AI and Optimization for Sustainable Applications

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Outline

- Sustainable applications
  - Employee planning and scheduling
  - Production planning and scheduling
  - Food waste reduction

- AI and optimization techniques
  - Modeling
  - Exact, heuristic and hybrid techniques
  - Machine learning
    - Supervised learning
    - Reinforcement learning
- Conclusions

Investigated Applications in our Lab

Rotating Workforce Scheduling

Shift Design

Break Scheduling

Nurse Rostering

Torpedo Scheduling

Electric Vehicle Charging

Tourist Trip Planning

Social Golfer Problem

High School Timetabling

Production Leveling Problem

Parallel Machine Scheduling

Industrial Oven Scheduling

Physician Scheduling During a Pandemic

Unicost Set Covering

(Hyper)tree Decomposition

Graph Coloring

Traveling Salesman Problem

Vehicle Routing

Sudoku

Bus Driver Scheduling

Test Laboratory Scheduling

Artificial Teeth Production Scheduling

Project Scheduling

Paint Shop Scheduling Problem

Curriculum-based Course Timetabling

Food Waste Reduction

https://www.un.org/en/sustainable-development-goals

Employee Scheduling

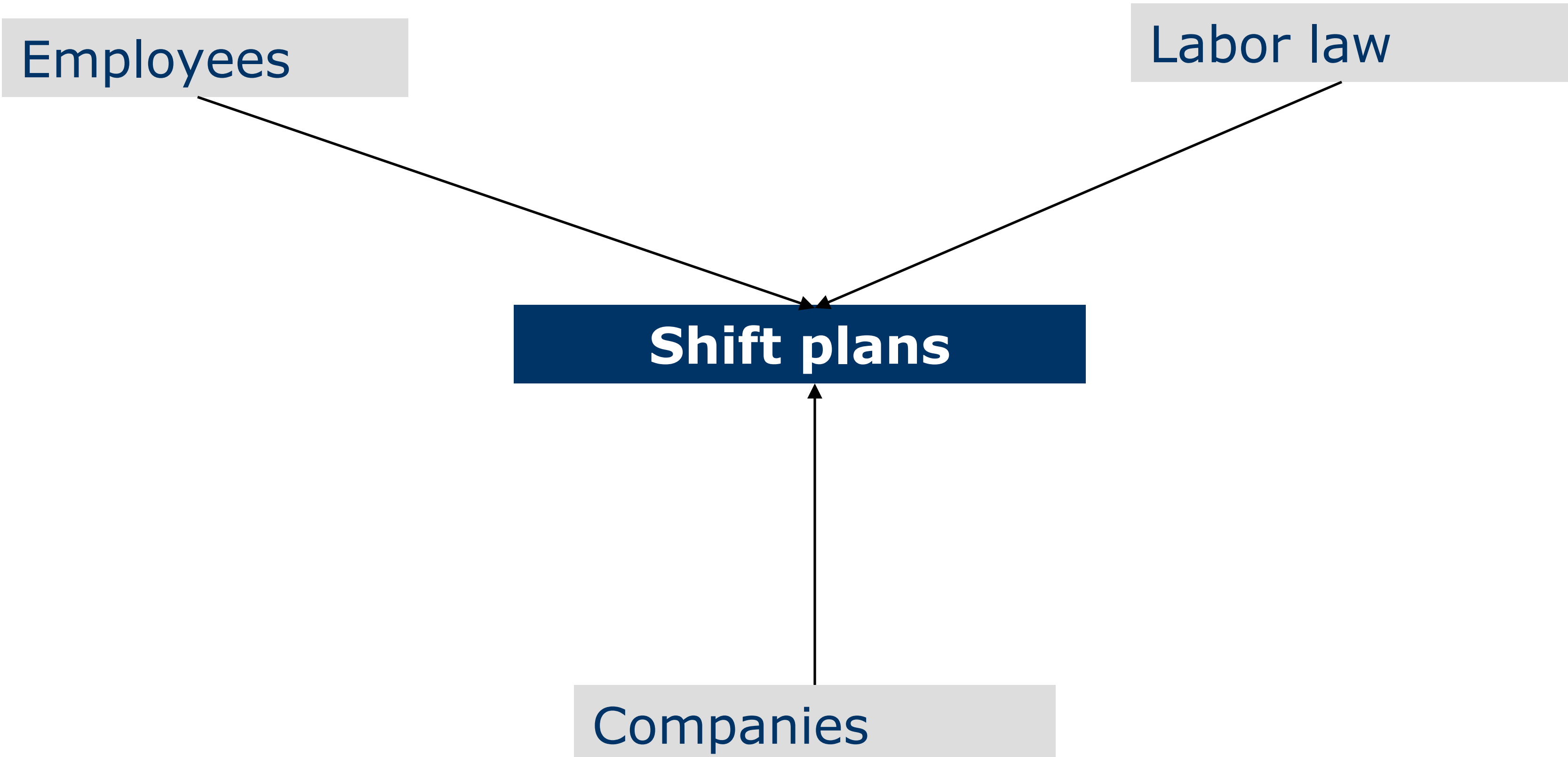
- Work schedules influence the lives of employees
- Unsuitable timetable can have a tremendous negative impact on one's health, social life, and motivation at work
- Organizations in the commercial and public sector must meet their workforce requirements and ensure the quality of their services and operations

Employee Scheduling

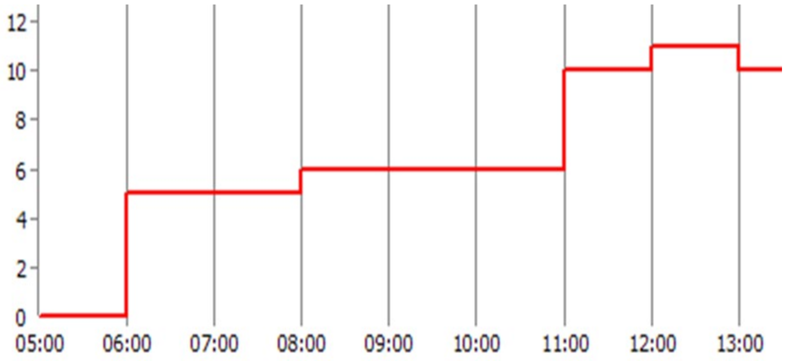
Real world employee scheduling problems appear in many companies

- Airports
- Call centers
- Air traffic control
- Hospitals
- Public transport
- Production plants
- …

