Optimize to learn to optimize: the Algorithm Configuration Problem

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Machine Learning NeEDS Mathematical Optimization

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Outline

1. Motivation
2. The Algorithm Configuration Problem
3. Our ML+MO take on the ACP
4. Implementation: the ML model counts – a lot!
5. Implementation: the nitty-gritty details count – a lot!
6. A glimpse to computational results
7. Conclusions

Motivation: Mathematical Optimization is HARD

- Most Mathematical Optimization (MO) problems are hard in practice
- In theory "all $\mathcal{NP}$-hard problems equally difficult", but in practice hard means very different things:
  - difficult to find any feasible solution at all, and/or
  - difficult to prove that a given solution is optimal, and/or
  - difficult to do anything because you need a huge formulation
  - difficult to do anything because functions nonlinear/hard to compute

  $\Longrightarrow$ no single approach will always work, need specialised ones
- Any solver (and especially general-purpose ones) need many of them:
  - bounding techniques (relaxations, cuts, ...), branching, dominance, ...
  - heuristics (math-, fast, expensive, ...)
  - preprocessing, reformulations, ...

  $\Longrightarrow$ any efficient approach is many approaches in one

Motivation (cont.d)

- Obviously even worse for
  huge-scale problems with multiple nested forms of structure
  that require multi-level nested decomposition approaches

  `https://gitlab.com/smspp/smspp-project`

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  `https://gitlab.com/smspp/smspp-project`
  . . . but that's another story
- Today it's general-purpose MO solvers and their 100s parameters
- Tuning them crucial for efficiency, but hard mostly manual process
  requiring skilled personnel with in-depth knowledge of the techniques
- This even assuming you really know what's going on, not always true
- Necessarily instance-specific because even "MILP" can be anything
- Clearly lots of scope to automatise experience-based process:
  if this does not say "ML", I do not know what does
- In fact, that's our (and a lot of other people's) take

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Algorithm Configuration Problem (ACP) [30]

