UNIVERSITÄT KLAGENFURT

Symbolic and Sub-Symbolic AI - Co-exist or Combine?

Gerhard Friedrich, Universität Klagenfurt

Why combine?

Currently, symbolic reasoning is great in narrow AI

- The user specifies the problem
- Very clever users apply KRR so that
- a computer solves it.

Why combine?

Currently, symbolic reasoning is great in narrow AI

- The user specifies the problem
- Very clever users apply KRR so that
- a computer solves it.

Towards broad AI

- The user specifies the problem
- ~~Very clever users apply KRR so that~~
- a computer solves it.

Why combine?

Currently, symbolic reasoning is great in narrow AI

- The user specifies the problem
- Very clever users apply KRR so that
- a computer solves it.

Towards broad AI

- The user specifies the problem
- ~~Very clever users apply KRR so that~~
- a computer solves it.

At most 10% of practical problems @ company in automation and digitalization in industry

Why combine?

Currently, symbolic reasoning is great in narrow AI

- The user specifies the problem
- Very clever users apply KRR so that
- a computer solves it.

Towards broad AI

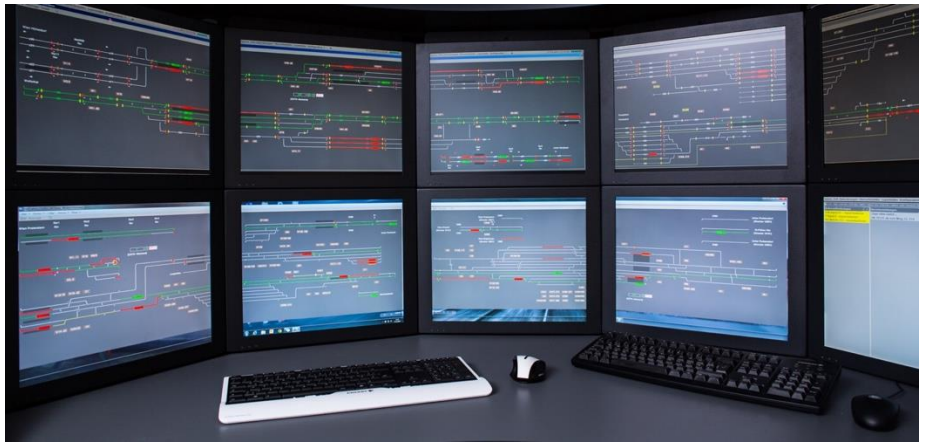
- The user specifies the problem
- ~~Very clever users apply KRR so that~~
- a computer solves it.

At most 10% of practical problems @ company in automation and digitalization in industry

No miracles, but general problem solving should surpass humans.

What buys symbols and symbolic AI?

- Correctness
- “Completeness”, difficult to achieve for practical problems
- Reasoning from first principles
- Solving new problems
- Explainability



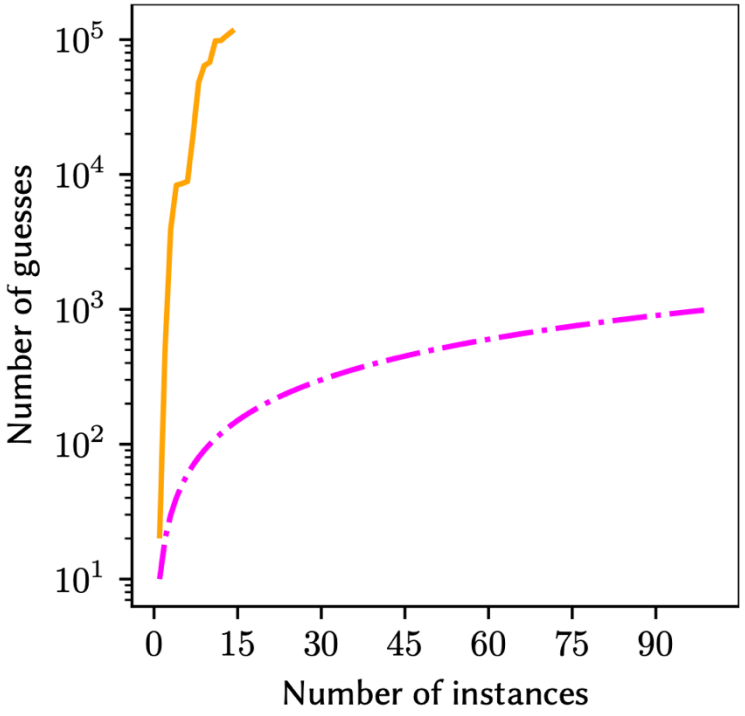
What buys symbols and symbolic AI?