Employee Scheduling

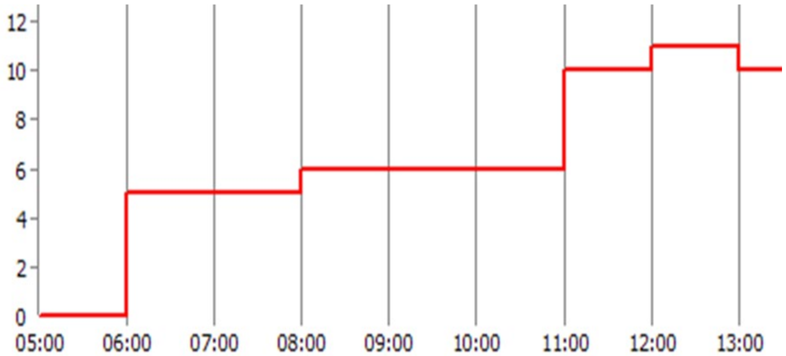


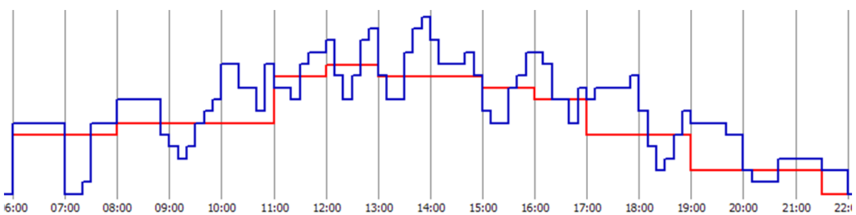
Employee Scheduling Problems

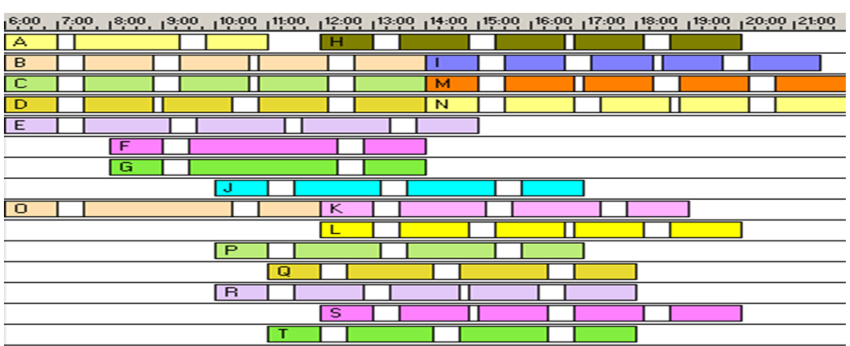


Phase 1:
Workforce requirements

Employee Scheduling Problems



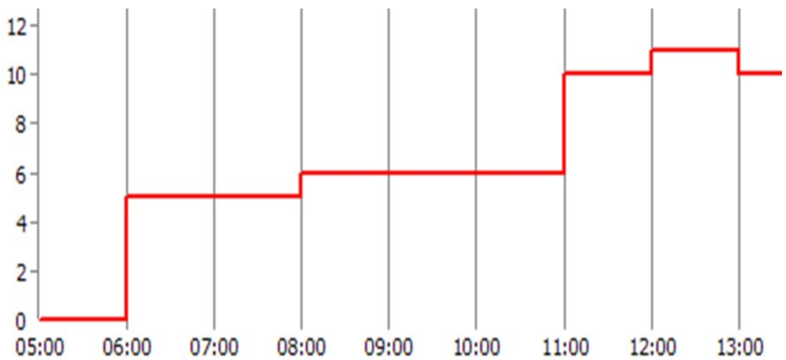


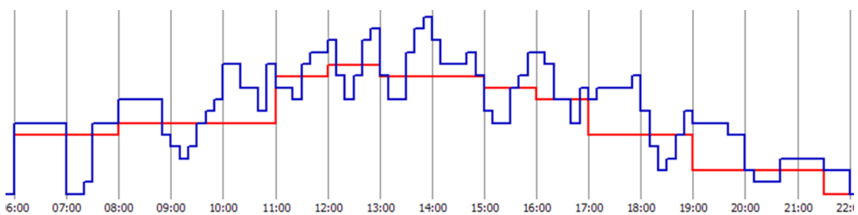


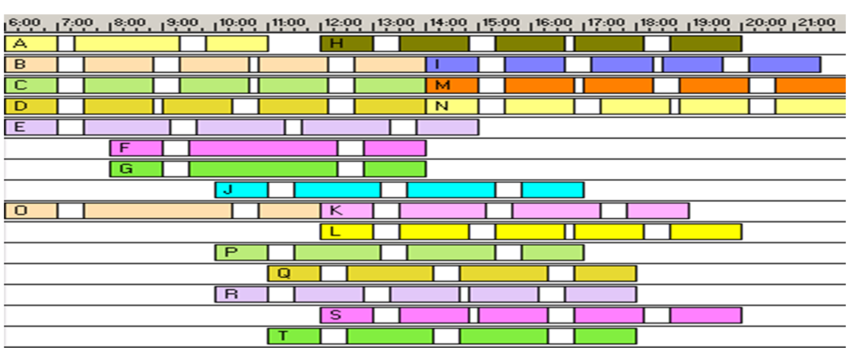
Phase 1:
Workforce requirements

Phase 2:
Shift Design/Break Scheduling

Employee Scheduling Problems







Phase 1:
Workforce requirements

Phase 2:
Shift Design/Break Scheduling

Phase 3:
Assignment of shifts

	Mo	Di	Mi	Do	Fr	Sa	So
A	F	F	F	S	S		
B		N	N	N	N		
C		F	F	N	N	N	N
D			S	S	S	N	N
E	N			F	F	S	S
F	S			F	F	F	F
G	S	S				F	F
H	F	S	S			S	S
I	N	N	N				

Selected papers: [3,4,11,12]

Example: Rotating Workforce Scheduling

Length of schedule: If the schedule is cyclic the total length of a planning period will be: NumberOfEmployees*7

	Mo	Tu	We	Th	Fr	Sa	Su
A	D	D	D			D	D
B	D	D	D	D			
C	A	A	A	A			A
D	A	A	A	A	A		
E	D	D	A	A	A		
F	A	A	N	N	N		
G	N	N	N	N	N		
H		N	N	N	N	N	
I			D	D	D	A	A
J				D	D	N	N
K	N				A	A	N
L	N	N			D	D	D

Number of employees

Employees working shifts:

D: Day shift ; A: Afternoon shift ,

N: Night shift; Day off

Constraints

	Mo	Tu	We	Th	Fr	Sa	Su
A	D	D	D			D	D
B	D	D	D	D			
C	A	A	A	A			A
D	A	A	A	A	A		
E	D	D	A	A	A		
F	A	A	N	N	N		
G	N	N	N	N	N		
H		N	N	N	N	N	
I			D	D	D	A	A
J				D	D	N	N
K	N				A	A	N
L	N	N			D	D	D

Not allowed sequences of shifts:

N - D
N D
A D
N A
N - A
A - D

Maximum and minimum length of periods of successive shifts.

e.g.: N: 2-5, D: 2-6

Temporal requirements: required number of employees in shift *i* during day *j*

Monday (Mo): D: 3, N: 3, A: 3

Maximum and minimum length of work days and days-off blocks

e.g.: days-off block: 2-4

work block: 2-6

Objective

Find a cyclic schedule (assignment of shifts to employees) that satisfies the temporal requirement, and all other constraints

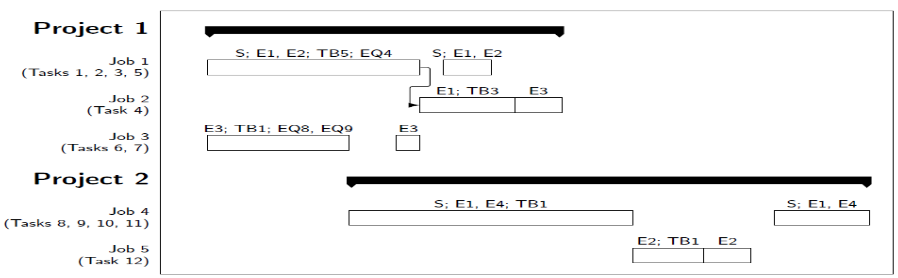
Possible soft constraints:

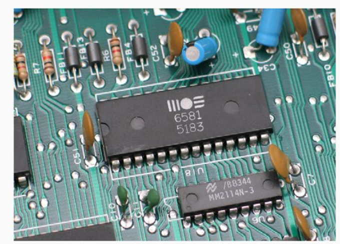
- Optimization of free weekends (weekends off)
- …

Production Planning and Scheduling/Project Scheduling

- In these applications it is important to
  - Reduce resource consumption, including energy
  - Increase production efficiency

  …



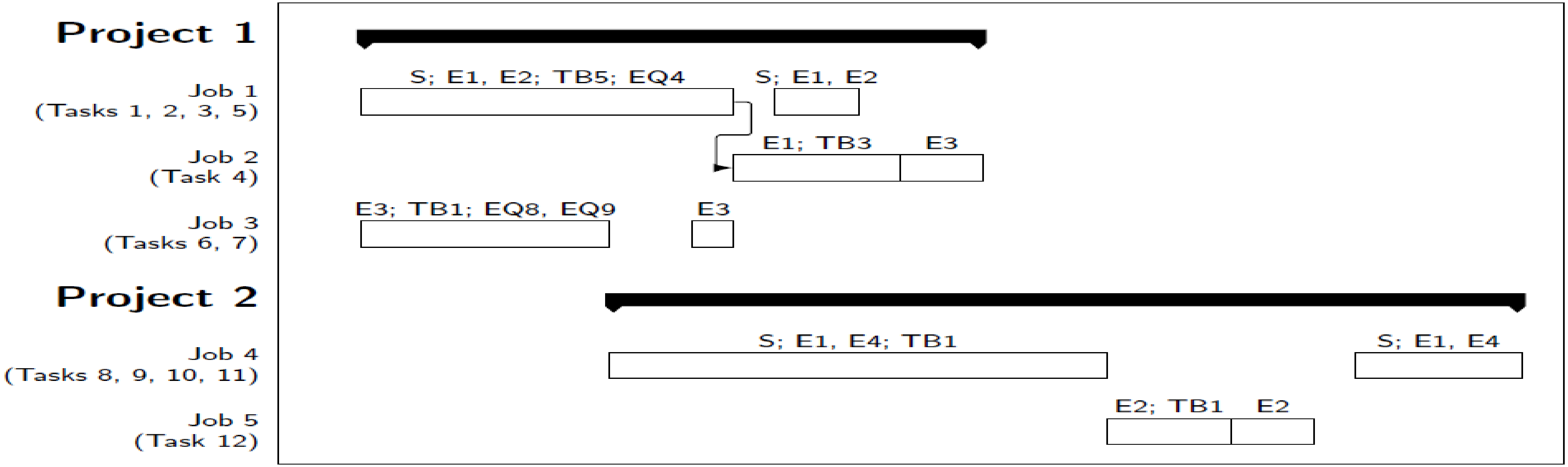


https://commons.wikimedia.org/wiki/File:MOS6581_chtaube061229.jpg, Christian Taube

