Hasso Plattner Institut
IT Systems Engineering | Universität Potsdam

Experimental methods

many slides by Sebastian Kruse & Thorsten Papenbrock

22.05.2017

Felix Naumann

Agenda

1. **Designing algorithms**
   - Definition of goals
   - Engineering pitfalls
   - Testing for correctness
   - Experimental evaluation
2. Interpreting experiments
3. Cross-cutting concerns
   - Data acquisition
   - Thoughts on complexity
   - Science vs. Engineering

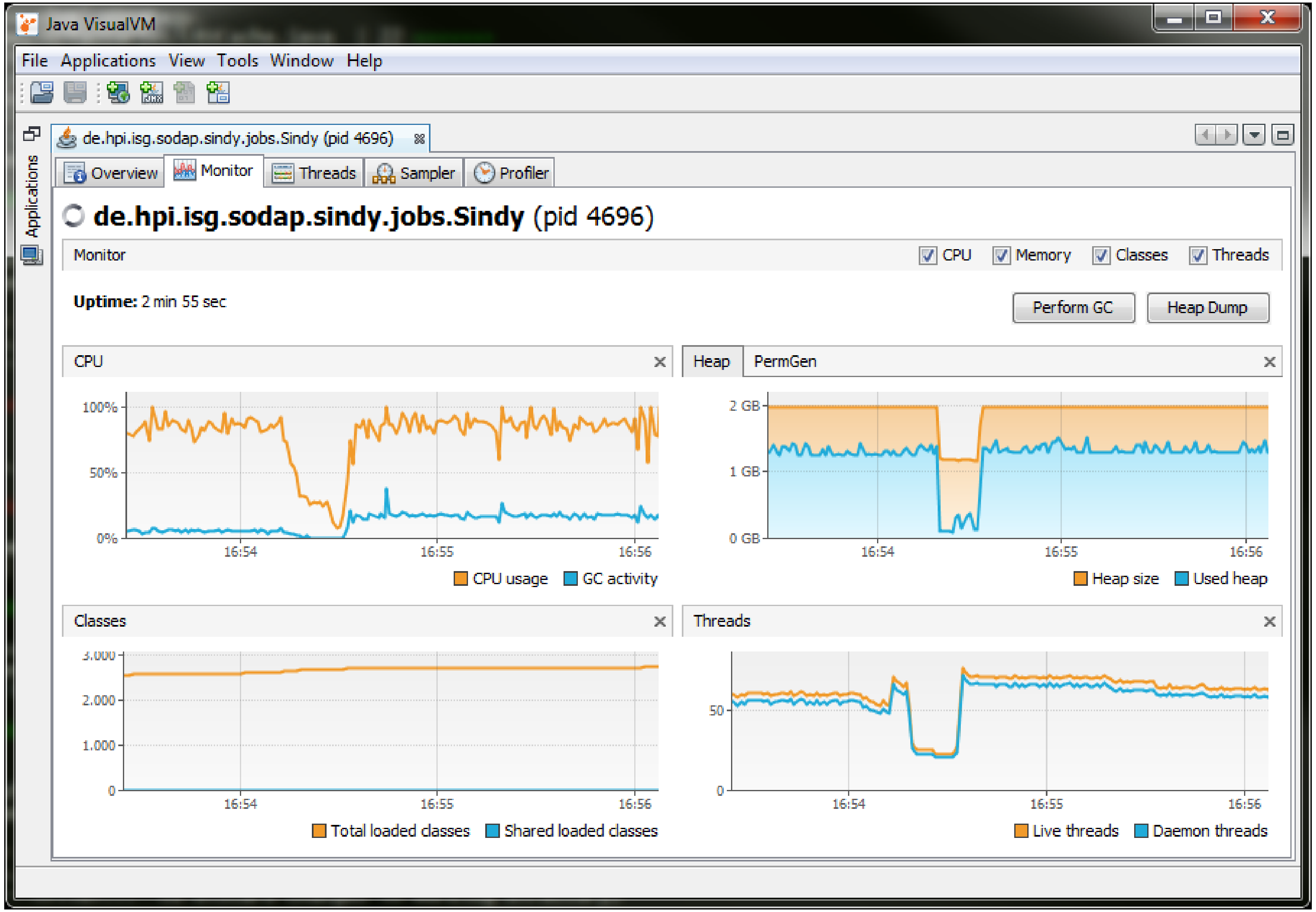
Definition of goals

- SMART goals https://de.wikipedia.org/wiki/SMART_(Projektmanagement)
  - **Specific:** What shall be the contribution of your algorithm?
    - Properties: efficiency, robustness, scalability, security
    - Solve a new problem or enter a new dimension of a problem
  - **Measurable:** How can you evaluate your progress?
    - Even better: can you monitor your progess?
  - **Assignable:** Make subgoals (and distribute them).
  - **Realistic:** Have a certain confidence in your ideas before taking them up.
  - **Time-boxed:** Answers give rise to new questions, so consider time limitations.
- Have a use-case

Engineering pitfalls

- A *good idea* has more potential than a highly tuned *implementation*.
- But: A good idea needs good code. Put your theory into practice properly.
- "Premature optimization is the root of all evil." – Donald E. Knuth
  - It is likely to obfuscate your code.
  - Measure, then optimize where it pays off (Pareto principle).
  - Know your bottlenecks! Profiling with jVisualVM
  - (De-)Optimization happens on lower levels
    - SQL, compiler optimizations, JIT, generational garbage collection
- Design for performance
  - *Performance Patterns:* Smith, C. U., & Williams, L. G. (2001). Performance Solutions: A Practical Guide to Creating Responsive, Scalable Software. ISBN 0201722291
  - *Performance Antipatterns:* Smith, C. U., & Williams, L. G. (2000, September). Software performance antipatterns. In *Workshop on Software and Performance* (pp. 127-136).

