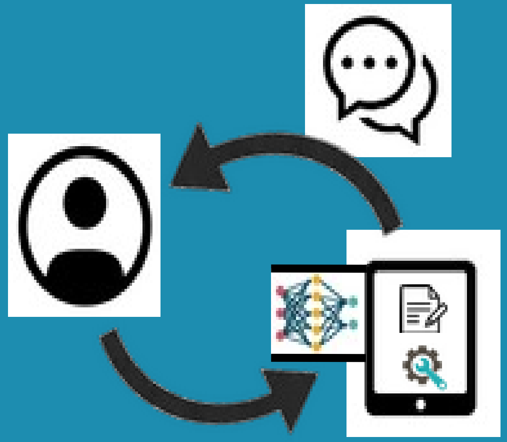
KU LEUVEN

Human-Aware Technology for Combinatorial Optimisation



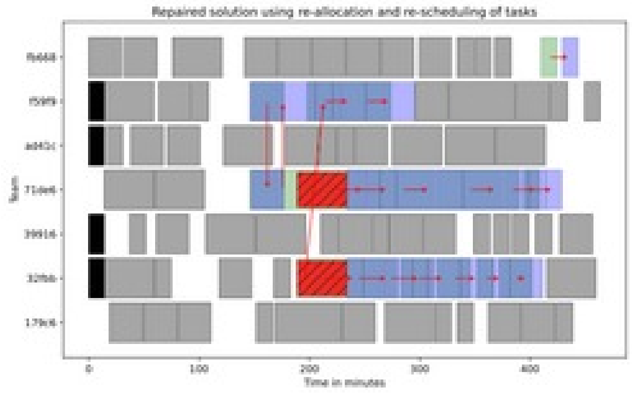
Prof. Tias Guns & Team
Leuven.AI
https://people.cs.kuleuven.be/~tias.guns/

European Research Council
Established by the European Commission

Combinatorial Optimisation

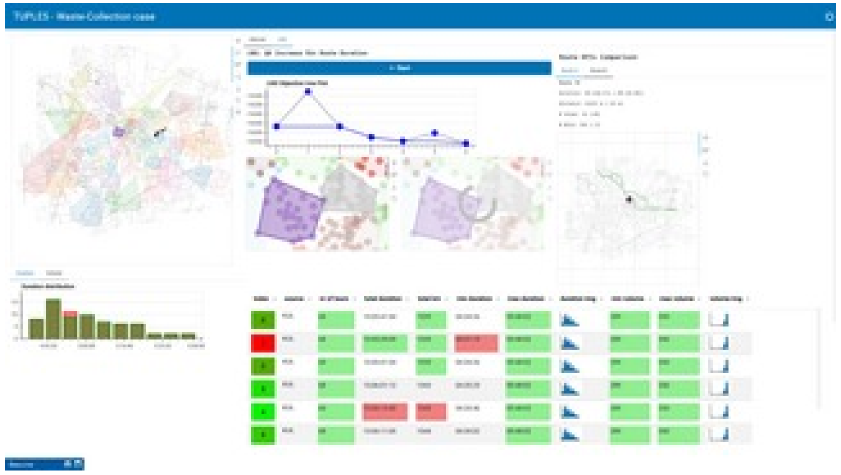
"Solving discrete, *constrained* optimisation problems"

Workforce allocation

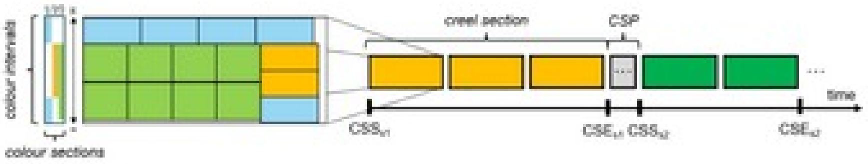


Assembly scheduling and topo. optimisation

Waste collection routing



Industrial weave production planning



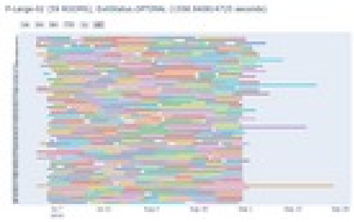
https://cpmpy.cs.kuleuven.be

Central role in AI and OR

- SAT & SMT
- Constraint Programming
- Mixed Integer & Mathematical Programming

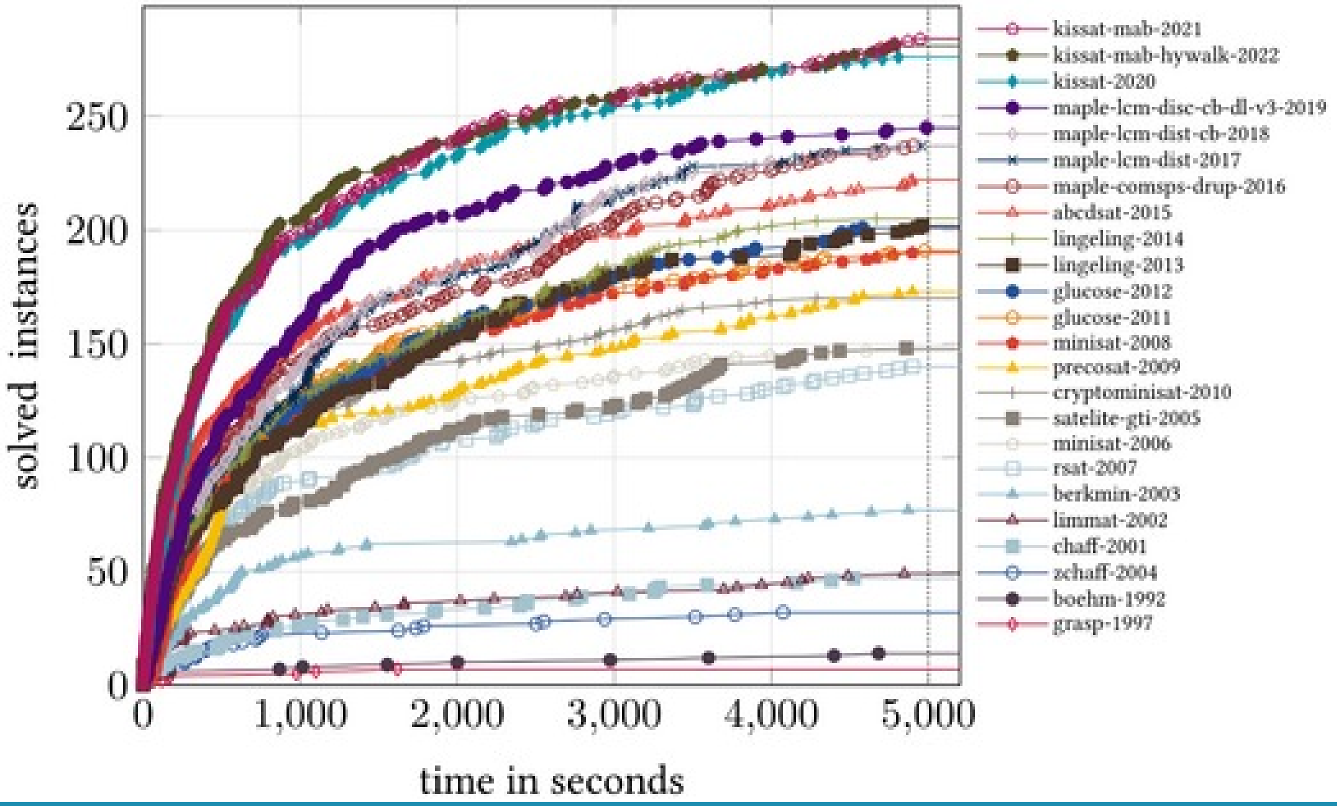
Model + Solve

Decision variables
Objective function
Constraints

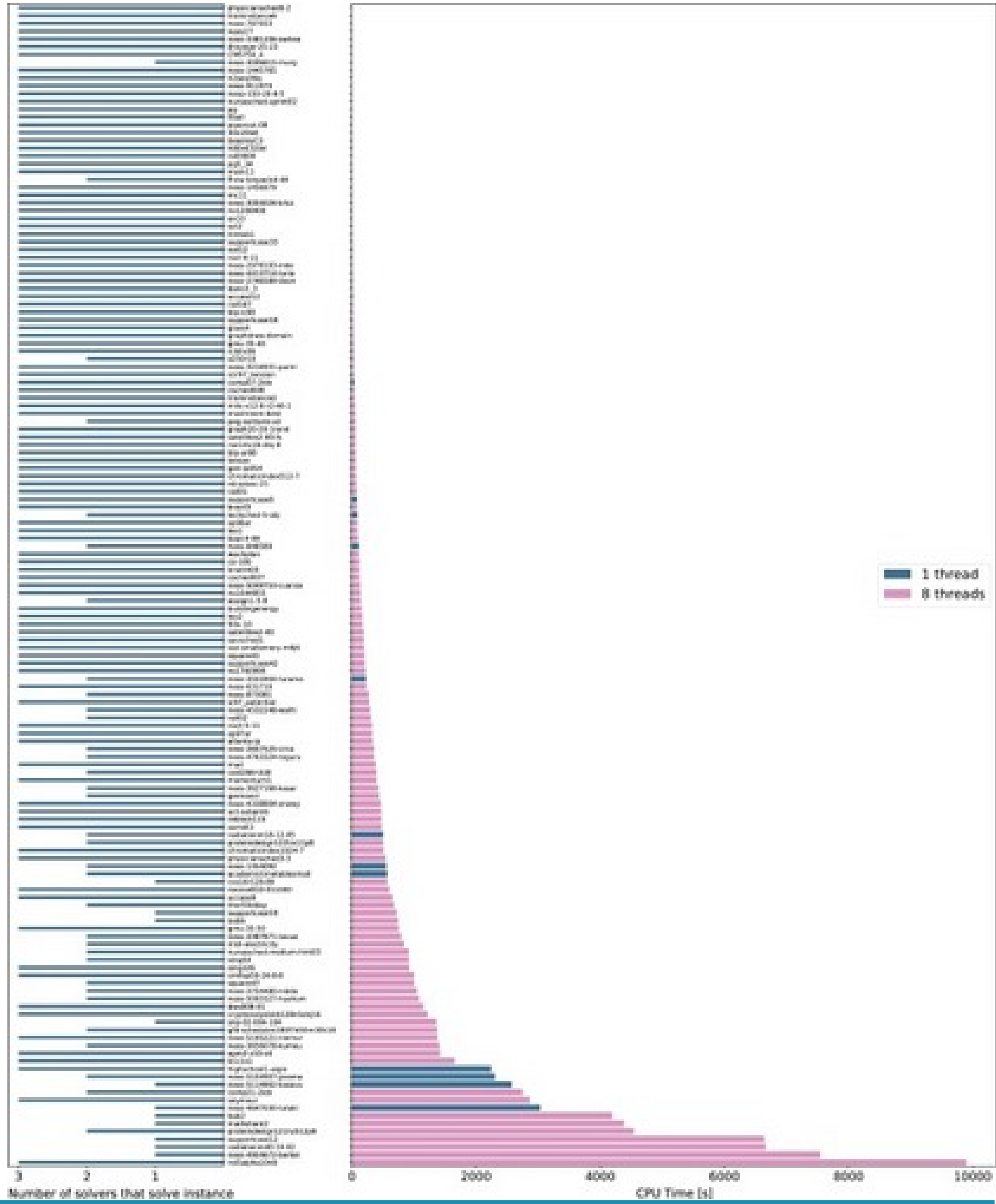


Tremendous progress in solver efficiency!

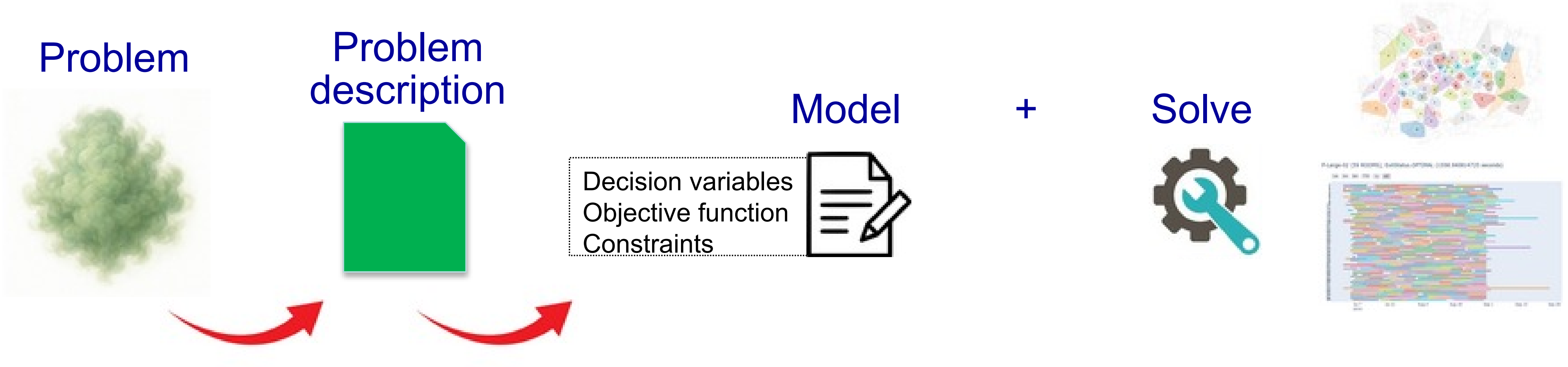
SAT



MIP



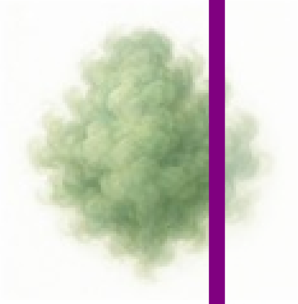
Model + Solve paradigm, in practice



- What if the model is UNSAT?
- What if a user doesn’t like the solution?
- What if the data involves uncertainty, requires learning?