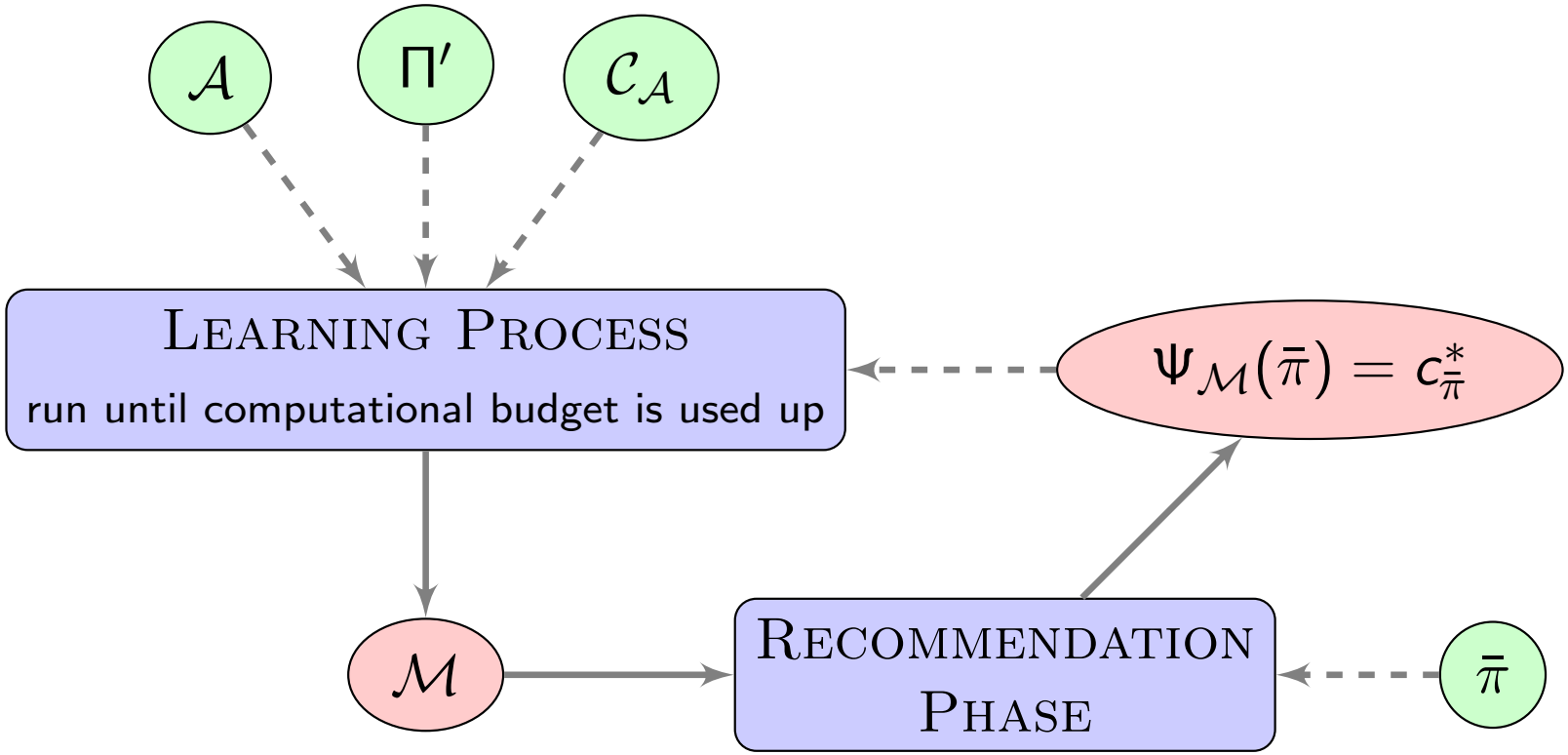
- Target algorithm $\mathcal{A}$ for problem Π = (infinite) set of instances
- Configuration c for $\mathcal{A}$ = finite (but not small) vector of parameters
- Set $\mathcal{C}_\mathcal{A}$ of feasible parameter configurations: typically bounded but nontrivial (continuous/categorical parameters, logic relationships)
- $p_\mathcal{A} : \Pi \times \mathcal{C}_\mathcal{A} \longrightarrow \mathbb{R}$ performance function measuring efficiency and effectiveness (nontrivial: find solution vs. solution quality vs. time)
- ACP: given $\bar{\pi} \in \Pi$ find $c^*_{\bar{\pi}} \in \mathcal{C}_\mathcal{A}$ providing optimal $p_\mathcal{A}(\bar{\pi}, c^*_{\bar{\pi}})$
  a meta optimization problem in our case
- "Simpler version": Algorithm Selection Problem (ASP)
- Can only be very hard (undecidable?)
- Wealth of other applications: hyperparameter tuning in ML, personalised medical treatment, ...

Algorithm Configuration Problem (ACP)

- Solution to ACP $=$ recommender $\Psi_{\mathcal{M}} : \Pi \rightarrow \mathcal{C}_{\mathcal{A}}$
  given $\pi \in \Pi$ returns optimal configuration $c^*_\pi \in \mathcal{C}_{\mathcal{A}}$
- $\Psi_{\mathcal{M}}$ need assess $p_{\mathcal{A}}$ over entire $\mathcal{C}_{\mathcal{A}}$, but
  - $\mathcal{C}_{\mathcal{A}}$ large, exhaustive evaluation of $p_{\mathcal{A}}$ on $\mathcal{C}_{\mathcal{A}}$ infeasible
  - $p_{\mathcal{A}}$ black-box: run $\mathcal{A}$ to evaluate $p_{\mathcal{A}}$ costly, defies the purpose
  - $\mathcal{A}$ may even be one-shot, non-repeatable process (medical treatment)

  $\Longrightarrow$ model $\mathcal{M}$: encodes knowledge about $p_{\mathcal{A}}$
- $\mathcal{M}$ worst case/average complexity theory: difficult and imprecise
- Data-driven approach: $\mathcal{M}$ is learnt out of experiments
- Requires learning phase, training set
- $\mathcal{M}$ itself can guide exploration of $\mathcal{C}_{\mathcal{A}}$ in learning phase

ACP: a general scheme



- $\Pi' \subset \Pi$ = training set of instances
- Initial subset of $\Pi' \times \mathcal{C}_{\mathcal{A}}$ typically by design of experiments
- Learning process often itself iterative, either $\mathcal{M}$ or different $\mathcal{M}'$ guides selection of new $(\bar{\pi}, \bar{c})$