Code profiling: jVisualVM



Engineering pitfalls

- I/O operations: latency vs. throughput
  - $10\,000 \cdot (t_{latency} + t_{write}) > t_{latency} + 10\,000 \cdot t_{write}$
  - Bundle I/O operations into batches
  - Employ latency hiding when necessary (threads)
- File operations are expensive
  - Reduce the (concurrent) number of files
  - Number of open file handles are limited
- If I/O still is a problem, there are some optimization opportunities
  - Avoid standard frameworks like Java serialization
  - Employ binary serialization instead of JSON/XML
    - Lower volume
  - Model strings as UTF-8 (not the default UTF-16), if possible.
  - Got free CPU cycles? Compression can pay off…

Testing for correctness

- Test your theory/hypothesis:
  - The ultimate verification: prove correctness of your algorithm
  - If formal proof is hard, make an informal proof to convince yourself
- Test your components:
  - Write unit tests for your utilities (e.g., parsers)
- Artificial test examples:
  - Good to get a first running version
  - Will likely not contain all edge cases
- Reference implementation:
  - Automatic result comparison with reference implementation
  - Helpful for debugging: output your delta with reference result
  - Do it on as many datasets as possible

Experimental evaluation

- Monitor your progress
  - Measure first, then optimize
  - Measure often
    - Use many different datasets for testing to avoid optimizing for specific dataset characteristics
    - Explore your parameters
  - Write a measurement framework early on!
    - Or use Metanome…
- If your goals are smart, you know when you are done.

Experimental evaluation

- Ultimate evaluation: Prove complexity of algorithm
- Otherwise: Empirical evidence of your claims/goals
- Evaluation results should therefore be
  - credible, significant, relevant, realistic, general/generalizable
  - Counterexamples?
- The fine art of evaluation: Support your claims with only a few experiments (on 10-12 pages)
  - Main goals: efficiency (compared to other algorithms), scalability
  - Optimizations: isolate and show effects of design choices
  - Use many datasets
    - Try to provide variety / use sampling to create variety
    - Real-world datasets are in general more convincing

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Forschersprache 1/2

- *It is believed*
  - Ich glaube
- *It is generally believed*
  - Ein paar andere glauben das auch
- *It has long been known*
  - Ich hab mir das Originalzitat nicht herausgesucht
- *In my experience*
  - Einmal
- *In case after case*
  - Zweimal
- *In a series of cases*
  - Dreimal
- *Preliminary experiments showed that…*
  - Wir hoffen, dass…
- *Several lines of evidence demonstrate that…*
  - Es würde uns sehr gut in den Kram passen
- *A definite trend is evident*
  - Diese Daten sind praktisch bedeutungslos
- *While it has not been possible to provide definite answers to the questions*
  - Ein nicht erfolgreiches Experiment, aber ich hoffe immer noch, dass es veröffentlicht wird
- *Three of the samples were chosen for detailed study*
  - Die anderen Ergebnisse machten überhaupt keinen Sinn
- *Typical results are shown in Fig. 1*
  - Das ist die schönste Grafik, die ich habe

Forschersprache 2/2

- *Correct within an order of magnitude*
  - Falsch
- *A statistically-oriented projection of the significance of these findings*
  - Eine wilde Spekulation
- *It is clear that much additional work will be required before a complete understanding of this phenomenon occurs*
  - Ich verstehe es nicht
- *After additional study by my colleagues*
  - Sie verstehen es auch nicht
- *The purpose of this study was…*
  - Es hat sich hinterher herausgestellt, dass ...
- *Our results confirm and extend previous conclusions that…*
  - Wir fanden nichts neues
- *It is hoped that this study will stimulate further investigation in this field*
  - Ich geb's auf!

Experimente kritisch begutachten

- Welche (vereinfachenden) Annahmen wurden getroffen
- Welche Daten wurden verwendet?
  - Real-World-Daten (Szenario?)
  - Künstliche Daten
  - Datenmenge
- Skalen der Grafiken
- Lesbarkeit der Graphiken
- Interpretation
  - Wurden Auffälligkeiten begründet?
- Vollständigkeit der Experimente
  - Wurden alle Aspekte der vorigen Abschnitte getestet?
  - Wurden alle Fragen beantwortet?
  - Funktionalität und Laufzeit (oder Beweis)