- Correctness
- “Completeness”, difficult to achieve for practical problems
- Reasoning from first principles
- Solving new problems
- Explainability

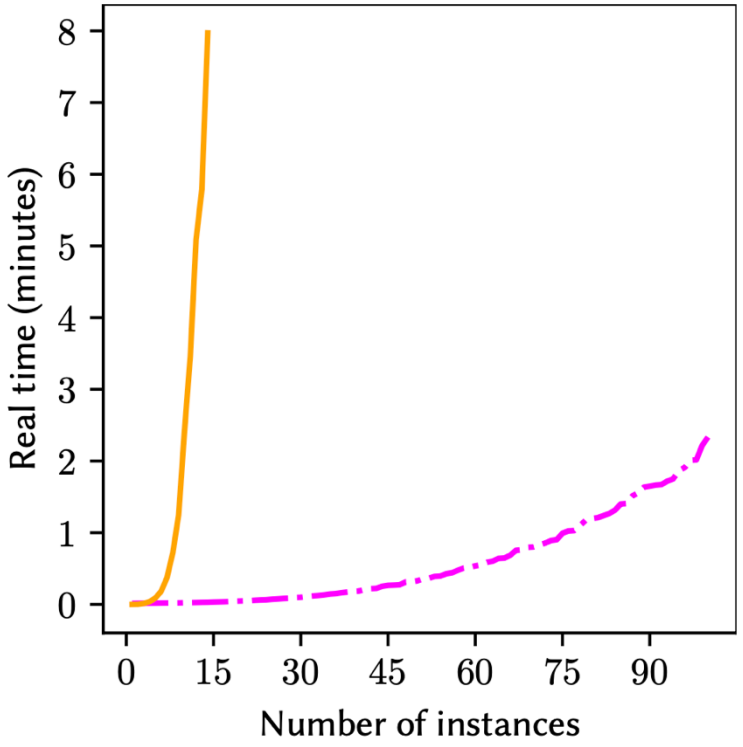
You want engineering to be correct!

Great challenges, even in simple engineering tasks

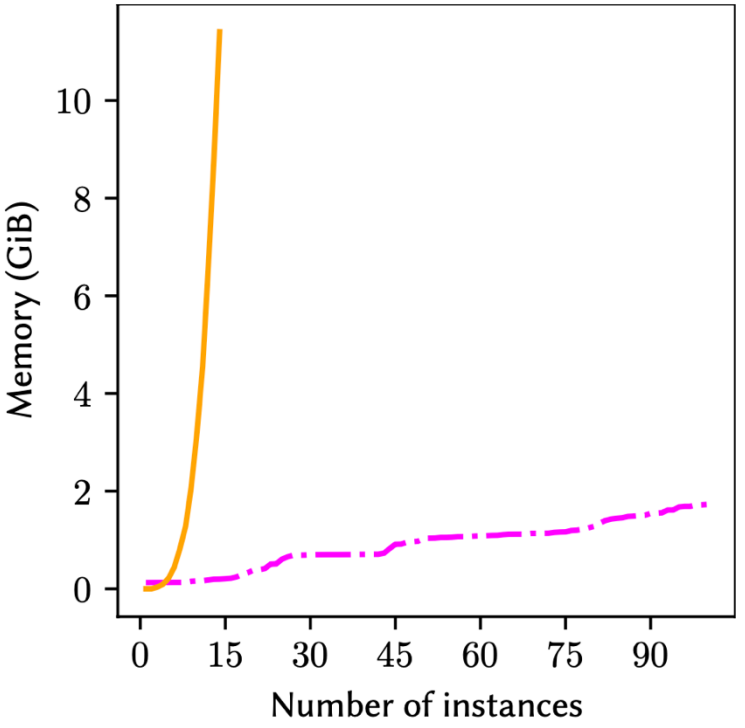
(a) Solver configurations, with numbers of solved instances



