Algorithmen II

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Übungen:

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`algo2.iti.kit.edu/AlgorithmenII_WS23.php`

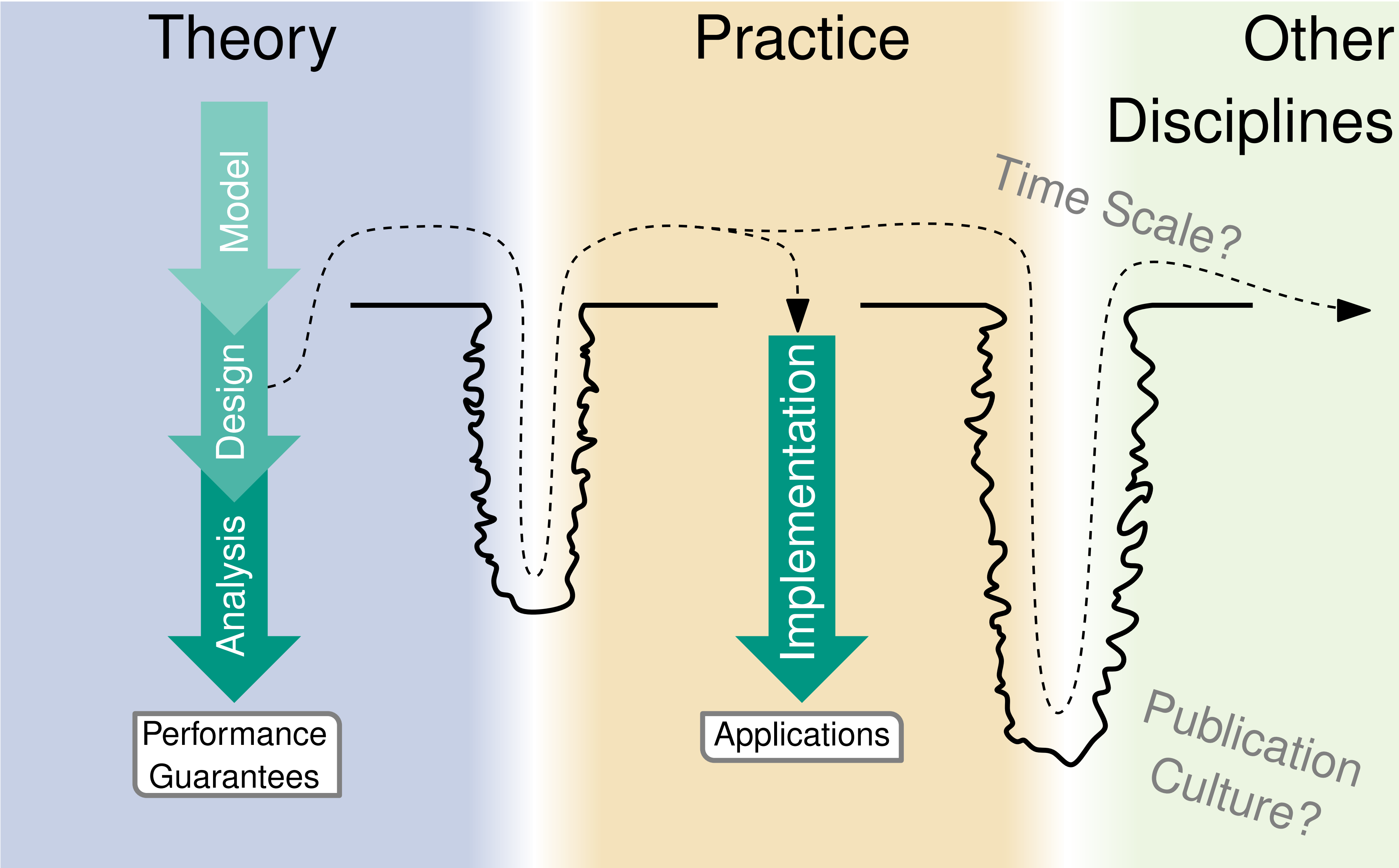
1 Algorithm Engineering

A detailed definition

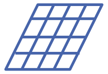
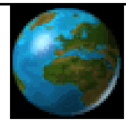
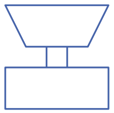
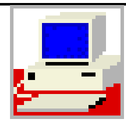
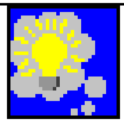
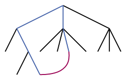
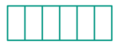
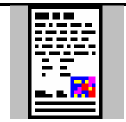
- In general

  [with Kurt Mehlhorn, Rolf Möhring, Petra Mutzel, Dorothea Wagner]
- A few examples, usually sorting
- A little bit on experimental methodology