Repeatability

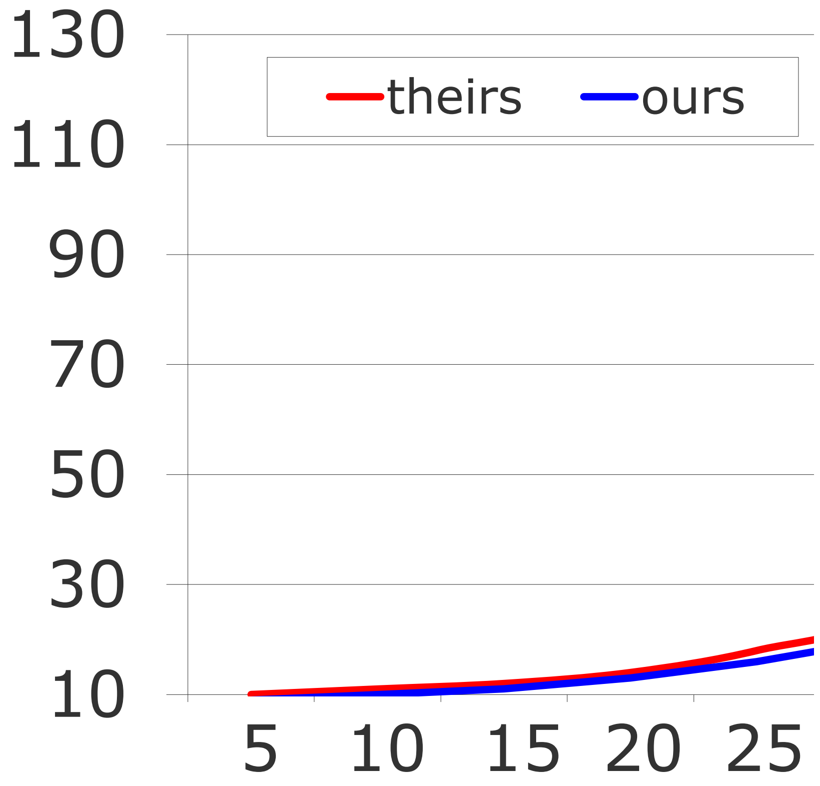
- SIGMOD since 2008: Repeatability
- VLDB since 2008: Experiments and Evaluation
  - Consolidation and Validation
    - „Motivated by these surprisingly excellent results, we take a look into the rearview mirror. We have re-implemented the Dwarf index from scratch and make three contributions. First, we successfully repeat several of the experiments of the original paper. Second, we **substantially correct some of the experimental results** reported by the inventors. Some of our results **differ by orders of magnitude**."
      From: Jens Dittrich, Lukas Blunschi, Marcos Antonio Vaz Salles. Dwarfs in the rearview mirror: how big are they really? VLDB 2008
    - "Entlarvung der Adaptive Sorted Neighborhood Method"
      "… Allerdings konnte ebenfalls gezeigt werden, dass die Autoren bei dem Vergleich ihrer Verfahren mit der SNM offensichtlich nicht die transitive Hülle berücksichtigten, denn nur so konnten die großen Unterschiede in den Vergleichen nachvollzogen werden. Unter Berücksichtigung der transitiven Hülle **schneidet die SNM dagegen im Vergleich zu den vorgestellten Verfahren sehr gut oder sogar besser ab**."
      By Oliver Wonneberg (HPI, BTW 2009 Studierendenprogramm)

An Aside (Gerhard Weikum)

- „Thoughts about the Experimental Culture in Our Community“
- An Experiment: How to Plan it, Run it, and Get it Published
- There are three kinds of lies: lies, damn lies, and workload assumptions.

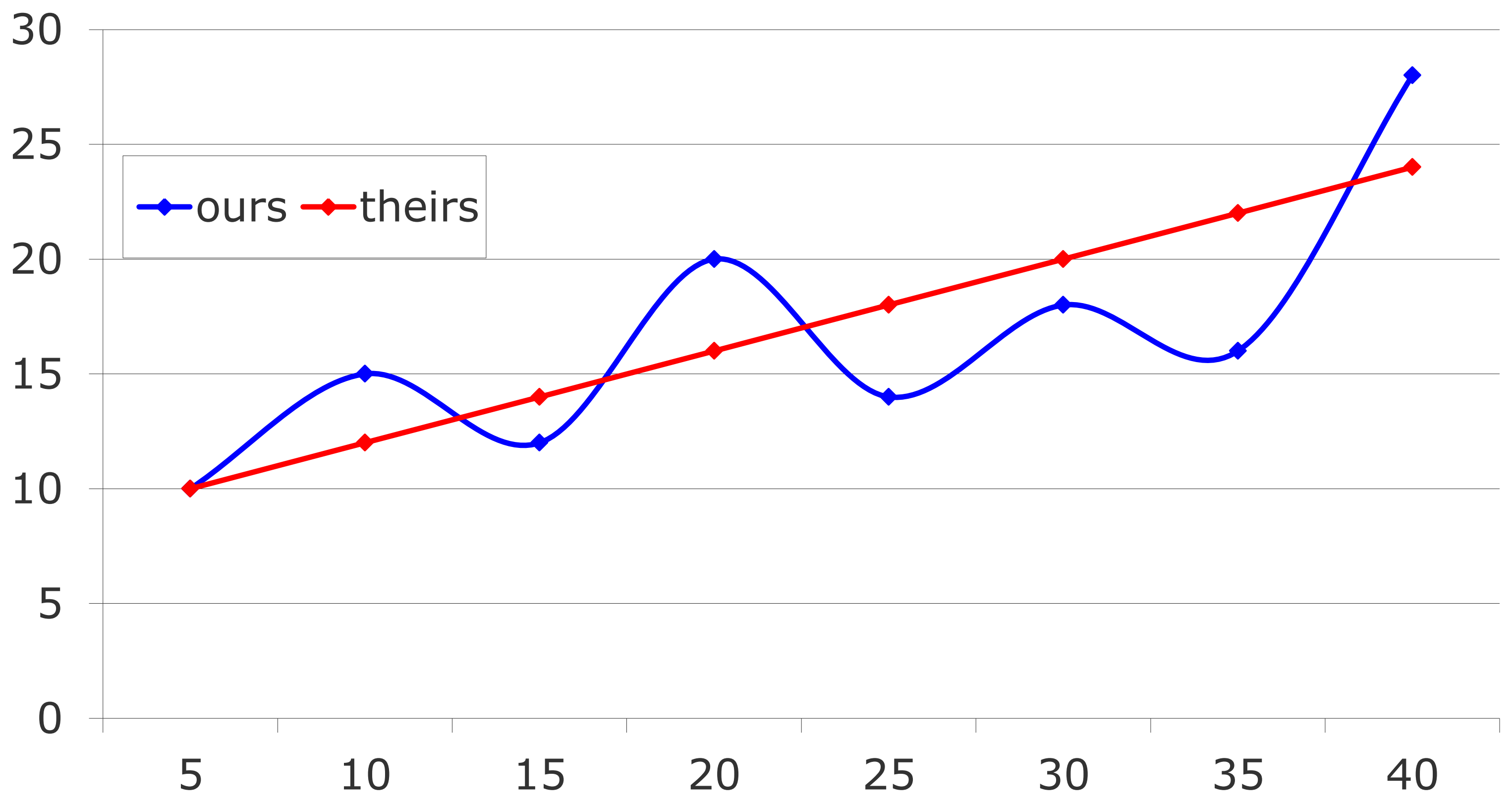
Performance Experiments (1)