Model + Solve paradigm, in practice

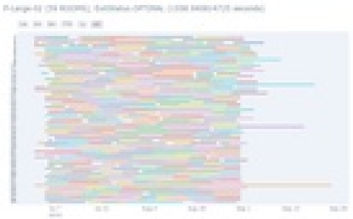
Problem



Problem description

Decision variables
Objective function
Constraints

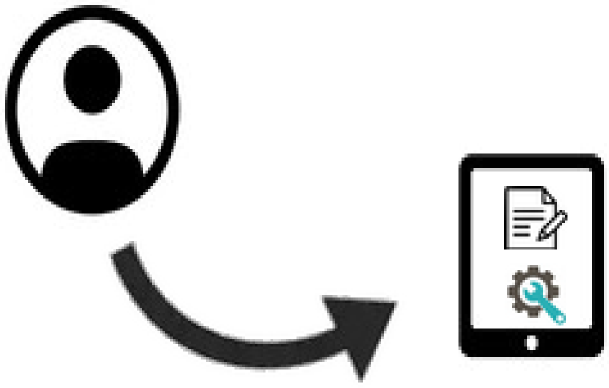
Model + Solve



An AI-first approach to optimisation

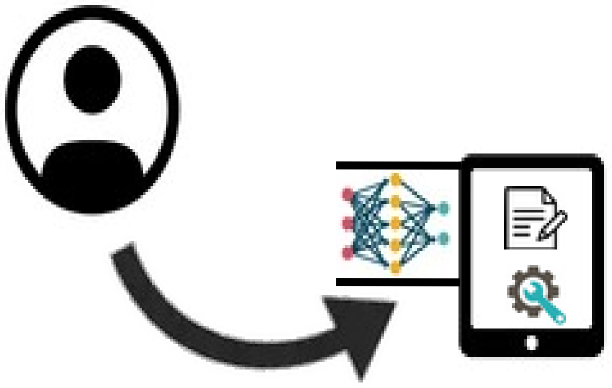
- What if the model is UNSAT?
- What if a user doesn't like the solution?
- What if the data involves uncertainty, requires learning?

An AI-first approach to combinatorial optimisation



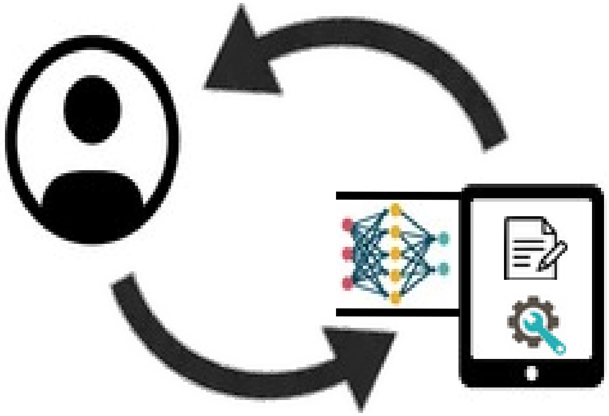
An AI-first approach to combinatorial optimisation

- Learning from images, production data, ...
- Learning user preferences



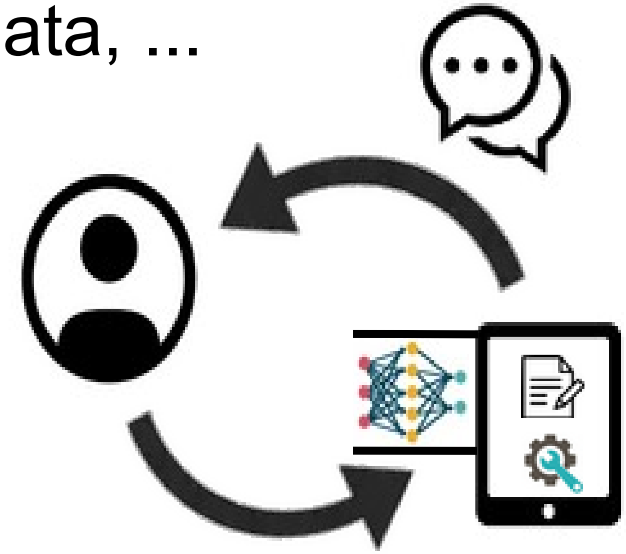
An AI-first approach to combinatorial optimisation

- Learning from images, production data, ...
- Learning user preferences
- Explaining constraint solving



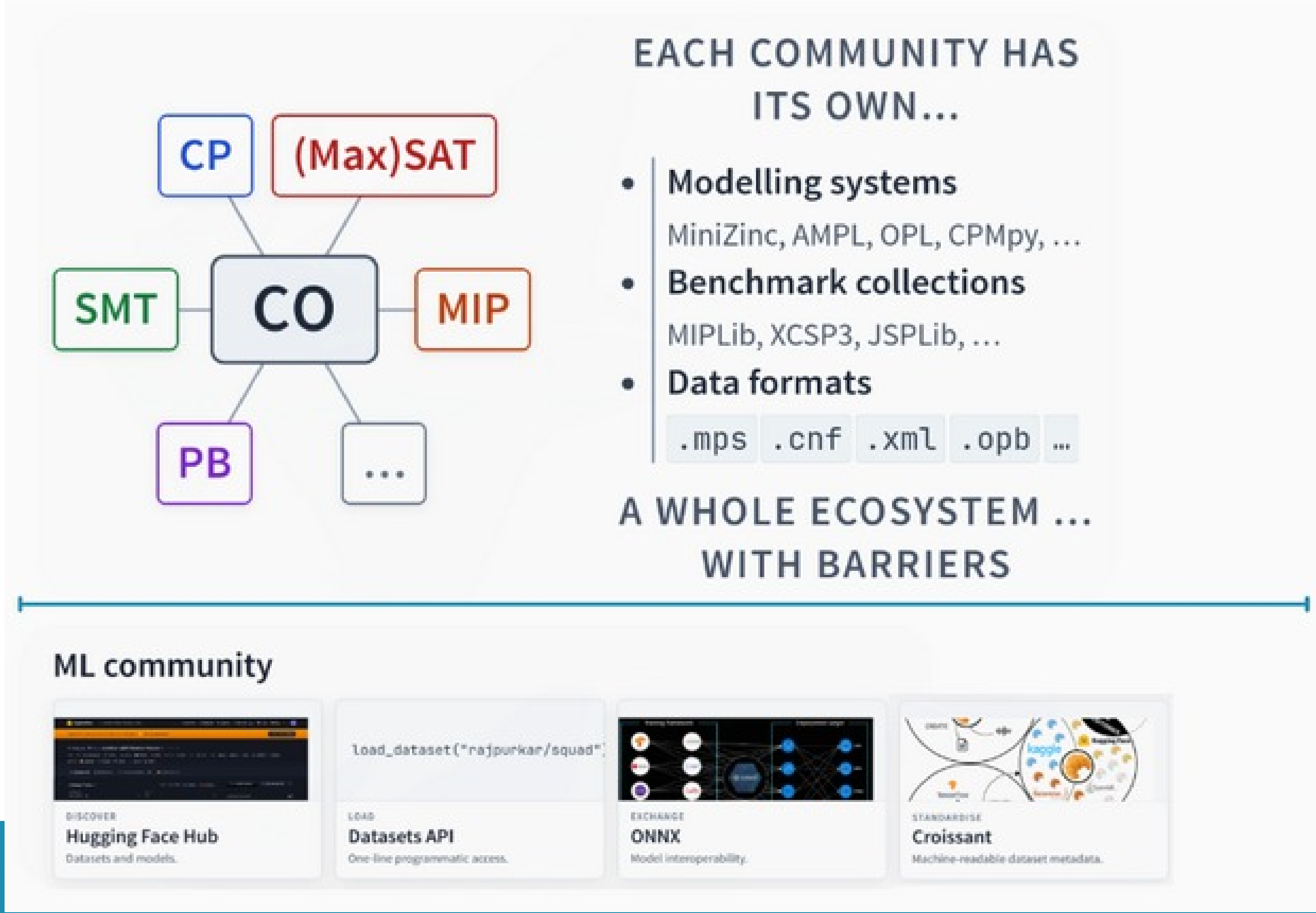
An AI-first approach to combinatorial optimisation

- Learning from images, production data, ...
- Learning user preferences
- Explaining constraint solving
- Stateful interaction



CHAT-Opt: Conversational Human-Aware Technology for Optimisation

Unified Programmatic Access to CO Benchmarks, to Connect Constraint Solving Communities



Key software platform: CPMpy

Decision variables
Objective function
Constraints

CPMpy: a **C**onstraint **P**rogramming and **M**odeling library in **Py**thon, based on numpy, with direct solver access.

Documentation: https://cpmpy.readthedocs.io/

Constraint solving at your finger tips

For combinatorial problems with Boolean and integer variables. With many high-level constraints that are automatically decomposed when not natively supported by the solver.

Lightweight, [well-documented](), used in research and industry.

🔑 Key Features

- **Solver-agnostic**: use and compare CP, ILP, SMT, PB and SAT solvers
- **ML-friendly**: decision variables are numpy arrays, with vectorized operations and constraints
- **Incremental solving**: assumption variables, adding constraints and updating objectives
- **Extensively tested**: large test-suite and [actively fuzz-tested]()
- **Tools**: for parameter-tuning, debugging and explanation generation
- **Flexible**: easy to add constraints or solvers, also direct solver access

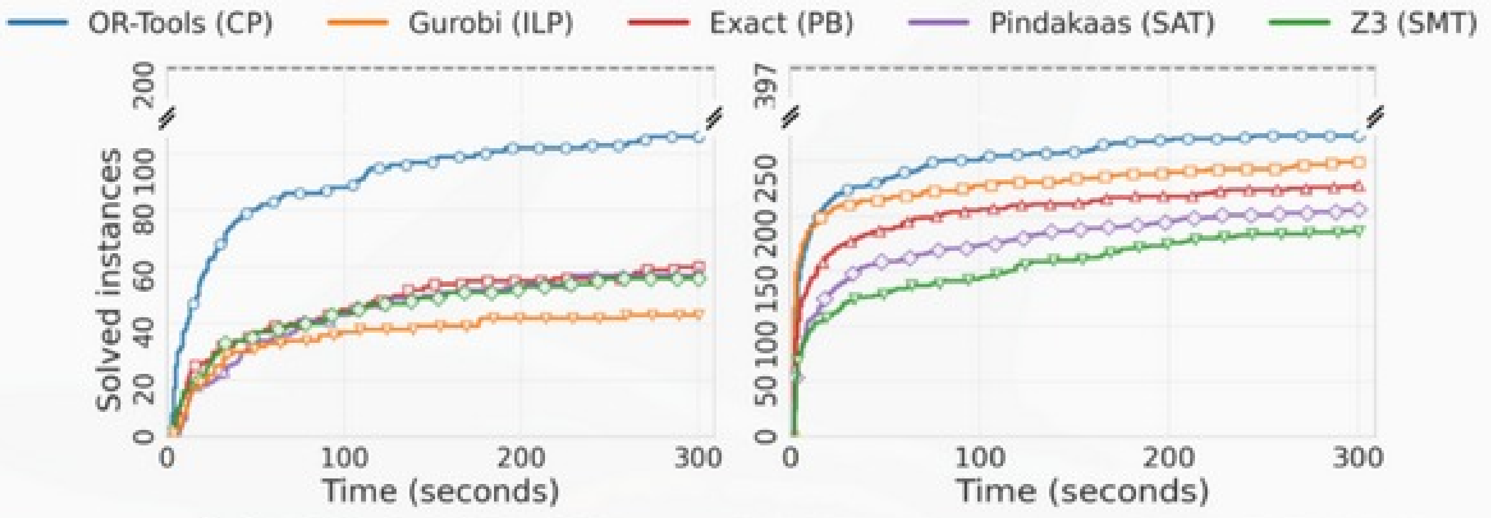
Solver	Technology	Capabilities
OR-Tools	CP (LCG)	SAT ASAT ALLSAT - OPT - PAR
Pumpkin	CP (LCG)	SAT ASAT ALLSAT - OPT - PROOF
GCS	CP	SAT ISAT ALLSAT - OPT - PROOF
Choco	CP	SAT ISAT ALLSAT - OPT
CP Optimizer	CP	SAT - OPT - PAR
MiniZinc	CP	SAT - OPT
Z3	SMT	SAT ASAT ISAT - OPT
Hexaly	Global Opt.	SAT ISAT ALLSAT - OPT IOPT
HiGHS	ILP	SAT ISAT - OPT IOPT - PAR
Gurobi	ILP	SAT ISAT - OPT IOPT - PAR
CPLEX	ILP	SAT - OPT IOPT - PAR
Exact	Pseudo-Boolean	SAT ASAT ISAT ALLSAT - OPT IOPT - PR
RC2	MaxSAT	OPT
Pindakaas	SAT	SAT ASAT ISAT
PySAT	SAT	SAT ASAT ISAT
PySDD	Decis. Diagram	SAT ISAT ALLSAT - KC

XCSP3 2025 competition: 2 gold, 1 silver medal

CPMpy tool paper (SAT26)

Supported datasets and formats

Format	Dataset	Read	Write
`jsplib`	JSPLib	✓	
`psplib`	PSPLib (RCPSP)	✓	
`nurserostering`	Nurse Rostering (instances 1–24)	✓	
`XCSP3`	XCSP3 competition	✓	
`OPB`	PB Competition	✓	✓
`MSE (wcnf)`	MaxSAT Evaluation	✓	✓
`MPS`	MIPLib	✓	✓
`DIMACS (cnf)`	SAT Competition	✓	✓