ACP Taxonomy

- Fundamental elements:
  - model $\mathcal{M}$ and associated recommender $\Psi_{\mathcal{M}}$
  - whether $\Psi_{\mathcal{M}}(\pi)$ really depends on π (Per-Instance) or always gives same answer (Per-Problem)
  - whether $\mathcal{M}$ is fixed during $\mathcal{A}$ run (offline) or information from the run is dynamically included (online)
- Three main types of recommenders:
  - $\zeta_{\mathcal{A}} : \Pi \longrightarrow \mathcal{C}_{\mathcal{A}}$: directly recommend a configuration
    $\Longrightarrow \quad \Psi_{\mathcal{M}}(\bar{\pi}) = \zeta_{\mathcal{A}}(\bar{\pi})$
  - $\bar{p}_{\mathcal{A}} : \Pi \times \mathcal{C}_{\mathcal{A}} \longrightarrow \mathbb{R}$: compute approximation of $p_{\mathcal{A}}$
    $\Longrightarrow \quad \Psi_{\mathcal{M}}(\bar{\pi}) = \arg\max_{c \in \mathcal{C}_{\mathcal{A}}} \bar{p}_{\mathcal{A}}(\,\bar{\pi}\,,\,c\,)$
  - $\mathscr{C}_{\mathcal{A}} = \{\,(\,\pi\,,\,c^*_{\pi}\,),\, \pi \in \Pi^*\,\}$: configurations for representative instances
    $\Longrightarrow \quad \Psi_{\mathcal{M}}(\bar{\pi}) = c^*_{\pi^*}$ where $\pi^* \in \arg\min_{\pi \in \Pi^*} \{\,||\,\pi - \bar{\pi}\,||\,\}$
    (PP special case where $\mathscr{C}_{\mathcal{A}}$ singleton)
- $\bar{p}_{\mathcal{A}} + \mathscr{C}_{\mathcal{A}}$: compute $\bar{p}_{\mathcal{A}}(\,\bar{\pi}\,,\,c\,)$ only for $c \in \mathscr{C}_{\mathcal{A}}$, choose best

ACP/ASP: a bird's eye on the literature

	PI		PP
$\mathcal{M}$	offline	online	offline
$\zeta_{\mathcal{A}}$	[9]*, [7, 10], [24]		
$\bar{p}_{\mathcal{A}}$	[6, 8, 20, 31, 32], [23]		
$\mathscr{C}_{\mathcal{A}}$ per-instance		[5, 29]	
$\mathscr{C}_{\mathcal{A}}$ clusters	[12, 16]*, [25]		
$\bar{p}_{\mathcal{A}} + \mathscr{C}_{\mathcal{A}}$	[17, 31, 32]	[17]	
$\mathscr{C}_{\mathcal{A}}$ singleton			[1, 2, 3, 4, 14, 15] [21, 22, 27, 28]

- Our contributions in red (* = ASP only)
- Our approach per-instance offline, but online would be possible
- In this talk: only $\bar{p}_{\mathcal{A}}$

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Our approach to the ACP

- Assumptions:
  - (mostly harmless) $\mathcal{C}_{\mathcal{A}} = \{ c \in \{0,1\}^q \mid Ac \leq d \}$: only categorical parameters, MILP representation of logical constraints
  - (not entirely harmless) performance function = gap within time-limit, special scaling when no solution $= \infty$
  - (not at all harmless) encoding $e(\pi) \in \mathbb{R}^m$ for all $\pi \in \Pi =$ knowing which features of the instance influence the behaviour of $\mathcal{A}$
- Two-phases process:
  - Performance Map Learning Phase (PMLP): learn an approximation $\bar{p}_{\mathcal{A}}$ of $p_{\mathcal{A}}$ via "any" supervised ML technique on the training set

$$\mathcal{S} = \{ (\underbrace{e(\pi_i), c_i}_{x_i}, \underbrace{p_{\mathcal{A}}(\pi_i, c_i)}_{f(x_i)}) \} \subseteq \underbrace{\mathbb{R}^m \times \mathcal{C}_{\mathcal{A}}}_{\mathcal{X}} \times \underbrace{\mathbb{R}}_{\mathcal{Y}}$$