throughput, response time, #IOs, CPU, wallclock,
„DB time", hit rates, space-time integrals, etc.
speed (RT, CPU, etc.)



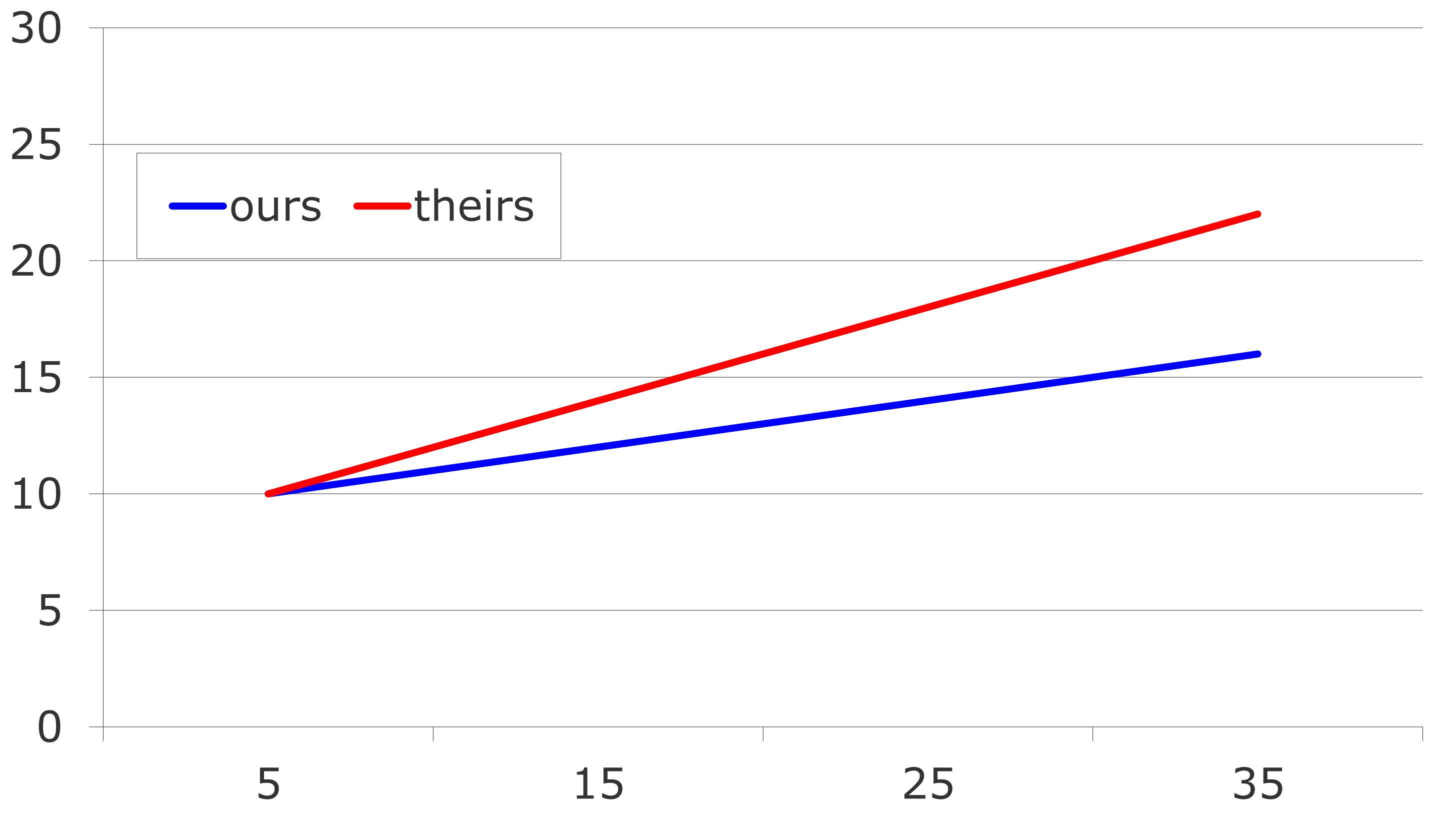
load (MPL,
arrival rate, etc.)