(a) XCSP3 2024 CSP **(b)** PB competition 2024 DEC-LIN

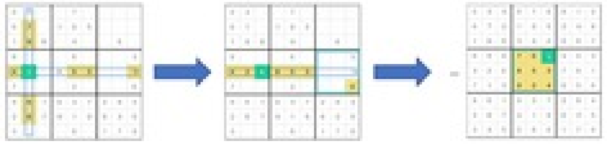
CHAT-Opt: Conversational Human-Aware Technology for Optimisation

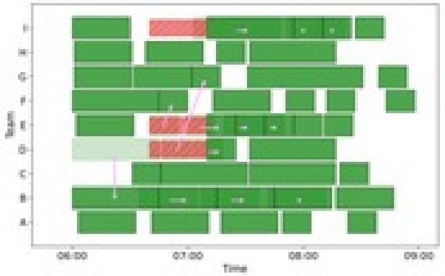
Learning

Algorithm 1 Template for CPE

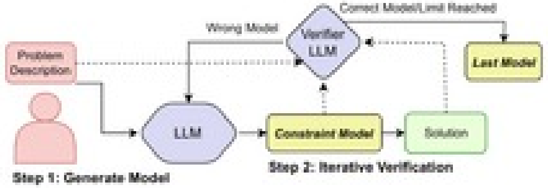
Initial weight estimate w^0
for $t < T$ **do**
  Observe problem instance p^t
  $(y_1, y_2) \leftarrow$ SELECT QUERY(p^t, w^t)
  DM chooses y_+ from (y_1, y_2)
  $w^{t+1} \leftarrow$ WEIGHT UPDATE(w^t, y_1, y_2)
end for
return $\hat{y} = \text{argmax}_{y \in \mathcal{F}} (w^T, \phi(y))$

Explaining

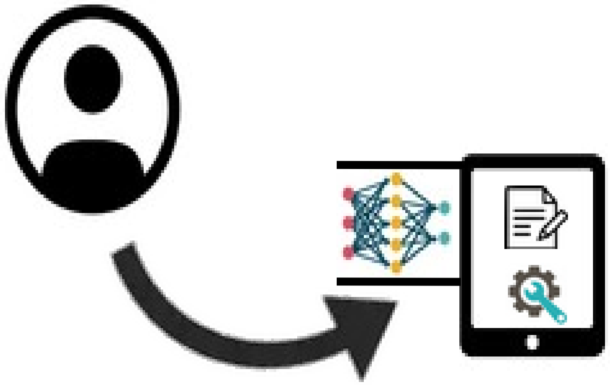




Conversational



Learning: underspecified CO problems

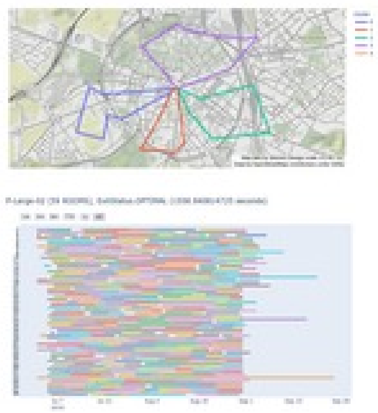


- Underspecified <u>parameters</u>:
  - From (image) classifiers
  - From (contextual) regression
- Underspecified <u>preferences</u>:
  - Learn from historic solutions
  - Learn from interaction with user
- Underspecified <u>structure</u>:
  - Interactive Constraint Acquisition

Prediction + Optimisation: NeuroSymbolic

Correlated Data

Model + Solve



D. variables
Obj function
Constraints

+ ML +

- Part <u>explicit</u> knowledge:
  easy to formalize
- Part <u>implicit</u> knowledge:
  hard to formalize,
  easy to learn?

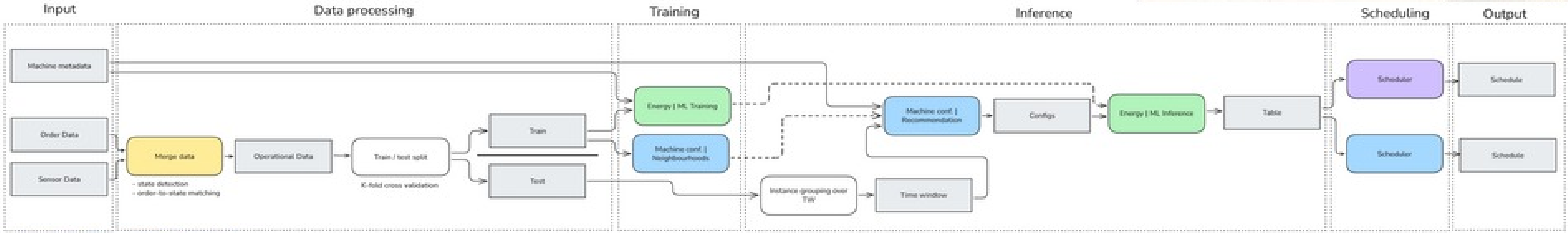
Artificial Intelligence: 2 families

Statistical Learning	Formal Reasoning
Focus on patterns and data (classifiers, neural networks)	Focus on knowledge and logical inference (planning, search)
Fast Thinking System 1: instinct, reflexes	Slow Thinking System 2: deliberate, logical, multi-step
Needs large data	Works well with small data

NeuroSymbolic AI:
integration of the two

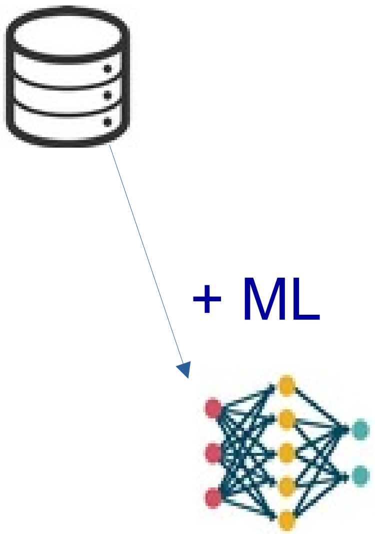
Saeling project

(Univ Klagenfurt, Siemens, VoestAlpine)



Prediction + Optimisation: ML view

Correlated Data



Standard ML

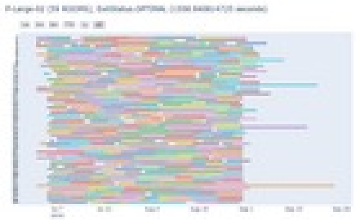
- Assumes plenty of data
- Easy to evaluate: Accuracy/MSE
- Many well-known loss functions available

Prediction + Optimisation: opt. view

Correlated Data

Model + Solve

D. variables
Obj function
Constraints

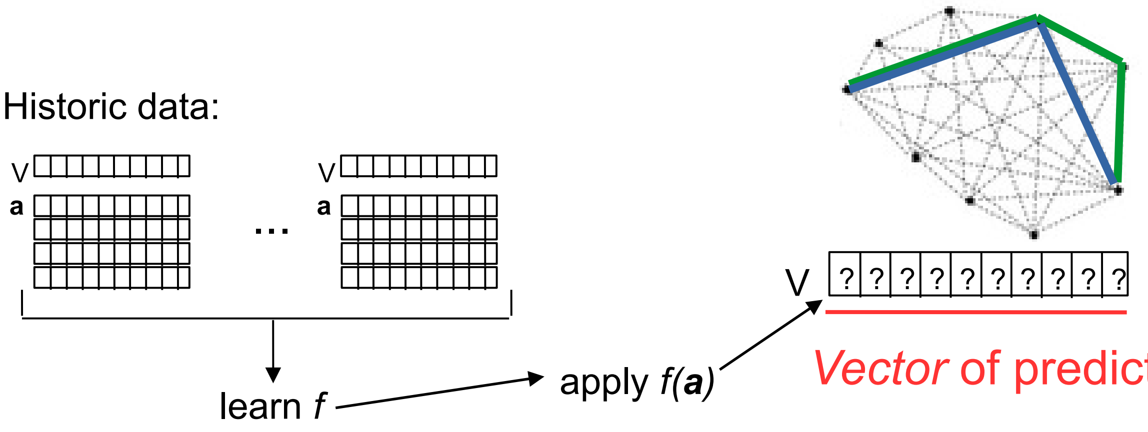


+ ML +

<u>Contexual</u> stochastic optimisation

- Predict costs/weights of the objective function
- Evaluate with solver, for multiple unknown instances (instance = context: features; no scenarios given)
- Predict expected costs? Distribution? Scenarios?

MSE loss not the best proxy for task loss....



Joint inference: trades off the individual predictions

Vector of predictions (one for each valid edge)

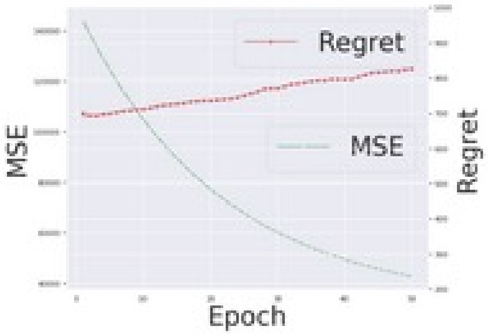
Why?

- $$MSE\left(\hat{\mathbf{c}}, \mathbf{c}\right) = \frac{1}{N}\|\mathbf{c} - \hat{\mathbf{c}}\|^2$$

  = average of individual errors of the vector

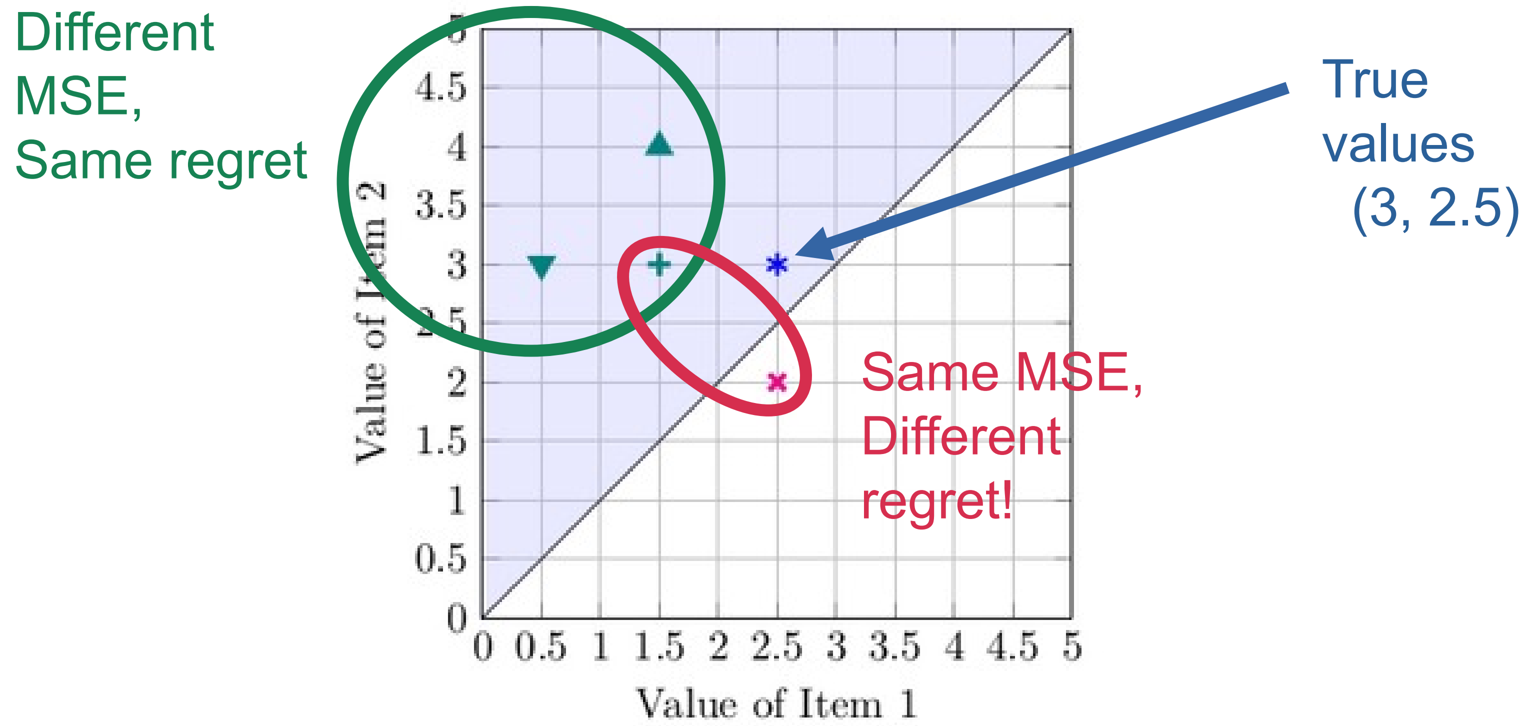
- Joint inference = *joint* error

  → some errors worse than others!



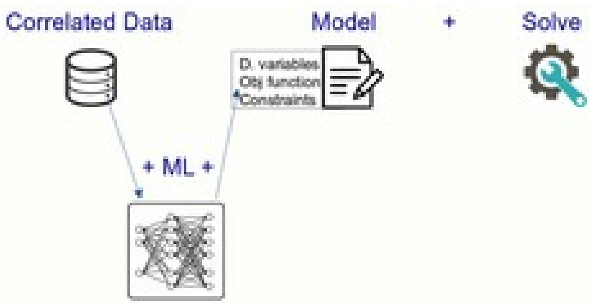
MSE loss not the best proxy for task loss....