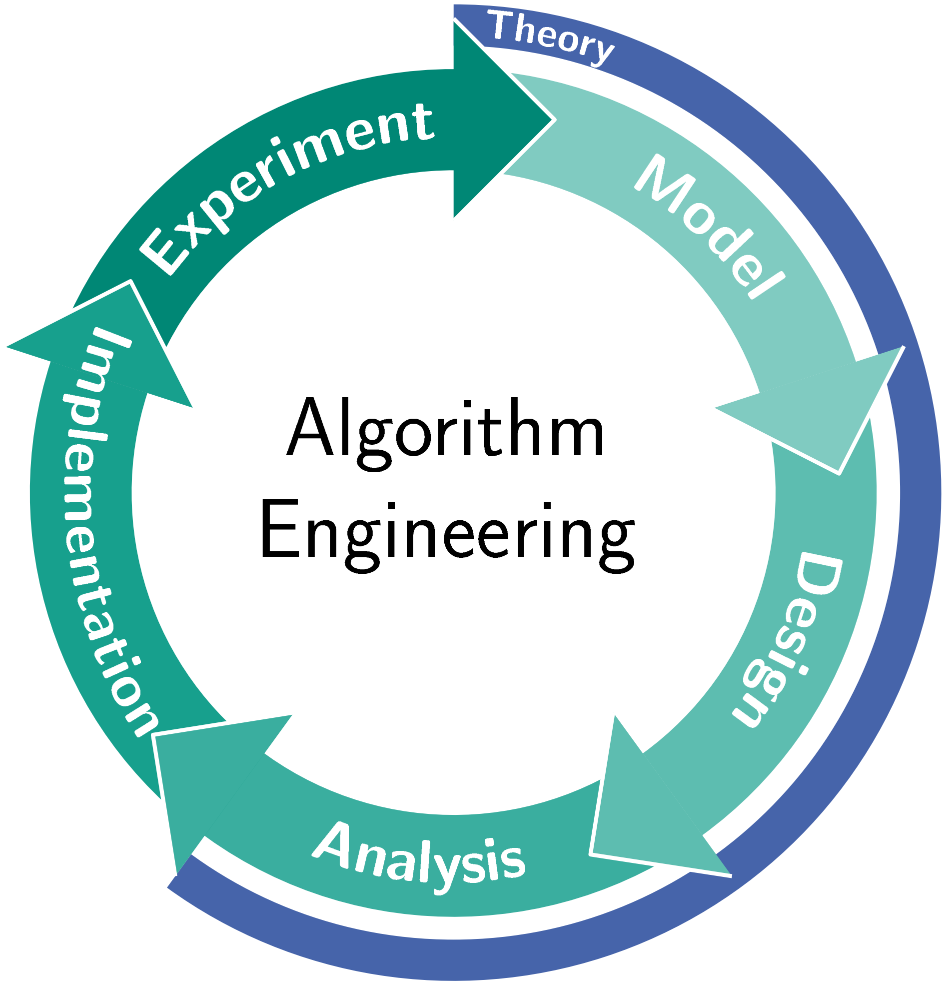
(Caricatured) Traditional View: Algorithm Theory



Gaps Between Theory & Practice

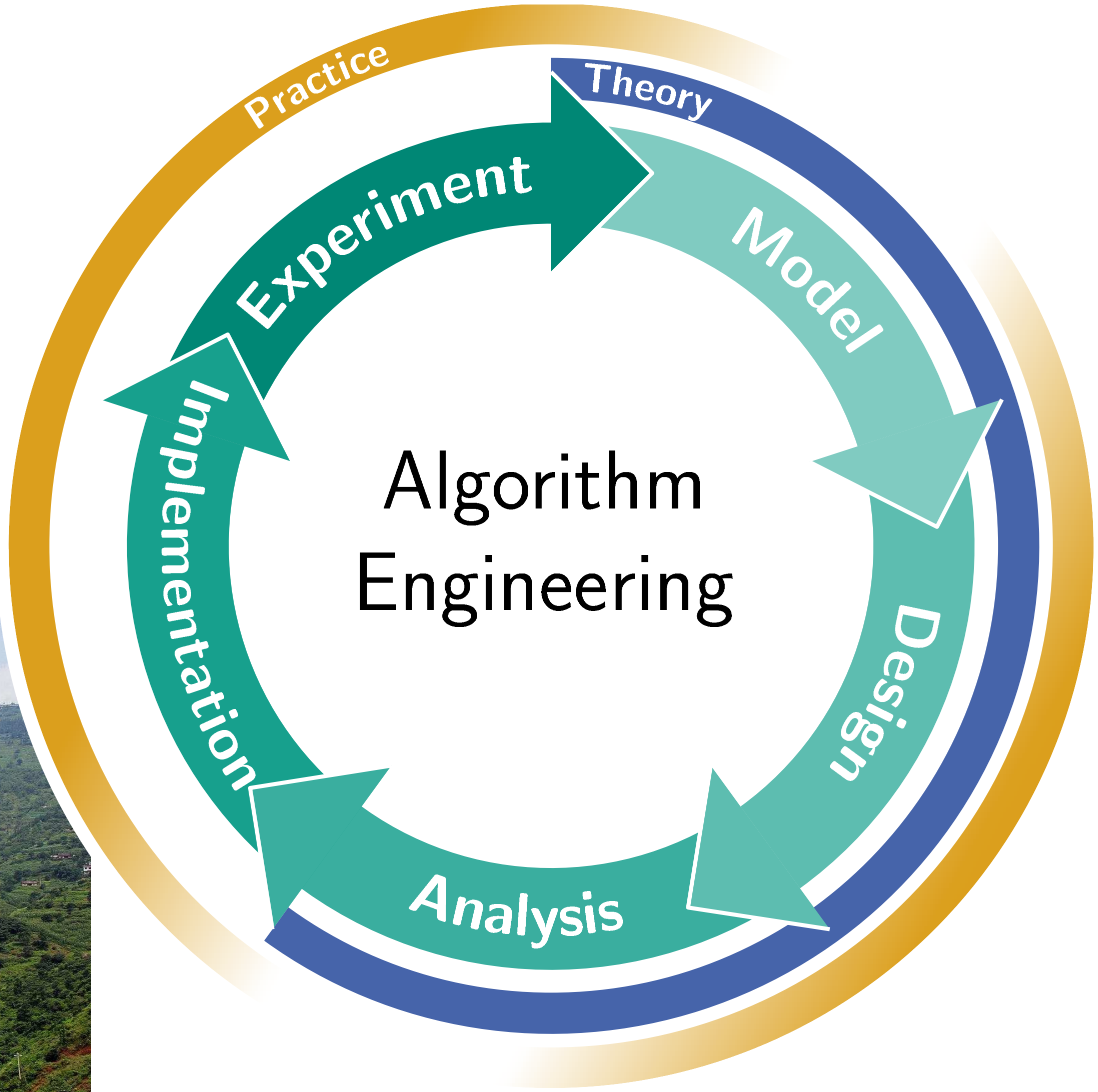
Theory	$\longleftrightarrow$	**Practice**
simple 	**appl. model**	 complex
simple 	**machine model**	 real
complex 	**algorithms**	FOR simple
advanced 	**data structures**	 arrays, . . .
worst case max	**complexity measure**	 inputs
asympt. $\mathrm{O}(\cdot)$	**efficiency**	42% constant factors