https://commons.wikimedia.org/wiki/File:Reflow_oven.jpg, Nelatan

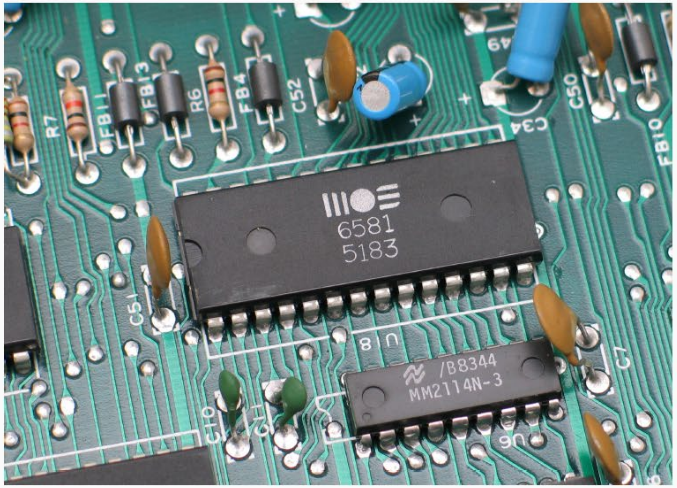
	R1	*R2*	*R3*	...
1	A	A	C	...
2	A	A	C	...
3	A	C	C	...
4	B	B	B	...
5	B	B	B	...

Test Laboratory Scheduling



Selected papers: [1,5]

Industrial Oven Scheduling



https://commons.wikimedia.org/wiki/File:MOS6581_chtaube061229.jpg, Christian Taube
CC BY-SA 2.5

https://commons.wikimedia.org/wiki/File:Reflow_oven.jpg, Nelatan
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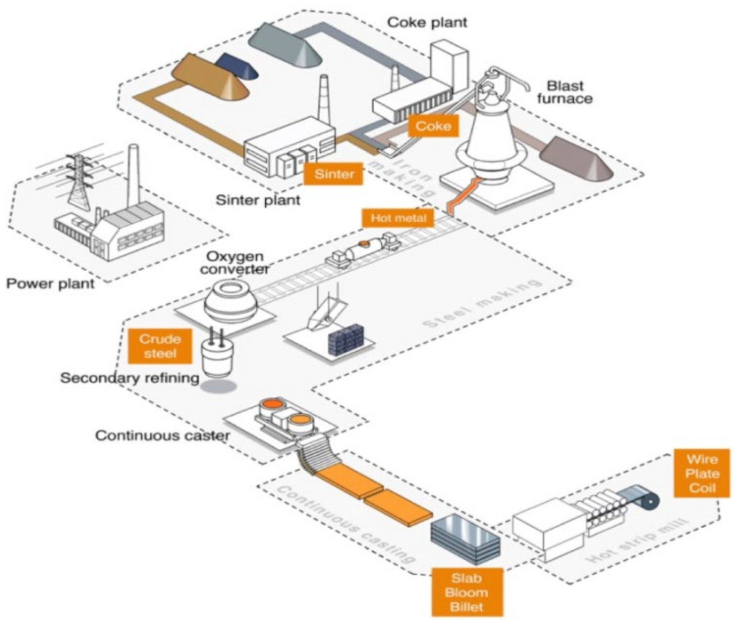
Task: Jobs need to be scheduled and batched efficiently for processing in ovens

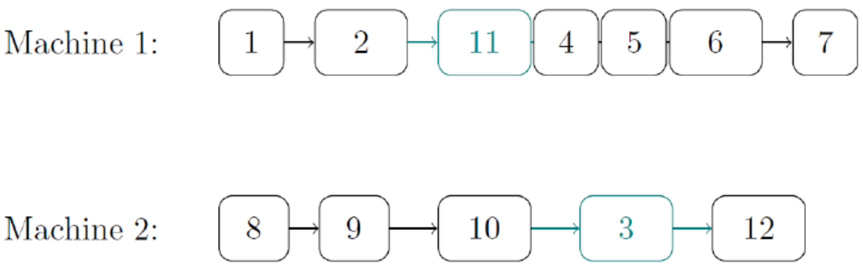
Challenge: Many constraints and solution objectives need to be considered

Selected papers: [8]

Other real-world problems…



Torpedo Scheduling, ACP Challenge, 2016



Parallel Machine Scheduling

	R1	*R2*	*R3*	...
1	A	A	C	...
2	A	A	C	...
3	A	C	C	...
4	B	B	B	...
5	B	B	B	...

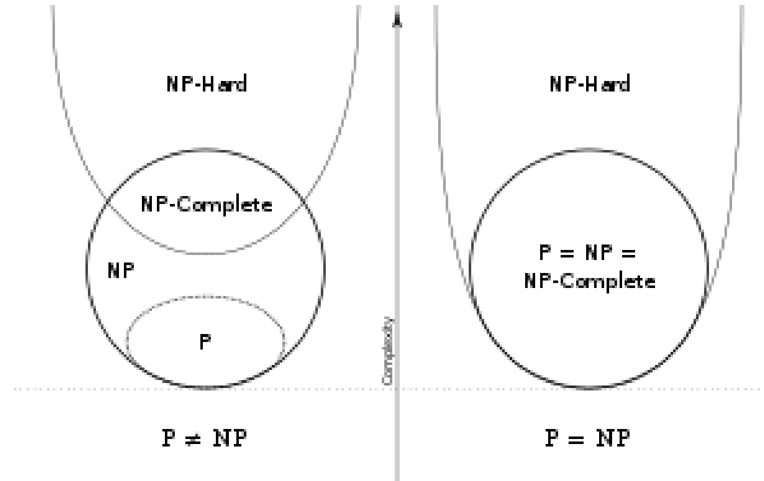
Paint Shop Scheduling

…

Selected papers: [6, 7, 9,10]

The General Obstacle

- NP-hard (intractable) problems
- No efficient algorithms could be found yet
- P problems can be solved efficiently (in polynomial time)
- P ≠ NP ? **(Millennium Prize Problem)**



https://en.wikipedia.org/wiki/NP-hardness

Tremendous size of the search space of possible solutions

Example: 12 employees, 1 week, 4 shifts

4^{84}

	Mo	Di	Mi	Do	Fr	Sa	So
A	F	F	F	S	S		
B		N	N	N	N		
C		F	F	N	N	N	N
D			S	S	S	N	N
E	N			F	F	S	S
F	S			F	F	F	F
G	S	S				F	F
H	F	S	S			S	S
I	N	N	N				

Food Waste Reduction

- APPETITE project aims to reduce food waste in retail environment
- Motivated by current waste of food
- Utilize integration of
  - Artificial Intelligence (AI) based prognosis algorithms
  - Logistical optimizations
- Collaboration of
  - TU Wien, Fraunhofer, WU Wien, IT-PS, Invenium, Kastner, Metro, Spar

Goals

- Reduce food waste through
  - Utilization of advanced forecasting methods (using AI)
  - Integration of forecasts into ordering process

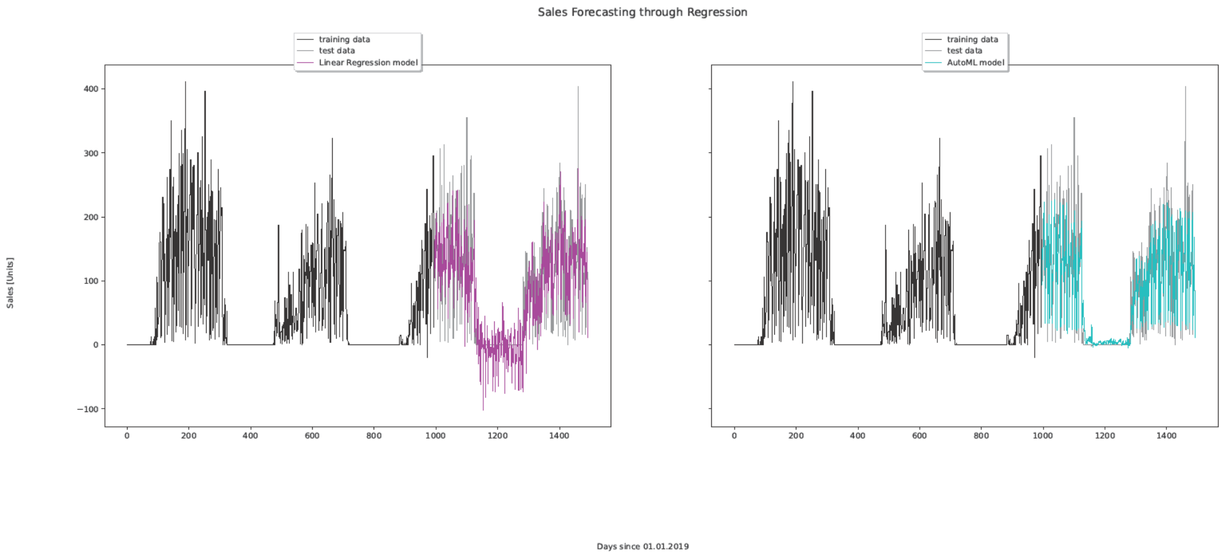
- Advanced forecasting using **Supervised Learning**
- Use provided sales and demand data for forecasting
  - Utilize weather and movement data to improve forecasts
- Empirically evaluate forecasting
  - Depending on algorithms chosen
  - Depending on input dataset(s) provided

