Algorithmen II

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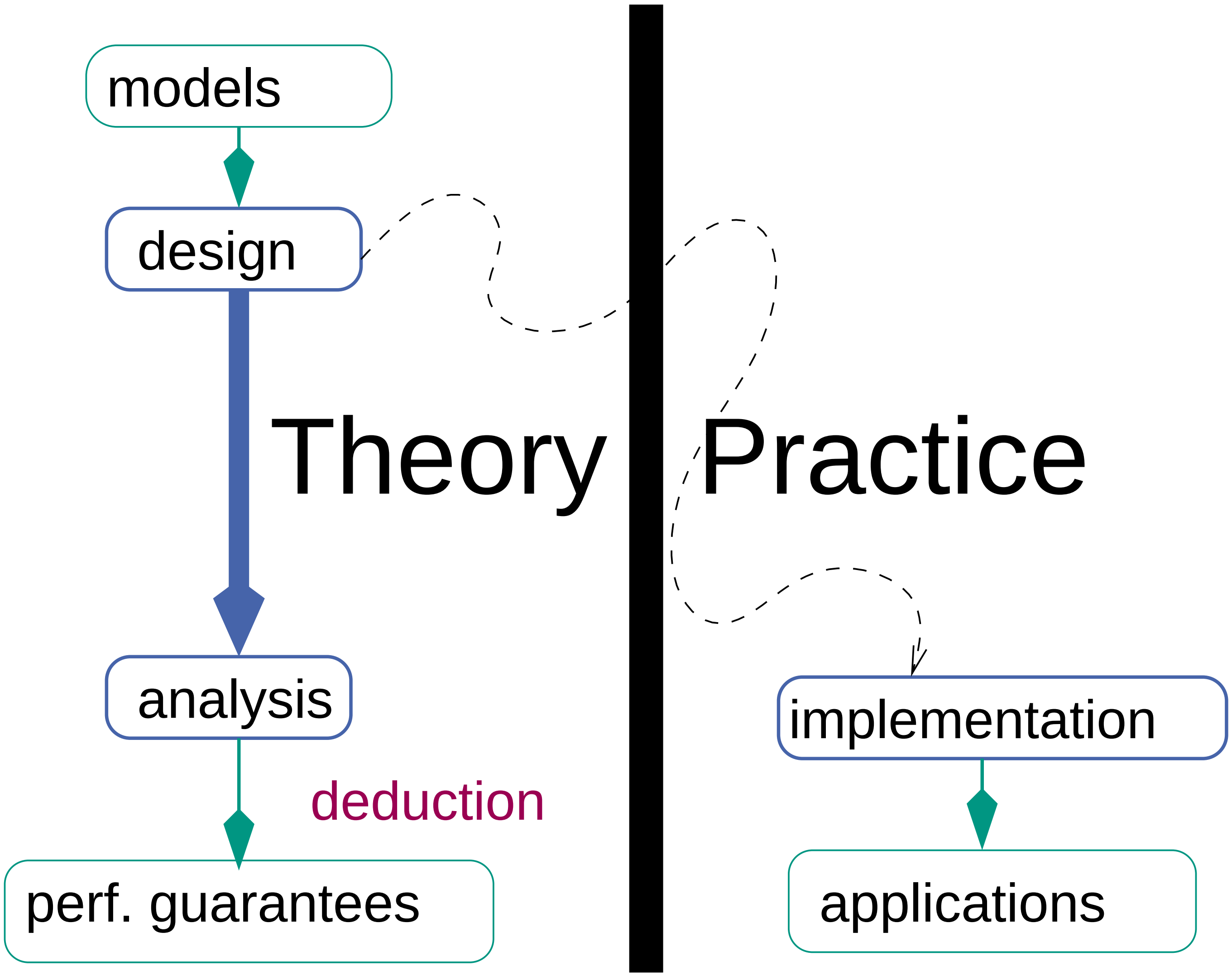
`http://algo2.iti.kit.edu/AlgorithmenII_WS17.php`

1 Algorithm Engineering

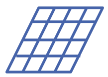
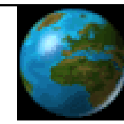
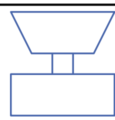
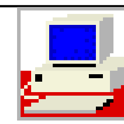
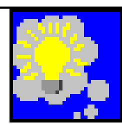
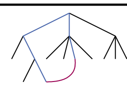
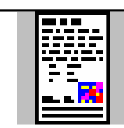
A detailed definition