Algorithmics as Algorithm Engineering



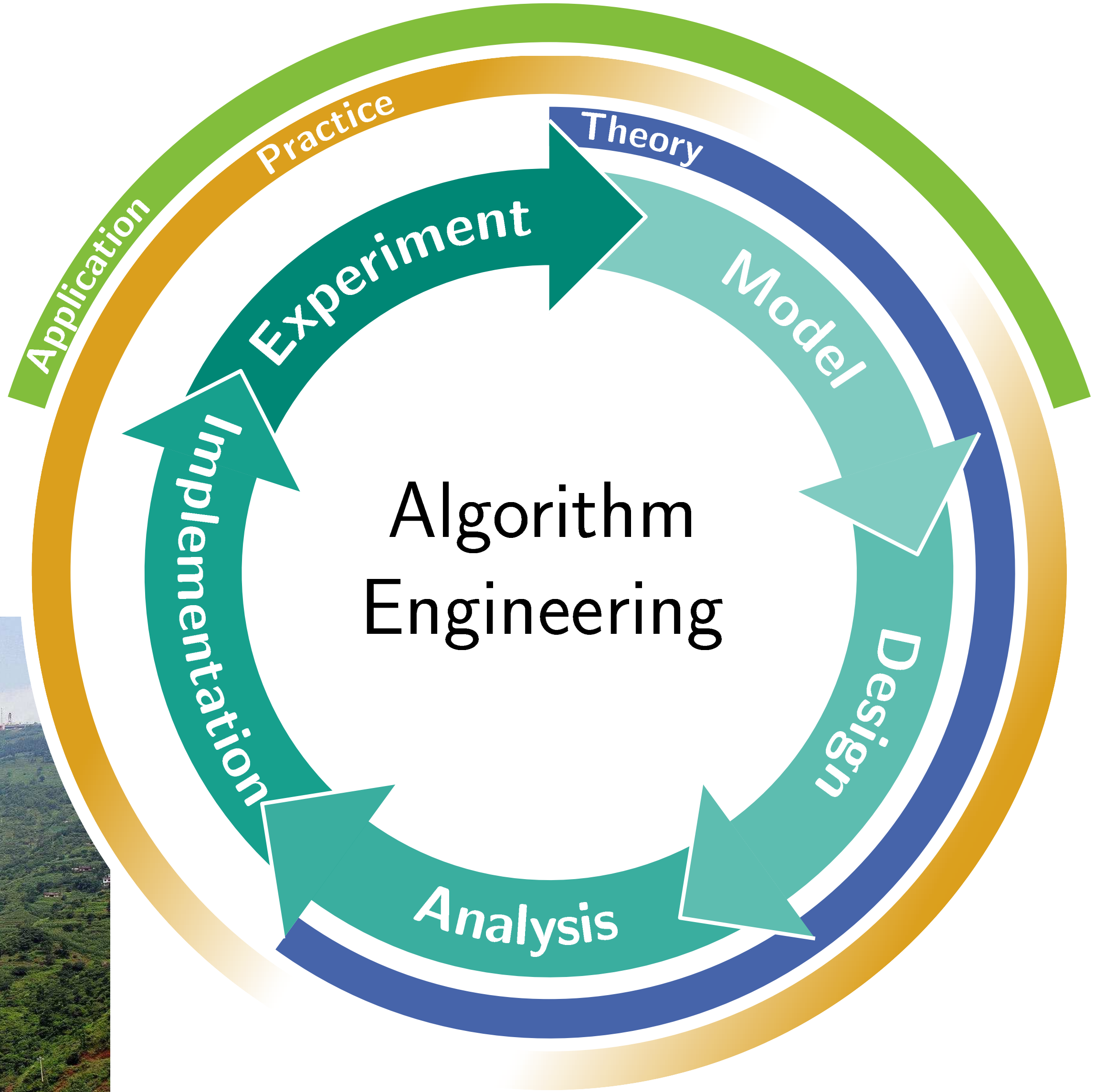
Algorithmics as Algorithm Engineering

- Bridge gaps between theory and practice

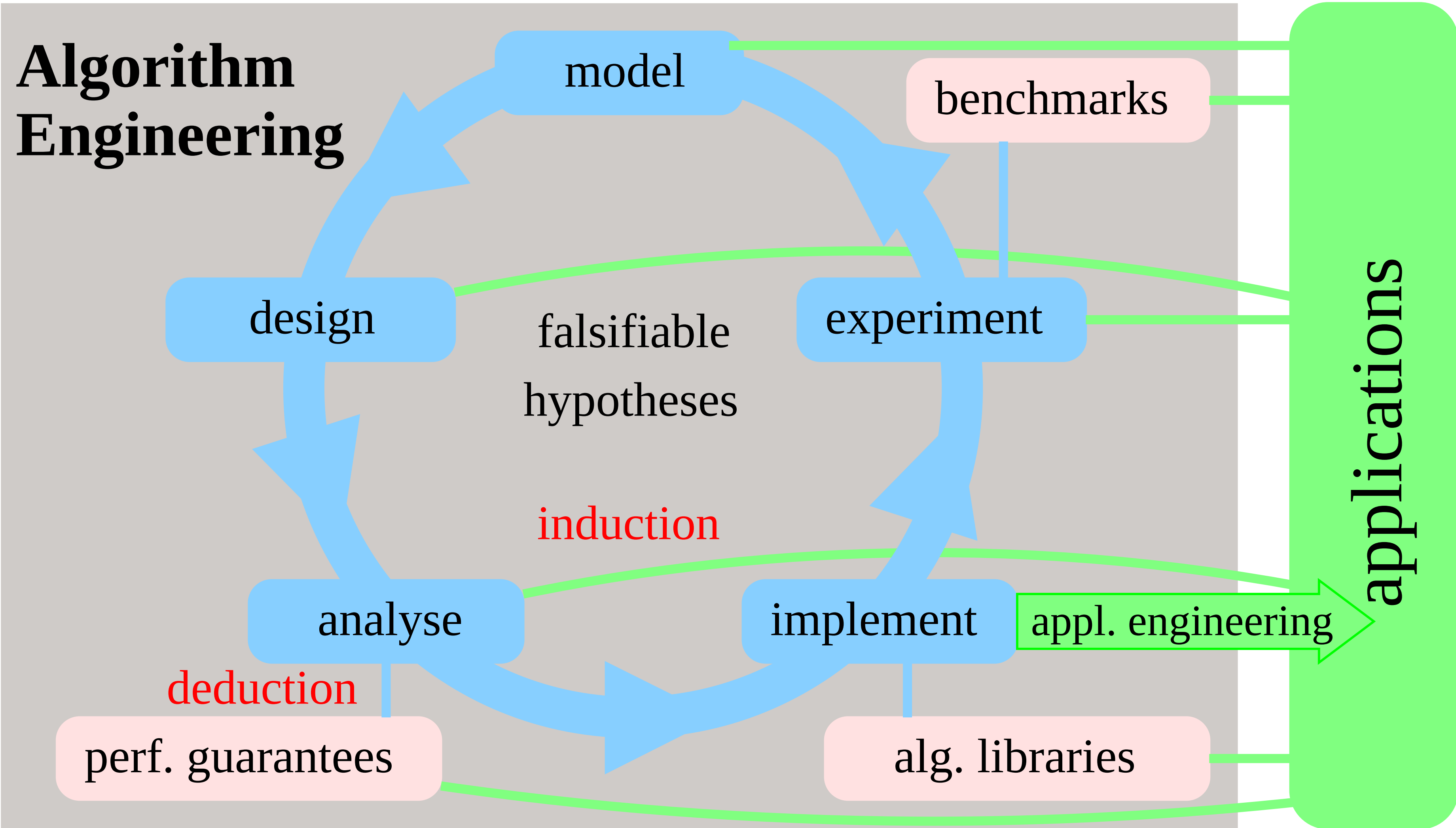


Algorithmics as Algorithm Engineering

- Bridge gaps between theory and practice
- Integrated interdisciplinary research



Algorithmics as Algorithm Engineering



Bits of History

1843– Algorithms in theory and practice

1950s,1960s Still infancy

1970s,1980s Paper and pencil algorithm theory.

Exceptions exist, e.g., [D. Johnson], [J. Bentley]

1986 Term used by [T. Beth],

lecture “Algorithmentechnik” in Karlsruhe.

1988– Library of Efficient Data Types and Algorithms (LEDA) [K. Mehlhorn]

1997– Workshop on Algorithm Engineering

$\rightsquigarrow$ ESA applied track [G. Italiano]

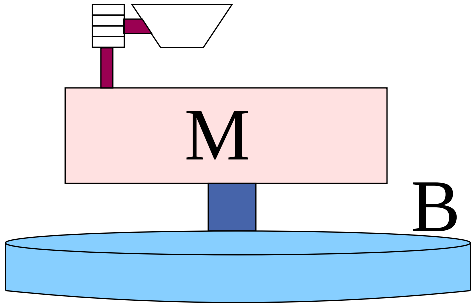
1997 Term used in US policy paper [Aho, Johnson, Karp, et. al]

1998 Alex workshop in Italy $\rightsquigarrow$ ALENEX

Realistic Models

Theory	$\longleftrightarrow$	**Practice**
simple	**appl. model**	complex
simple	**machine model**	real

- Careful refinements
- Try to preserve (partial) analyzability / simple results



Design

of algorithms that work well in practice

- simplicity
- reuse
- constant factors
- exploit easy instances

Analysis

- Constant factors matter

  Example: quicksort

- Beyond worst case analysis

- Practical algorithms might be difficult to analyze

  (randomization, meta heuristics,. . .)

Implementation

sanity check for algorithms !