Input Data

- Internal data
  - Product data (and "related" products)
  - Product acquisition data
  - Sales data and promotions
- External data
  - Weather data
  - Movement data (from cellular network)
- Contextual data
  - Day of the week, holidays, …

Current Status of APPETITE Project

- Area analysis for the locations has been finished
- Weather and movement data are being gathered
- Data preprocessing and dataset creation is being finalized
- Large-scale evaluation of performance across different datasets



- Current work: Platform implementation

AI and Optimization Techniques

Research work in the CD-Lab Artis

Existing problems

New challenging problems provided by the industry

- Formal mathematical formulations
- Identification of related problems in the literature
- Complexity analysis
- General variants of problems
- New problem instances provided to the literature

- Modelling techniques
- AI/Optimization solving techniques
- Meta/Hyper-heuristics
- Hybrid algorithms
- Algorithm selection and instance space analysis

AI and optimization methods

Complete approaches

Mathematical programming
Constraint programming
Answer set programming
SAT/SMT
…

Heuristic techniques

Tabu Search
Simulated Annealing
Evolutionary Strategies
Memetic Algorithms
…

Hybrid methods
Large Neighborhood Search
Hyper-heuristics
Machine learning based approaches
…

Modeling approaches

- Mathematical Programming
  - Solvers: Gurobi, CPLEX, SCIP, …
- Constraint Programming
  - Solvers: OR-Tools, Chuffed, CP Optimizer…
  - The MiniZinc challenge: https://www.minizinc.org/challenge.html
- Answer Set Programming
  - Solvers: Potassco (the Potsdam Answer Set Solving Collection), DLV, …
- SAT
  - Solvers: http://www.satcompetition.org/
- …

Rotating workforce scheduling: A constraint model

$$\sum\nolimits_{k\in 0}^{u_w}(T_{t(j+k)} = O) > 0, \quad j \in TT \tag{1}$$

$$\sum\nolimits_{k\in 1}^{l_w}(T_{t(j+k)} = O) = 0, \quad j \in TT, T_j = O \wedge T_{t(j+1)} \neq O \tag{2}$$

$$\sum\nolimits_{k\in 0}^{u_O}(T_{t(j+k)} \neq O) > 0, \quad j \in TT \tag{3}$$

$$\sum\nolimits_{k\in 1}^{l_O}(T_{t(j+k)} \neq O) = 0, \quad j \in TT, T_j \neq O \wedge T_{t(j+1)} = O \tag{4}$$

$$\sum\nolimits_{k\in 0}^{u_{sh}}(T_{t(j+k)} \neq sh) > 0, \quad j \in TT, sh \in \mathbf{A} \tag{5}$$

$$\sum\nolimits_{k\in 1}^{l_{sh}}(T_{t(j+k)} \neq sh) = 0, \quad j \in TT, sh \in \mathbf{A}, T_j \neq sh \wedge T_{t(j+1)} = sh \tag{6}$$

$$T_j = sh_1 \rightarrow T_{t(j+1)} \neq sh_2, \quad j \in TT, (sh_1, sh_2) \in F_2 \tag{7}$$

$$T_j = sh_1 \wedge T_{t(j+1)} = O \rightarrow T_{t(j+2)} \neq sh_2, \quad j \in TT, (sh_1, sh_2) \in F_3 \tag{8}$$

$$\sum\nolimits_{i\in 1..n}(S_{i,j} = sh) = R_{sh,j}, \quad j \in 1..w, sh \in \mathbf{A} \tag{9}$$

$$\sum\nolimits_{i\in 1..n}(S_{i,j} = O) = o_j, \quad j \in 1..w \tag{10}$$

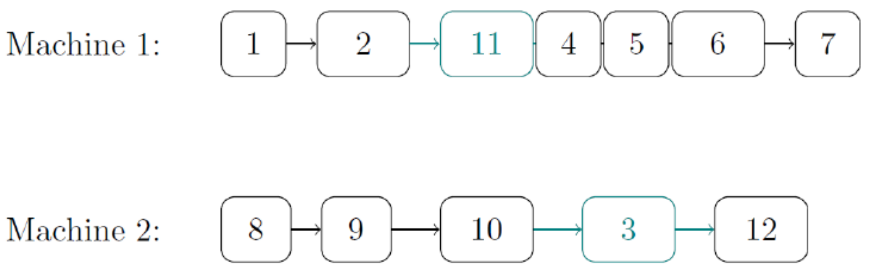
Selected papers: [11, 13]

Alternative model: global constraints for (9) and (10)

$$gcc\_low\_up([S_{i,j}|i \in 1..n], \mathbf{A}, [R_{sh,j}|sh \in \mathbf{A}], [R_{sh,j}|sh \in \mathbf{A}]) \tag{11}$$

$$gcc\_low\_up([S_{i,j}|i \in 1..n], \mathbf{A}^+, [R_{sh,j}|sh \in \mathbf{A}^+], [R_{sh,j}|sh \in \mathbf{A}^+]) \tag{12}$$

Example MIP: Parallel Machine Scheduling



Selected papers: [10]

minimise $Lex(\Sigma_{j \in J}(T_j), C_{max})$, subject to

$$\Sigma_{m \in M}(Y_{j,m}) = 1, \forall j \in J$$

$$\Sigma_{i \in J_0, i \neq j}(X_{i,j,m}) = Y_{j,m}, \forall j \in J, m \in M$$

$$\Sigma_{j \in J_0, i \neq j}(X_{i,j,m}) = Y_{i,m}, \forall i \in J, m \in M$$

$$C_j \geq C_i + s_{i,j,m} + p_{j,m} + V \cdot (X_{i,j,m} - 1), \\ \forall i \in J_0, j \in J, m \in M$$

$$\Sigma_{j \in J}(X_{0,j,m}) \leq 1, \forall m \in M$$

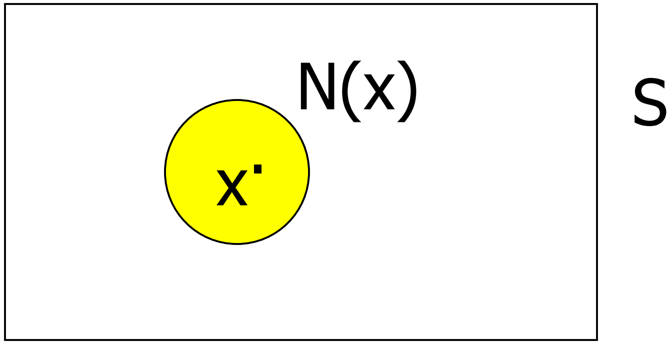
$$\Sigma_{i \in J_0, j \in J, i \neq j}(s_{i,j,m} \cdot X_{i,j,m}) + \\ \Sigma_{i \in J}(p_{i,m} \cdot Y_{i,m} + s_{i,0,m} \cdot X_{i,0,m}) \leq C_{max}, \\ \forall m \in M$$

$$T_j \geq C_j - d_j, \forall j \in J$$

$$T_j \geq 0, \forall j \in J$$

Local Search Techniques

- Are based on the neighbourhood of the current solution



- The solution is changed iteratively with so called neighbourhood relations (moves) until an acceptable or optimal solution is reached

Local Search Techniques

1. Construct the initial solution s
2. Generate neighbourhood N(s) of solution s
3. Select from the neighbourhood the descendant of the current solution
4. Go to step 2

Advanced metaheuristic techniques

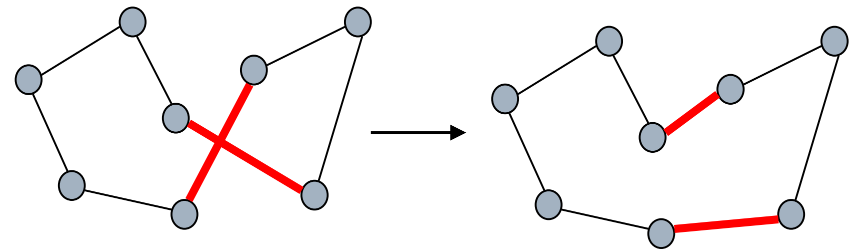
- Simulated Annealing
- Tabu Search
- Large Neighborhood Search
- …