  - Configuration Space Search Problem (CSSP): solve

$$\text{CSSP}(\bar{\pi}) \qquad c^* \in \arg\max_{c \in \mathcal{C}_{\mathcal{A}}} \bar{p}_{\mathcal{A}}(\bar{\pi}, c)$$

    using the most appropriate MO technique

Our specific twists

- PP is not enough, it just isn't for general-purpose MO solvers
  $\Longrightarrow$ has to make nontrivial decisions when $\bar{\pi}$ arrives
- Cannot assume q small, it just isn't for general-purpose MO solvers
  $\Longrightarrow$ cannot treat $\bar{p}_{\mathcal{A}}$ as black-box
  (derivative-free optimization just does not scale) $\Longrightarrow$
  pry open the black-box and use powerful available MO tools
- Idea not entirely new [26] but successful applications limited, application to ACP context new
- Optimizing to learn to optimize: use MO techniques to improve on MO techniques via ML

Easier said than done

- Several significant implementation challenges
- Each ML paradigm gives rise to entirely different CSSP, requiring a separate implementation effort and specific tools
- Trade-offs in ML paradigm: more "complex" ones may yield higher generalization but result in more difficult CSSP
- Which performance function to be learned (feasibility vs. optimality)?
- Traditional ML loss metrics do not necessarily reflect the purpose: the "right" $\bar{p}_{\mathcal{A}}$ ideally has the same global minima as $p_{\mathcal{A}}$ even if the function values are very different
- Dimensionality reduction techniques (FS) modify/shrink $x = (e, c) \implies$ eliminate configuration variables $\implies$ c^* may not be immediate to reconstruct out of the CSSP solution

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PMLP: Support Vector Regression

- Several techniques (e.g., linear SVR) yield $\bar{f}(x) = wx + b$
- Cannot be used in a PI approach: $x = (\, e\,,\, c\,) \implies$
  $\bar{f}(\, e\,,\, c\,) = w_c c + w_e e + b \implies$
  the solution of CSSP is always the same for each π
- Must use nonlinear SVR: with kernel trick this is

$$\begin{aligned} \min & \sum_i \sum_j \alpha_i \kappa(x_i, x_j) \alpha_j + \varepsilon \sum_i |\alpha_i| - \sum_i y_i \alpha_i \\ & \sum_i \alpha_i = 0 \;\;,\;\; -C \le \alpha_i \le C \qquad \forall i \end{aligned}$$

  yielding $\bar{f}(x) = \sum_i \alpha_i^* \kappa(x_i, x) + b^*$
- Actual form of CSSP then depends on kernel; with Gaussian one

$$\text{CSSP}(\bar{\pi}) \quad \min_{c \in \mathcal{C}_{\mathcal{A}}} \; \sum_i \alpha_i^* \, e^{-\gamma^* \| (\, e_i\,,\, c_i\,) - (\, e(\bar{\pi})\,,\, c\,) \|_2^2} + b^*$$

  a linearly constrained nonconvex MINLP

PMLP: Neural Networks (NN)

- NN [19]: digraph $G = (I \cup H \cup \{o\}, A)$, arc weights w, node biases b, activation functions σ_n (linear, ReLU, sigmoid, ...)
- $a_n = x_n$ for $n \in I$, $a_n = \sigma_n(\sum_u w_{un} a_u + b_n)$ otherwise
- In our case, $I = E \cup C$ (features and controls)
- CSSP($\bar{\pi}$) in general a nonconvex MINLP

$$
\begin{aligned}
\max\ & \sigma_o(\textstyle\sum_u w^*_{uo} a_u + b^*_o) \\
& a_n = c_n && n \in C \\
& a_n = e(\bar{\pi})_n && n \in E \\
& a_n = \sigma_n(\textstyle\sum_u w^*_{un} a_u + b^*_n) && n \in H \\
& c \in \mathcal{C}_{\mathcal{A}}
\end{aligned}
$$

- With σ = linear or ReLU actually a MILP, although not necessarily "easy" (nasty big-M [18] + many extra variables)

PMLP: "poorman's NN" = Logistic Regression (LR)

- Conditional probability $\mathrm{P}(\mathcal{Y} = y \| \mathcal{X} = x)$ of Bernoulli variable $\mathcal{Y}$ [13]: $\bar{f}(x) = \frac{1}{1+e^{-z}}$ if $\exists w \in \mathbb{R}^d, b \in \mathbb{R}$ s.t. $z = wx + b$
- Convex training program to find best w^*, b^*
- CSSP($\bar{\pi}$) a linearly constrained MINLP with concave objective

$$\max_{c \in \mathcal{C}_{\mathcal{A}}} \left\{ \ln \left(\sigma(c) = \frac{1}{1 + e^{-(w^*(\, e(\bar{\pi})\, ,\, c\,) + b^*\,)}} \right) \right\}$$