(b) Number of guesses

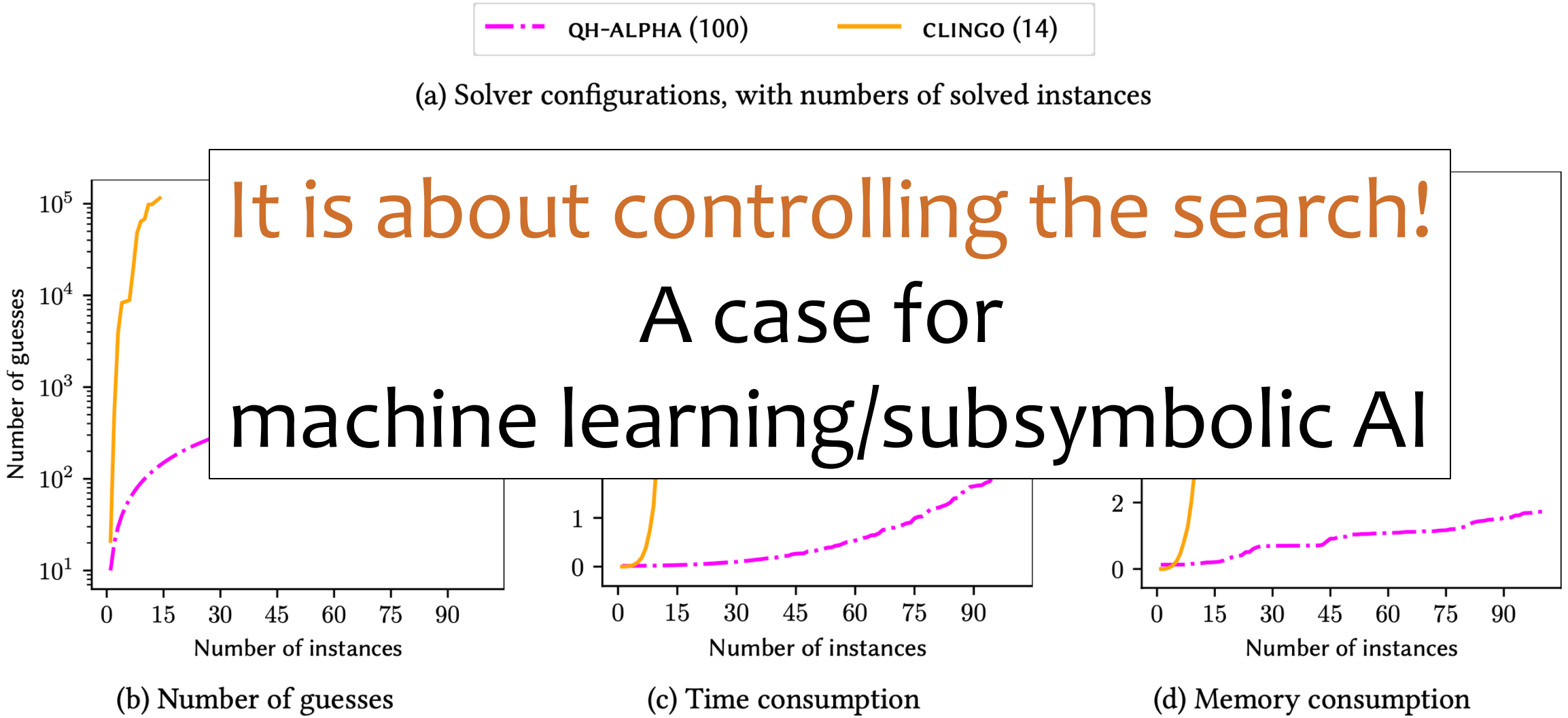


(c) Time consumption



(d) Memory consumption

Great challenges, even in simple engineering tasks

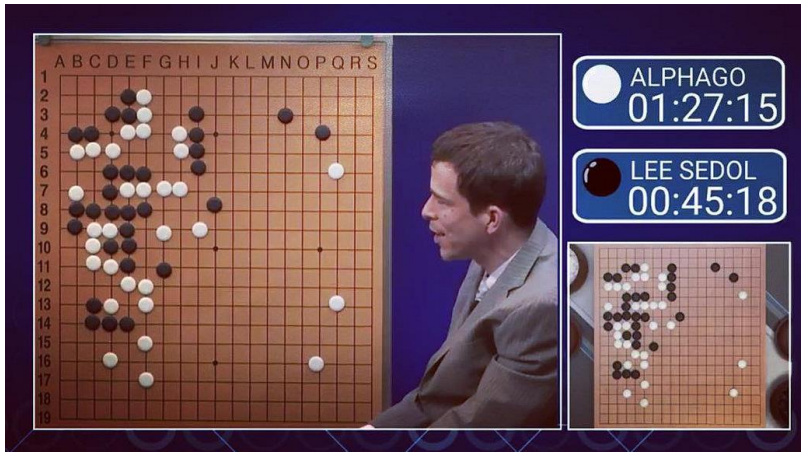


It is about controlling the search!

A case for machine learning/subsymbolic AI

ML/subsymbolic AI offers a solution

AlphaGo beats the world's best Go player



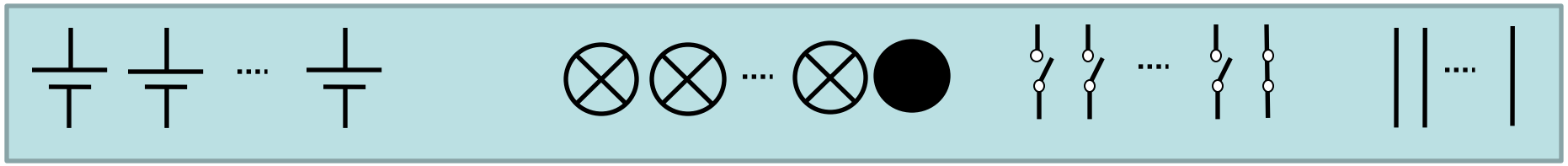
Combination of

- Deep Learning
  (controlling the search process)