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

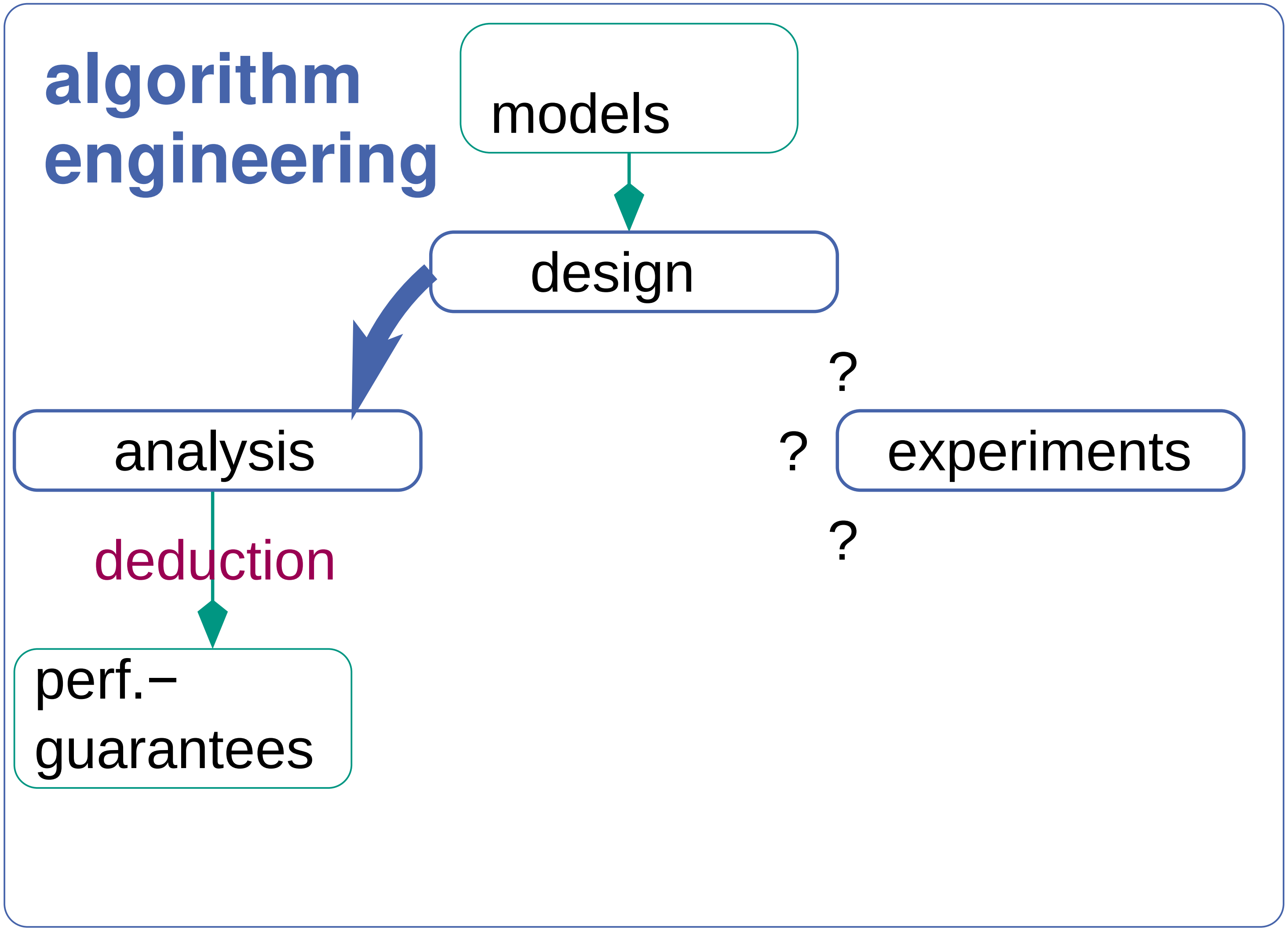
(Caricatured) Traditional View: Algorithm Theory