- A very simple NN with $H = \emptyset$ (and it probably shows)
- However, interesting different probabilistic-motivated CSSP forms

$$\max_{c \in \mathcal{C}_{\mathcal{A}}\, ,\, r \in [0,1]} \left\{ r \ln(\sigma(c)) + (1 - r)(1 - \ln(\sigma(c))) + r \; ; \; \ldots \right\}$$

($r \approx$ estimate of the conditional probability)

- May work better [24] but nastier to solve

PMLP: Decision Tree (DT)

- Decision Tree (DT): binary tree $T = (V_I \cup V_L, A)$, labels λ_n on leaves $n \in V_L$, threshold/index function $\tau/\rho : V_I \to I$ otherwise
- In our case, $V_I = V_E \cup V_C$ (features and controls) depending on $\rho(n)$
- Training = construct T^*, λ^*, τ^* and ρ^*
- CSSP($\bar{\pi}$): $T^* \to T' = (V_C^* \cup V_L^*, A')$ (may be much smaller, entire sub-trees not reachable) as $\tau^*(n)$ for $n \in V_E$ can be verified statically
- CSSP($\bar{\pi}$) a MILP: path variables $y_{p[n],n} \in \{0, 1\}$ ($y_{p[r],r} = 1$)

$$
\begin{aligned}
\max \ & \textstyle\sum_{n \in V_L^*} y_{p[n],n} \lambda_n^* & \\
& y_{p[n],n} = y_{n,n_-} + y_{n,n_+} & n \in V_C^* \\
& y_{p[n],n} - c_{\rho^*(n)} \leq y_{n,n_-} & n \in V_C^* \\
& y_{p[n],n} + c_{\rho^*(n)} - 1 \leq y_{n,n_+} & n \in V_C^* \\
& c \in \mathcal{C}_{\mathcal{A}} &
\end{aligned}
$$

- No nasty big-M constraints, but $c \in \{0, 1\}$ not general

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Challenges: choice of $p_{\mathcal{A}}$

- $p_{\mathcal{A}} \approx$ gap for fixed time limit (60s), but details count
- Solver ran 3 times with $\neq$ seeds to weed out impact of random choices, $\varrho(\pi, c) =$ middle value
- $\varrho(\pi, c)$ can be large ($\infty =$ no solution), compute max $\bar{\varrho}$ for $\varrho \leq$ 1e+5
- re-set all $\varrho >$ 1e+5 to max $\bar{\varrho} + 100$
- re-scale ϱ in $[0, 1]$
- Not terribly general (but proper scaling important in ML)
- Extending to non-fixed time limit?

Challenges: PMLP loss metrics

- Prediction error $\rho_i = p_i - \bar{p}_i = p_{\mathcal{A}}(\pi_i, c_i) - \bar{p}_{\mathcal{A}}(\pi_i, c_i)$
- Standard ML loss $= \sum_i \ell(p_i, \bar{p}_i)$, some choices for ℓ:
  - MAE $= |\rho_i|$: robust to outliers, sparse solutions, nonsmooth
  - MSE $= (\rho_i)^2$: different for $\gg 1$ and $\ll 1$, sensitive to outliers, smooth
  - others with intermediate traits (log cosh loss, elastic net, ...)

  None of them really measures correspondence of global minima
- CMAE$_\delta$ for $\delta \in [0, 1]$ (requires p_i scaled in $[0, 1]$)

$$\ell_\delta(p_i, \bar{p}_i) = \begin{cases} \rho_i(1 + 1/(1 + \exp(\rho_i))) & \text{if } p_i \leq \delta \text{ and } \rho_i < 0 \\ \rho_i(1 + 1/(1 + \exp(-\rho_i))) & \text{if } p_i \geq 1 - \delta \text{ and } \rho_i > 0 \\ \rho_i & \text{if } \delta \leq p_i \leq 1 - \delta \\ 0 & \text{otherwise} \end{cases}$$

  Penalize overestimates but allow underestimates "on δ-minima" ($p_i \leq \delta$), vice-versa "on δ-maxima" ($p_i \geq 1 - \delta$), MAE elsewhere
- Rather crude, but at least tries