- Monte Carlo tree search
  (search method)

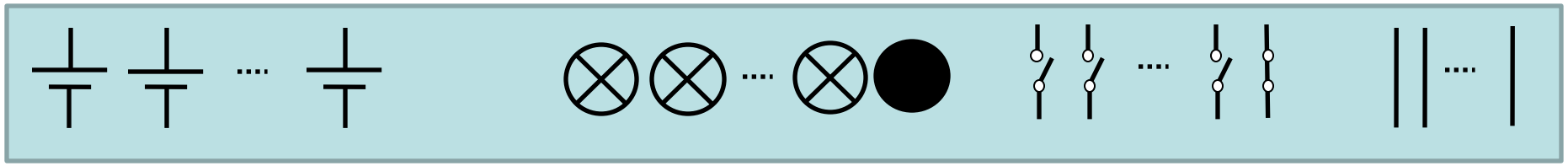
Problem is the size of the search space

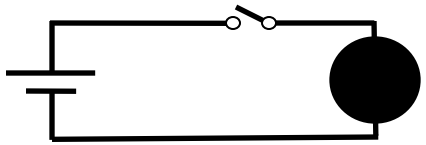
- Go significantly larger search space than Chess (Deep Blue)
- Some industrial applications (chip manufacturing) have significantly larger search space than Go
  - Tic-tac-Toe: 9!
  - Chess: approx. 10^{120} (80 moves)
  - Go: approx. 10^{360} (150 moves)
  - Chip manufacturing: > $2^{500,000}$