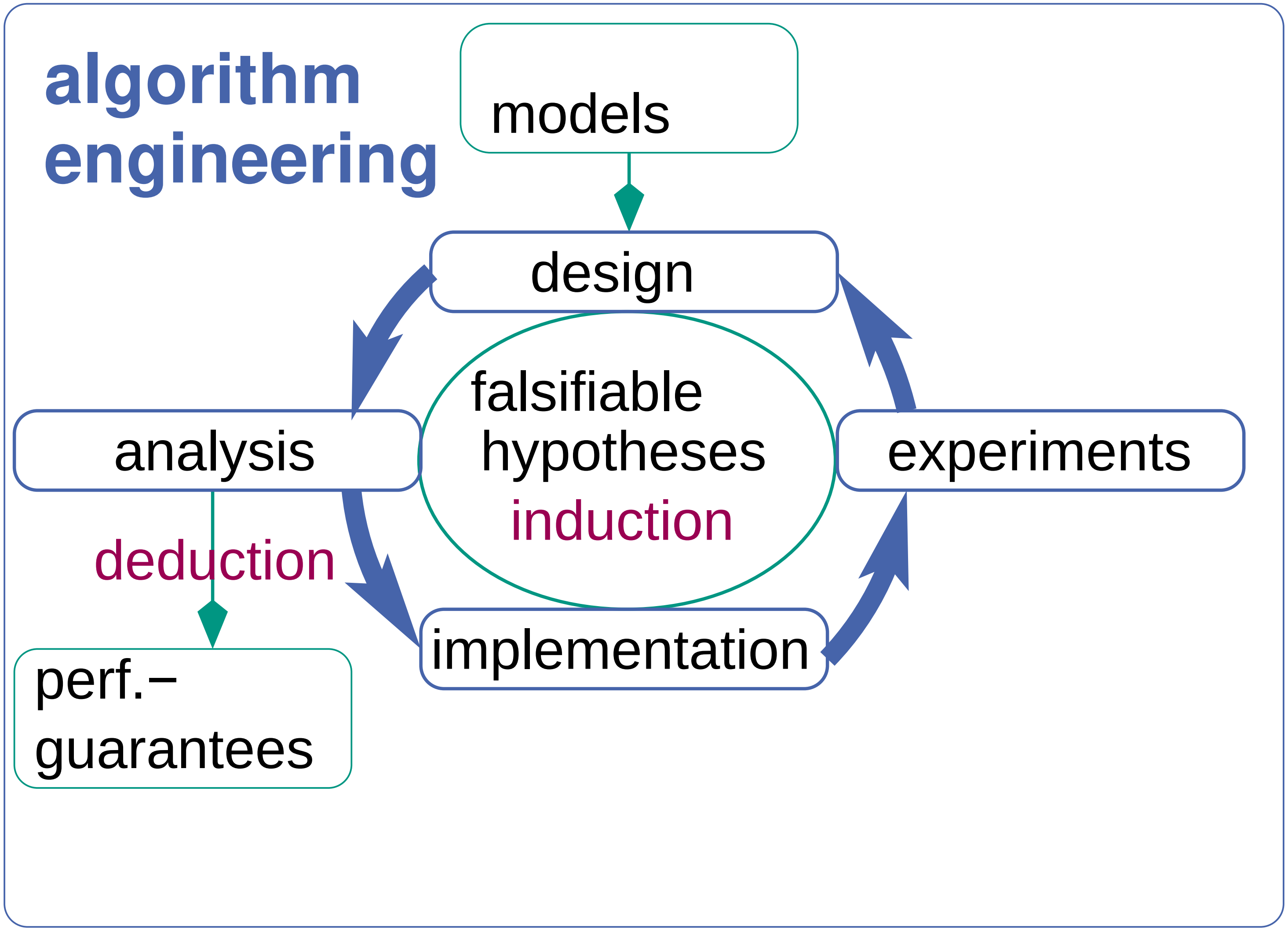
Gaps Between Theory & Practice

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. $O(\cdot)$	**efficiency**	42% constant factors

