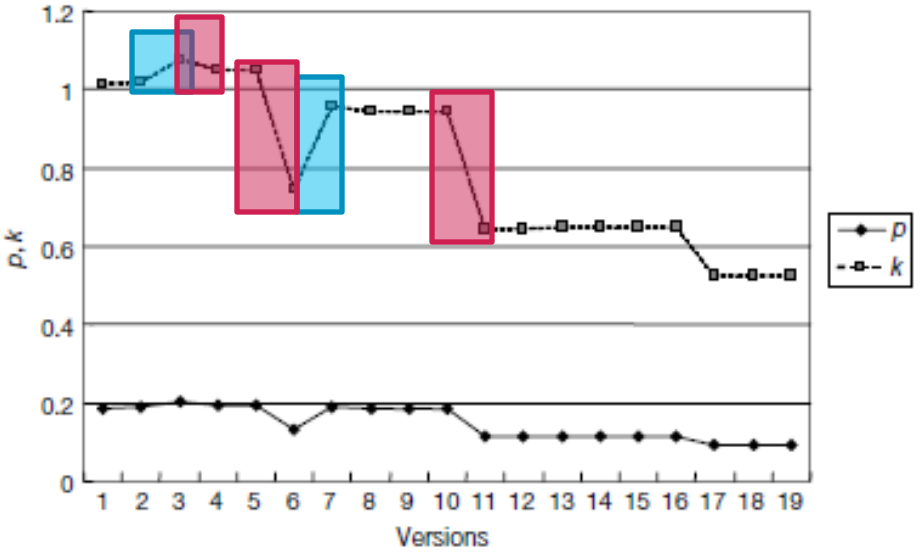
1. Collect the metrics values for the lower-level elements
2. Present a histogram
3. Fit a (theoretical) probability distribution to describe the sample distribution
   a) Select a family of theoretical distributions
   b) Fit the parameters of the probability distribution
   c) Assess the goodness of fit
4. If a theoretical distribution can be fitted, use the fitted parameters as the aggregated value

What about the evolution of the aggregated values?

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

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

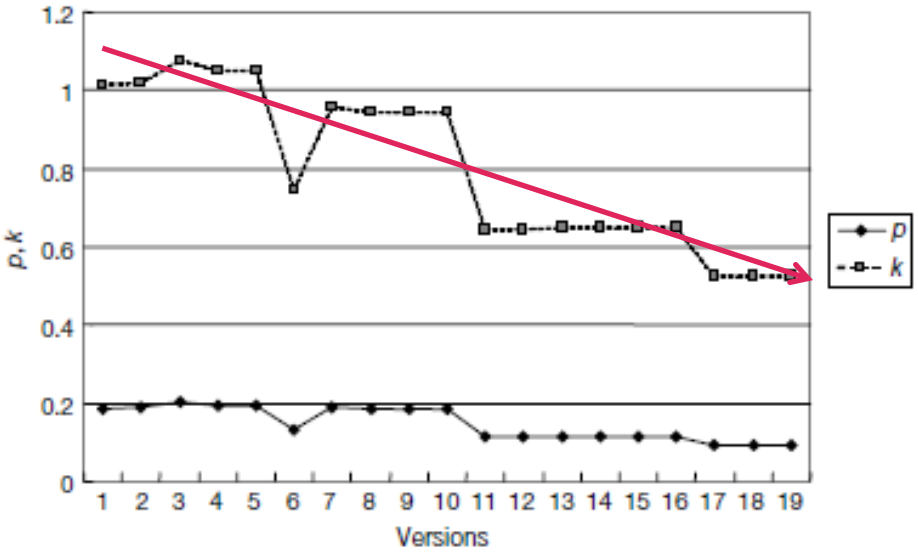
- p, k – distribution parameters
- $\binom{x-1}{k-1}$ - binomial coefficient extended to the reals