Challenges

Semantic gaps:

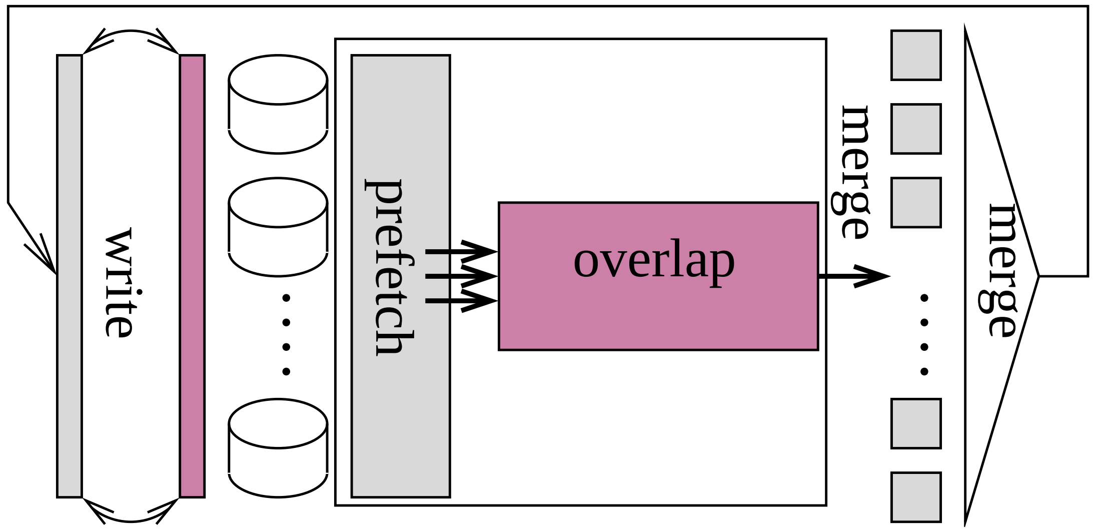
Abstract algorithm

$\leftrightarrow$

C++...

$\leftrightarrow$

hardware



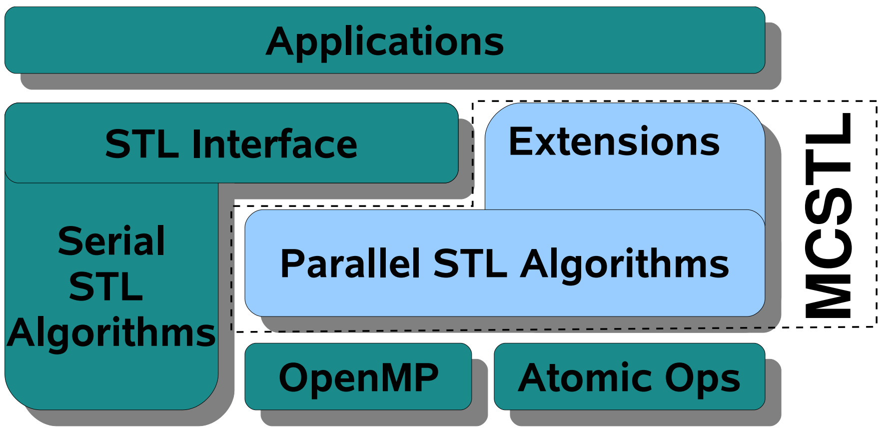
Experiments

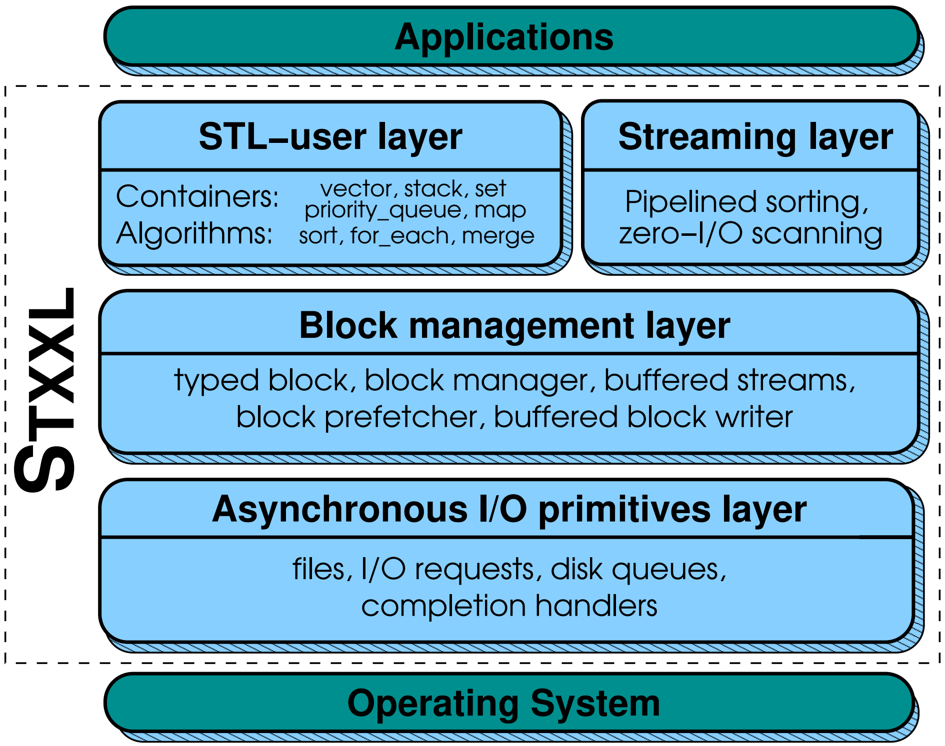
- Sometimes a good surrogate for analysis
- Too much rather than too little output data
- Reproducibility (10 years!)
- Software engineering

Stay tuned.