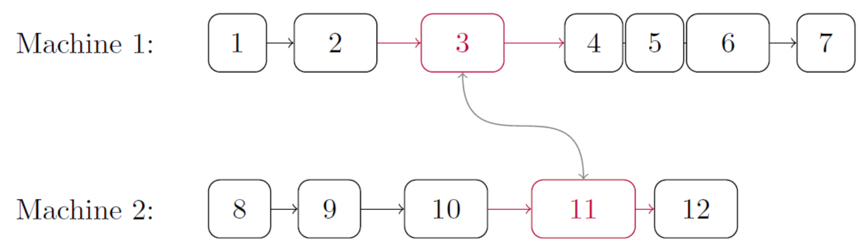
Metaheuristics include a mechanism to escape local optima

Neighborhoods

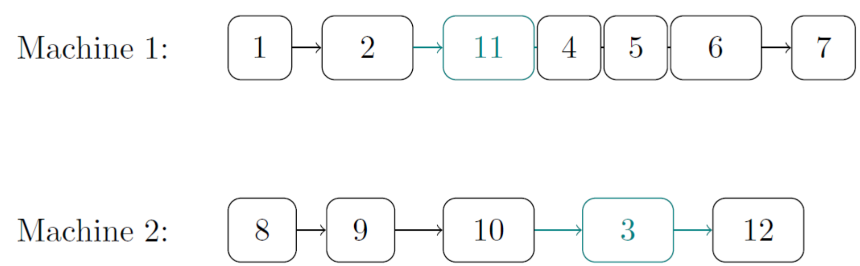
	Mon	Tue	Wed	Thu	Fri	Sat	Sun
A		D	D	A	D	D	
B		D	A	N	D	N	D
C	D		N	D	D	A	N
D	N				A		A
E	D	N	D			A	D
F	N	A	A	D	A		
G	D	D	A	A	N	N	
H				A	A	D	N
I	A	N					A
J	A	N	N	N			
K	N	A	N	D	N		
L	A	A	D	N	N		

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
A		D	D	A	D	D	
B		D	A	N	D	N	D
C	D		N	D	D	A	N
D	N				A		A
E	D	N	D			A	D
F	N	A	A	D	A		
G	D	D	A	A	N	N	
H				A	A	D	N
I	A	N					A
J	A	N	N	N			
K	N	A	N	D	N		
L	A	A	D	N	N		





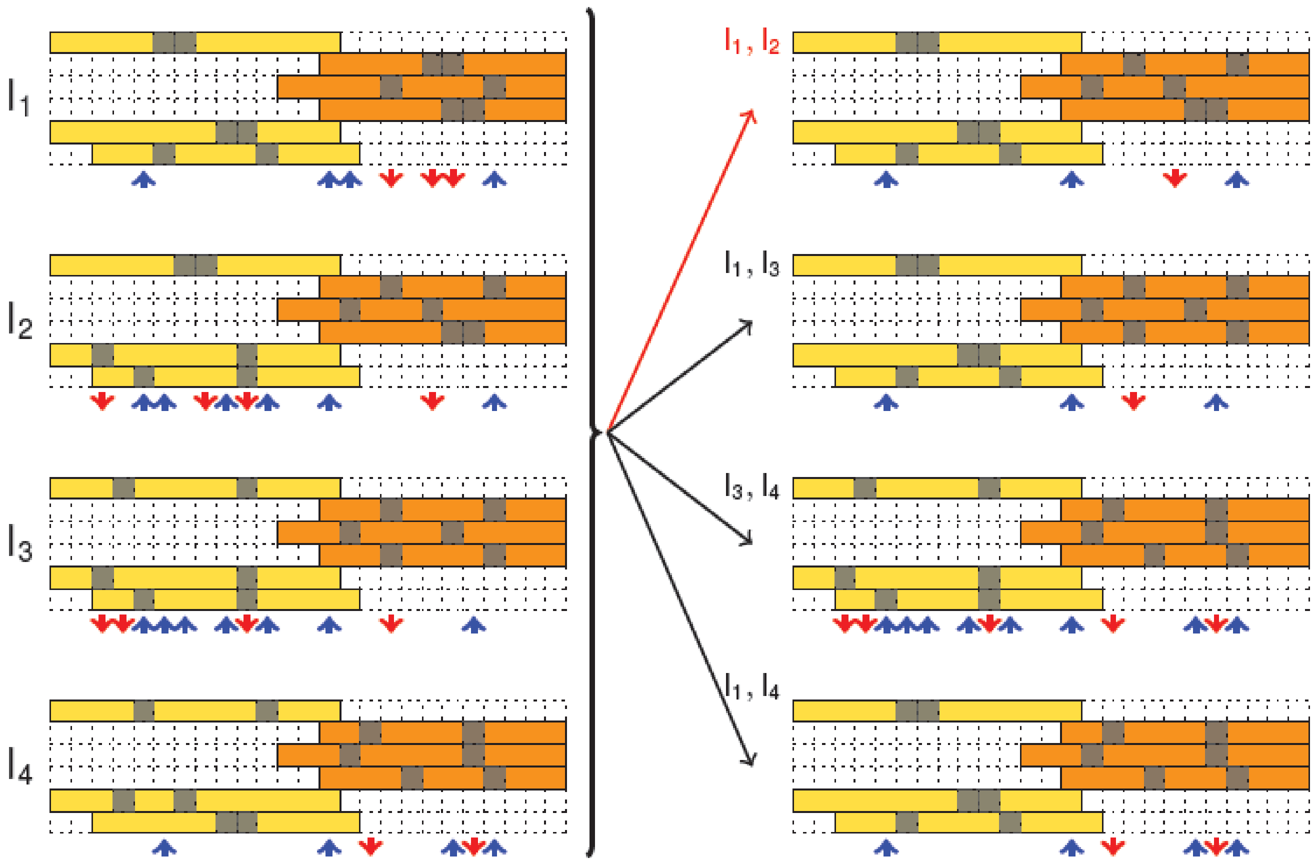
(a) Before Move Application



(b) After Move Application

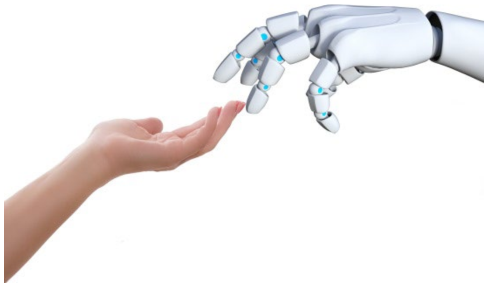
Selected papers: [10,14,3]

Memetic Algorithms: Crossover



Selected papers: [16]

Hybrid techniques



Methods of Artificial Intelligence (Machine Learning, Heuristics…)

Methods of Logic

Mathematical Optimization

…

$$S_{i,d,t} \leftrightarrow \bigwedge_{x=1}^{sl_t} U_{i,d,x} \bigwedge_{y=sl_t}^{sl_{max}} \neg U_{i,d,y}$$

$$\begin{aligned} minimize\ f = \ & 30 * \sum_{\substack{s\in S\\ k\in K\\ d\in\{1\ldots7\}}} C_{skd}^{S1} \\ & +15 * \sum_{\substack{n\in N\\ s\in S\\ d\in\{1\ldots7\}}} (C_{nsd}^{S2a} + C_{nsd}^{S2b}) \\ & +30 * \sum_{\substack{n\in N\\ d\in\{1\ldots7\}}} (C_{nd}^{S2c} + C_{nd}^{S2d}) \end{aligned}$$

Algorithm Selection

- Usually several search algorithms are available for solving a particular problem

- **No free lunch theorem**

  "…for any algorithm, any elevated performance over one class of problems is offset by performance over another class" [1]