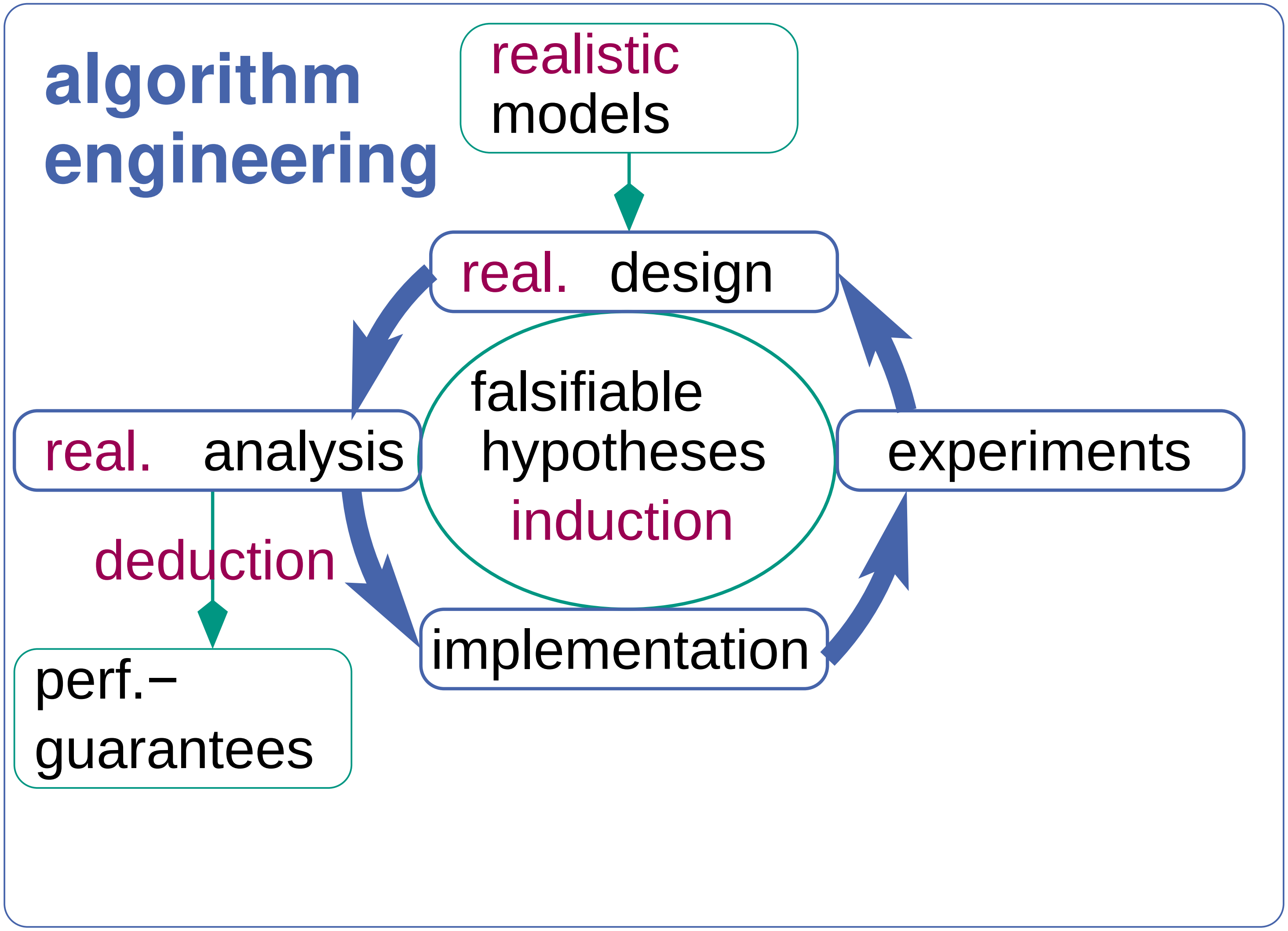
Algorithmics as Algorithm Engineering



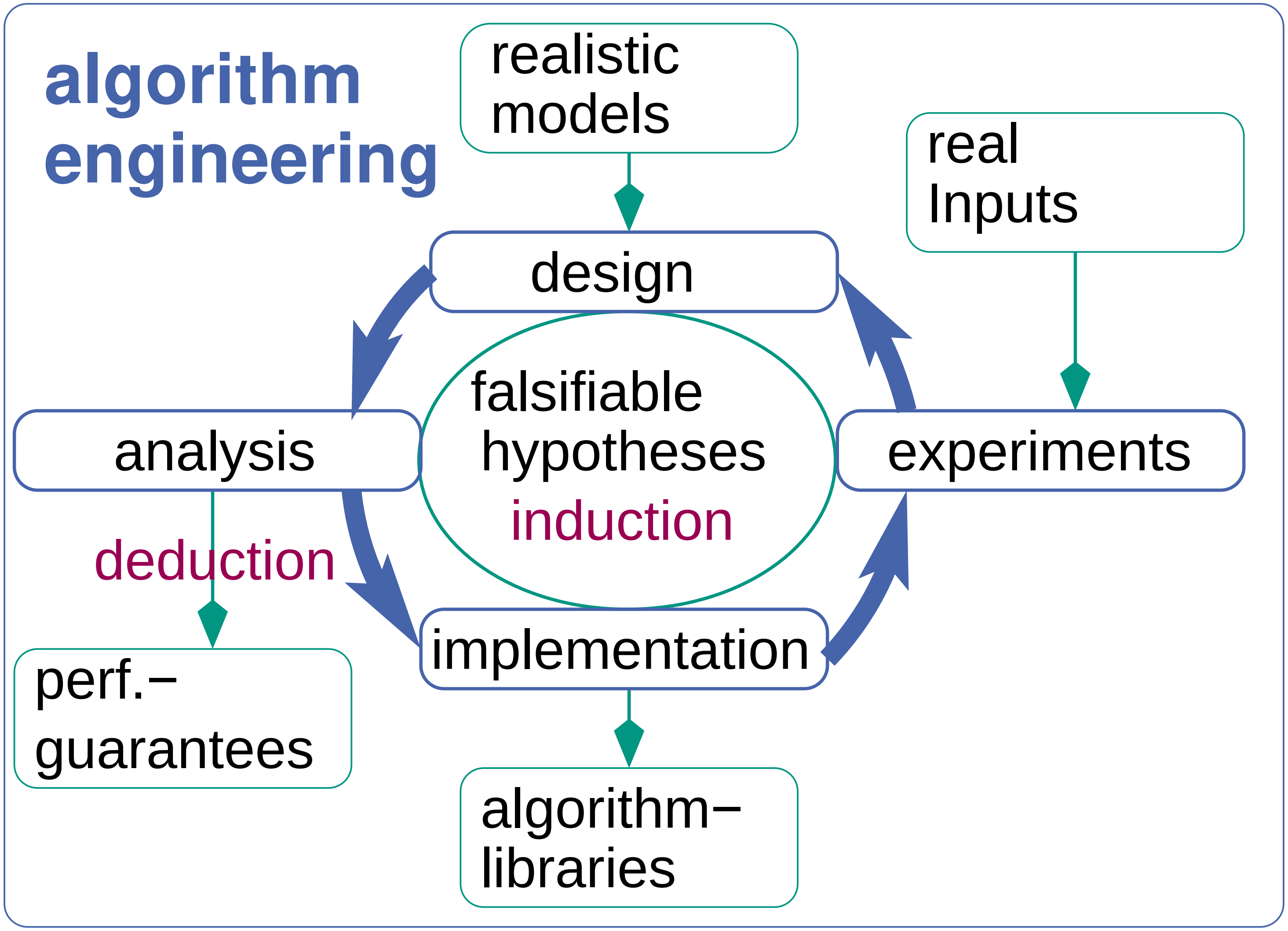
Algorithmics as Algorithm Engineering



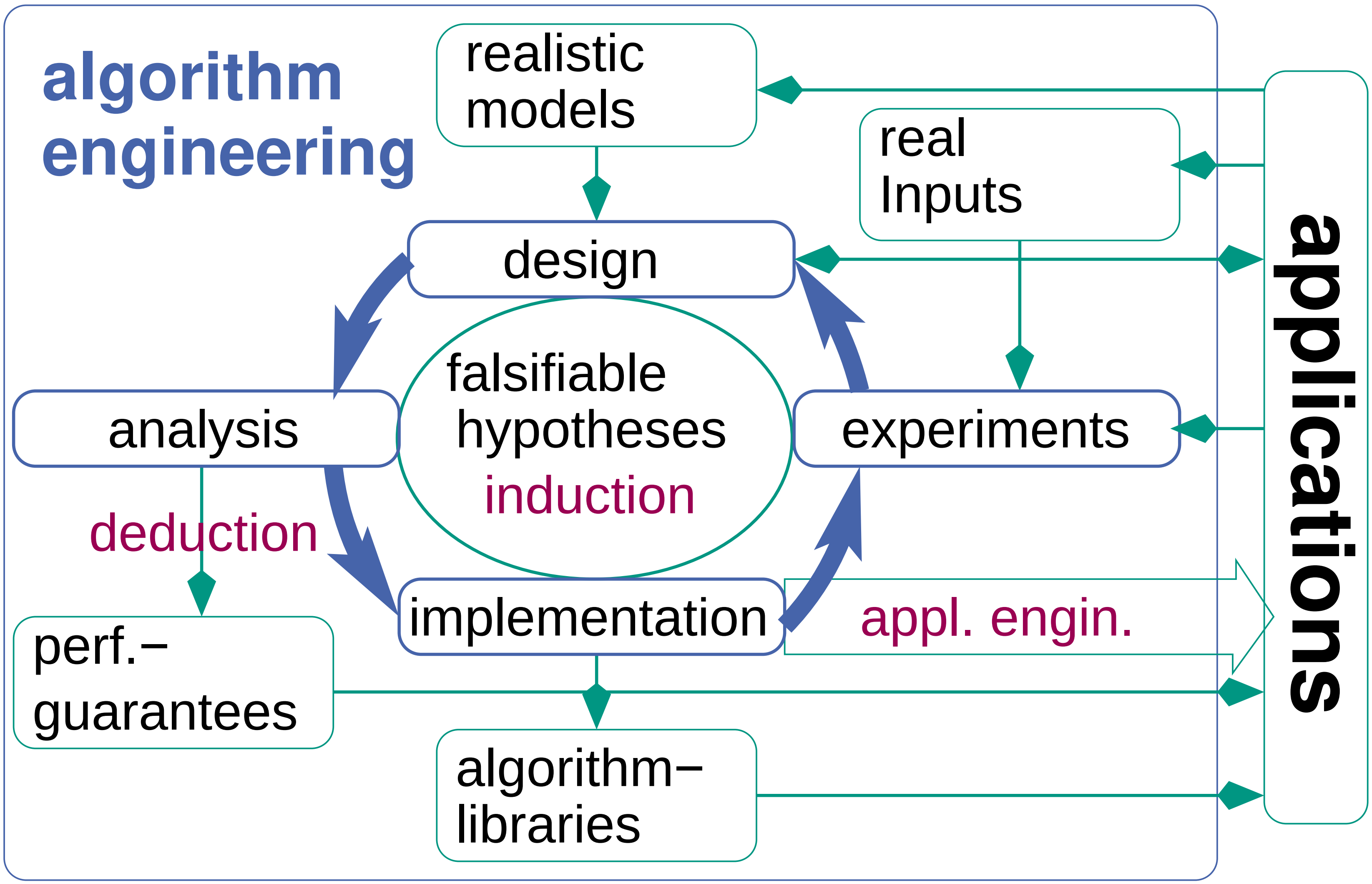
Algorithmics as Algorithm Engineering



Algorithmics as Algorithm Engineering



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]

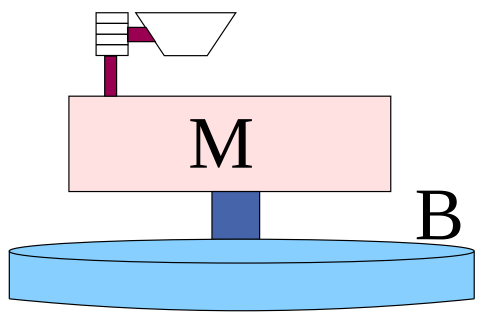
1997 Term used in US policy paper [Aho, Johnson, Karp, et. al]

1998 Alex workshop in Italy $\rightsquigarrow$ ALENEX

Realistic Models