Algorithm Libraries — Challenges

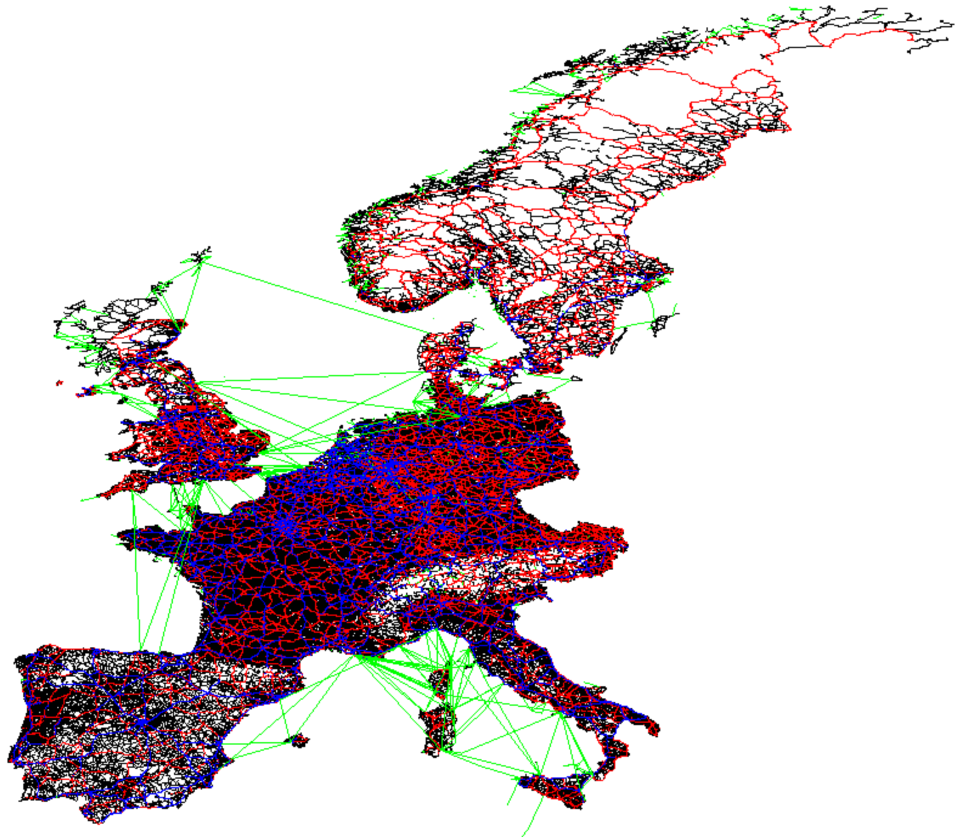
- Software engineering
- Standardization, e.g. java.util, C++ STL and BOOST
- Performance $\leftrightarrow$ generality $\leftrightarrow$ simplicity
- Applications are a priori unknown
- Result checking, verification





Problem Instances

Benchmark instances are essential for development of practical algorithms



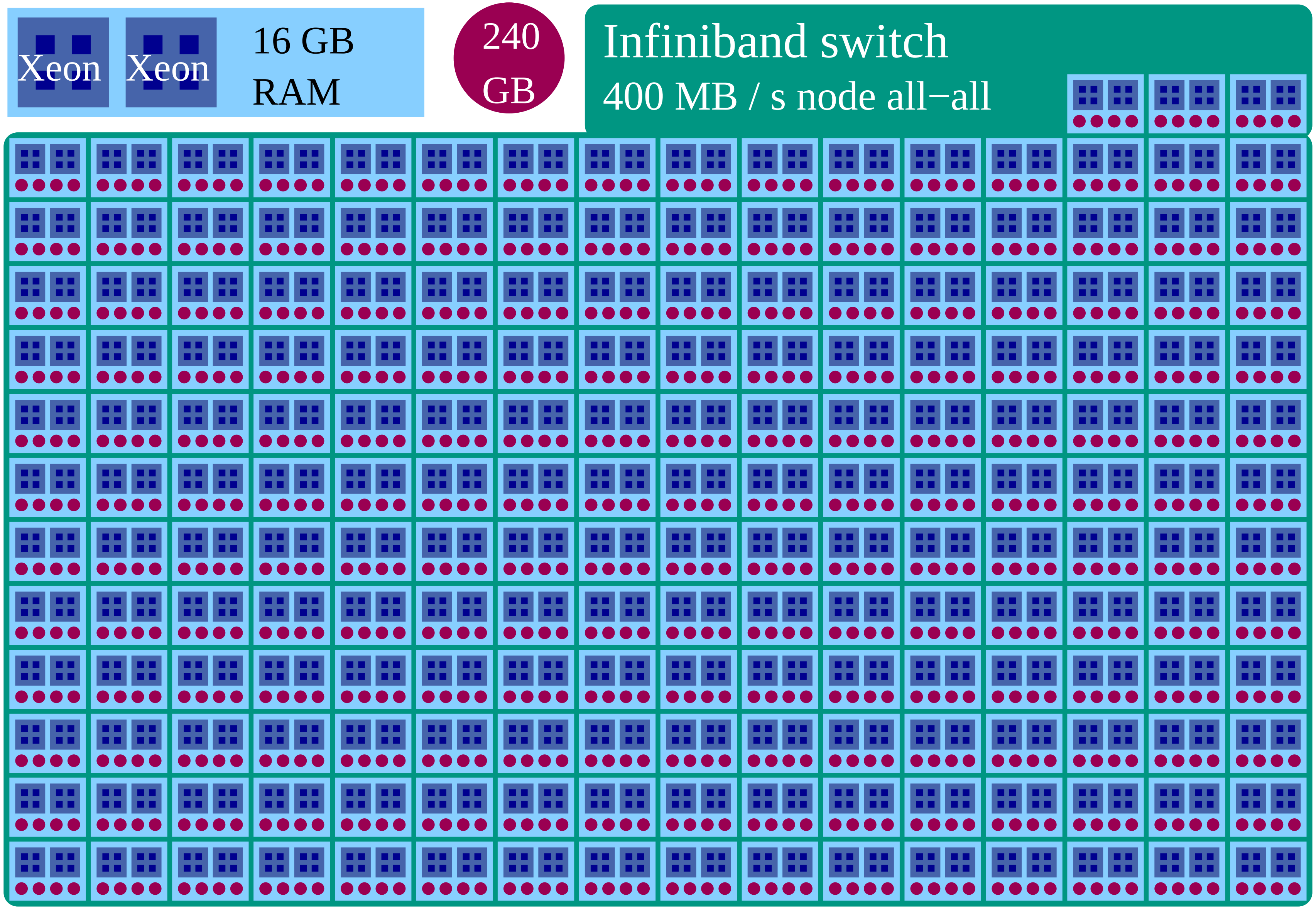
Example: Sorting Benchmark (Indy)