- Increase – functionality enhancement
- Decrease – refactoring

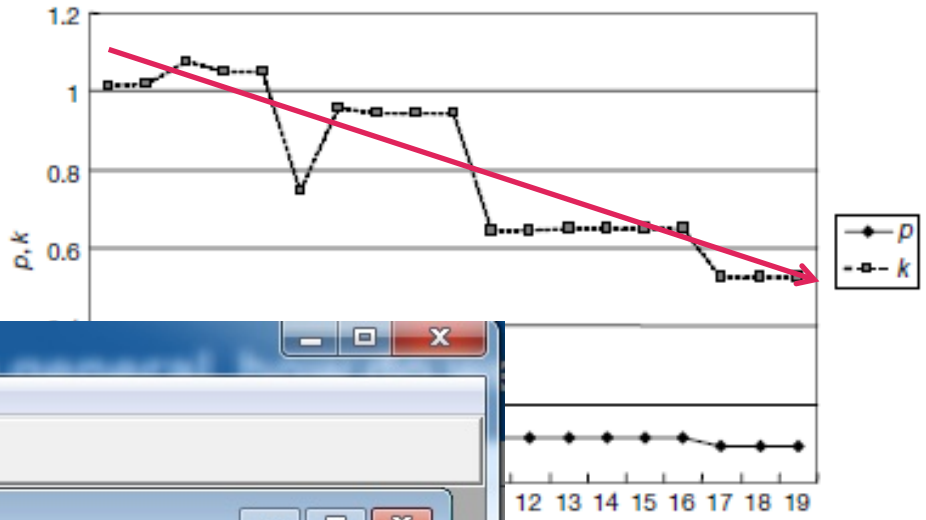
In general, how do we study evolution?

- **Visual inspection**
  - **Is this a real "trend" or just noise?**



In general, how do we study evolution?

- **Time-series analysis**
  - **Simplest form: linear regression with *time***



RGui

File Edit View Misc Packages Windows Help

R Console

```
> cor.test(data,time)

        Pearson's product-moment correlation

data:  data and time
t = -7.4684, df = 16, p-value = 1.337e-06
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.9552531 -0.7046643
sample estimates:
       cor
-0.8815246
```

Linear trend

Significant

Strong

More advanced techniques:

2DD23 - Time series analysis and forecasting

Conclusions: Aggregation

- **Aggregation:**
  - **Metrics-independent**
    - **Applicable for any metrics to be aggregated**
      - **Traditional: mean, median...**
        - **“By no means”**
      - **Econometric: inequality indices**
  - **Metrics-dependent**
    - **Produce more precise results**
    - **BUT: need to be redone for any new metrics**
    - **Based on fitting probability distributions**

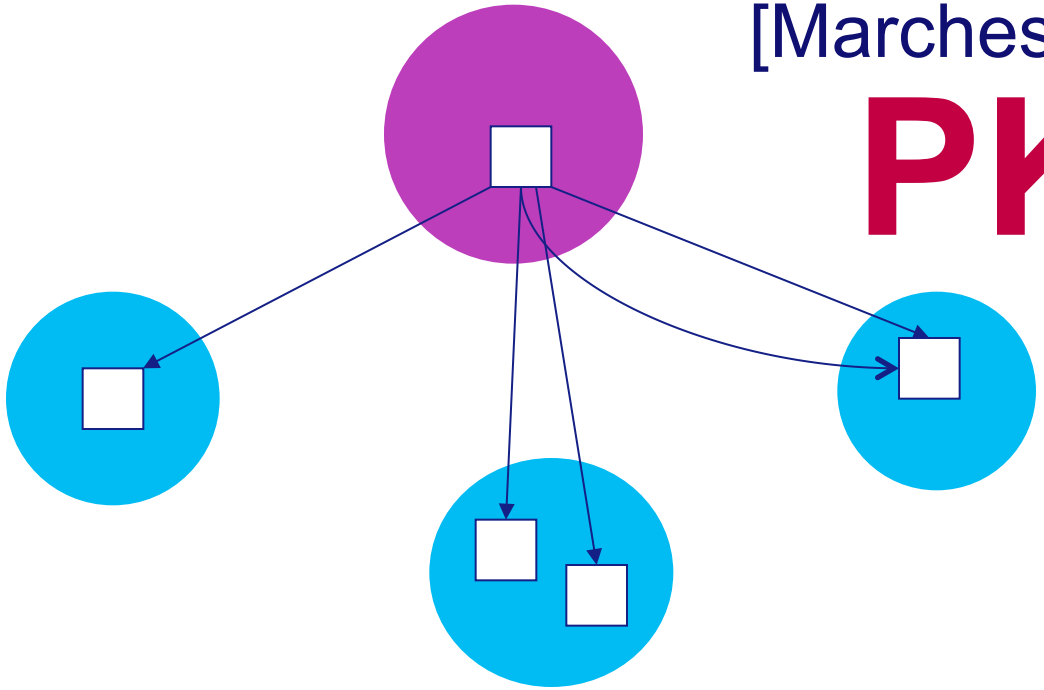
Metrics so far…

Level	Metrics
Method	LOC, McCabe
Class	WMC, NOC, DIT, LCOM (and variants), LCC/TCC
Packages	Aggregation
	Direct metrics???