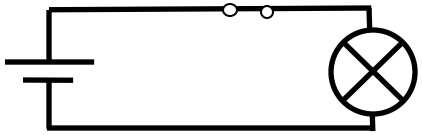
The power of reasoning from first principles and qualitative reasoning



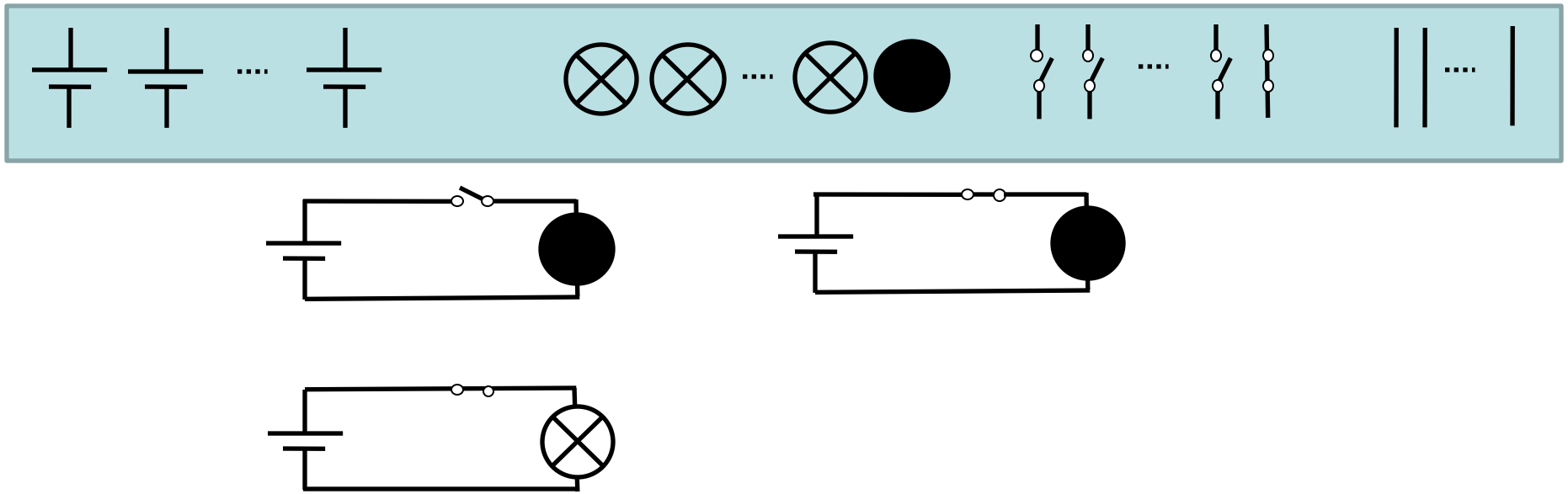
The power of reasoning from first principles and qualitative reasoning