Example: 2-item knapsack problem, unit weights, capacity 1



[Decision-Focused Learning: Foundations, State of the Art, Benchmark and Future Opportunities: Mandi, et al. JAIR 2024]

Contextual Stochastic Optimisation, linear obj



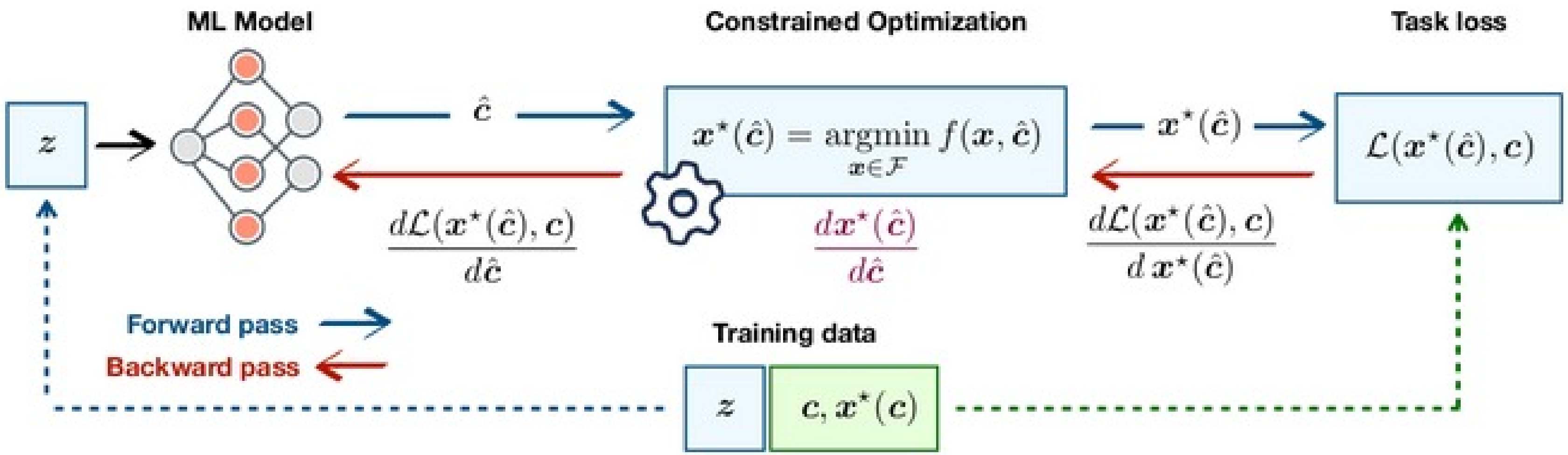
When used in the objective (price, travel time, value):

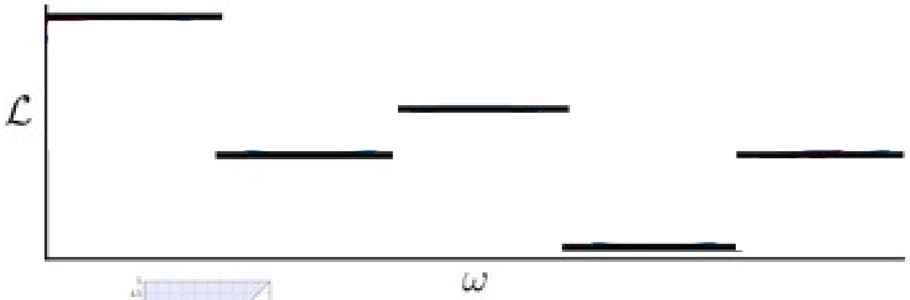
- Wrong prediction = different price/time/value
- No ‘recourse action’, only *regret*

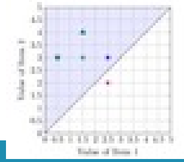
When linear in objective:

- exp. value of sum is sum of exp. value
- => point prediction equally expressive

End-to-end "Decision Focused Learning"





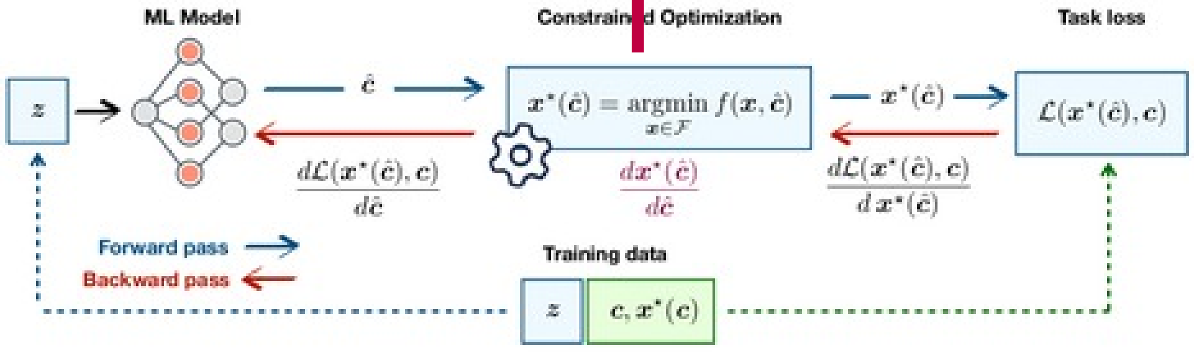


Gradient descent? But changing the weights:

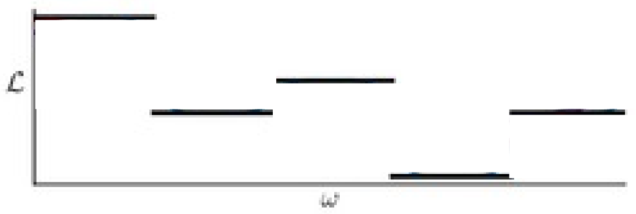
- Either does not change the opt. solution (=0 gradient)
- Or jumps to another optimal solution (=undefined grad)

[Decision-Focused Learning: Foundations, State of the Art, Benchmark and Future Opportunities: Mandi, et al. JAIR 2024]

End-to-end “Decision Focused Learning”

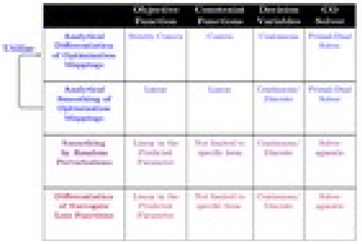


	Objective Function	Constraint Functions	Decision Variables	CO Solver
Analytical Differentiation of Optimization Mappings	Strictly Convex	Convex	Continuous	Primal-Dual Solver
Analytical Smoothing of Optimization Mappings	Linear	Linear	Continuous/ Discrete	Primal-Dual Solver
Smoothing by Random Perturbations	Linear in the Predicted Parameter	Not limited to specific form	Continuous/ Discrete	Solver agnostic
Differentiation of Surrogate Loss Functions	Linear in the Predicted Parameter	Not limited to specific form	Continuous/ Discrete	Solver agnostic



[Decision-Focused Learning: Foundations, State of the Art, Benchmark and Future Opportunities: Mandi, et al. JAIR 2024]

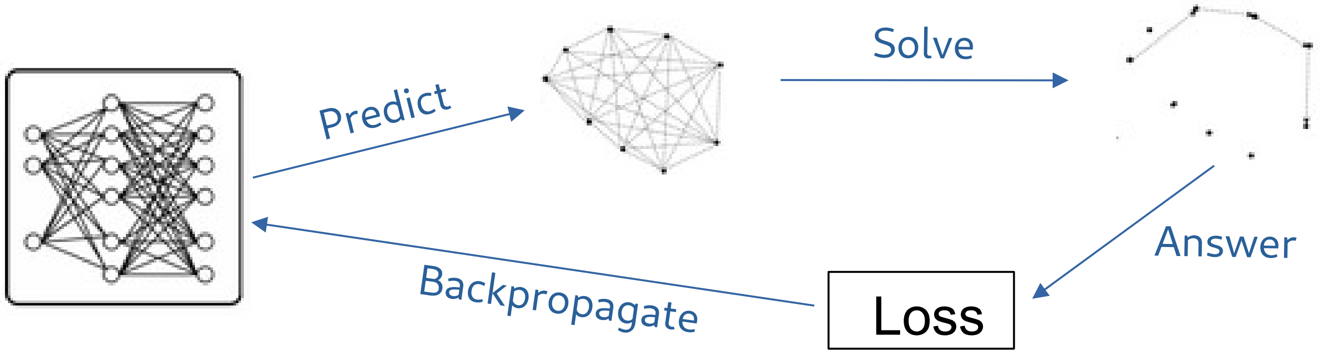
4. Differentiation of surrogate losses

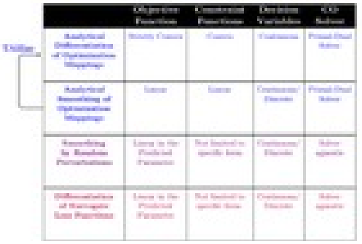


SPO+ loss [Elmachtoub and Grigas, 2017 2021]

Proposes a convex surrogate upper bound on regret:

$$\mathcal{L}_{SPO+}(\mathbf{x}^{\star}(\hat{\mathbf{c}})) = 2\hat{\mathbf{c}}^{\top}\mathbf{x}^{\star}(\mathbf{c}) - \mathbf{c}^{\top}\mathbf{x}^{\star}(\mathbf{c}) + \max_{\mathbf{x}\in\mathcal{F}}\{\mathbf{c}^{\top}\mathbf{x} - 2\hat{\mathbf{c}}^{\top}\mathbf{x}\}$$





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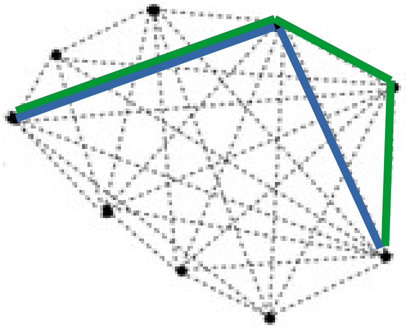
… and has a simple subgradient

$$\underbrace{\mathbf{x}^\star(\mathbf{c})}_{\text{True optimal solution}} - \underbrace{\mathbf{x}^\star(2\hat{\mathbf{c}} - \mathbf{c})}_{\text{Optimal solution under predicted, perturbed cost vector}} \in \partial\mathcal{L}_{SPO+}$$

True optimal solution

Optimal solution under predicted, *perturbed* cost vector (perturbed by error: c^ - c)



requires knowing the true cost vector *c*

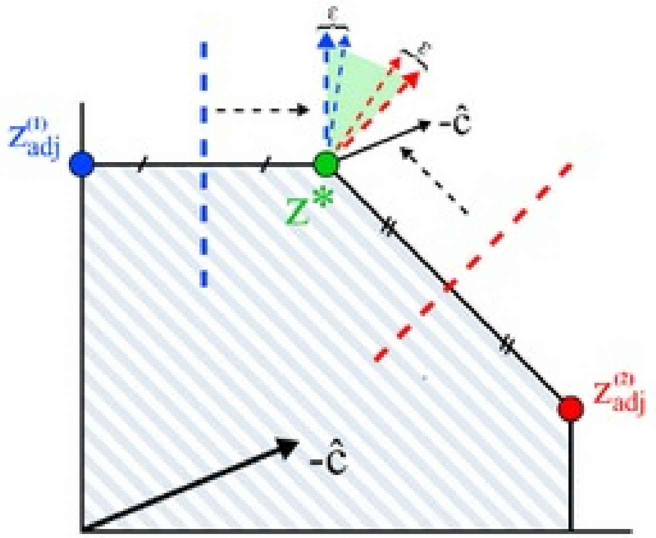
Highlight:

Solver-Free Decision-Focused Learning for Linear Optimization

$$\min \quad c^\top z$$
$$\text{s.t.} \quad Az = b$$
$$z \geq 0$$

$$\mathcal{L}_{\text{AVA}}(\hat{c}, z^\star(c)) = \sum_{z_{adj} \in Z_{adj}(z^\star(c))} \max(\hat{c}^\top z^\star(c) - \hat{c}^\top z_{adj}, -\epsilon) \quad \text{where } \epsilon \geq 0$$

All neighboring vertices
of the optimal solution
(simplex pivots + *smth*)



Predict *c* by neural network.