Package metrics

- **Size:**
  - **number of classes/interfaces**
  - **number of classes in the subpackages**
- **Dependencies**
  - **visualization**
  - **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"**

“Fan-out”



[Marchesi 1998] [Martin 2000]

PK_1 or R: 5

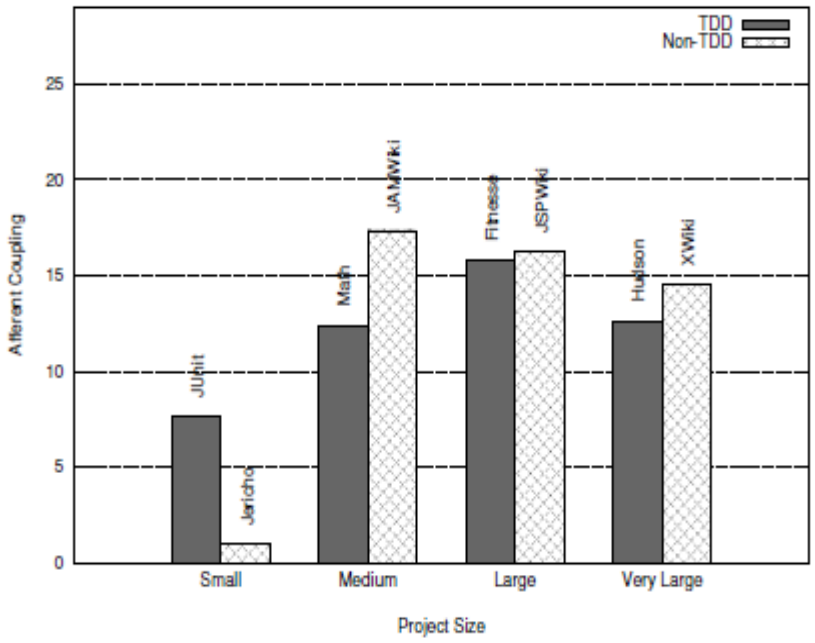
C_e: 1 [Martin 1994]

3 [JDepend]

4 [Martin 2000]

Fan-in

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



- 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)

[Hilton 2009]