Performance Experiments (2)



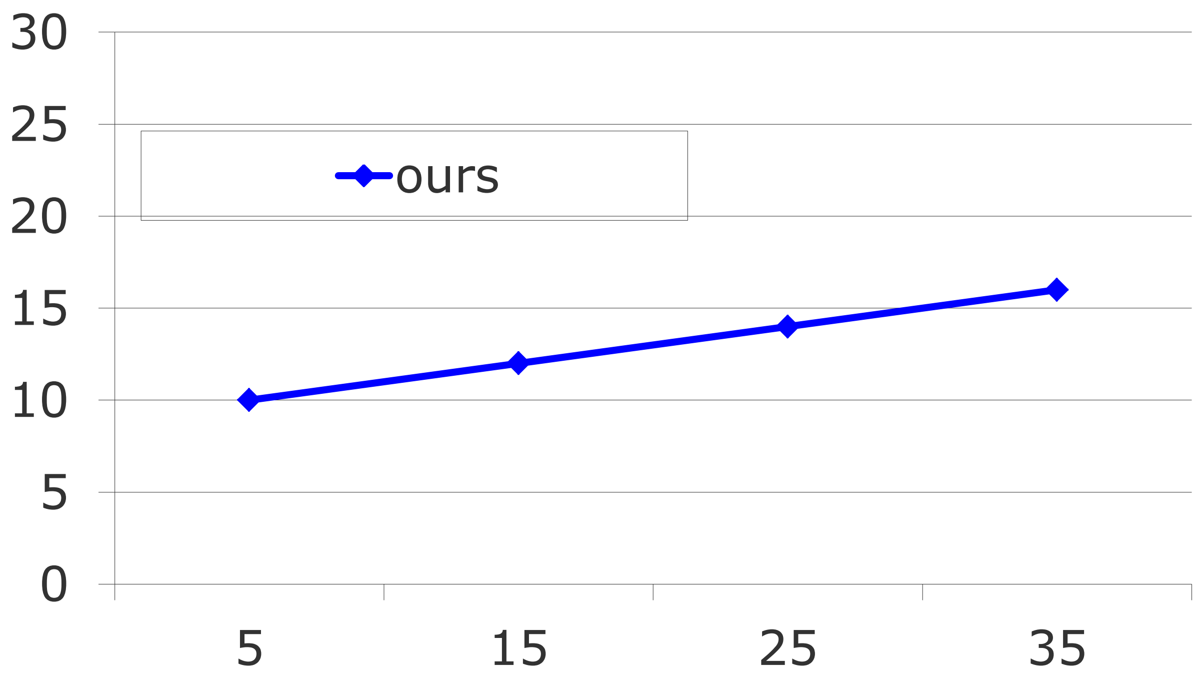
If you can‘t reproduce it, run it only once

Performance Experiments (2)



If you can‘t reproduce it, run it only once, and smoothe it.

Performance Experiments (3)



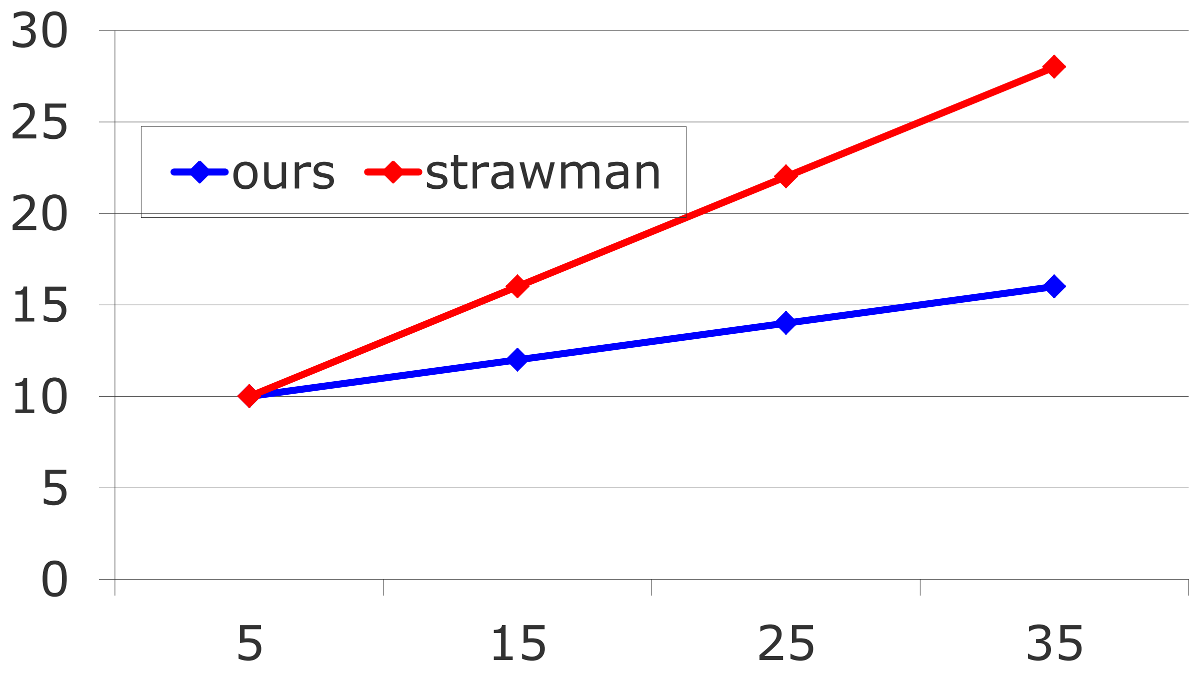
Lonesome winner:
If you can't beat them, cheat them