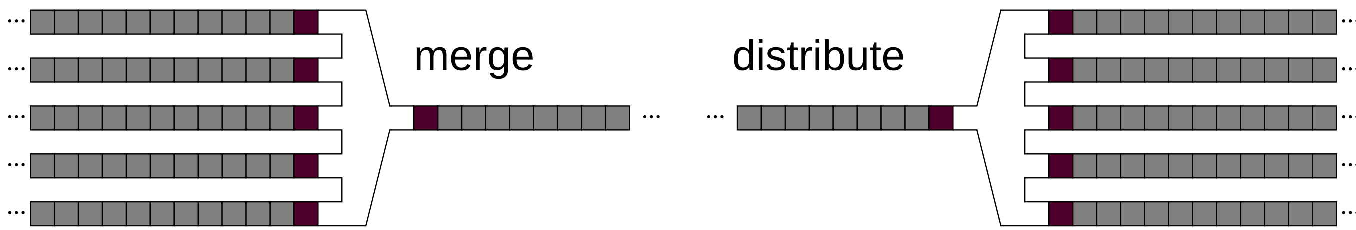
Theory	$\longleftrightarrow$	**Practice**
simple	**appl. model**	complex
simple	**machine model**	real

- 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

  Beispiel: quicksort

- Beyond worst case analysis

- Practical algorithms might be difficult to analyze

  (randomization, meta heuristics,. . .)

Implementation

sanity check for algorithms !

Challenges

Semantic gaps:

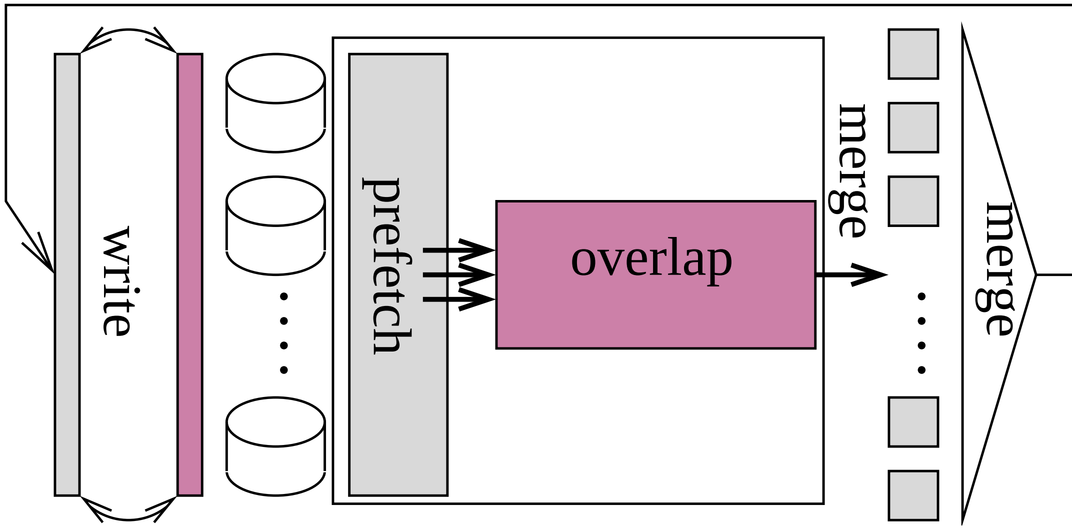
Abstract algorithm

$\leftrightarrow$

C++...