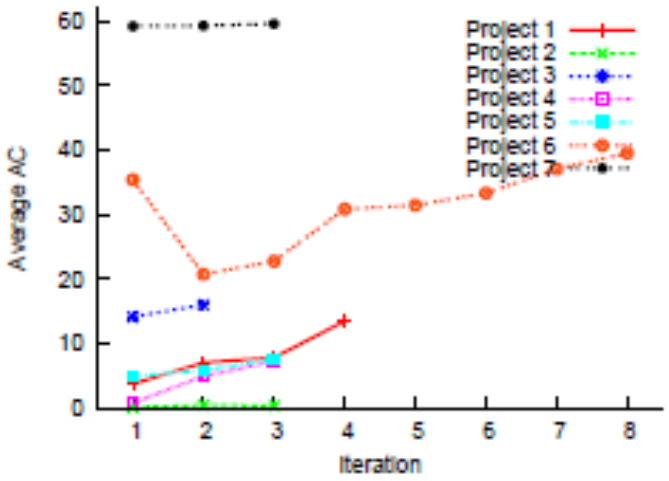
More fan-in and fan-out

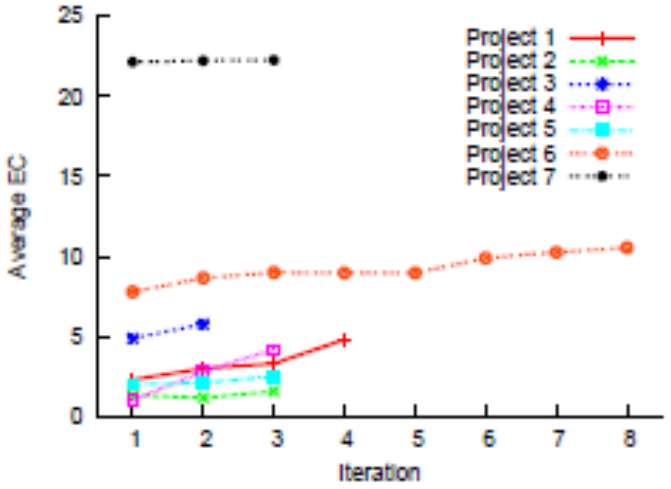
- "Fan-in" similarly to the "Fan-out"
  - Afferent coupling (Martin)
  - PK_2 (Marchesi)

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

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

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
  - Should be extensible via inheritance (*abstract*)
- **Instable** packages
  - Depend upon many classes outside
  - No dependents
  - Should not be 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