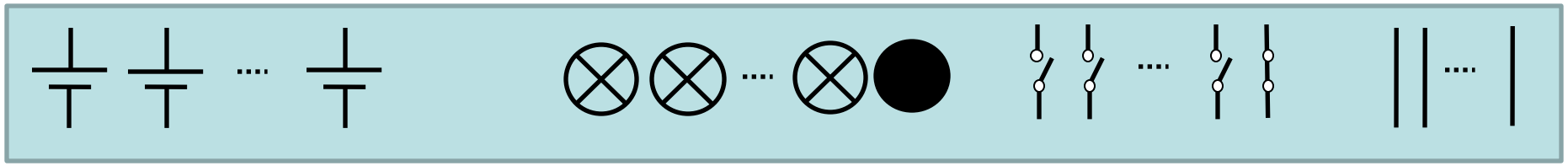


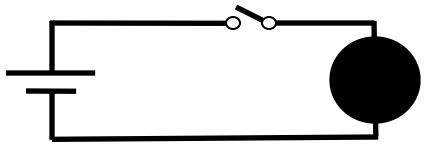


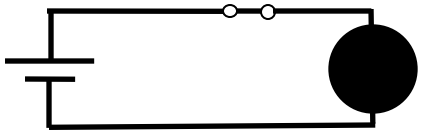
The power of reasoning from first principles and qualitative reasoning

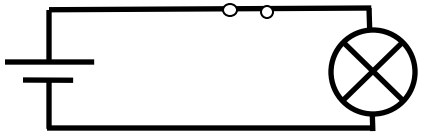


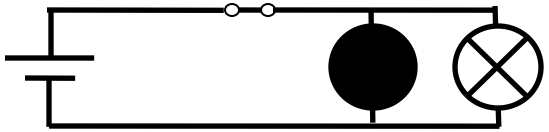
The power of reasoning from first principles and qualitative reasoning