Challenges: CSSP solution completion

- Ideally, CSSP defined on $\mathcal{C}_{\mathcal{A}} = \{ c \in \{0, 1\}^q \mid Ac \leq d \}$
- But after FS, $\mathcal{C}_{\mathcal{A}} = \{ c' \in \{0, 1\}^{q'} \mid A'c' \leq d' \}$, $q' < q$
- Work on single parameter ω hit-encoded (q_ω bits summing to ≤ 1)
- $q_\omega - q'_\omega < 2 \implies$ leftout variables values determined univocally
- $q_\omega - q'_\omega \geq 2 \implies$ leftout variables values determined heuristically
- $\mathcal{S}$ encoded by matrix $M_{\mathcal{S}}$; after FS, $M'_{\mathcal{S}'}$ (less columns and rows)
- Heuristic 1: given c^*, separately for each ω
  1. group rows of $M'_{\mathcal{S}'}$ by all q_ω variables
  2. for each group apply `mean` or `min` to $p_{\mathcal{A}} \longrightarrow$ new column $p'_{\mathcal{A}}$
  3. delete rows in grouped matrix where selected variable values are $\neq c^*$
  4. leftout variable values: choose grouped matrix row with minimum p'
- Heuristic 2: group rows of $M'_{\mathcal{S}'}$ by q' variables, for each group apply `min` and retrieve row with min $p_{\mathcal{A}}$, use leftout variable values of that row to complete c^*

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Experimental setup: SVR

- $\mathcal{A}$: IBM ILOG CPLEX (100+ algorithmic parameters)
- $\mathcal{C}_{\mathcal{A}}$: 2304 combinations of 9 hit-encoded CPLEX params ($q = 23$)
- All combinations tested on all instances (conceptual experiment)
- FS: "kind" ($q = 14$) or "aggressive" ($q = 10$)
- Π: Hydro UC instances [11], hand-picked $e(\pi)$ of 43 components
- Π': 187 in-sample instances + 63 out-of-sample ones
- training set size $\approx$ 11000 rows; losses MAE and CMAE$_\delta$ (hyperparameter selection)
- CSSP solver: Bonmin (heuristic for nonconvex problems)

Experiment metrics

- Global optimum c^{**} of CSSP, Bonmin solution c^{*} of CSSP
- Comparison with default CPLEX configuration $c^{\mathtt{cpx}}$
- "% glob": $c^{**} = c^{*}$ frequency, "gap": relative error when $c^{**} \neq c^{*}$
- For all configs, p = true gap and p^{ml} = rescaled gap
- Separately, primal / dual gap ϱ_{prim} / ϱ_{dual}, % of feasible solutions
- "%w" = wins, "%w+d" = wins + draws, "%w-d" = wins over non-draws, "gap d" = relative gap of c^{*} (or $c^{\mathtt{cpx}}$, same) w.r.t. c^{**}
- When something unspecified, average on all possible choices

Solving the CSSP, FS impact

	FS	% glob	gap	time
IS	no	83.69	2.01e-2	15.36
	kind	87.70	2.76e-2	10.73
	agg	84.49	3.12e-2	5.95
OS	no	85.32	1.59e-2	13.44
	kind	90.48	2.01e-2	12.23
	agg	93.25	1.96e-2	6.15

- FS improves "% glob" and reduces time (smaller problems)
- local optima c^* never too worse than c^{**} (at most 3.2%)

Solving the CSSP, metric impact

	metric	% glob	gap	time
IS	$CMAE_{.2}$	84.85	3.00e-2	11.41
	$CMAE_{.4}$	83.07	2.80e-2	10.34
	MAE	87.34	2.26e-2	10.91
OS	$CMAE_{.2}$	93.12	2.32e-2	10.68
	$CMAE_{.4}$	88.89	1.75e-2	10.08
	MAE	88.36	1.20e-2	10.75

- No impact on time
- Minor difference on solution quality, no clear trend

Recommender performance, FS impact

	p	FS	%w	%w+d	%w-d	gap d
IS	p	no	47.06	96.12	92.39	0
		kind	48.91	98.02	96.12	0
		agg	48.98	97.79	95.70	0
	p^{ml}	no	78.74	92.11	90.89	2.79e-1
		kind	81.60	93.94	93.08	1.52e-1
		agg	83.16	95.19	94.53	1.23e-1
OS	p	no	33.73	83.73	67.50	0
		kind	36.64	82.61	68.06	0
		agg	33.86	77.05	59.78	0
	p^{ml}	no	59.13	76.59	71.77	3.39e-1
		kind	60.71	77.05	72.54	2.83e-1
		agg	55.82	71.89	66.55	3.28e-1