Non-differentiable loss function:

$$Regret(\hat{c}, c) = c^\top z^\star(\hat{c}) - c^\top z^\star(c)$$

[Berden, Mahmutogullari, Tsouros, Guns. NeurIPS 2025]

Highlight:

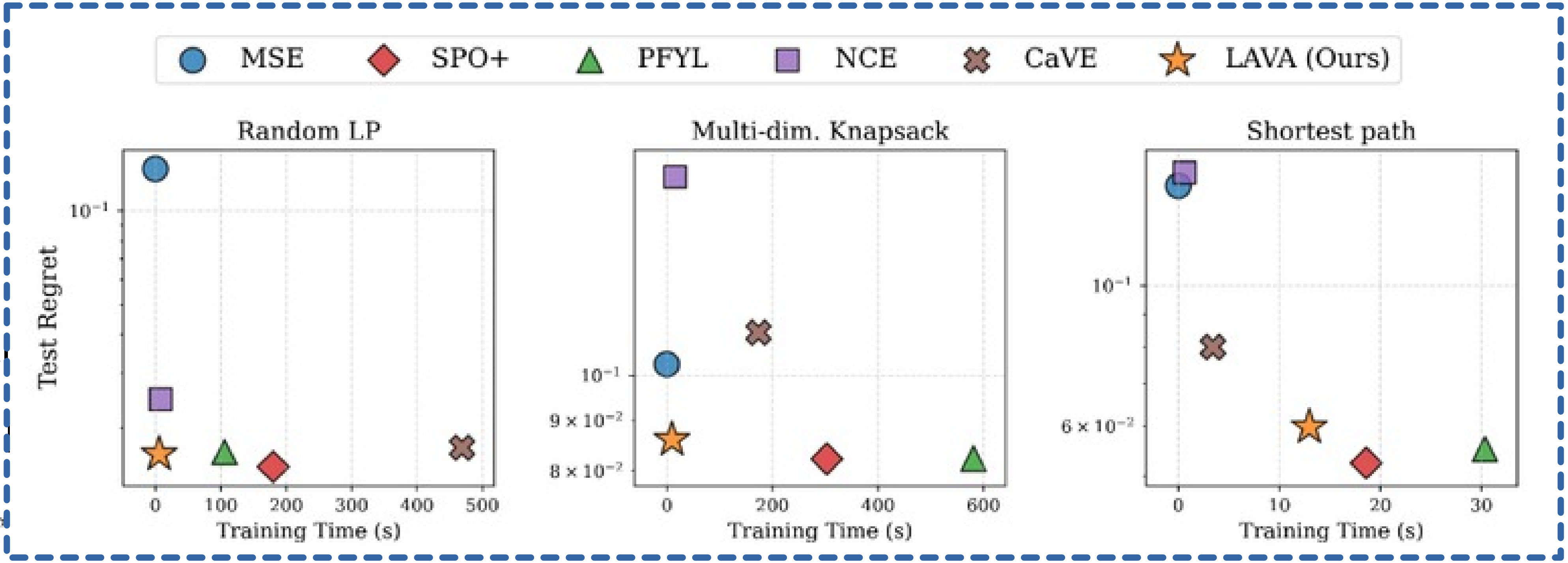
Solver-Free Decision-Focused Learning for Linear Optimization

$$\min \quad c^\top z$$
$$\text{s.t.} \quad Az = b$$
$$z \geq 0$$

Predict *c* by neura

Non-differentiable

$Regret(\hat{c}, c) = c^\top z$

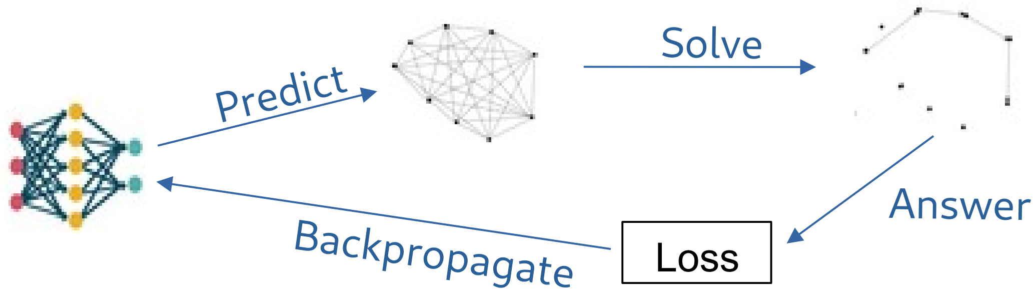


[Berden, Mahmutogullari, Tsouros, Guns. NeurIPS 2025]

Learning

Uncertainty from the environment

Duration, cost, demand, capacity, ...



"Contextual Stochastic Optimisation"
"Decision-Focused Learning"

[Decision-Focused Learning: Foundations, State of the Art, Benchmark and Future Opportunities: Mandi, et al. JAIR 2024]

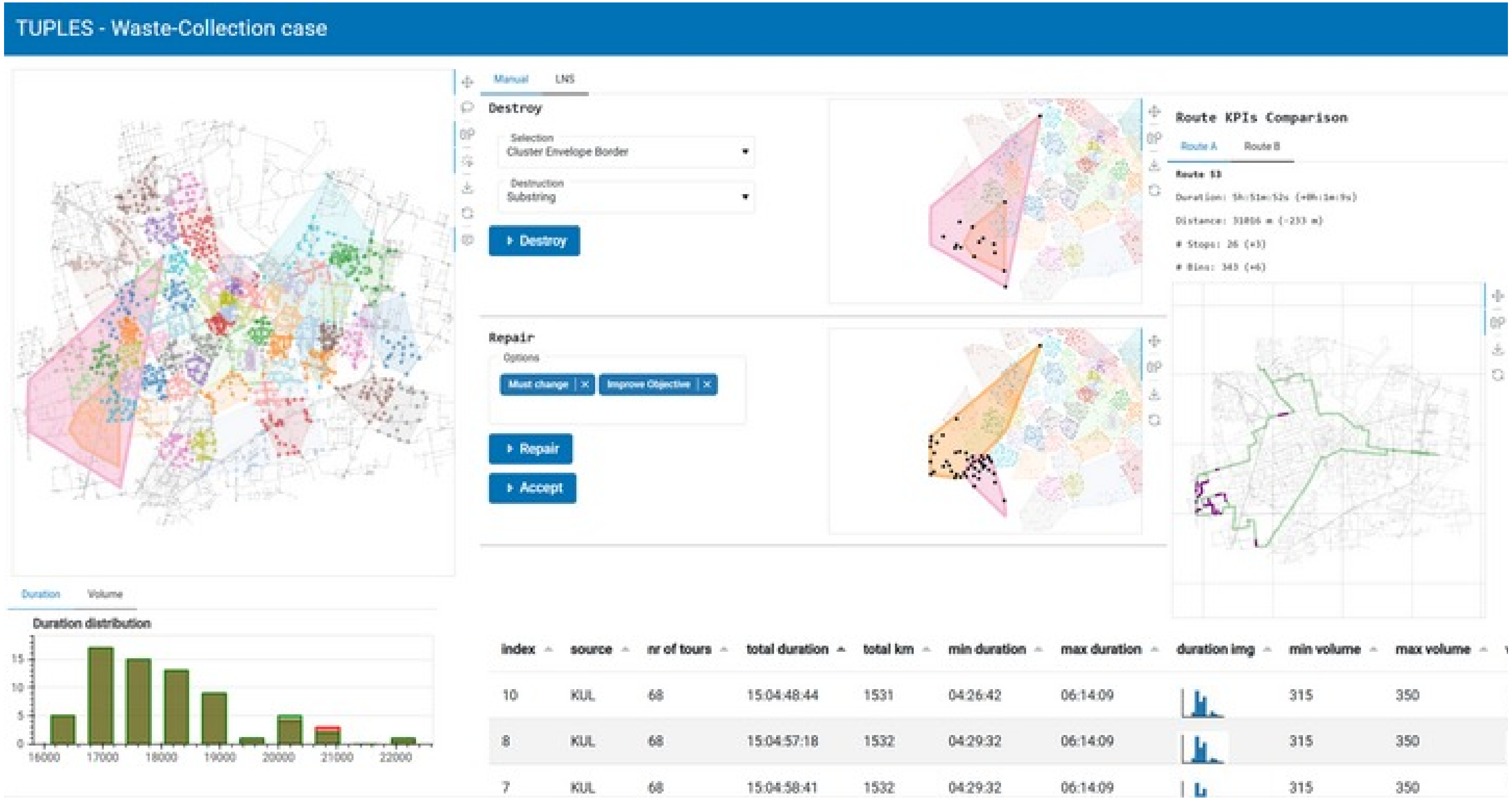
Objective not fully known

We are focussing on learning from pairwise comparisons:

(Multi-Objective) "Preference elicitation"

[Preference Elicitation for Multi-objective Combinatorial Optimization with Active Learning and Maximum Likelihood Estimation: Defresne et al. IJCAI 2025]

Multiple-objective Optimisation



Active preference learning for Comb Opt

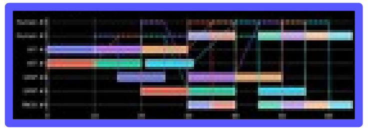
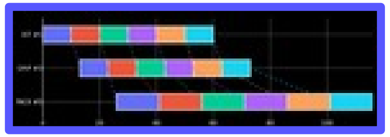
- Multi-objective optimisation (*n* objs.)

$$\hat{y} = \operatorname*{argmax}_{y \in \mathcal{F}} u(y) = \langle w, \phi(y) \rangle = \sum_{i=1}^{n} w_i \phi_i(y)$$

- Constructive Preference Elicitation [Dragone et al, 2018]

Algorithm 1 Template for CPE

Initial weight estimate w^0
for $t < T$ **do**
  Observe problem instance p^t
  $(y_1, y_2) \leftarrow$ SELECT QUERY(p^t, w^t)
  DM chooses y_+ from (y_1, y_2)
  $w^{t+1} \leftarrow$ WEIGHT UPDATE(w^t, y_1, y_2)
end for
return $\hat{y} = \text{argmax}_{y \in \mathcal{F}} \langle w^T, \phi(y) \rangle$


or?


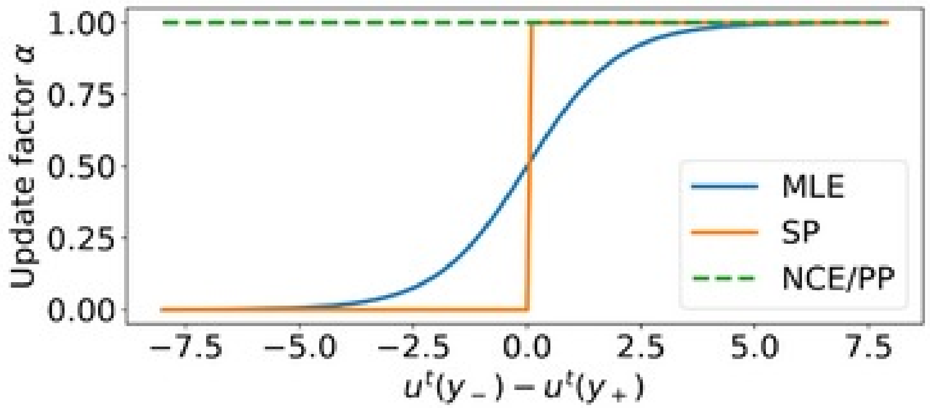
Active preference learning for Comb Opt $= \sum_{i=1}^{n} w_i \phi_i(y)$

Weight Update (user chose y_+)

$$w^{t+1} = w^t + \eta . \alpha^t \Delta \qquad \Delta = \phi(y_+, p) - \phi(y_-, p)$$

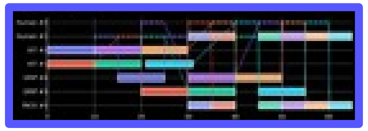
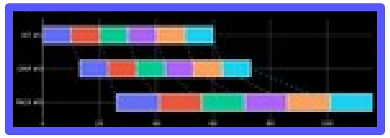
Unified view:

- Struct. Perceptron: $\alpha^t = \mathbb{1}_{u^t(y_+) < u^t(y_-)}$
- Pref. Perceptron/InfoNCE: $\alpha^t = 1$
- Max. Likelihood of Bradley-Terry pref:
  $\alpha^t = \mathcal{S}(u^t(y_-) - u^t(y_+))$



[Preference Elicitation for Multi-objective Combinatorial Optimiza… Defresne et al. IJCAI-25]

Active preference learning for Comb Opt

 or? 

Select Query = solve two comb opt problems:

$$y_1 = \operatorname*{argmax}_{y \in \mathcal{F}} u(y) \quad = \sum_{i=1}^{n} w_i \phi_i(y)$$

$$y_2 = \operatorname*{argmax}_{y \in \mathcal{F}} (1-\gamma) u(y) + \gamma ||\phi(y_1) - \phi(y)||_1 \qquad \text{diversity wrt. } y_1$$

- 2 x NP-hard + restricted to linear diversity/exploration functions

Our approach:

- Pre-computed solution pool
- UCB-based acquisition function for y_2 (non-linear)
- Cluster solutions for additional diversity (requires pool)

[Preference Elicitation for Multi-objective Combinatorial Optimiza… Defresne et al. IJCAI-25]

Active preference learning for Comb Opt

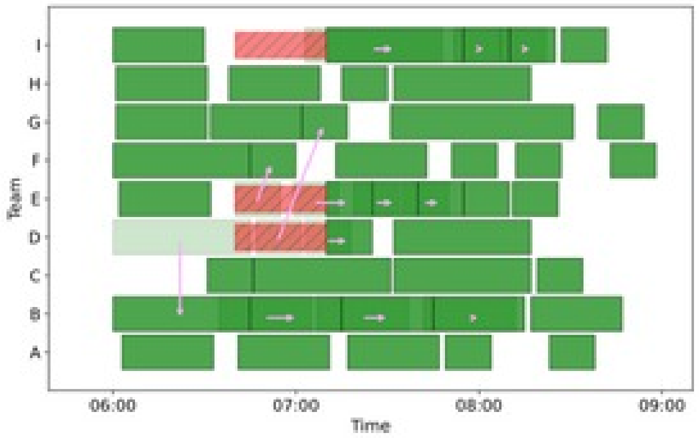
	Configuration						Prize-Collecting TSP					
Query	ChoicePerc			UCB, rpool (ours)			ChoicePerc			UCB, rpool (ours)		
Update	Regret (%)	#Q	% DM	Regret (%)	#Q	% DM	Regret (%)	#Q	% DM	Regret (%)	#Q	% DM
PP-online	6.6 ± 0.5	51	55	7.7 ± 0.5	67	45	2.7 ± 0.2	66	75	1.1 ± 0.05	29	**100**
SP-online	14.6 ± 0.7	-	20	8.9 ± 0.5	69	55	12.1 ± 0.7	-	40	1.2 ± 0.06	22	**100**
MLE-online	8.2 ± 0.6	90	65	4.9 ± 0.6	70	60	1.7 ± 0.1	39	90	0.6 ± 0.03	24	**100**
MLE-batch	8.6 ± 0.6	**47**	50	$\mathbf{2.2 \pm 0.2}$	50	**80**	1.4 ± 0.1	25	**100**	$\mathbf{0.5 \pm 0.02}$	**20**	**100**