100 byte records, 10 byte random keys, with file I/O

Category	data volume	performance	improvement
GraySort	100 000 GB	564 GB / min	$17\times$
MinuteSort	955 GB	955 GB / min	$>10\times$
JouleSort	100 000 GB	3 400 Recs/Joule	$???\times$
JouleSort	1 000 GB	17 500 Recs/Joule	$5.1\times$
JouleSort	100 GB	39 800 Recs/Joule	$3.4\times$
JouleSort	10 GB	43 500 Recs/Joule	$5.7\times$

Also: PennySort

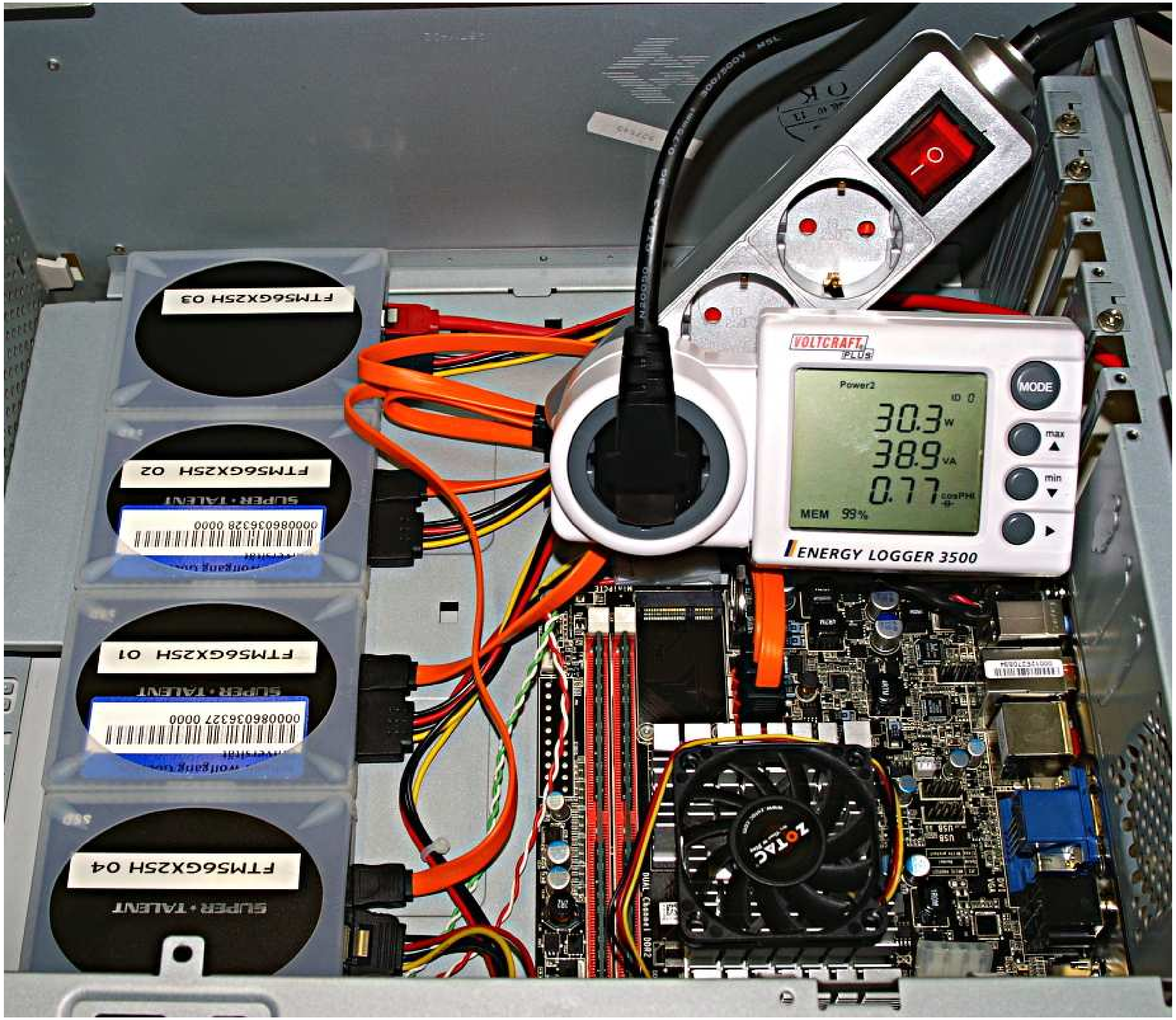
GraySort: inplace multiway mergesort, exact splitting



JouleSort

- Intel Atom N330
- 4 GB RAM
- 4×256 GB SSD (SuperTalent)

Algorithm similar to GraySort



Applications that “Change the World”

Algorithmics has the potential to SHAPE applications
(not just the other way round) [G. Myers]

Bioinformatics: sequencing, proteomics, phylogenetic trees,. . .