$\leftrightarrow$

hardware



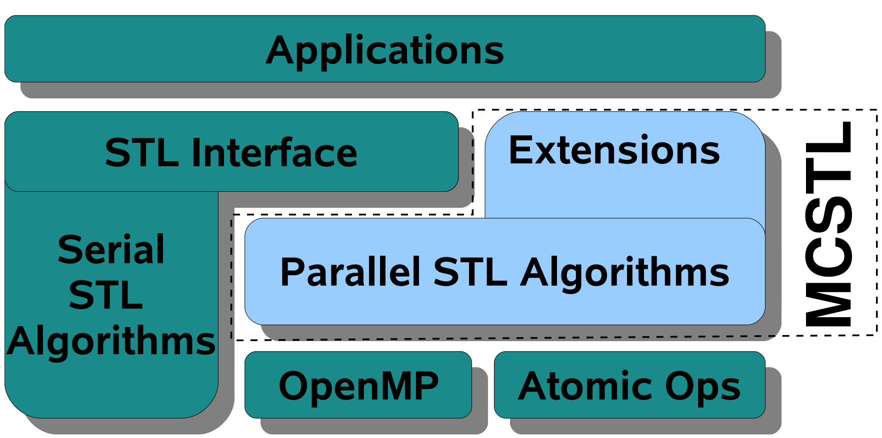
Experiments

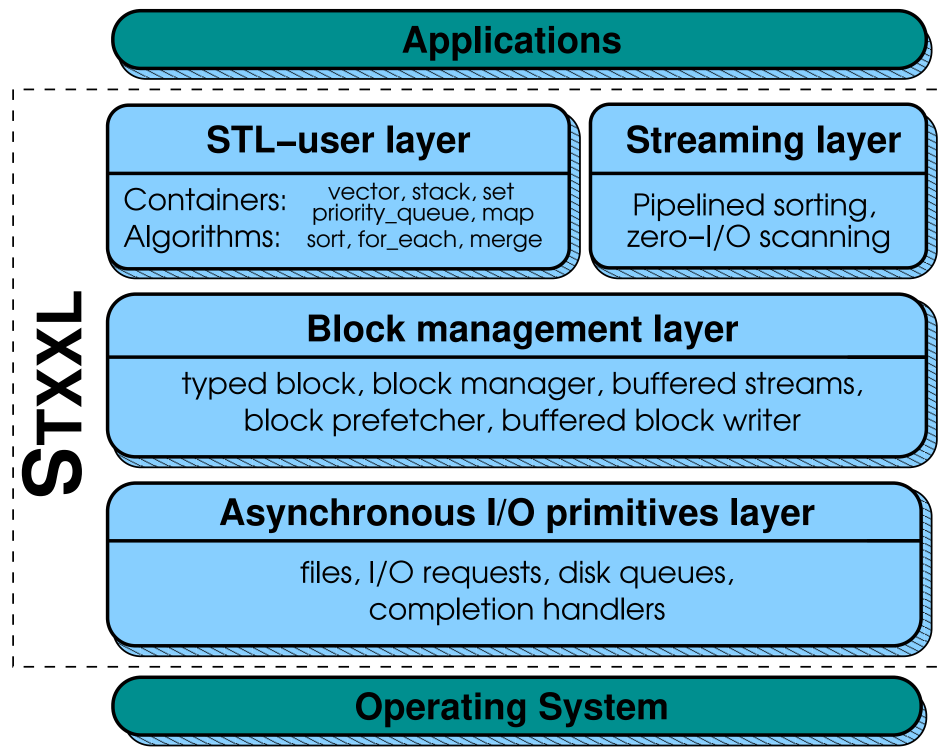
- sometimes a good surrogate for analysis
- too much rather than too little output data
- reproducibility (10 years!)
- software engineering

Stay tuned.

Algorithm Libraries — Challenges

- software engineering , e.g. CGAL
- standardization, e.g. java.util, C++ STL and BOOST
- performance $\leftrightarrow$ generality $\leftrightarrow$ simplicity
- applications are a priori unknown
- result checking, verification

