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Using ML and AI to Speed-Up Large-Scale Optimization Problems

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Increasing complexity

- Digitalization of industrial production processes
- Maximize synergies through more integrated operations
- Scheduling problems larger → both modeling and solution procedures are cumbersome
- Automate the decision making

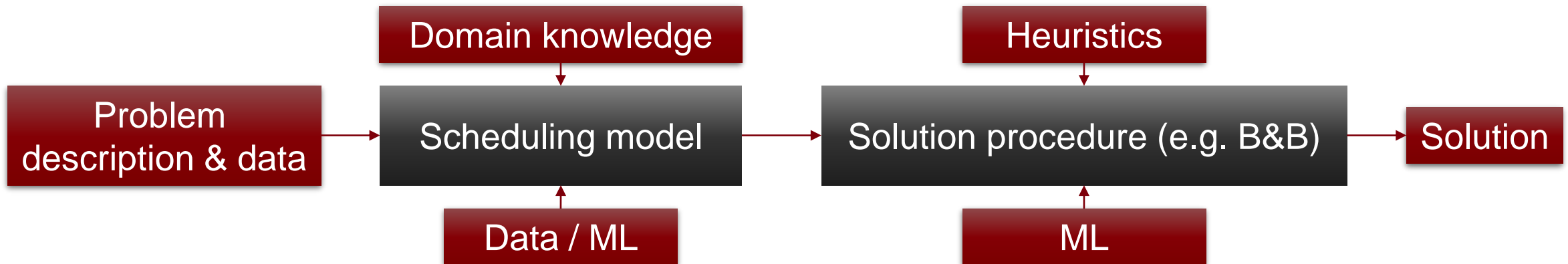
Common approaches to speed up the optimization

- Simplify the problem (i.e., balancing between the solution quality and computing time)
- Apply heuristics to reduce solution space
- Deploy simulation tools to predict complex variable values
- Use decomposition: Divide the problem into smaller subproblems
- + mixture of all of the above



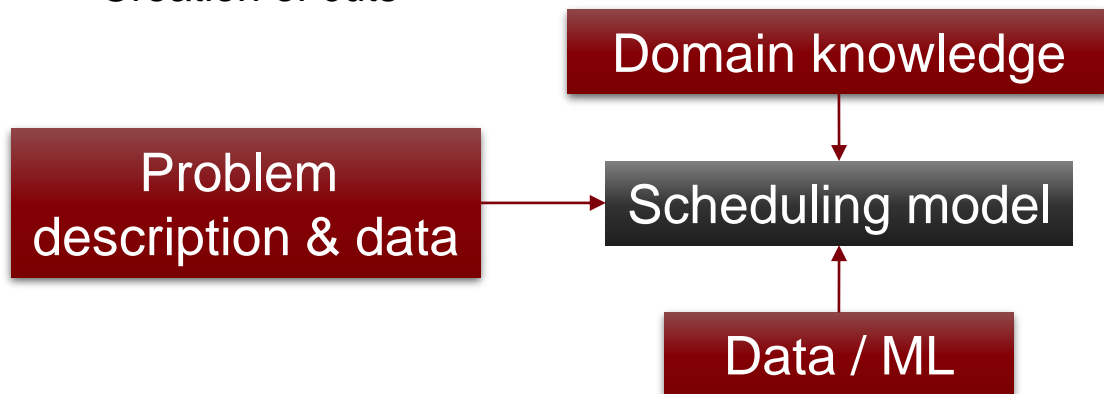
Main steps

- Building the model – often manual effort
 - User / Operator: Apply domain knowledge
 - Automated: Data processing
- Solving the model (mostly 100% automated) but the solution engine can be supported by
 - Manually defined heuristics based on problem understanding
 - Machine Learning (designed by an expert)



Use ML to reduce the sometimes significant and error-prone engineering efforts that can occupy highly-trained personnel on routine tasks