[Preference Elicitation for Multi-objective Combinatorial Optimiza… Defresne et al. IJCAI-25]

CHAT-Opt: Conversational Human-Aware Technology for Optimisation

Explaining

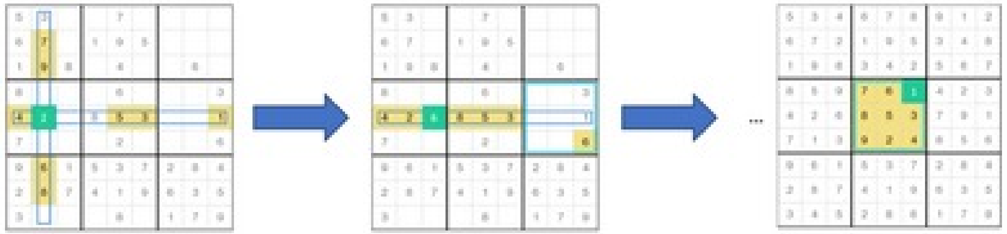
Feasibility restoration



"MCS" computation and MaxCSPs

[Modeling and Explaining an Industrial Workforce Allocation and Scheduling problem. Bleukx et al. : **CP 2025 Best Application Paper award**]

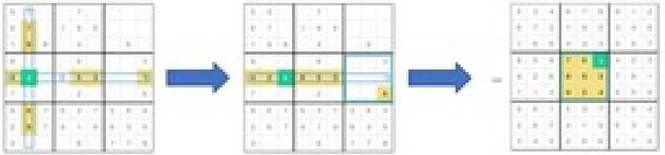
Step-wise explanations



Series of "MUS" computations

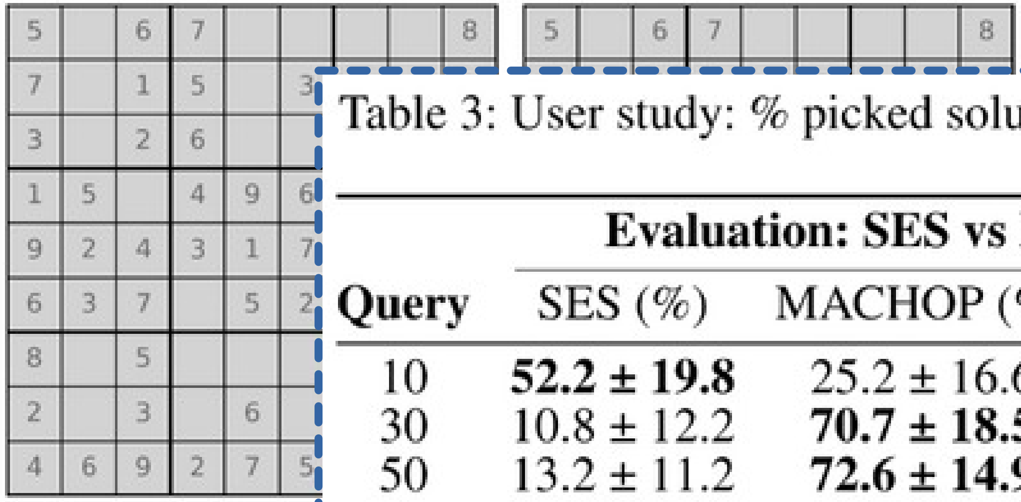
Computationally very challenging!
(incrementality, algorithmic improvements, ...)

[Efficiently explaining CSPs with unsatisfiable subset optimization. Gamba, Bogaerts, Guns. JAIR 2023]



Highlight:

Preference Elicitation for Step-Wise Explanations in Logic Puzzles



[Dragone, Teso and Passerini, 2018]

Algorithm 1: Constructive Preference Elicitation framework

Table 3: User study: % picked solutions from SES with MACHOP and Choice Perceptron (C

	Evaluation: SES vs MACHOP			Evaluation: SES vs ChoPerc		
Query	SES (%)	MACHOP (%)	Indiff. (%)	SES (%)	ChoPerc (%)	Indiff. (%)
10	**52.2 ± 19.8**	25.2 ± 16.6	22.6 ± 12.5	**63.3 ± 18.2**	16.2 ± 14.8	20.5 ± 12.0
30	10.8 ± 12.2	**70.7 ± 18.5**	18.5 ± 13.8	33.2 ± 17.1	**44.8 ± 21.2**	22.1 ± 14.1
50	13.2 ± 11.2	**72.6 ± 14.9**	14.3 ± 9.3	**42.5 ± 25.2**	38.8 ± 25.7	18.7 ± 13.0

Features	Left	Right
Facts	8	4
Block Cons.	1	2
Row Cons.	0	1
Column Cons.	0	0

+ smart 'fact to explain' generation
+ UCB-style weighting
+ subobjective normalisation
+ non-domination criteria

Explanation generation as Multi-Objective optimisation!

[Foschini, Defresne, Gamba, Bogaerts, Guns. AAAI 2026, **best poster award**]

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The Challenge: Workforce Allocation at Airbus

Airbus manufacturing sites

Toulouse/Hamburg/…

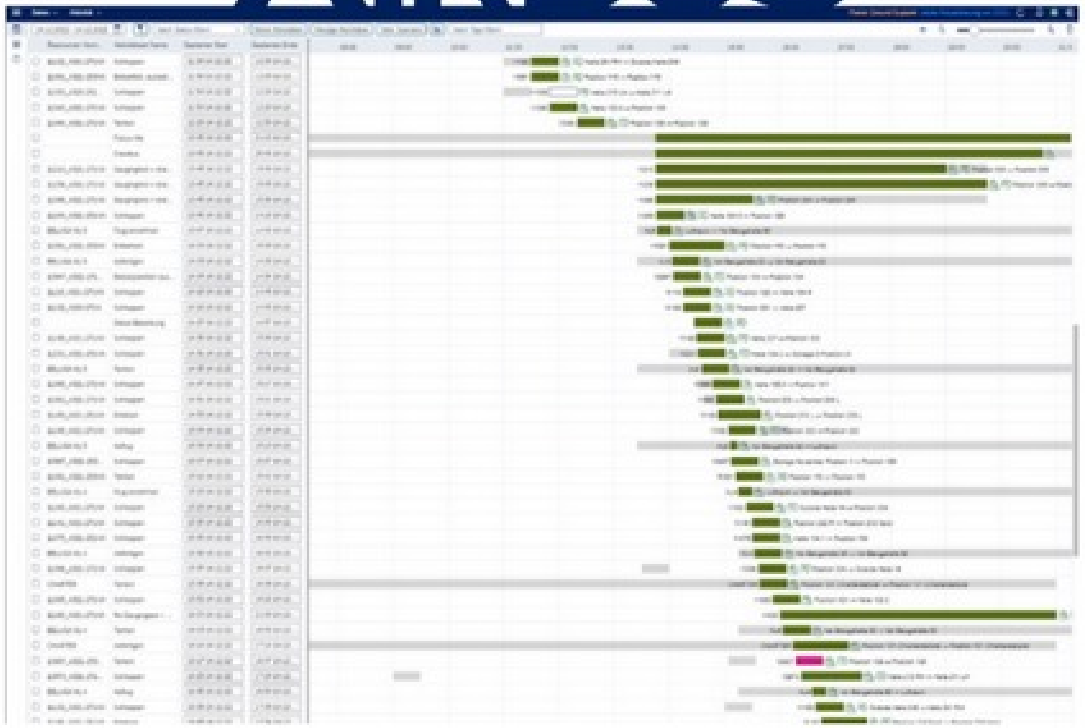
Assigning worker teams to logistical tasks

e.g., transporting aircraft parts

Transportation “tasks”

Equipment, duration, deadlines …

Current situation



Team of human planners:

1. Schedules tasks (±500/day)
2. Assigns teams to each task

While considering

Working team qualifications + calendars,

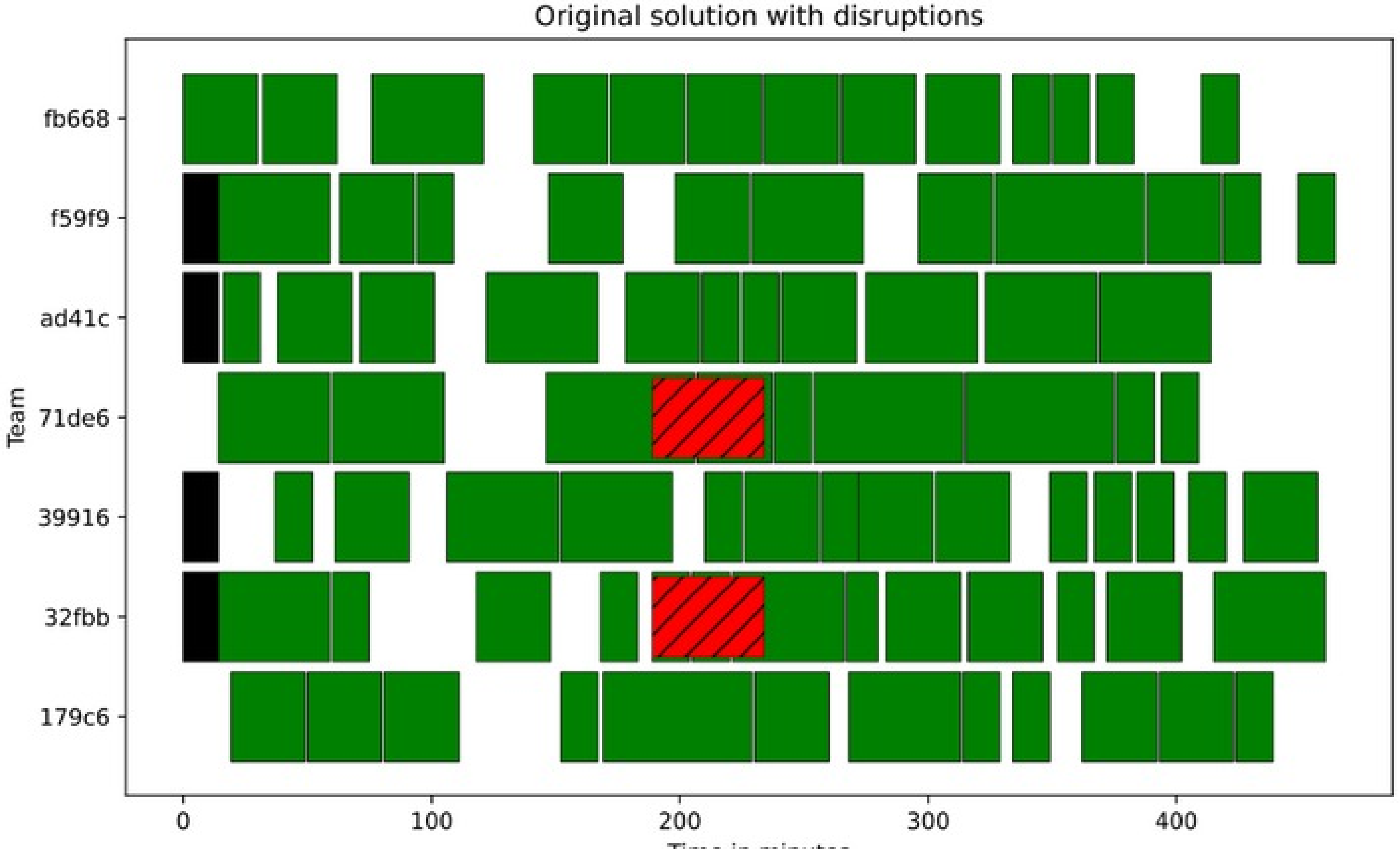
Manufacturing deadlines,

Task precedences,

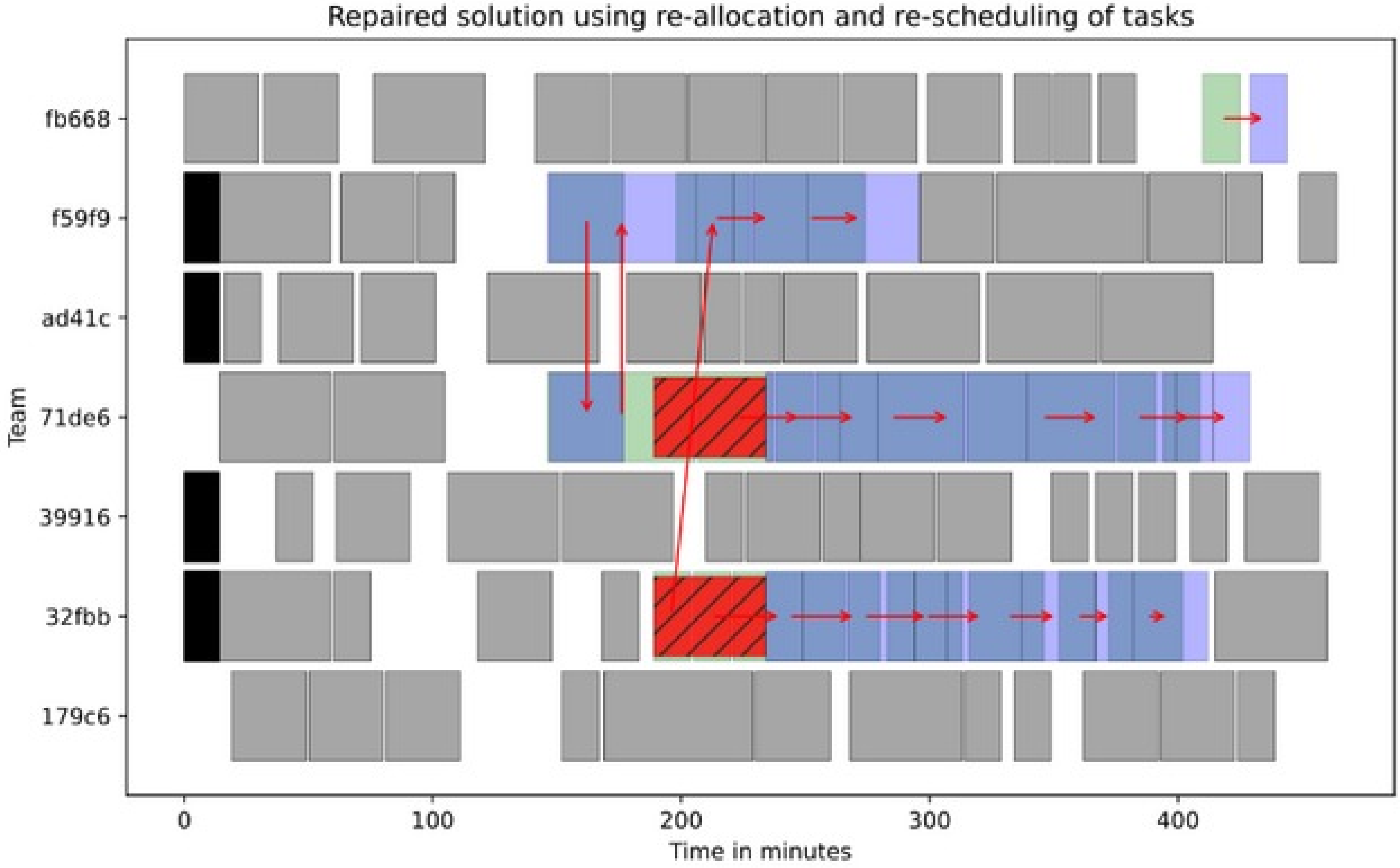
High-level logistics

...