- FS most often improves
- Draws are invariably on "easy" instances solved to optimality
- Results much better in "ML metric": you get what you learn

Recommender performance, metric impact

	p	metric	%w	%w+d	%w-d	avg d
IS	p	$CMAE_{.2}$	47.98	97.09	94.30	0
		$CMAE_{.4}$	48.46	97.59	95.27	0
		MAE	47.86	96.73	93.62	0
	p^{ml}	$CMAE_{.2}$	80.99	93.35	92.41	1.97e-1
		$CMAE_{.4}$	81.61	93.79	92.93	1.51e-1
		MAE	80.54	93.94	92.99	2.20e-1
OS	p	$CMAE_{.2}$	34.74	79.72	63.34	0
		$CMAE_{.4}$	35.63	81.39	65.99	0
		MAE	36.16	85.36	71.78	0
	p^{ml}	$CMAE_{.2}$	59.08	76.01	71.16	3.04e-1
		$CMAE_{.4}$	58.29	72.57	68.00	2.36e-1
		MAE	62.26	79.45	75.16	3.68e-1

- Metric does move something (only used in hyperparameter selection)
- Not much and not always in the right direction

Recommender performance, heuristic impact

set	p	heuristic	%w	%w+d	%w-d	gap d
IS	p	none	47.06	96.12	92.40	0
		clustF_h1_gbMean	49.67	98.80	97.65	0
		clustF_h1_gbMin	48.86	97.86	95.82	0
		clustF_h2	48.20	97.19	94.51	0
		noClust_h1_gbMean	48.86	97.86	95.82	0
		noClust_h1_gbMin	48.86	97.86	95.82	0
		noClust_h2	48.06	97.19	94.50	0
	p^{ml}	none	78.48	92.25	91.00	2.88e-1
		clustF_h1_gbMean	83.42	94.52	93.83	5.67e-2
		clustF_h1_gbMin	81.95	93.85	93.02	1.43e-1
		clustF_h2	82.29	95.25	94.55	1.62e-1
		noClust_h1_gbMean	81.95	93.85	93.02	1.43e-1
		noClust_h1_gbMin	81.95	93.85	93.02	1.43e-1
		noClust_h2	82.55	95.19	94.49	1.88e-1
OS	p	none	35.32	85.71	71.30	0
		clustF_h1_gbMean	35.91	80.95	65.72	0
		clustF_h1_gbMin	34.92	81.15	65.20	0
		clustF_h2	32.94	75.99	58.21	0
		noClust_h1_gbMean	34.92	81.15	65.20	0
		noClust_h1_gbMin	34.92	81.15	65.20	0
		noClust_h2	34.52	78.17	61.55	0
	p^{ml}	none	61.90	78.17	74.05	3.01e-1
		clustF_h1_gbMean	59.72	74.60	70.15	2.97e-1
		clustF_h1_gbMin	58.93	76.19	71.19	2.97e-1
		clustF_h2	53.17	70.04	63.95	3.86e-1
		noClust_h1_gbMean	58.93	76.19	71.19	2.97e-1
		noClust_h1_gbMin	58.93	76.19	71.19	2.97e-1
		noClust_h2	56.75	73.02	67.81	3.49e-1

- It has some effects (not really clear)