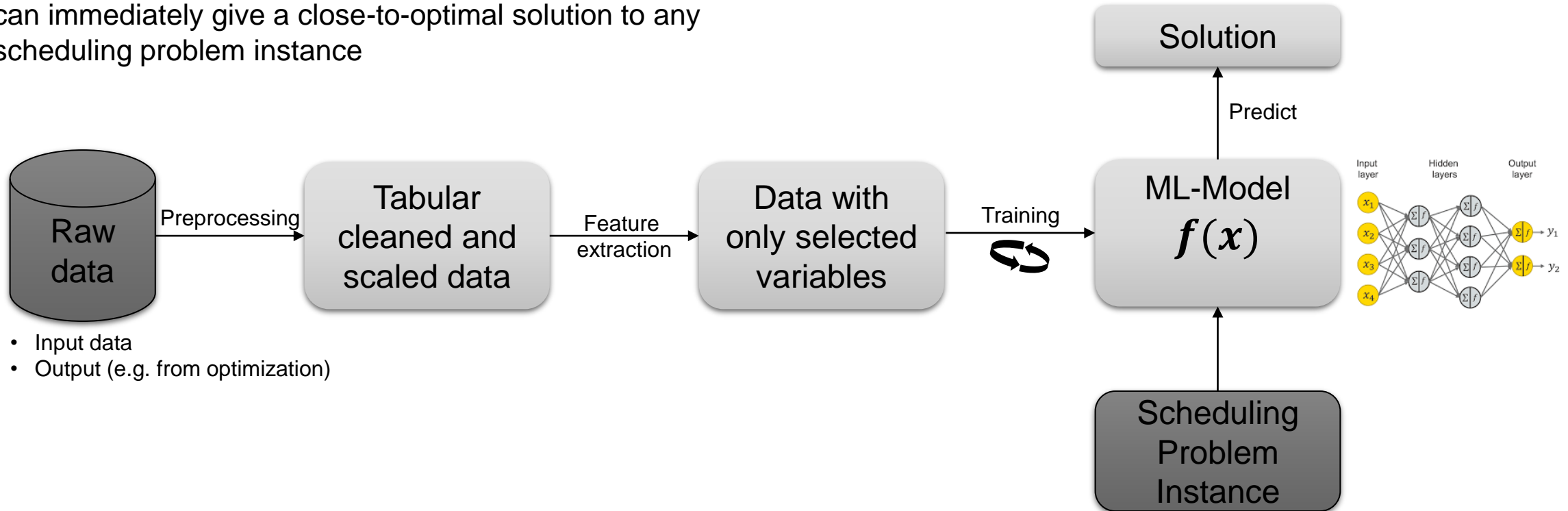
- Can true domain expertise be reliably generated by a system that mainly builds on already existing data?
- If using ML, it is important that the system identifies its own capability limitations / boundaries!
- Modeling of true problems require domain knowledge / problem understanding + data
- Machine Learning can contribute to e.g.
 - Processing large datasets (clustering, forecasting, ...)
 - Parameter tuning, surrogate modeling
 - Automatically generated constraints (ALAMO)
 - Creation of cuts



Many contributions in the literature!

“The Dream”

In an ideal world we can train a prediction model such that it can immediately give a close-to-optimal solution to any scheduling problem instance

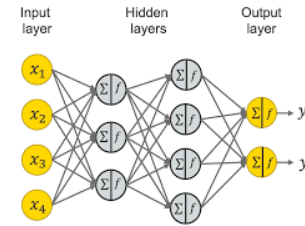


- Input data
- Output (e.g. from optimization)

“Reality” – Many avenues, no clear “winner”