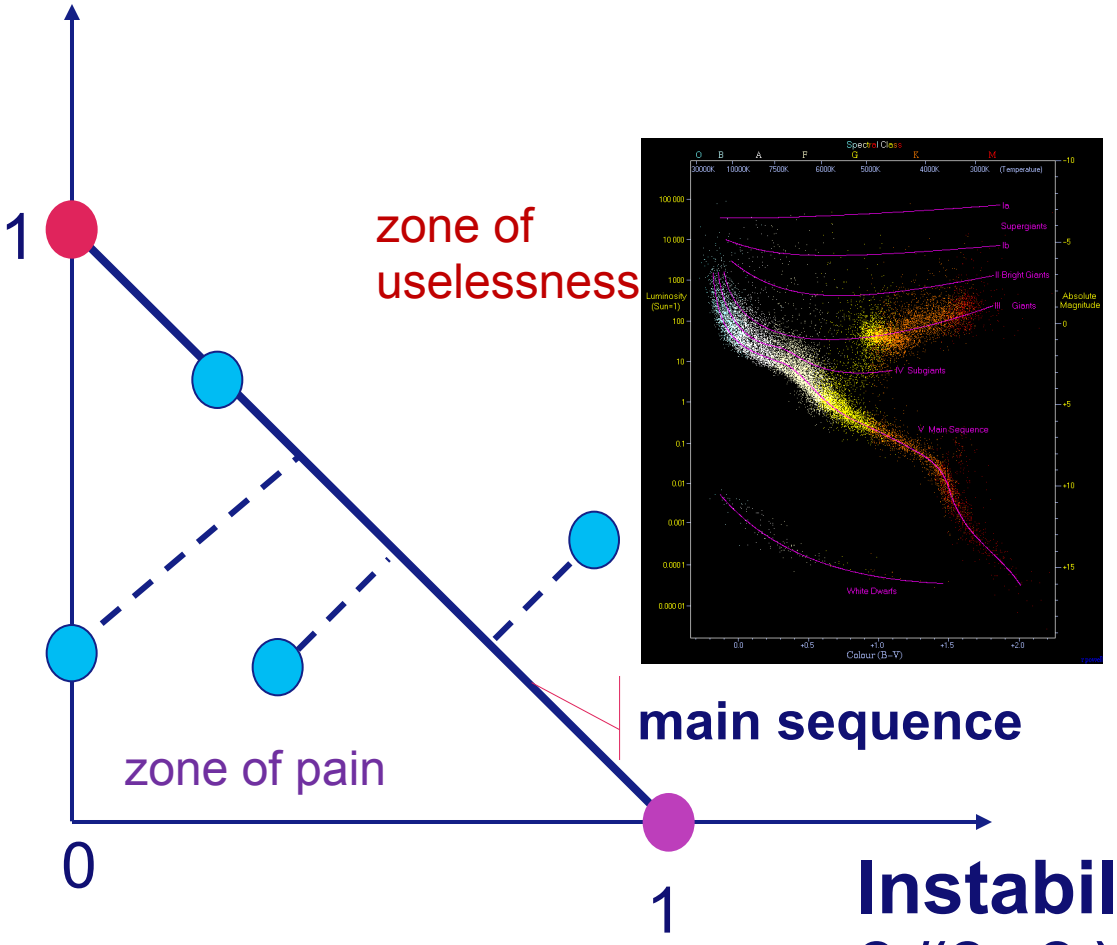
Abstractness =
#AbstrClasses/#Classes

D_n =

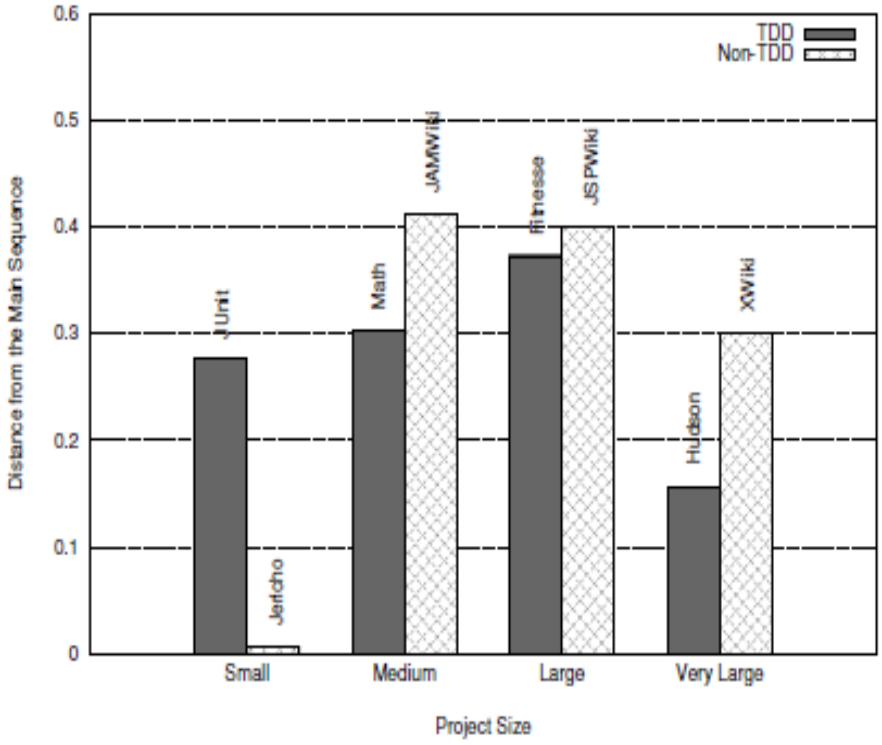
| Abstractness +

Instability – 1 |

[R.Martin 1994]



Normalized distance from the main sequence



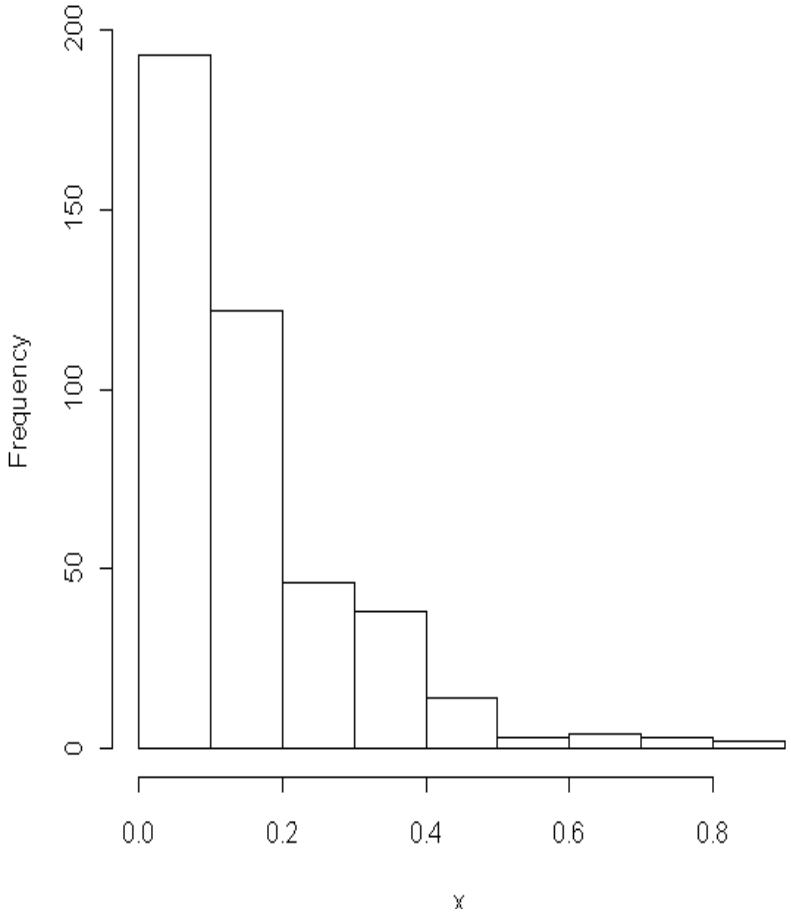
- Dark: TDD, light: no-TDD
- Test-driven development positively affects D_n
  - The lower D_n - the better.
- The same exception (Jericho vs. JUnit)