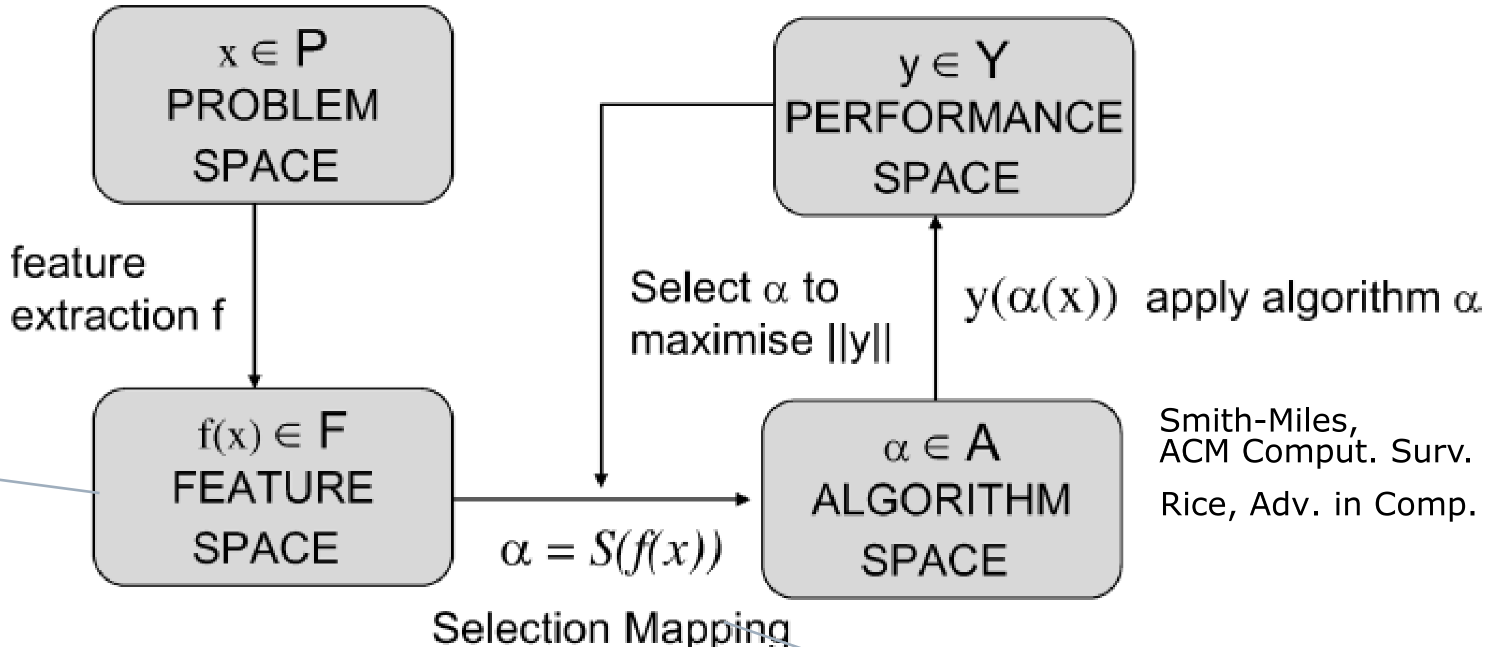
  "…any two algorithms are equivalent when their performance is averaged across all possible problems" [2]

How to select the best algorithm for a specific problem instance?

[1] David Wolpert, William G. Macready: No free lunch theorems for optimization. IEEE Transac. Evolutionary Computation 1(1): 67-82 (1997)

[2] Wolpert, D.H., and Macready, W.G. (2005) "Coevolutionary free lunches," IEEE Transac. on Evolutionary Computation, 9(6): 721-735

Algorithm Selection



Crucial

Smith-Miles,
ACM Comput. Surv. (2008)

Rice, Adv. in Comp. (1976)

Machine Learning

Many success stories

Planning and Scheduling, Routing, Combinatorial Auctions, SAT, TSP, Graph Coloring, Tree Decomposition, Timetabling, …

Selected papers: [15,17,18]

Algorithm selection

Input (see [8] and [9]):

- Problem space P that represents the set of instances of a problem class
- A feature space F that contains measurable characteristics of the instances generated by a computational feature extraction process applied to P
- Set A of all considered algorithms for tackling the problem
- The performance space Y represents the mapping of each algorithm to a set of performance metrics

Problem:

For a given problem instance *x E P, with features f(x) E F, find the selection mapping S(f(x)) into algorithm space , such that the selected algorithm a E A maximizes the performance mapping y(a(x)) E Y*

[8] John R. Rice: The Algorithm Selection Problem. Advances in Computers 15: 65-118 (1976)
[9] Kate Smith-Miles: Cross-disciplinary perspectives on meta-learning for algorithm selection. ACM Comput. Surv. 41(1): (2008)

Supervised machine learning: Classification

NrClauses	NrVariables	...	Best Algorithm
100	80		Alg1
4000	400		Alg1
30000	8500		Alg3
300	78		Alg2
2000	540		Alg3
10000	**450**		**?**
…			

Example: SAT problem

$$F(x)=(x_{17}\vee\overline{x}_{37}\vee x_{73})\wedge(\overline{x}_{11}\vee\overline{x_{12}})\wedge\ldots\wedge(\overline{x}_{2}\vee x_{43}\vee x_{22})$$

Supervised machine learning: Regression

NrClauses	**NrVariables**	**…**	**Alg1: Time (sec)**
100	80		10
4000	400		450
30000	8500		2350
300	78		25
2000	540		170
10000	**450**		**?**
…			

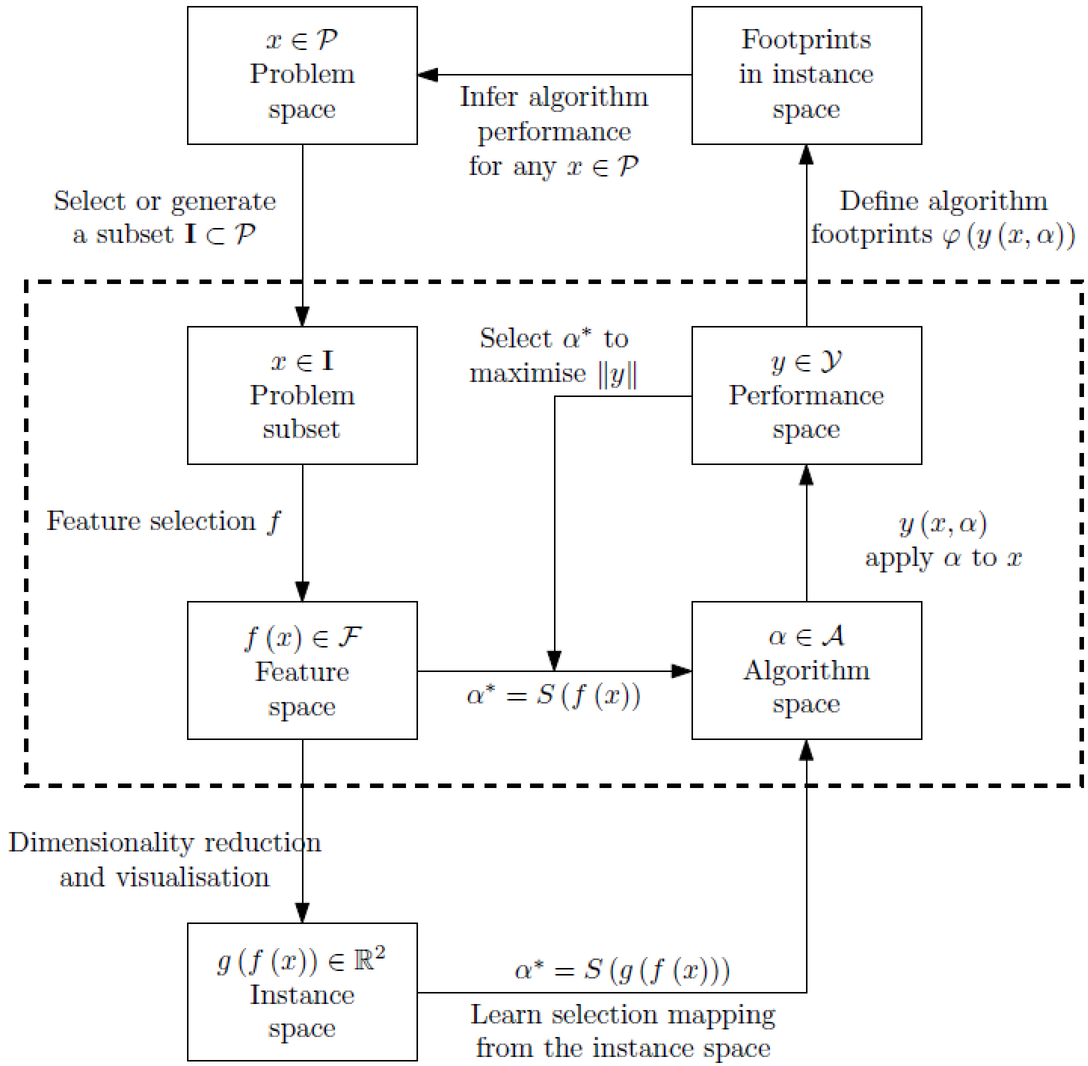
Supervised machine learning techniques

- Decision/Regression Trees
- Random Forest
- Bayesian Networks
- Neural Networks
- …

Automated Machine Learning:

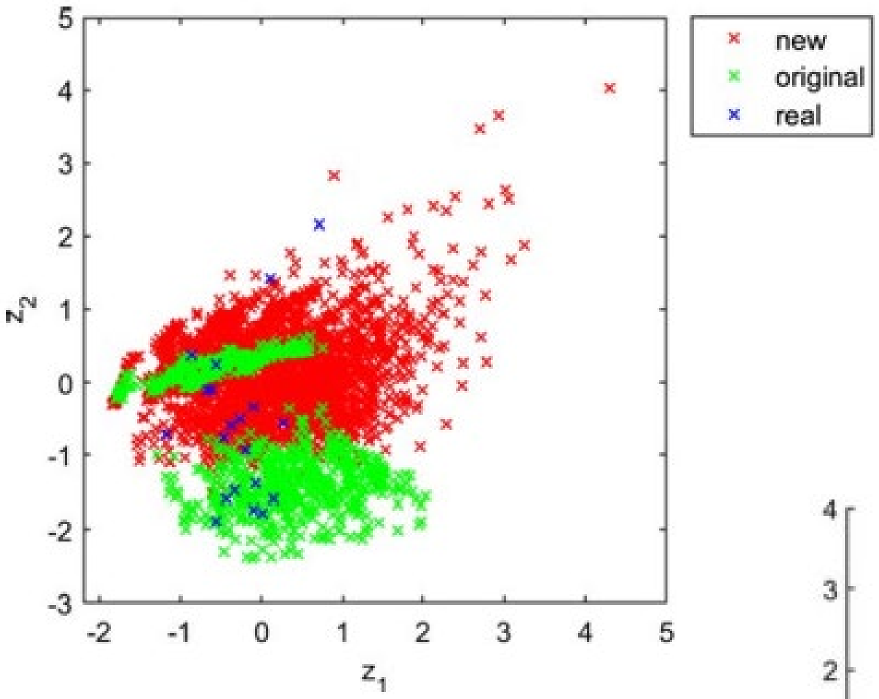
- Process of automating of machine learning when applied to a data set
- Automated optimization of hyperparameters
- Automated algorithm selection
- Automated feature selection, preprocessing…

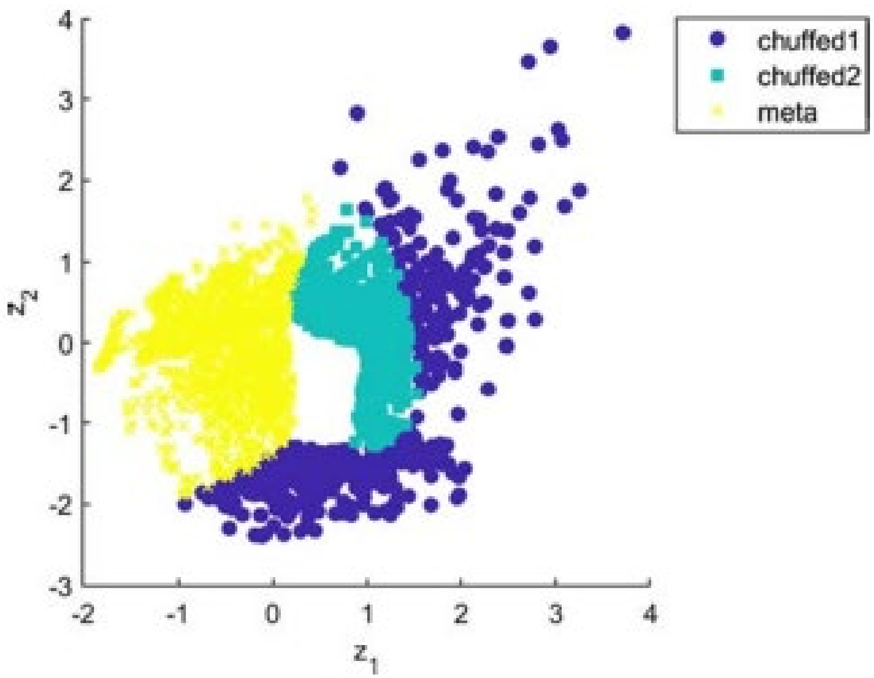
Instance Space Analysis and Algorithm Selection



K. Smith-Miles, D. Baatar, B. Wreford, and R. Lewis. Towards objective measures of algorithm performance across instance space. Comput. Oper. Res., 45:12–24, 2014.

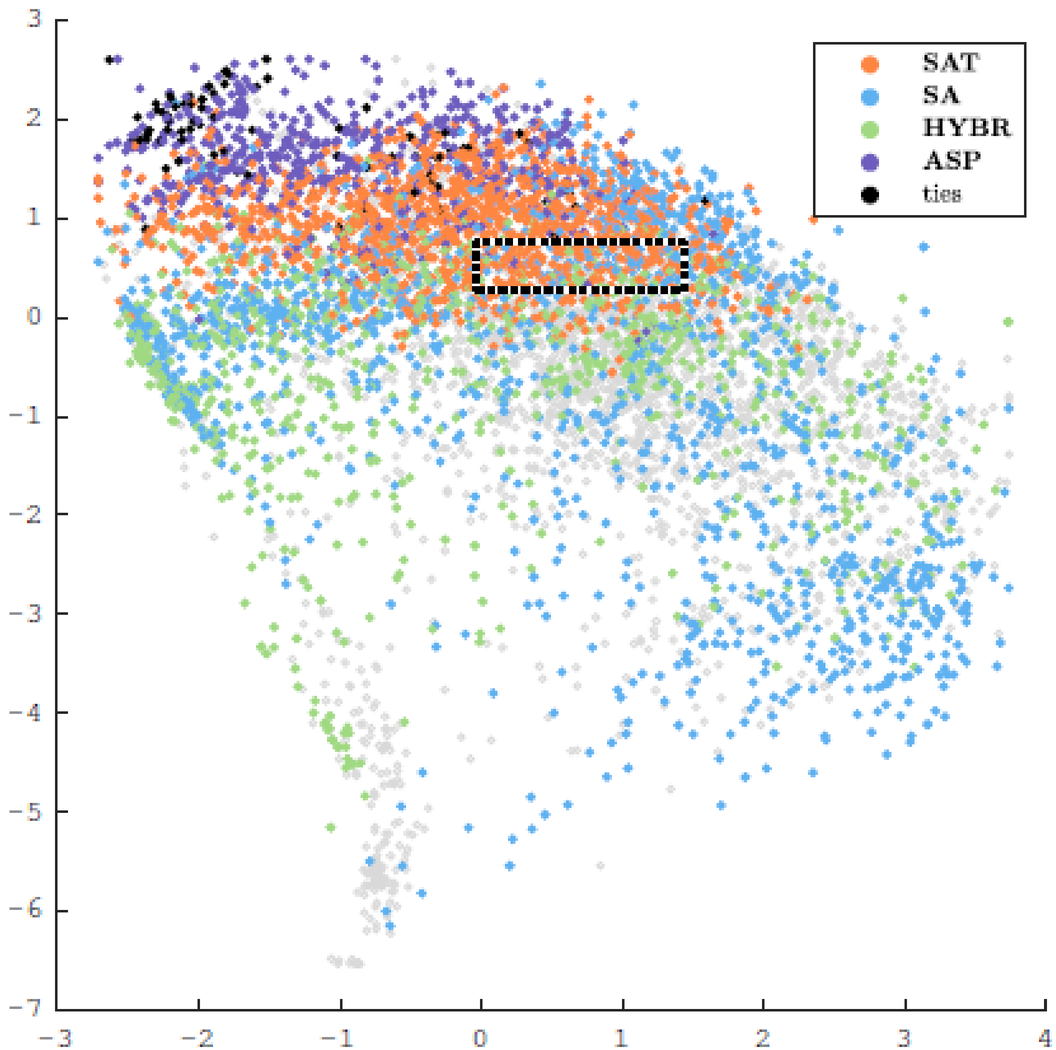
Rotating Workforce Scheduling





Selected papers: [19]

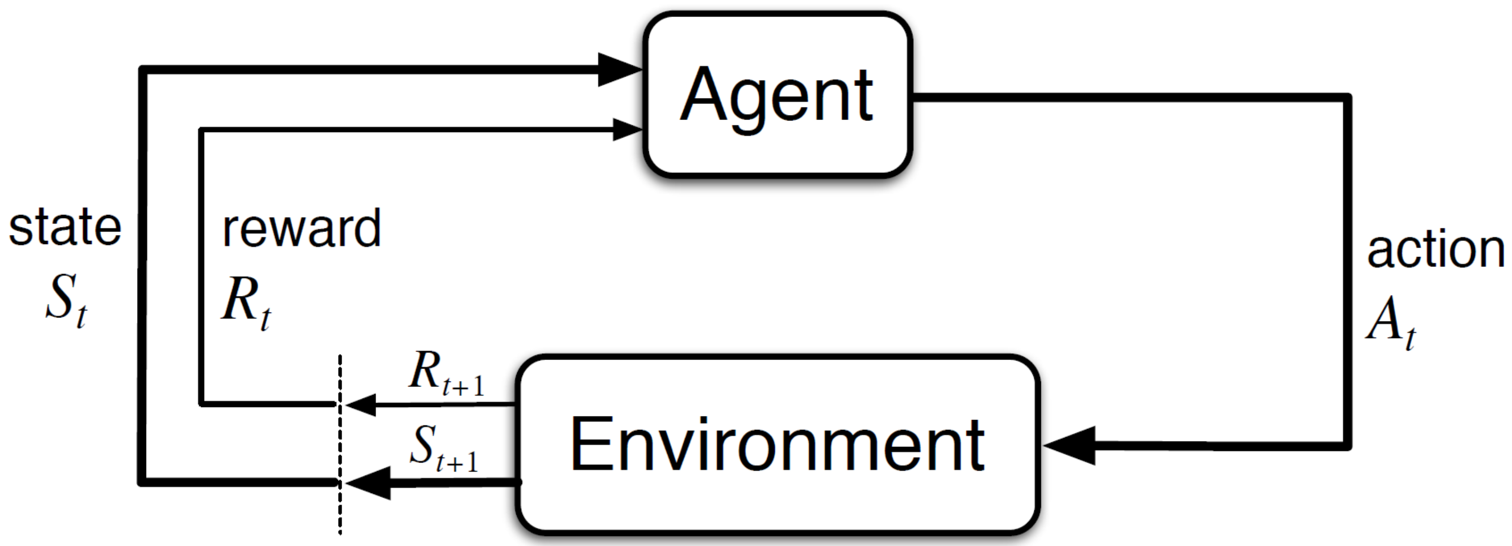
Course timetabling



(b) Best performance (with time)