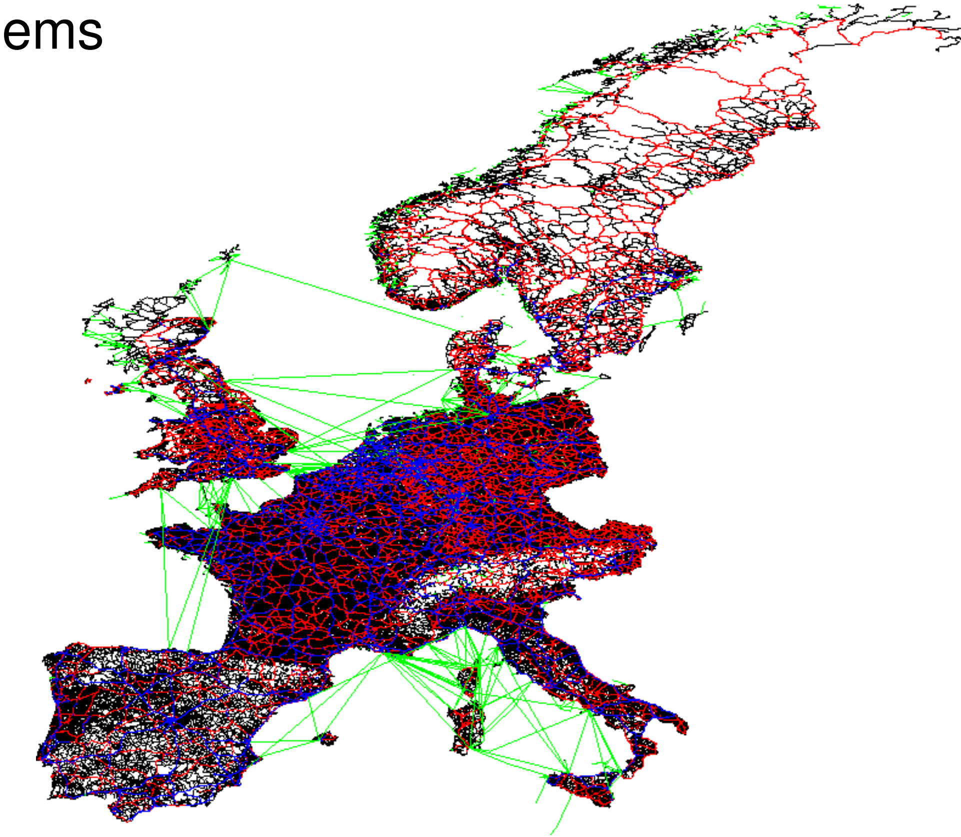




Problem Instances

Benchmark instances for NP-hard problems

- TSP
- Steiner-Tree
- SAT
- set covering
- graph partitioning
- ...



have proved essential for development of practical algorithms

Strange: much less real world instances for polynomial problems

(MST, shortest path, max flow, matching. . .)

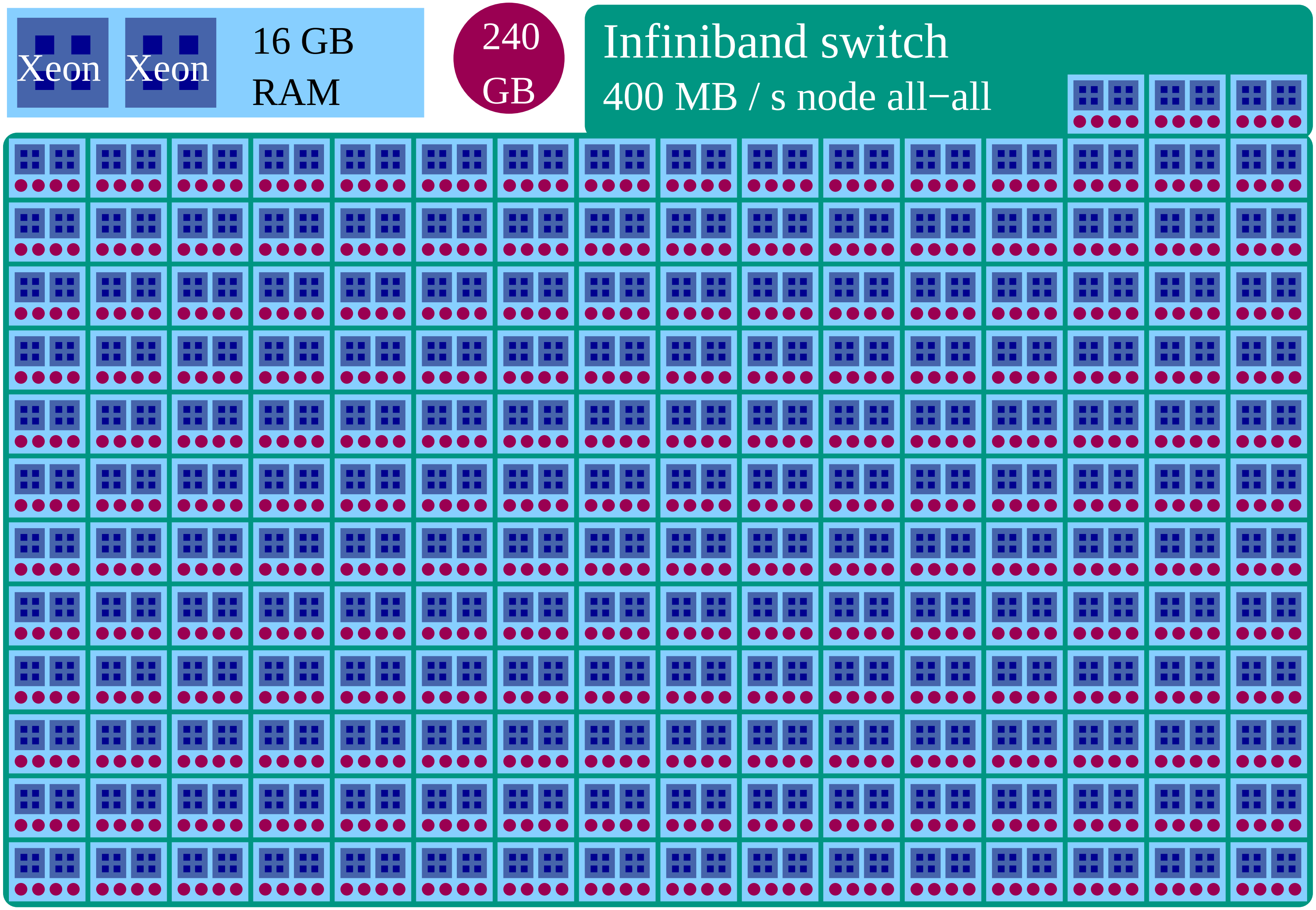
Example: Sorting Benchmark (Indy)