[Hilton 2009]

Distribution

“Exponential” distribution

For all benchmark systems studied, here Vuze 4.0.0.4



PASTA [Hautus 2002]

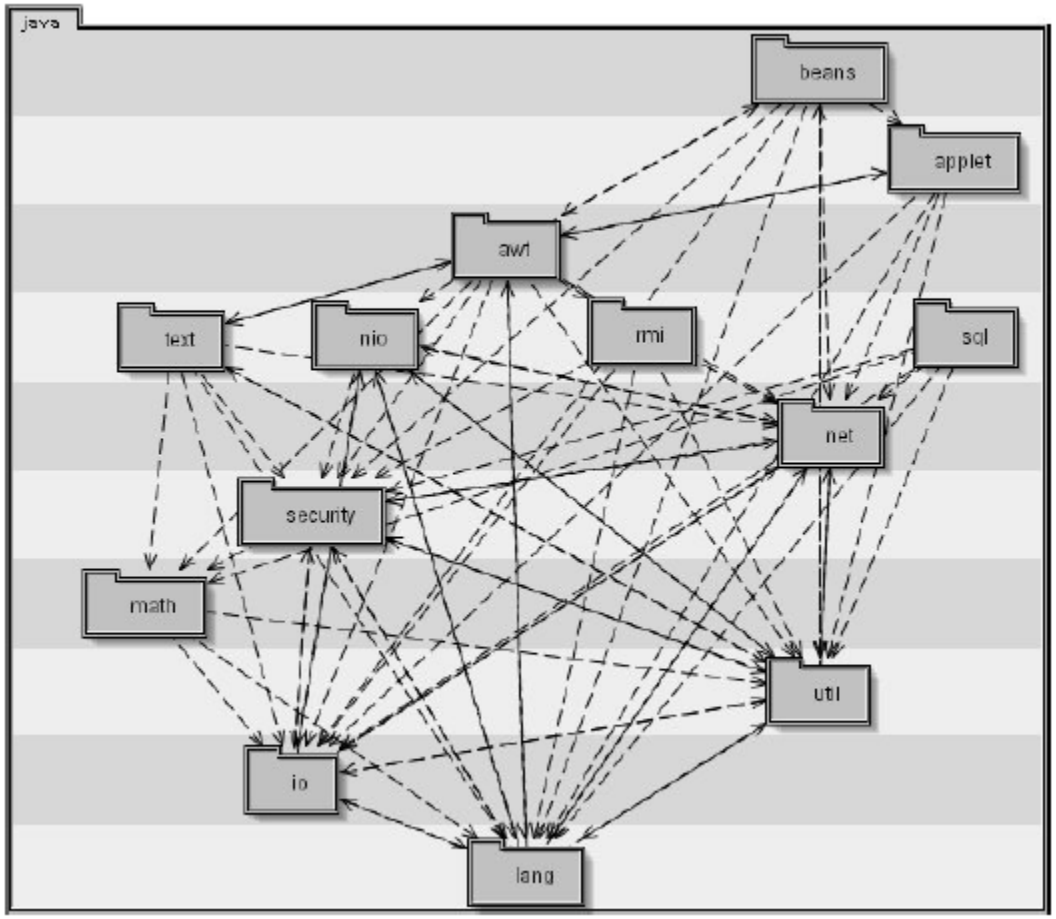
- PASTA – Package structure analysis tool

- Metrics
  - Similarly “fan-in/fan-out”: based on dependencies between packages
  - Go beyond calculating numbers of dependencies

- Focus on dependencies between the 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%

One metric is good, more metrics are better (?)