Felix Naumann
Data Profiling
Summer 2017

90% of all algorithms are among the best 10%

93.274% of all statistics are made up

Performance Experiments (3)



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cheat them

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93.274% of all statistics
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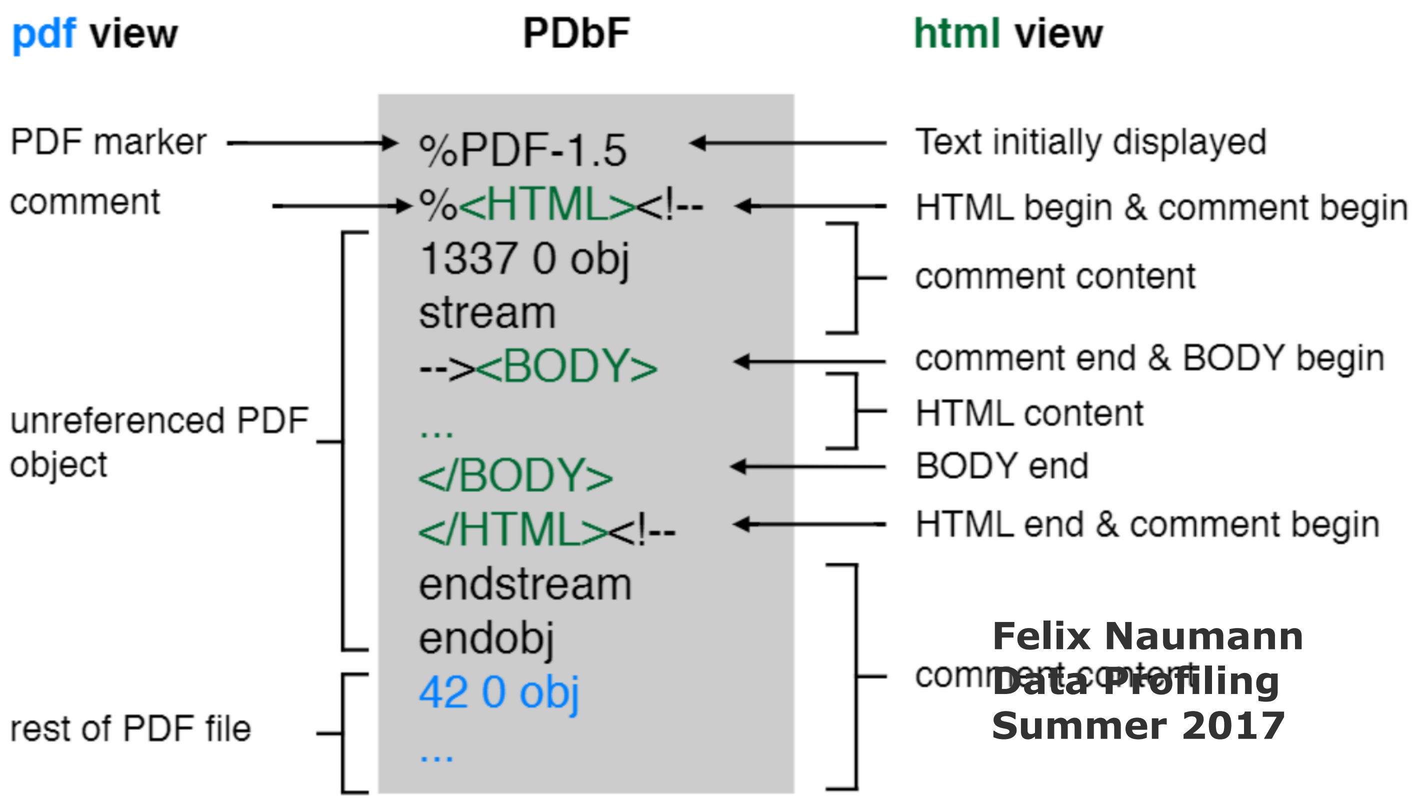
Janiform Papers

- PDbF: Portable database file
  - PDF file & HTML file (& virtual image)
  - Includes database
- Demo: https://www.infosys.uni-saarland.de/publications/p1972-dittrich.html
- https://github.com/uds-datalab/PDBF



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Data acquisition

- Data Profiling is data-driven
  - Data is important to …
    - Define the problem and your goals
    - Develop ideas for good solutions
    - Test for correctness
    - Test for performance
- But data owners usually do not give their data away
  - Data is the core capital of companies (strategic resource)
  - Data is private property (sensitive information)
  - Data fiefdoms

Data collection

- Some good sources:
  - WDC web tables project: http://webdatacommons.org/webtables/index.html
  - UCI machine learning repository: http://archive.ics.uci.edu/ml/
  - Public competitions: www.kaggle.com/competitions
  - Collection: www.quora.com/Where-can-I-find-large-datasets-open-to-the-public
- Which data to consider?
  - Use datasets from different **domains**
  - Use datasets of different **size**
  - Use datasets in different **formats**
  - Use datasets from different **sources**

Data generation

- "At some point, every company writes its own data generator"
  - HPI: dbtesma, hanaGenerator, …
  - IBM, SAP, …
- Public data generators:
  - www.tpc.org/tpch/
  - www.generatedata.com/
  - www.red-gate.com/products/sql-development/sql-data-generator/
- Advantage
  - As much data as you want!
  - Data fits your needs! (?)