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

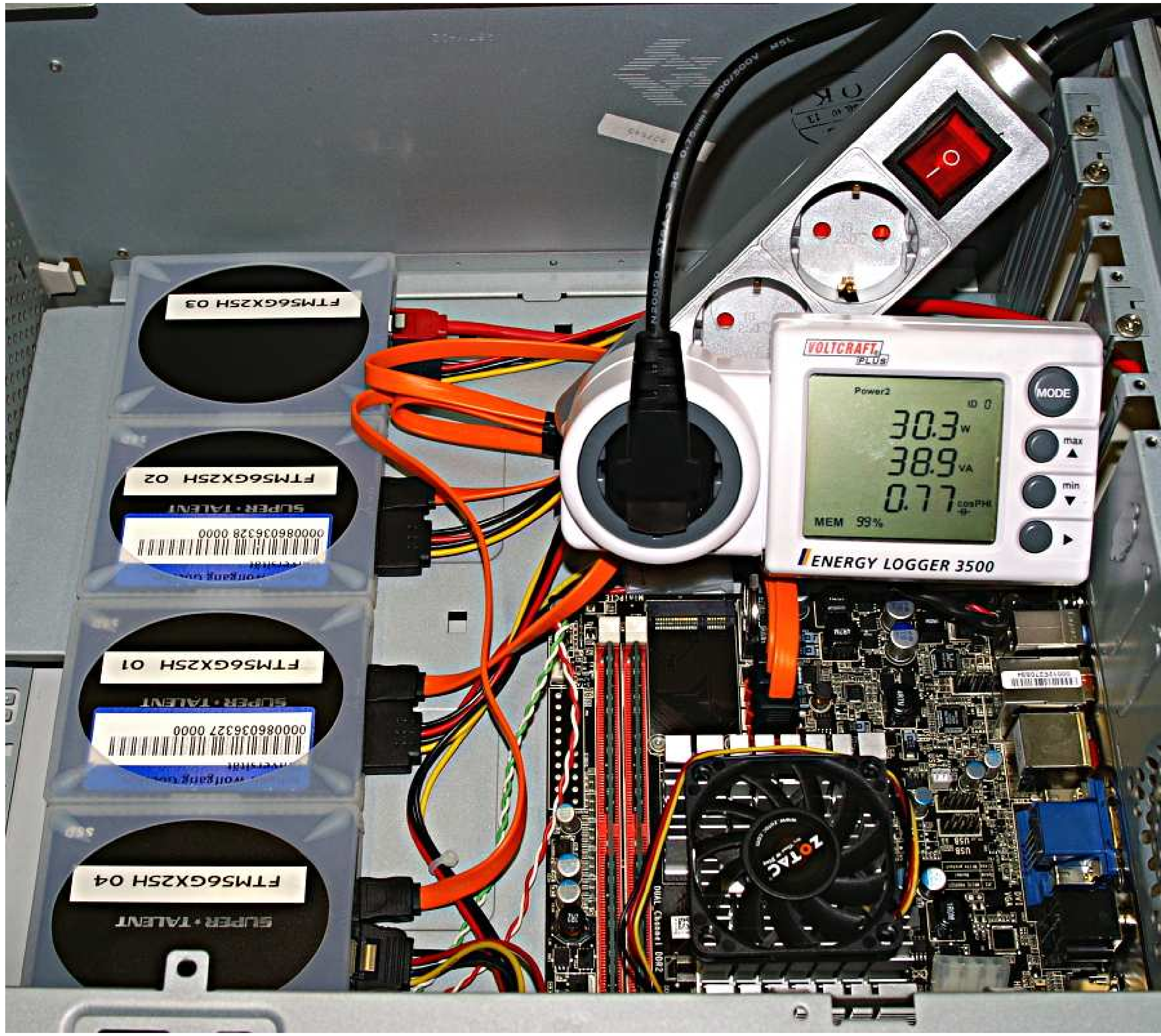
GraySort: inplace multiway mergesort, exact splitting



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,. . .

Communication Networks: mobile, P2P, cloud, selfish users,. . .

Conclusion:

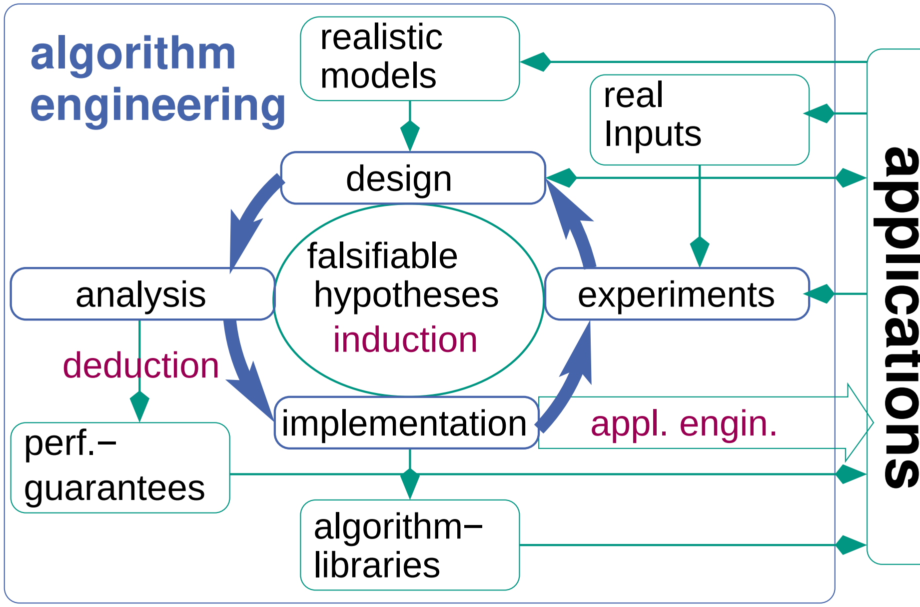
Algorithm Engineering $\leftrightarrow$ Algorithm Theory

- 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 inputs as possible
  - its fine if you are better just on some (important) inputs

Not Here but Important

- describing the setup
- 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 $\neq$ many other sciences

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