- **Recall…**

$$MI_1 = 171 - 5.2\ln(V) - 0.23V(g) - 16.2\ln(LOC)$$

Halstead McCabe LOC

- **[Kaur, Singh 2011] propose an adaptation…**

$$MIP = 171 - 5.2CC - 0.23\ln(S) - 16.2\ln(NC)$$

Related to PK_1 and instability

Related to NOC and NOM

Related to nesting, strongly connected components, abstractness and PK_2

Summary: 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: reminder
  - Metrics independent: average, sum, Gini/Theil coefficients
  - 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:
Churned LOC, Deleted LOC, File Count, Weeks of Churn, Churn Count, Files Churned

Relative:

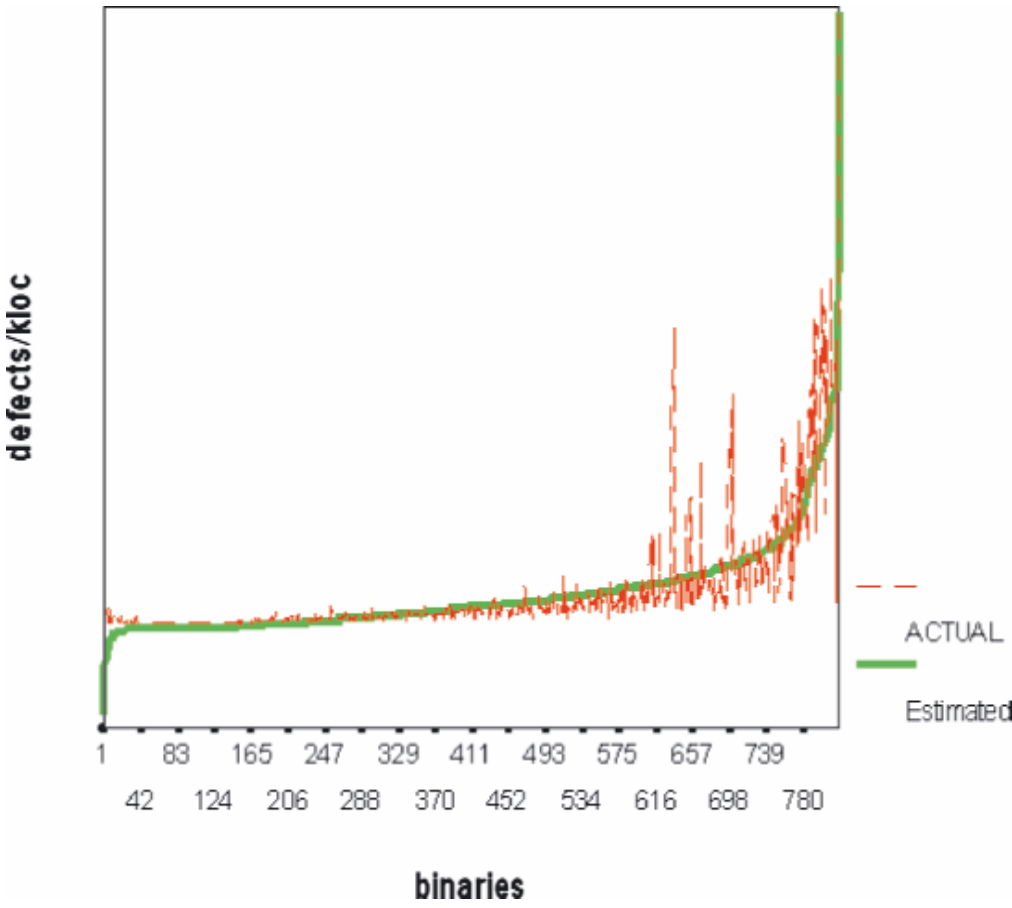
M1: Churned LOC / Total LOC
M2: Deleted LOC / Total LOC
M3: Files churned / File count
M4: Churn count / Files churned
M5: Weeks of churn/ File count
M6: Lines worked on / Weeks of churn
M7: Churned LOC / Deleted LOC
M8: Lines worked on / Churn count

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**
  - **Results of aggregation**

- **Churn metrics**