Data generation

- Challenge: Generate data with real world characteristics
  - Benford Law Frequency, UCCs, INDs, FDs, …
- Suspicious:

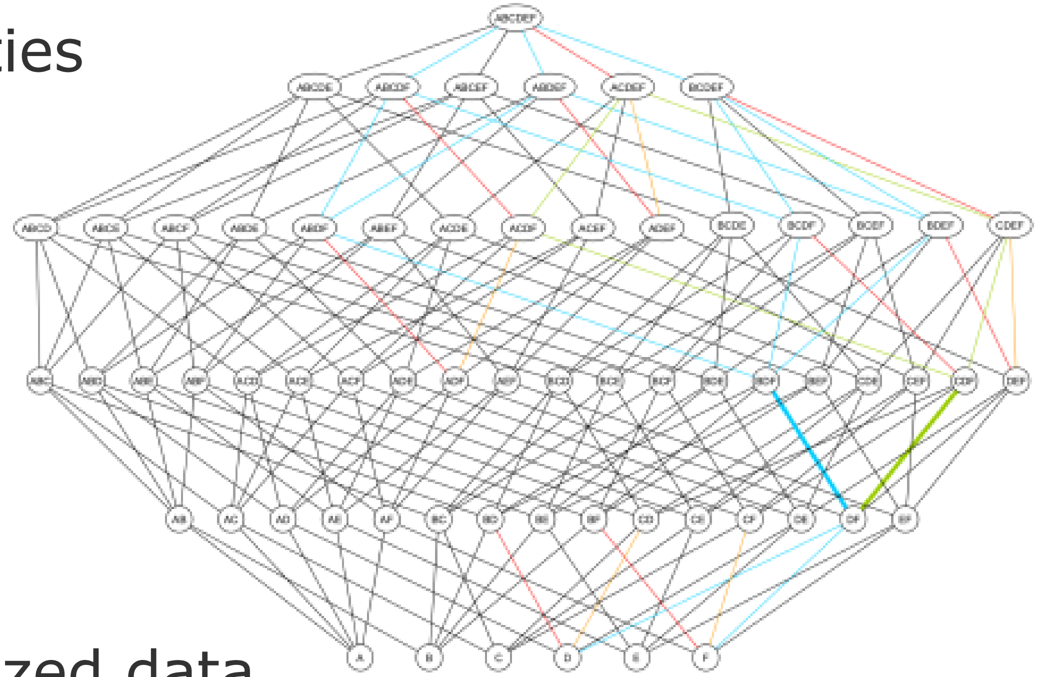
Use profiling algorithms to generate data with natural meta data characteristics!

Use data with natural meta data characteristics to build and test profiling algorithms!

- Typical problems
  - Less variety in INDs, UCCs, and FDs
  - Data replication (at some point) due to the use of seed data
  - Specific optimization for only a few metadata characteristics
  - Too many degrees of freedeom

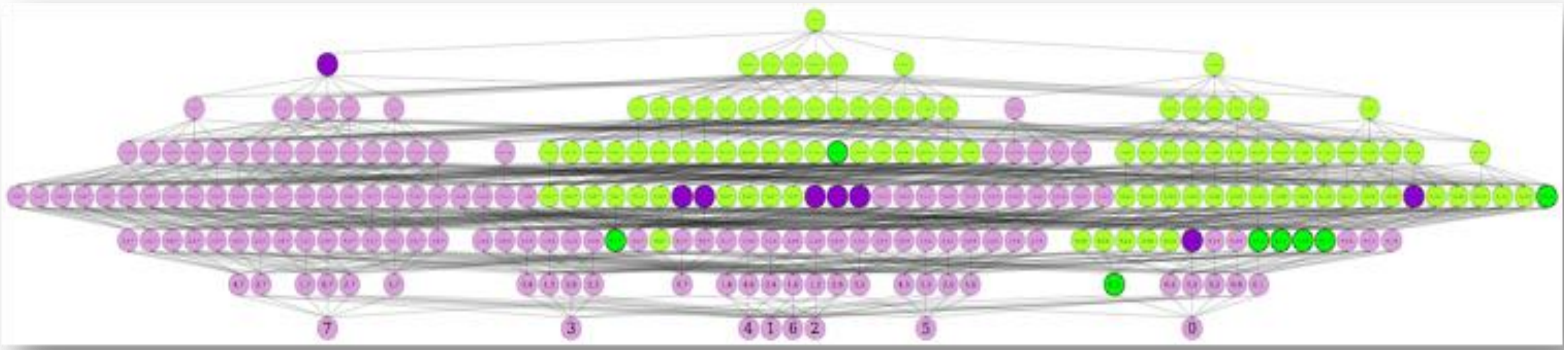
Data generation and testing

- Generate volumes of data with certain properties
  - Test extreme cases
  - Test scalability
- Problem: Position of dependencies
- Problem: Interaction between properties
  - FDs vs. uniqueness
  - Patterns vs. conditional INDs
  - Distributions vs. all others…
- Problem: Consistently produce same, randomized data
- Problem: Create realistic data
  - Distributions, patterns
  - Example: TPCH (next slide)