Information Retrieval: Searching, ranking,. . .

Traffic Planning: navigation, flow optimization,
adaptive toll, disruption management

Geographic Information Systems: agriculture, environmental
protection, disaster management, tourism,. . .

Machine Learning/AI: translation, chatbots,. . .

Conclusion:

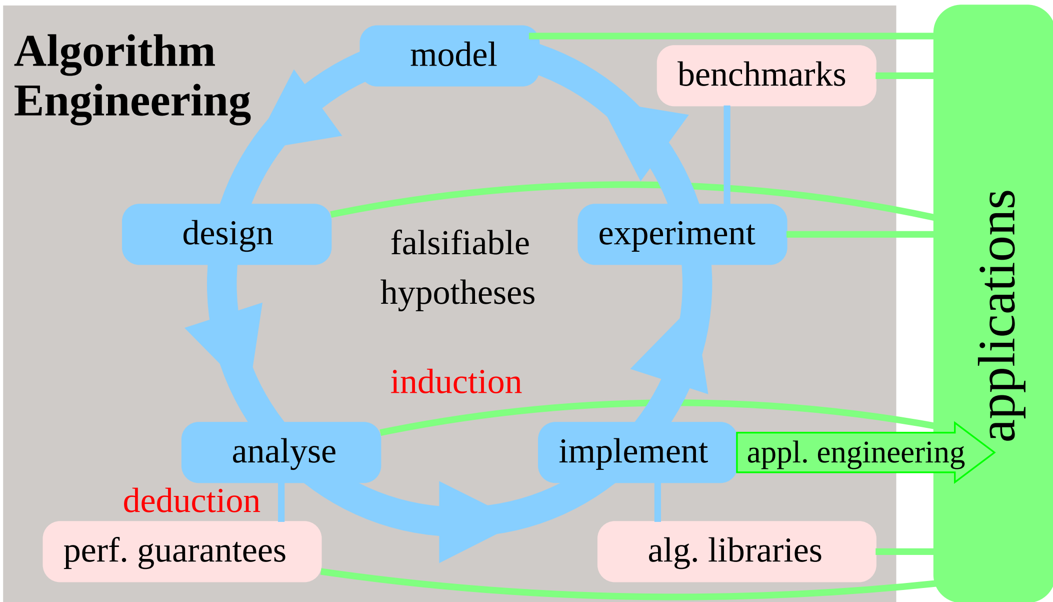
Algorithm Engineering $\leftrightarrow$ Algorithm Theory

- Algorithm engineering is a wider view on algorithmics (but no revolution. None of the ingredients is really new)
- Rich methodology
- Better coupling to applications
- Experimental algorithmics $\ll$ algorithm engineering
- Algorithm theory $\subset$ algorithm engineering
- Sometimes different theoretical questions
- Algorithm theory may still yield the strongest, deepest and most persistent results within algorithm engineering

More On Experimental Methodology

Scientific Method:

- Experiment need a possible outcome that falsifies a hypothesis
- Reproducible
  - Keep data/code for at least 10 years
    + documentation (aka laboratory journal (Laborbuch))
  - Clear and detailed description in papers / TRs
  - Share instances and code



Quality Criteria

- Beat the state of the art, globally – (not your own toy codes or the toy codes used in your community!)
- Clearly demonstrate this !
  - Both codes use same data ideally from accepted benchmarks (not just your favorite data!)
  - Comparable machines or fair (conservative) scaling
  - Avoid uncomparabilities like: “Yeah we have worse quality but are twice as fast”
  - Real world data wherever possible
  - As much different, fresh inputs as possible
  - its fine if you are better just on some (important) inputs

Not Here but Important

- Describing the setup (machine, compiler, OS, instances, repetitions,. . .)
- Finding sources of measurement errors
- Reducing measurement errors (averaging, median,unloaded machine. . .)
- Measurements in the creative phase of experimental algorithmics.

The Starting Point

- (Several) Algorithm(s)
- A few quantities to be measured: time, space, solution quality, comparisons, cache faults,... There may also be measurement errors.
- An unlimited number of potential inputs. $\rightsquigarrow$ condense to a few characteristic ones (size, $|V|$, $|E|$, ... or problem instances from applications)

Usually there is not a lack but an abundance of data

The Process

Waterfall model?

1. Design
2. Measurement
3. Interpretation

Perhaps the paper should at least look like that.

The Process

- Eventually stop asking questions (Advisors/Referees listen !)
- Build measurement tools
- Automate (re)measurements
- Choice of Experiments driven by risk and opportunity
- Distinguish mode

  Explorative: many different parameter settings, interactive, short turnaround times

  Consolidating: many large instances, standardized measurement conditions, batch mode, many machines

Of Risks and Opportunities

Example: Hypothesis $=$ my algorithm is the best

Big risk: untried main competitor

Small risk: tuning of a subroutine that takes 20 % of the time.

Big opportunity: use algorithm for a new application

$\rightsquigarrow$ new input instances