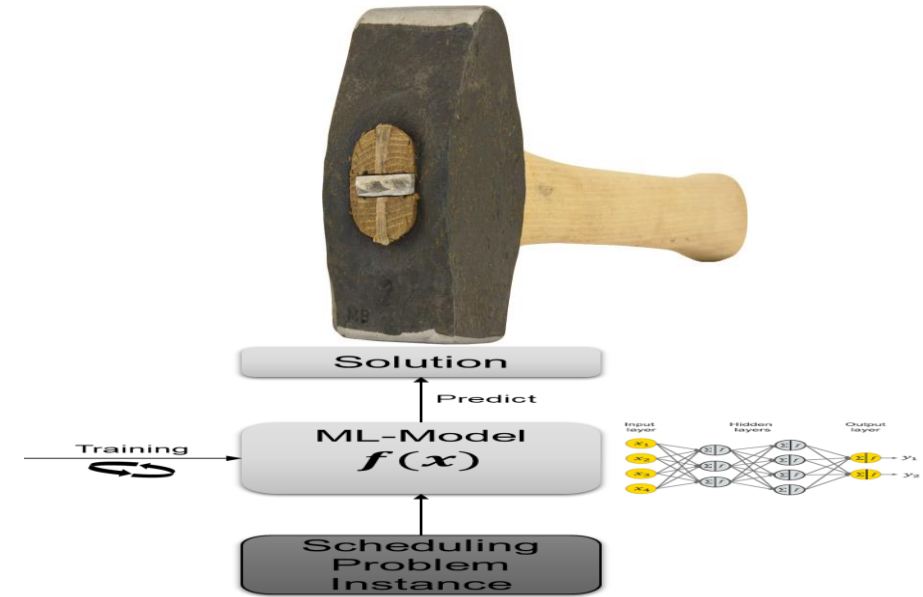
Use machine learning to

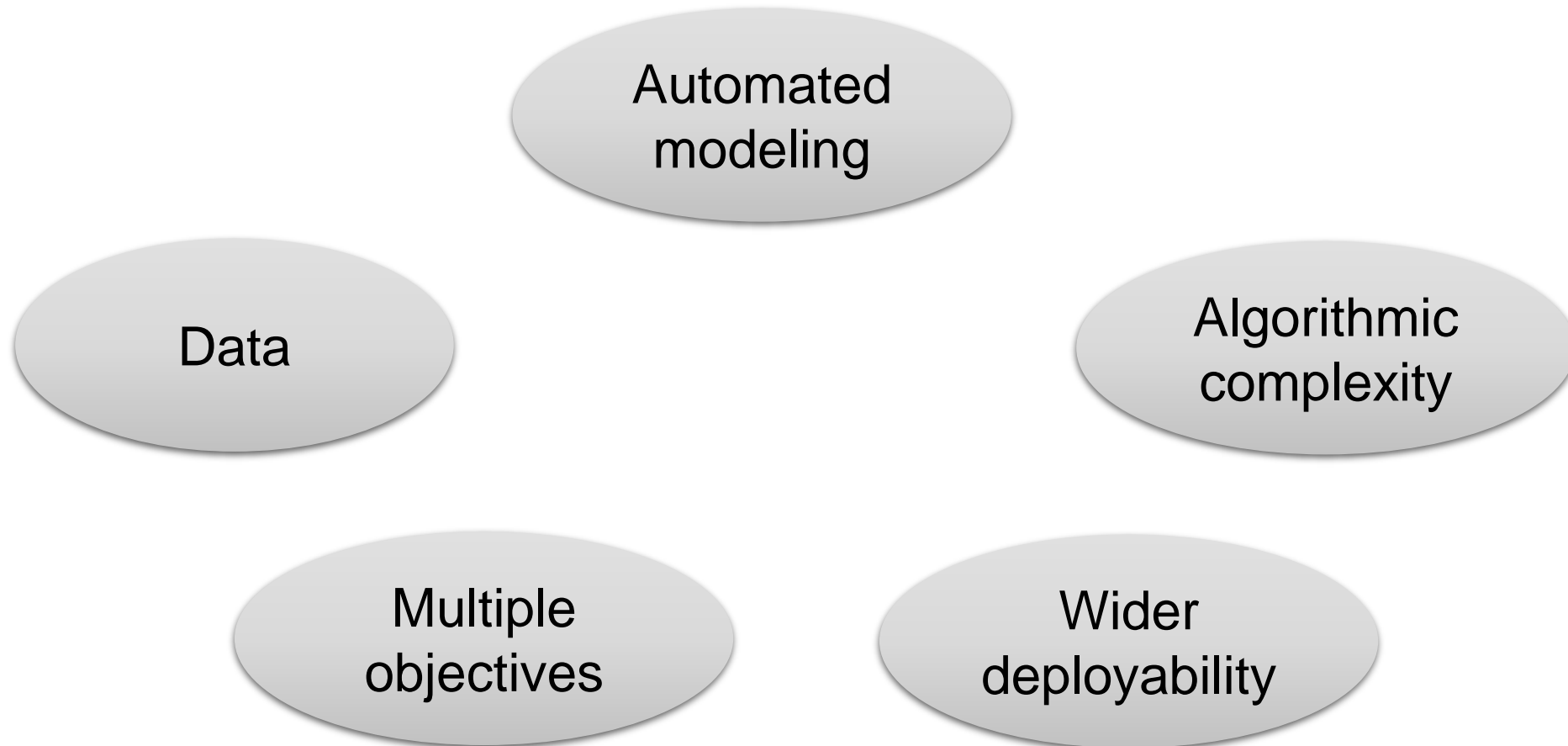
- Dynamically generate more accurate (up-to-date) scheduling parameters – “forgetting factor”?
- Creating more generic decision-making patterns – solving part of the problem
- Understand and learn to solve a problem (Xavier et al., 2019)
 - ML in B&B search e.g. ECOLE (Provoust et al., 2020)
- IBM CPLEX/Gurobi: Automatically decide upon algorithmic choices in solving QPs, tune parameters during solution
- Use deep reinforcement learning in process scheduling, e.g. OR-GYM (Hubbs et al., 2020b)
- Deploy reinforcement learning to decide on the timing of rescheduling, scheduling algorithms and time budget for the optimization (hyperparameters)



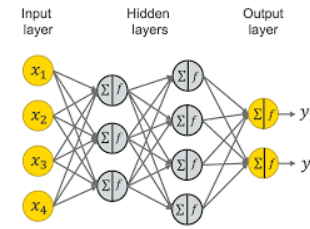
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maximize $\mathbf{c}^T \mathbf{x}$
 subject to $A\mathbf{x} + \mathbf{s} = \mathbf{b},$
 $\mathbf{s} \geq \mathbf{0},$
 $\mathbf{x} \geq \mathbf{0},$
 and $\mathbf{x} \in \mathbb{Z}^n,$





- Combining machine learning to support or complement mixed integer linear programming – already many contributions
 - So far no silver-bullet (will there ever be...)
- Largest benefits (at least “low hanging fruit”) seem to come from effectively combining ML-prediction or clustering & MILP-solution
 - Rather on the modeling than solution level
- Important to have realistic expectations
 - Hype vs. reality
- Needed: Sufficiently large, shared datasets for development
- MILP alone will “hit the wall”
 - Some form of collaborative approaches will become the standard for efficient and successful solution of complex scheduling problems
- Data does not go anywhere... and problems are growing!



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