Disrupted schedule



Fine-grained repair of schedules

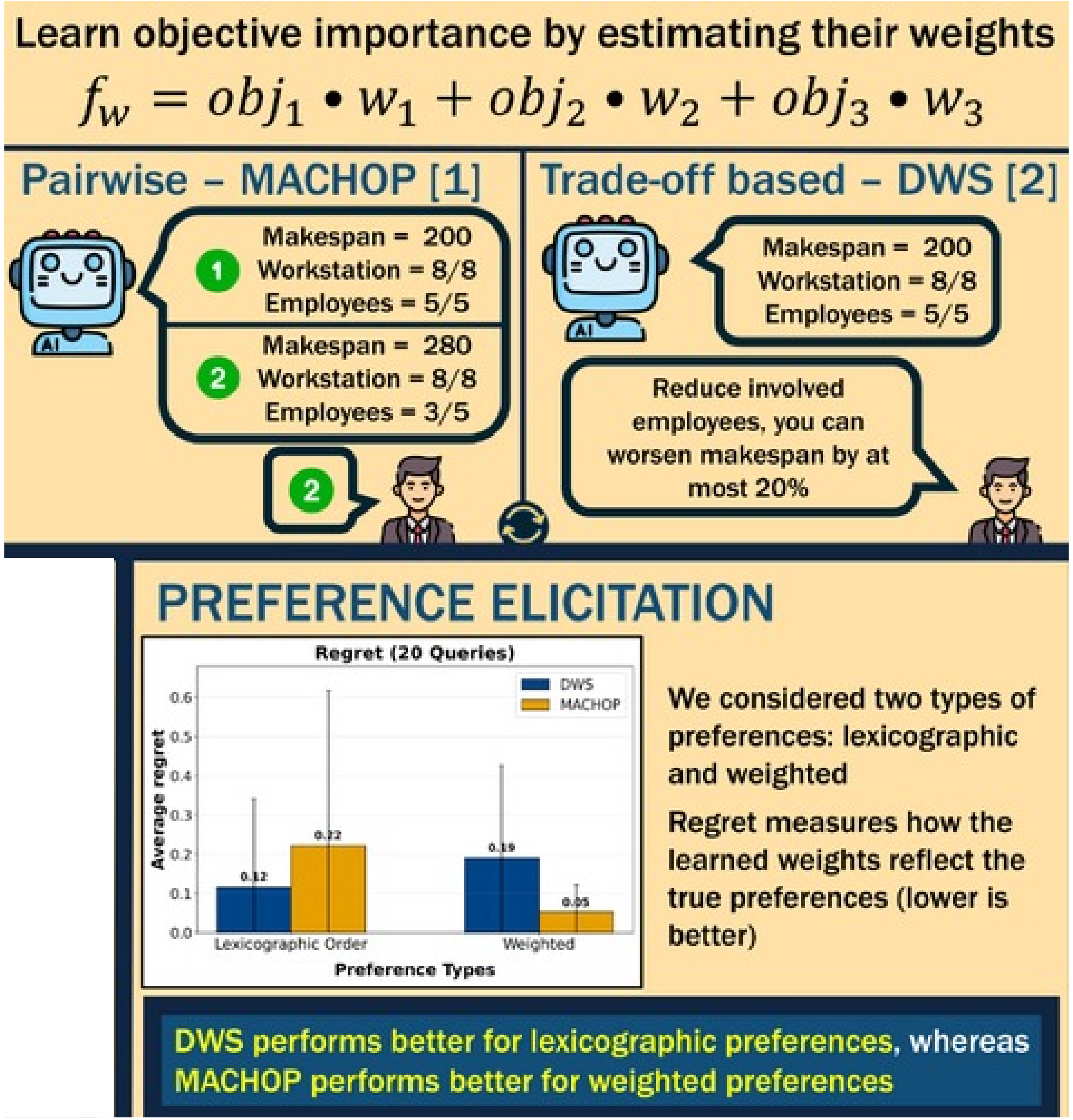


Optimize:

1. #tasks allocated
2. #tasks re-allocated
3. #tasks re-scheduled
4. Max-shift of tasks
5. Avg-shift of tasks

Dynamic weight setting?

FAIR AI project,
Joint work with Lucas Kletzander, TU Wien

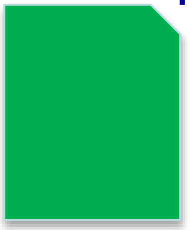


CHAT-Opt: Conversational Human-Aware Technology for Optimisation

Conversational

Problem

Problem description



Model + Solve

Decision variables
Objective function
Constraints

Can LLMs write constraint models?

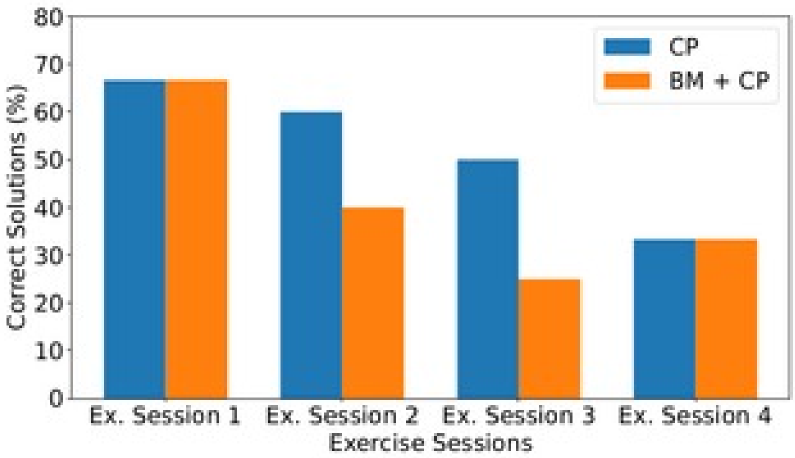
Insert anecdotal evidence *"I once asked ChatGPT…"*, and strong opinions *"you cannot trust..."*

Using LLMs to help solve CO problems?

Dataset	Method	#Err	Accuracy (%)		
			Solution	Declaration	Model
NL4Opt	Direct	1	11.46	N/A	N/A
	CP	7	81.31	87.81	79.24
	+ BM	8	84.43	89.93	82.01
	+ NER	8	85.47	88.60	80.62
LGPs	Direct	4	9.36	N/A	N/A
	CP	11	57.00	80.45	55.00
	+ BM	18	58.00	70.69	58.00
	+ NER	20	54.00	67.77	50.00

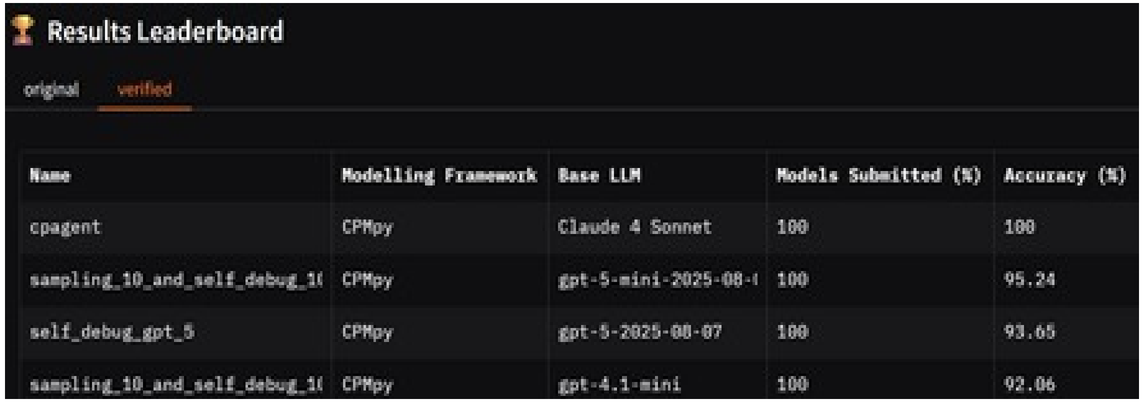
A retired professor wants to invest up to $50000 in the airline and railway industries. Each dollar invested in the airline industry yields a $0.30 profit and each dollar invested in the railway industry yields a $0.10 profit. A minimum of $10000 must be invested in the railway industry and at least 25% of all money invested must be in the airline industry. How to maximize the professor's profit?

Constraint Solving course exercises



[Michailidis K, Tsouros D, Guns T. Constraint modelling with LLMs using in-context learning. CP 2024]

- CP-Bench (60+ models): https://huggingface.co/datasets/kostis-init/CP-Bench
- HF Leaderboard: https://huggingface.co/spaces/kostis-init/CP-Bench-



Results Leaderboard

original verified

Name	Modelling Framework	Base LLM	Models Submitted (%)	Accuracy (%)
cpagent	CPMpy	Claude 4 Sonnet	100	100
sampling_10_and_self_debug_1(	CPMpy	gpt-5-mini-2025-08-(	100	95.24
self_debug_gpt_5	CPMpy	gpt-5-2025-08-07	100	93.65
sampling_10_and_self_debug_1(	CPMpy	gpt-4.1-mini	100	92.06

[Michailidis K, Tsouros D, Guns T. ECAI 25]

Conversational

~~Can LLMs write constraint models?~~

Of course, public demo (1.5 yrs old): https://chatopt.cs.kuleuven.be

Let’s do science…

- What is an appropriate dataset?
- What is an appropriate evaluation measure?

Only then: what LLM models, what prompts, what harness, ….

DCP-Bench-open

- Discrete Combinatorial Problems (Bool/int, satisfaction and optimisation)
- **164** diverse problems, many have **multiple** instances

Built-in evaluation with CPMpy, MiniZinc and Ortools

Call for collaboration:

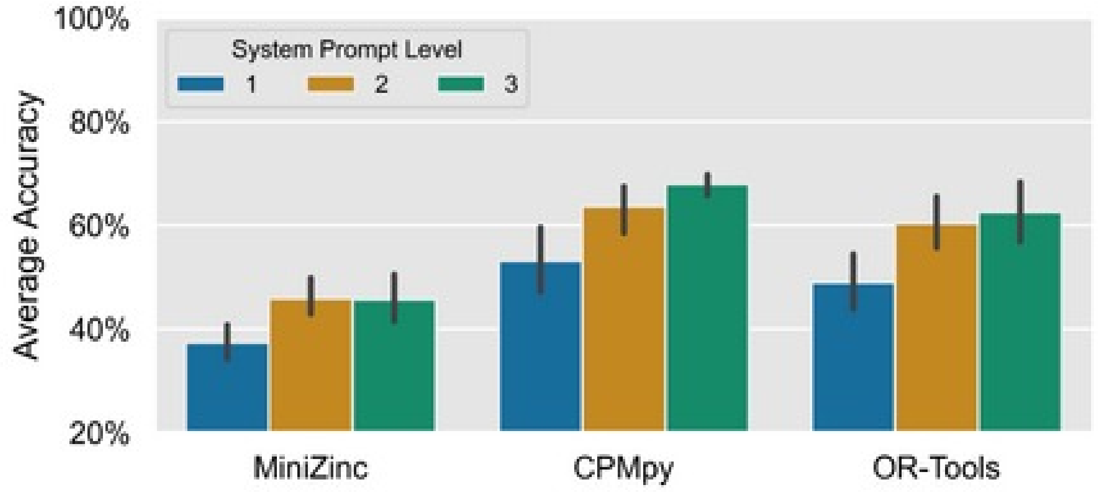
https://github.com/DCP-Bench/DCP-Bench-Open