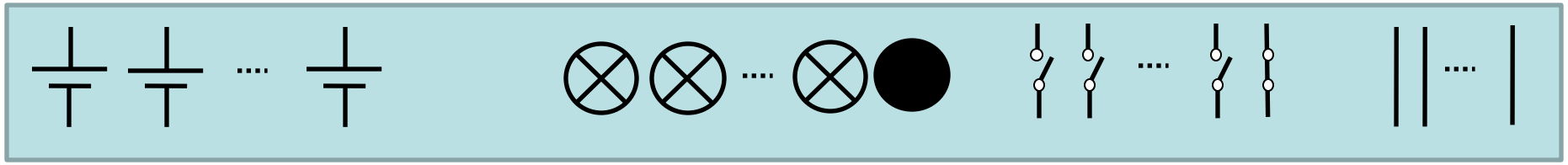


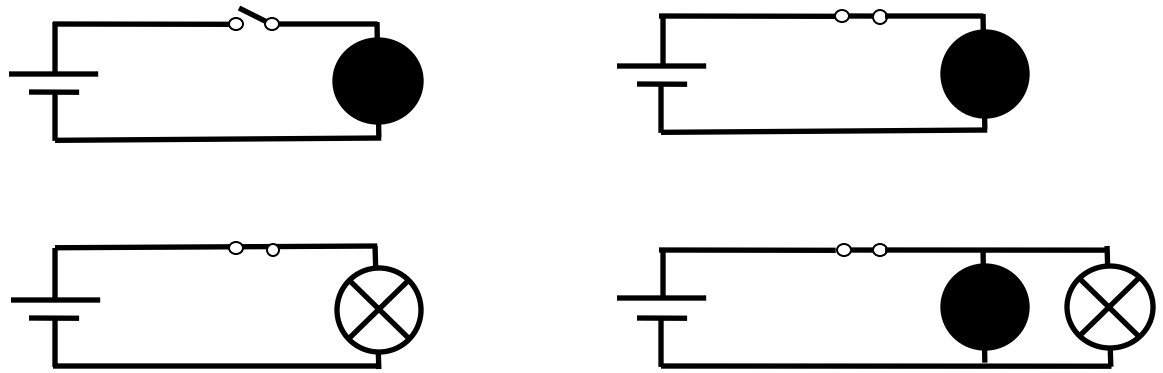






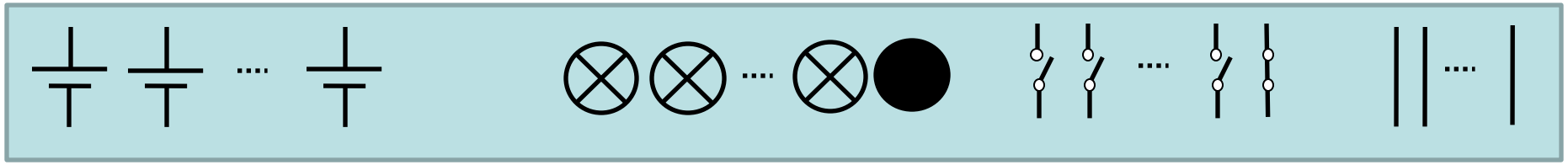
The power of reasoning from first principles and qualitative reasoning

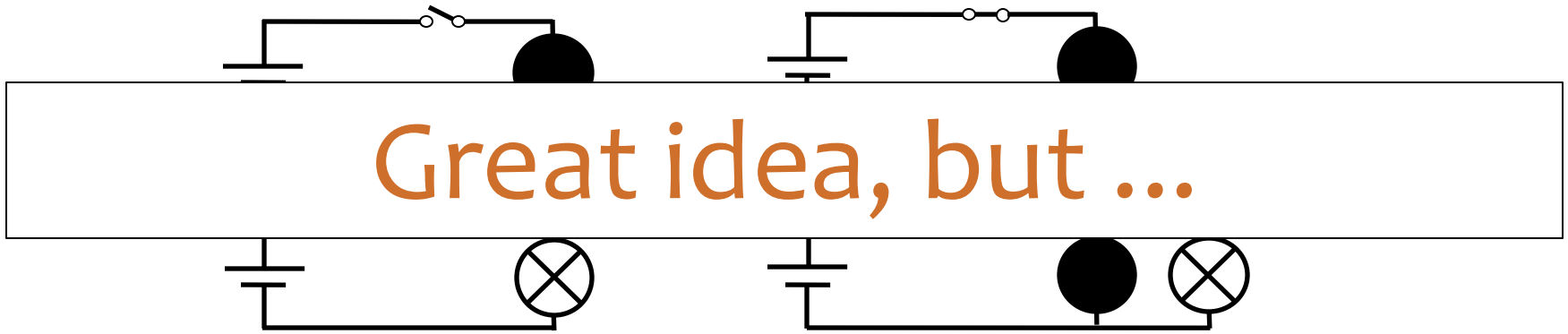




- Reasoning from first principles, model-based reasoning, causality
- E.g., automated diagnosis, repair, configuration
- Implemented by logic as representation language and logical reasoning
- Complete and correct

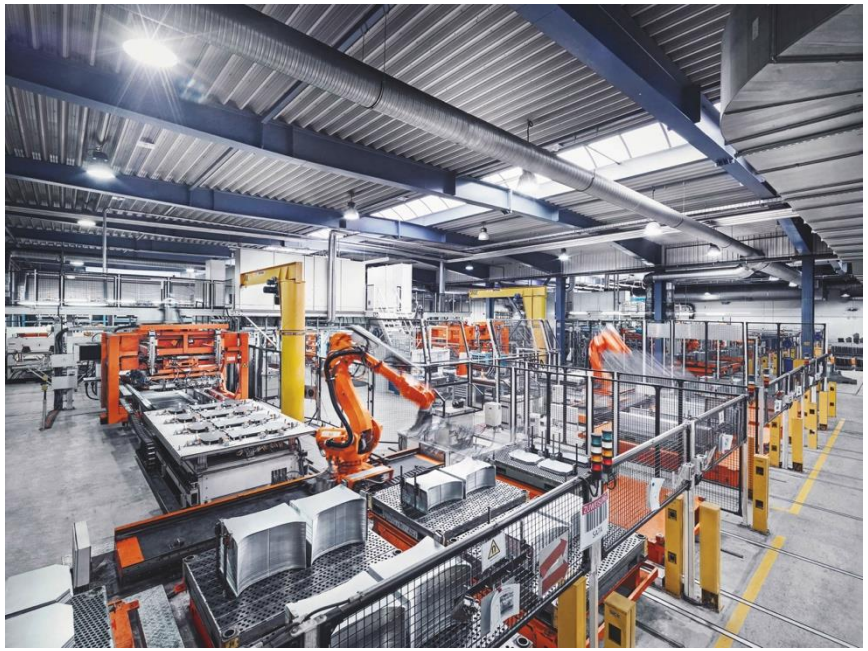
The power of reasoning from first principles and qualitative reasoning