TPCH – Uniques and Non-Uniques

- Using the first 8 columns of the lineitems table
- Using a scale-factor of 0.1



LINEITEM (L_) SF*6,000,000
ORDERKEY
PARTKEY
SUPPKEY
LINENUMBER
QUANTITY
EXTENDEDPRICE
DISCOUNT
TAX
RETURNFLAG
LINESTATUS
SHIPDATE
COMMITDATE
RECEIPTDATE
SHIPINSTRUCT
SHIPMODE
COMMENT

Goal: Data profiling benchmark

- Define data
  - Data generation
  - Real-world dataset(s)
  - Different scale-factors: Rows and columns
- Define tasks
  - Individual tasks
  - Sets of tasks
- Define measures
  - Speed
  - Speed/cost
  - Minimum hardware requirements
  - Accuracy for approximate approaches

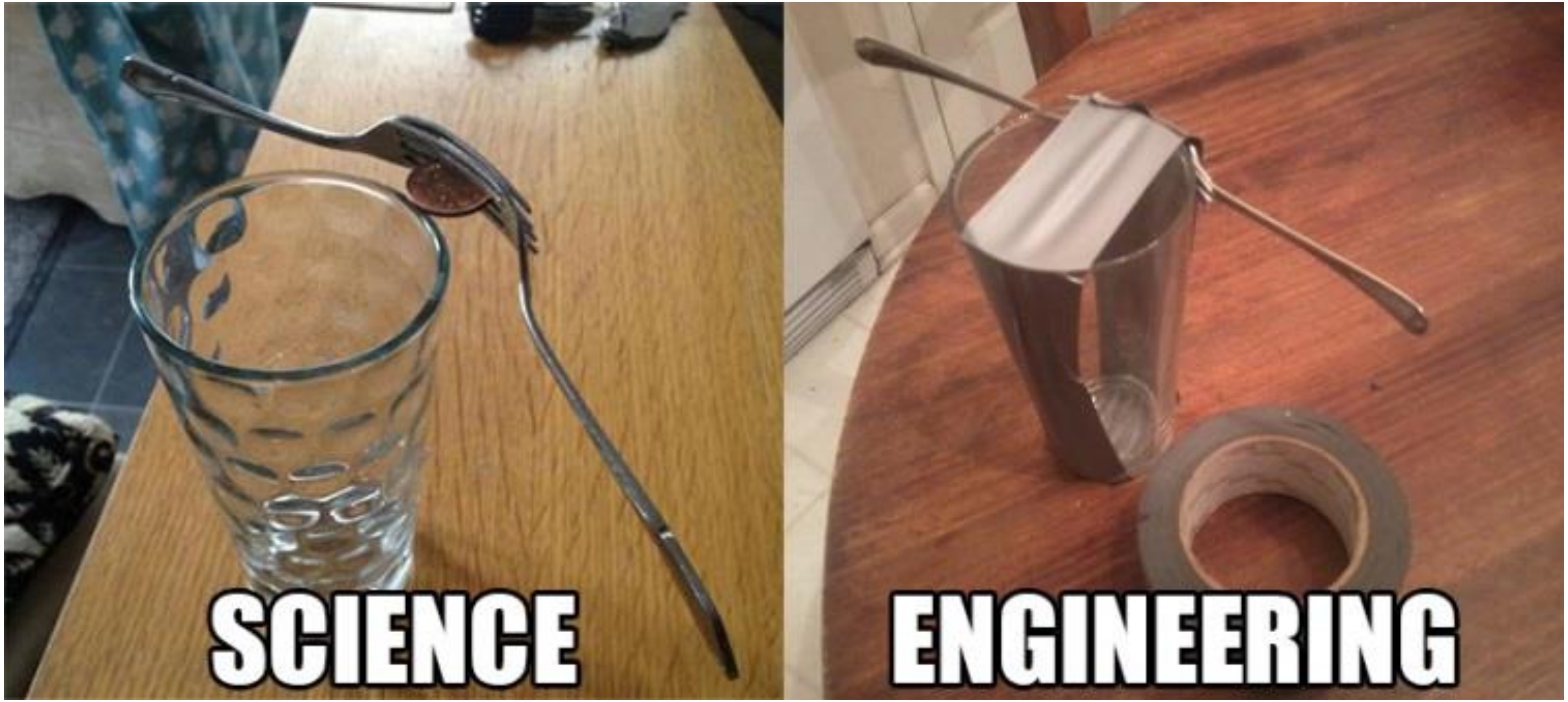
Thoughts on complexity

- We often optimize for efficiency
  - New complexity class:
    - e.g. $O(n^3) \rightarrow O(n^2)$
    - great, but do not try if complexity of problem is proven!
  - Factorial improvement, e.g., $O(3n) \rightarrow O(2n)$
    - Great, but factor should be significant!
    - Otherwise the performance gain could be due to engineering
- Consider edge cases
  - Worst case, best case, and average case complexity

Thoughts on complexity

http://pr0gramm.com/top/440934

Science vs. Engineering



http://imgur.com/KkUB0dL

Science vs. Engineering

Science	Engineering
Science is concerned with **understanding fundamental laws** of nature and the behavior of materials and living things.	Engineering is the **application of science and technology to create useful products and services** for the whole community, within economic, environmental and resource constraints.

- Solve general problems!
- Do not optimize for very specific data, situations, use cases, …
  - e.g., UCC discovery for only the NCVoter dataset