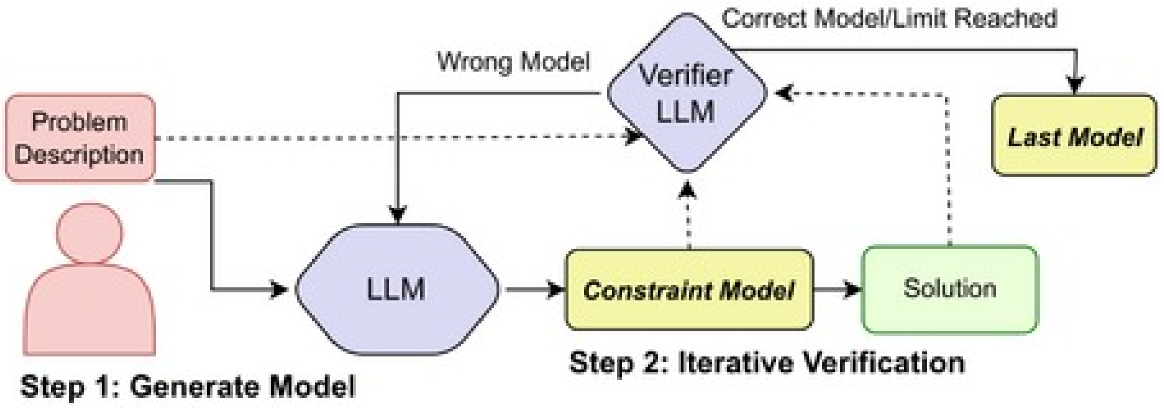
abbots_puzzle/
added_corners/
age_changing/
ages_of_the_sons/
aircraft_assignment/
aircraft_landing/
allergy/
among/
appointment_scheduling/
archery_puzzle/
arch_friends/
assignment_costs/
autoref/
bales_of_hay/
bananas/
best_host/
big_bang2/
bin_packing/
birthday_coins/
bowls_and_oranges/
broken_weights/
building_blocks/
bus_scheduling/
cabling/
calvin_puzzle/
candies/
capital_budget/
car_selection/
cell_tower/
chess_set/
circling_squares/
circular_table_averbach_1_2/
clock_triplets/
cmo_2012/
coin3_application/
coins_grid/
contracting_costs/
covering_opl/
crew/
crossword/
crypta/

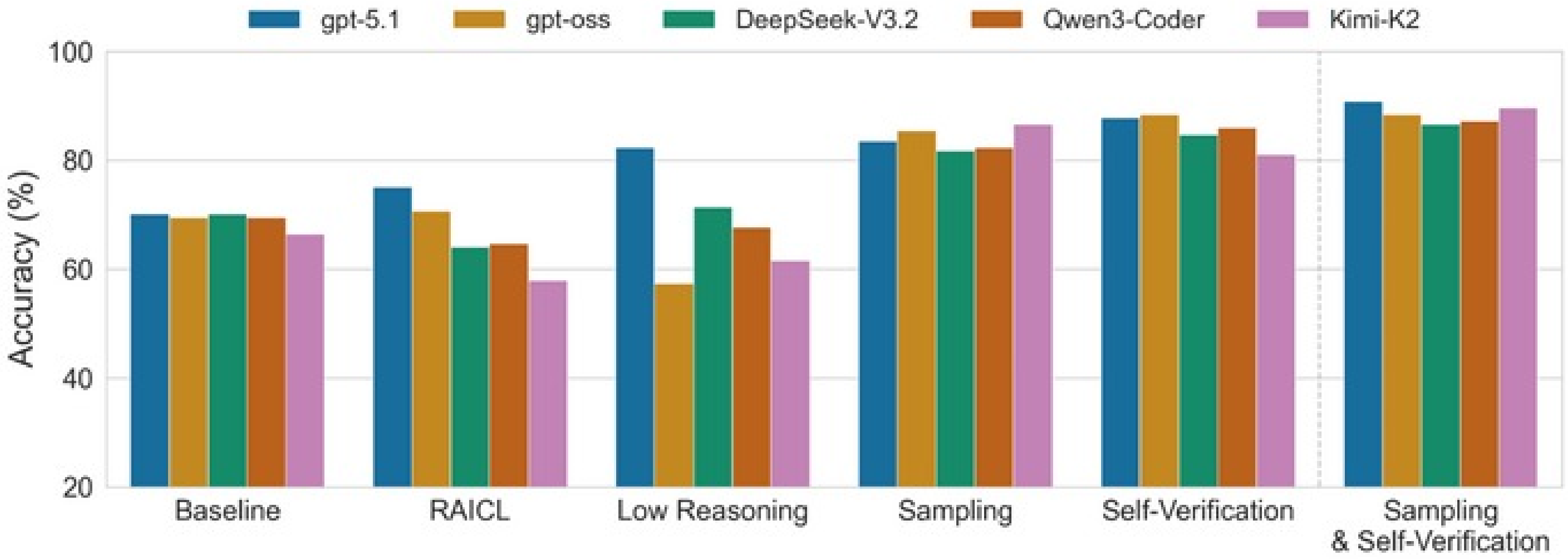
csplib_001_car_sequencing/
csplib_002_template_design/
csplib_003_quasigroup_existence/
csplib_005_autocorrelation/
csplib_006_golomb_rulers/
csplib_007_all_interval/
csplib_008_vessel_loading/
csplib_009_perfect_square_placement/
csplib_010_social_golfers_problem/
csplib_011_acc_basketball_schedule/
csplib_012_nonogram/
csplib_013_progressive_party_problem/
csplib_014_solitaire_battleships/
csplib_015_schurs_lemma/
csplib_016_traffic_lights/
csplib_018_water_bucket/
csplib_019_magic_squares_and_sequences/
csplib_021_crossfigures/
csplib_022_bus_driver_scheduling/
csplib_023_magic_hexagon/
csplib_024_langford/
csplib_026_sports_tournament_scheduling/
csplib_028_bibd/
csplib_032_max_density_still_life/
csplib_033_word_design/
csplib_034_warehouse_location/
csplib_039_rehearsal/
csplib_041_n_fractions/
csplib_044_steiner/
csplib_049_number_partitioning/
csplib_050_diamond_free/
csplib_053_graceful_graphs/
csplib_054_n_queens/
csplib_056_sonet/
csplib_057_killer_sudoku/
csplib_067_quasigroup_completion/
csplib_074_maximum_clique/
csplib_076_costas_arrays/
csplib_084_hadamard_matrix/

curious_set_of_integers/
cur_num/
cutting_stock/
de_bruijn_sequence/
devils_word/
diet/
dinner/
discrete_tomography/
divisible_by_1_through_9/
dudeney_numbers/
eighteen_hole_golf/
equal_sized_groups/
facility_location/
fancy_dress/
fibonacci_even/
fifty_puzzle/
finding_celebrities/
five_brigands/
five_statements/
fixed_charge/
flip_rows_cols/
flow_free_game/
flowshop_scheduling/
football/
four_islands/
four_numbers/
frog_circle/
futoshiki/
general_store/
giant_cat_army/
handshaking/
hanging_weights/
heterosquare/
hidato/
huey_dewey_louie/
initials_queue/
isbn/
jobshop/
jobs_puzzle/
just_forgotten/
kakuro/

kenken/
knapsack/
knights_tour/
mario/
media_selection/
minesweeper/
multi/
netasgn/
n_puzzle/
packing_rectangles/
prod/
pythagorean_triplet/
resource_constrained_p
revenue_maximization/
room_assignment/
send_more_money/
session1_bank_card/
session1_five_floors/
session1_guards_and_a
session1_magic_square
session1_money_chang
session1_thick_as_thiev
session2_color_simple/
session2_maximal_inde
session2_movie_schedu
session2_subsets_100/
session2_subset_sum/
session3_exodus/
session3_farmer_and_c
session3_kidney_exchar
session3_people_in_a_r
session5_climbing_stairs
session5_grocery/
session5_hardy_1729_s
set_game/
sudoku/
three_coins/
three_sum/
tsp/
twelve_pack/
who_killed_agatha/
wolf_goat_cabbage/
zebra/





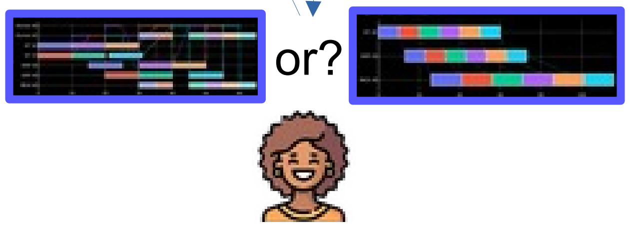


[Michailidis, Tsouros, Guns. ECAI 2025 + JAIR submission]

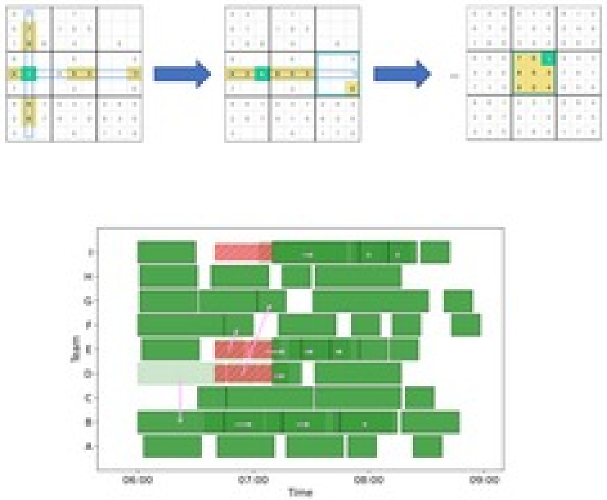
CHAT-Opt: Conversational Human-Aware Technology for Optimisation

Learning

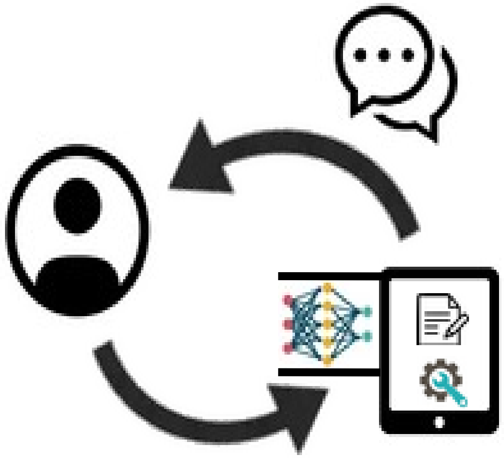
```
Algorithm 1 Template for CPE
  Initial weight estimate w^0
  for t < T do
      Observe problem instance p^t
      (y_1, y_2) ← SELECT QUERY(p^t, w^t)
      DM chooses y_+ from (y_1, y_2)
      w^{t+1} ← WEIGHT UPDATE(w^t, y_1, y_2)
  end for
  return ŷ = argmax_{y∈F} (w^T, φ(y))
```



Explaining

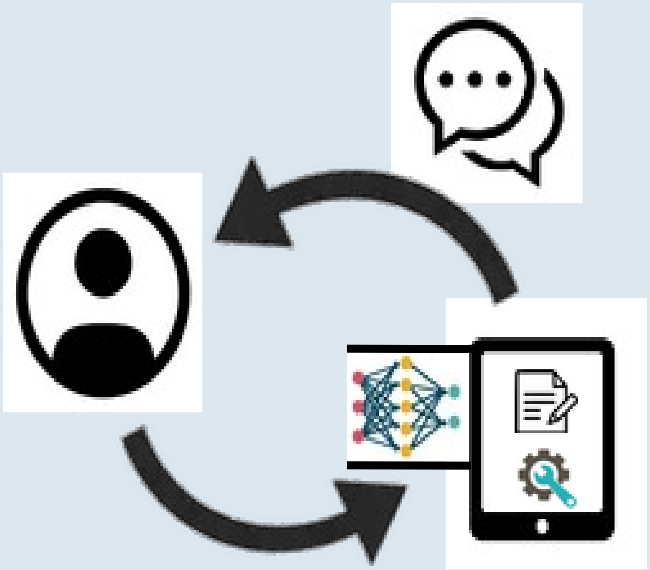


Conversational



Looking ahead, CHAT-Opt and more

- Learning: prediction + optimisation problems
  - - *Sample-efficient (=few solver calls) learning?*
  - - *Foundation models?*
- Explaining:
- - *Conversational?*
- - *Solving the right problem: human evaluations*
- Conversational
  - - *Datasets? Solving the right problem…*
  - - *Correctness and leaks*

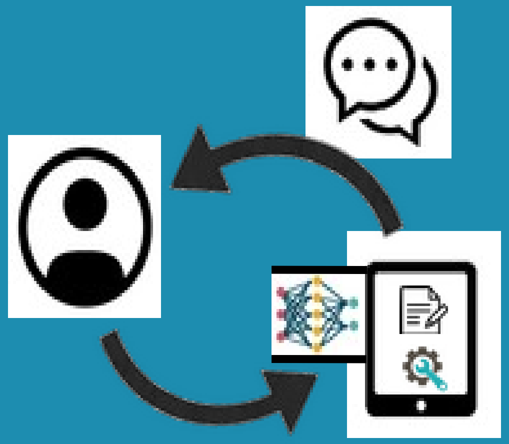


Collaboration is key!

Questions?

Prof. Tias Guns

https://people.cs.kuleuven.be/~tias.guns/



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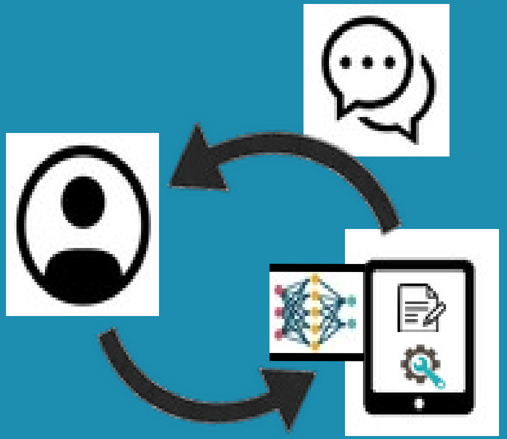

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