Recommender performance in "natural" metrics

set	FS	metric	%feas c^*_{cssp}	%feas c_{cpx}	$\varrho^{\text{cssp}}_{\text{prim}}$	$\varrho^{\text{cpx}}_{\text{prim}}$	$\varrho^{\text{cssp}}_{\text{dual}}$	$\varrho^{\text{cpx}}_{\text{dual}}$
IS	no	$\text{CMAE}_{.2}$	96.79	100	1.50e-1	5.81e-1	9.71e-2	1.02e-1
		$\text{CMAE}_{.4}$	98.40		1.14e-1		7.25e-2	
		MAE	98.93		1.06e-1		4.70e-2	
	kind	$\text{CMAE}_{.2}$	98.75		6.96e-2		3.79e-2	
		$\text{CMAE}_{.4}$	98.48		7.09e-2		5.02e-2	
		MAE	96.43		7.18e-2		4.16e-2	
	agg	$\text{CMAE}_{.2}$	98.04		7.85e-2		5.18e-2	
		$\text{CMAE}_{.4}$	97.59		9.27e-2		6.68e-2	
		MAE	97.59		7.745e-2		5.00e-2	
OS	no	$\text{CMAE}_{.2}$	87.30	100	7.00e-2	4.63e-1	7.93e-2	8.12e-2
		$\text{CMAE}_{.4}$	88.89		1.31e-1		9.69e-2	
		MAE	93.65		1.37e-1		6.61e-2	
	kind	$\text{CMAE}_{.2}$	89.68		1.47e-1		6.47e-2	
		$\text{CMAE}_{.4}$	91.01		1.54e-1		1.28e-1	
		MAE	92.86		1.49e-1		1.08e-1	
	agg	$\text{CMAE}_{.2}$	89.42		2.05e-1		9.06e-2	
		$\text{CMAE}_{.4}$	88.10		2.08e-1		9.87e-2	
		MAE	88.62		1.79e-1		7.73e-2	

- CPLEX default emphasises feasibility, we got what we learnt
- We always do better in all other metrics

Recommender performance in "natural" metrics (cont'd)

	FS	metric	%feas c^*_{bm}	%feas c_{cpx}	ϱ^{bm}_{prim}	ϱ^{cpx}_{prim}	ϱ^{bm}_{dual}	ϱ^{cpx}_{dual}
IS	no	none	97.46	100	1.23e-1	5.81e-1	7.44e-2	1.02e-1
	kind	clustF_h1_gbMean	98.53		7.08e-2		4.27e-2	
		clustF_h1_gbMin	98.66		7.34e-2		4.22e-2	
		clustF_h2	97.59		7.26e-2		4.49e-2	
		noClust_h1_gbMean	98.66		7.34e-2		4.22e-2	
		noClust_h1_gbMin	98.66		7.34e-2		4.22e-2	
		noClust_h2	97.46		7.91e-2		4.40e-2	
	agg	clustF_h1_gbMean	98.93		8.35e-2		5.71e-2	
		clustF_h1_gbMin	97.59		7.46e-2		4.71e-2	
		clustF_h2	97.59		9.16e-2		6.87e-2	
		noClust_h1_gbMean	97.59		7.45e-2		4.71e-2	
		noClust_h1_gbMin	97.59		7.45e-2		4.71e-2	
		noClust_h2	97.33		8.93e-2		6.23e-2	
OS	no	none	90.48	100	1.15e-1	4.63e-1	8.18e-2	8.12e-2
	kind	clustF_h1_gbMean	91.67		1.54e-1		1.05e-1	
		clustF_h1_gbMin	90.87		1.41e-1		1.01e-1	
		clustF_h2	88.89		1.43e-1		1.16e-1	
		noClust_h1_gbMean	90.87		1.41e-1		1.01e-1	
		noClust_h1_gbMin	90.87		1.41e-1		1.01e-1	
		noClust_h2	88.89		1.45e-1		1.08e-1	
	agg	clustF_h1_gbMean	90.87		2.03e-1		8.81e-2	
		clustF_h1_gbMin	88.89		1.85e-1		7.97e-2	
		clustF_h2	86.51		2.23e-1		1.28e-1	
		noClust_h1_gbMean	88.89		1.85e-1		7.97e-2	
		noClust_h1_gbMin	88.89		1.85e-1		7.97e-2	
		noClust_h2	88.49		2.16e-1		8.60e-2	

Outline

1. Motivation
2. The Algorithm Configuration Problem
3. Our ML+MO take on the ACP
4. Implementation: the ML model counts – a lot!
5. Implementation: the nitty-gritty details count – a lot!
6. A glimpse to computational results
7. Conclusions

Conclusions and (a lot of) future work

- General concept and initial results promising
- Many other things to test, among which
  - results with more ML paradigms (Gabriele's talk)
  - different solvers (Octeract?) & classes of problems (MINLP)
  - different/wider sets of instances (MI[N]LPLib, . . .)
  - different performance metrics
- Most interesting ideas (to me):
  - different performance metrics during learning
  - specialised approaches for different CSSPs
  - extension to multilevel nested decomposition (SMS++)
- Most difficult challenges to overcome:
  - automatically finding the right set of features (SMS++?)
  - what if Feature Transformation (SVD) rather than FS?
  - designing a system/community to share the enormous training cost
- Lots of fun to be had


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