- Reasoning from first principles, model-based reasoning, causality
- E.g., automated diagnosis, repair, configuration
- Implemented by logic as representation language and logical reasoning
- Complete and correct

We have a modelling/specification problem



(c) Voestalpine

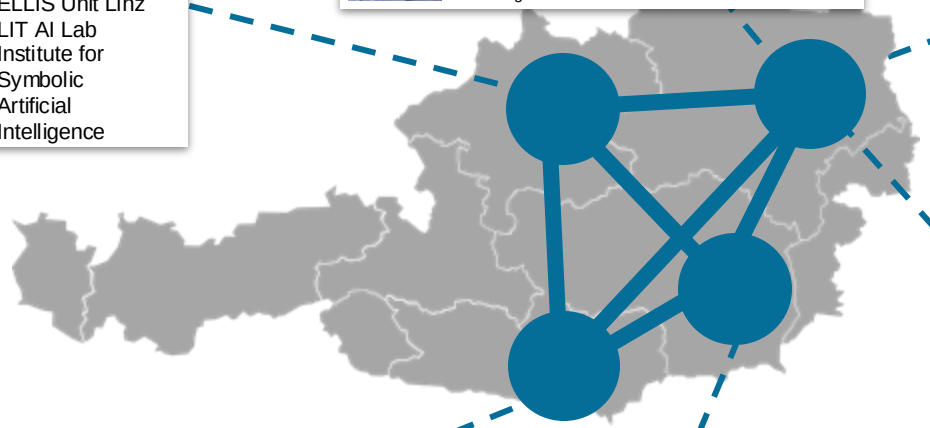
Engineers cannot specify sufficiently detailed physical model for

- Diagnosis and repair
- Predicting energy consumption
- Predicting wear of tools
- …

We apply ML/subsymbolic approaches to learn the detailed physics/parameters.

Broad AI for diagnosing, designing, and optimizing complex technical system.

Cluster of Excellence: Bilateral AI



JOHANNES KEPLER UNIVERSITÄT LINZ

Martina Seidl
Symbolic AI
SAT Solving
Formal methods

Sepp Hochreiter
Machine Learning
LSTM
Vanishing gradient

- Institute for Machine Learning
- ELLIS Unit Linz
- LIT AI Lab
- Institute for Symbolic Artificial Intelligence

ISTA Institute of Science and Technology Austria

Christoph Lampert
Machine Learning
Trustworthy Learning

- Machine Learning and Computer Vision group
- ELLIS Unit ISTA

WU WIRTSCHAFTS UNIVERSITÄT WIEN VIENNA UNIVERSITY OF ECONOMICS AND BUSINESS

Axel Polleres
Knowledge Graphs

- Institute for Data Process and Knowledge Management

UNIVERSITÄT KLAGENFURT

Gerhard Friedrich
Symbolic AI
Model-based reasoning

- Institute for Artificial Intelligence and Cybersecurity

TU Graz

Robert Legenstein
Machine Learning
Computational Neuroscience

- Institute of Theoretical Computer Science

TU WIEN TECHNISCHE UNIVERSITÄT WIEN

Agata Ciabattoni
Logic
Reasoning

- Institute for Logic and Computation

Thomas Eiter
Symbolic AI
Knowledge representation

18

Vision of a broad AI

Narrow AIs for specific tasks

In contrast, we envision a

Broad AI

by combining and advancing the strengths of

sub-symbolic and **symbolic AI**