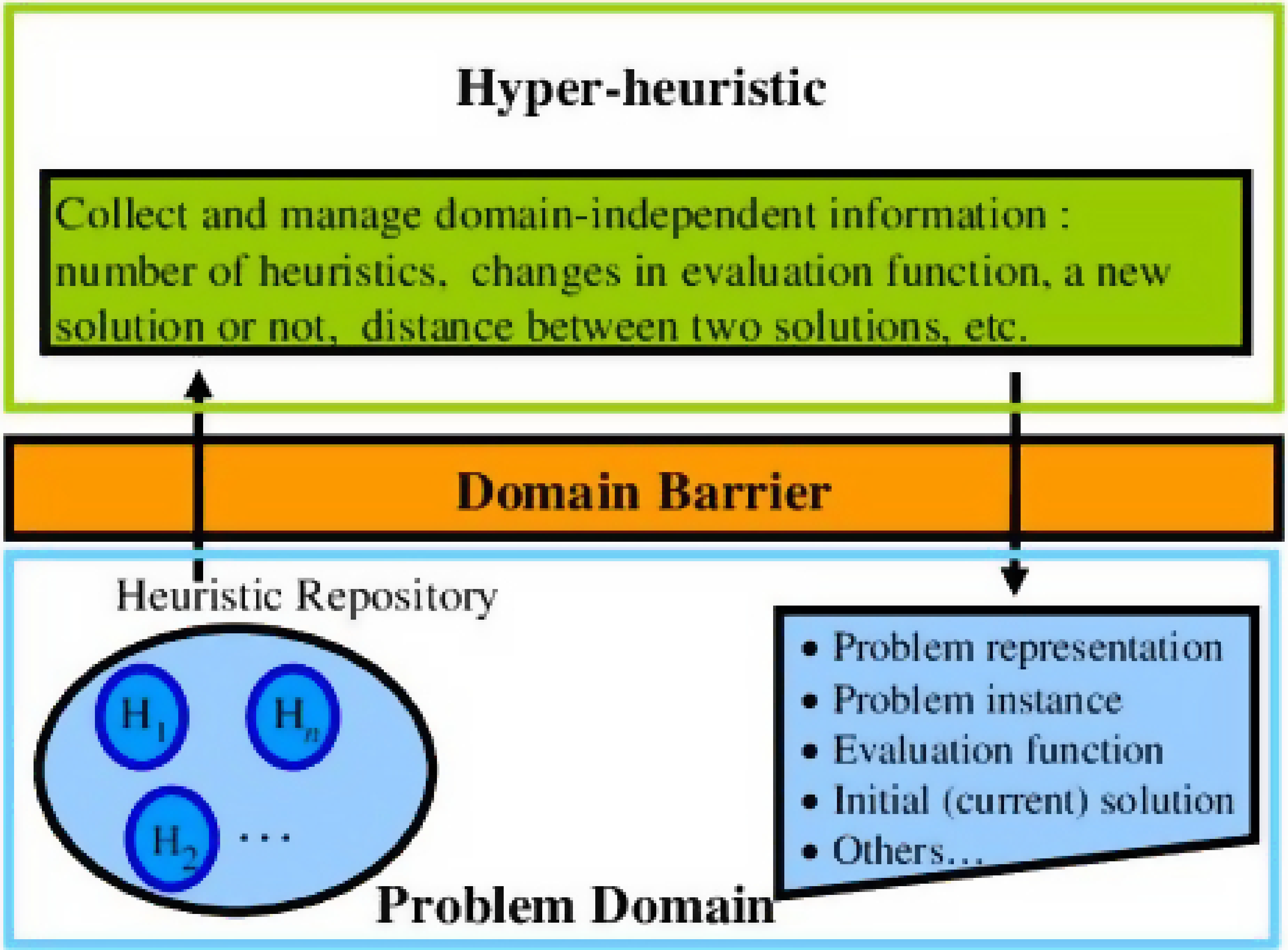
Selected papers: [18]

Reinforcement learning



Sutton and Barto. Reinforcement Learning, 2018

Hyper-heuristics

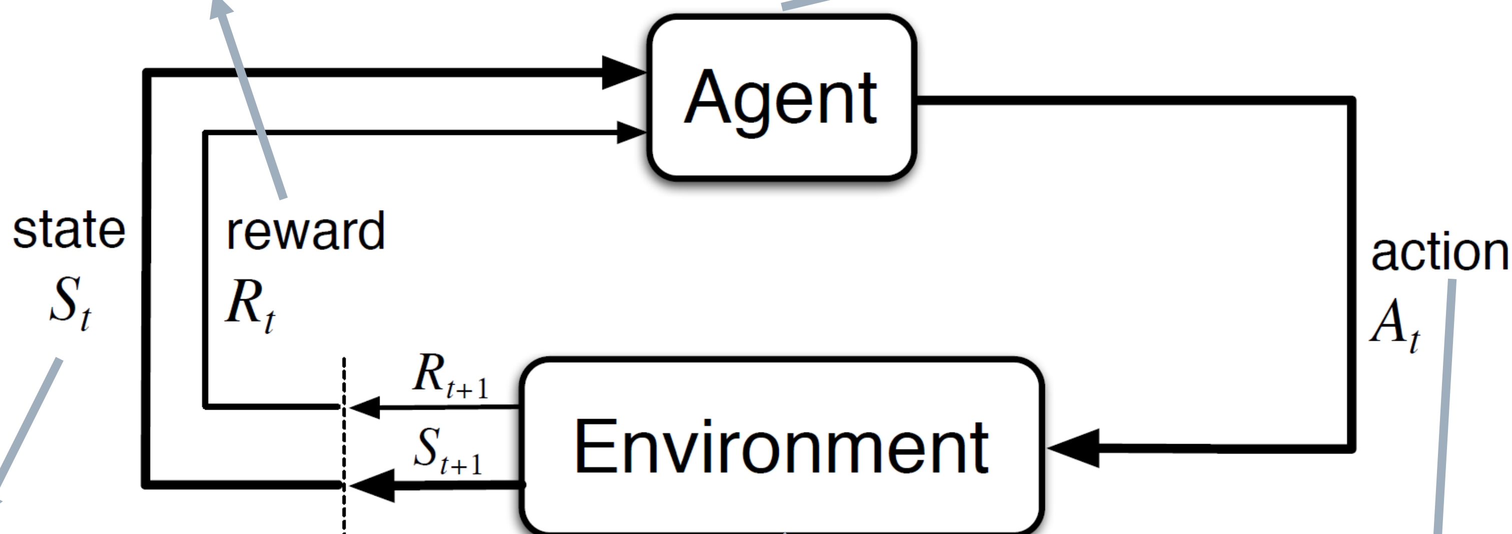


Burke, Edmund et al. The Cross-Domain Heuristic Search Challenge - An International Research Competition. 2011.

Reinforcement learning for Hyper-heuristics

Based on objective value difference and time

Hyper-heuristic



Last heuristic applied

Last heuristic type

Last change magnitude

Steps since last improvement

Chain progress …

Low-level heuristics

Problem domain

Selected papers: [20,21,22]

Conclusions

- Many problems within sustainable applications are still solved manually
- AI and optimization offer tremendous potential for further improving solutions in these domains
- Combination of AI and optimization techniques is crucial

Success stories:

- Test lab scheduling
- Workforce scheduling
- Machine scheduling
- Oven scheduling
- Educational timetabling
- …

Conclusions

- Many problems within sustainable applications are still solved manually
- AI and optimization offer tremendous potential for further improving solutions in these domains
- Combination of AI and optimization techniques is crucial

Challenges

- Domain specific solutions
- New challenging/large-scale problems
- The availability of data is critical for machine learning
  - Usually, most of the time is invested in the collection and preparation of the data
- …

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