ALICE

Analysis & Learning Iterative Consecutive Executions

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Introduction

Motivation:

⋆ The general goal is to train optimisation algorithms, for an arbitrary problem domain, using data.

Contribution:

⋆ The main contribution of this thesis is towards a better understanding of how this training data should be constructed.

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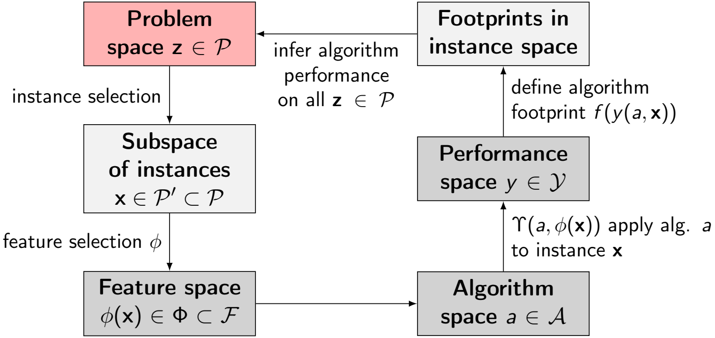
Framework for Algorithm Learning



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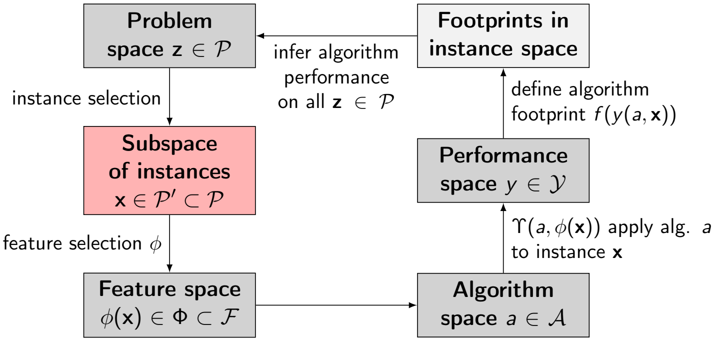

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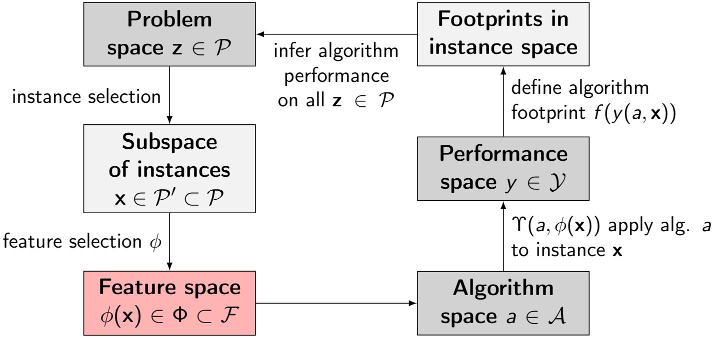

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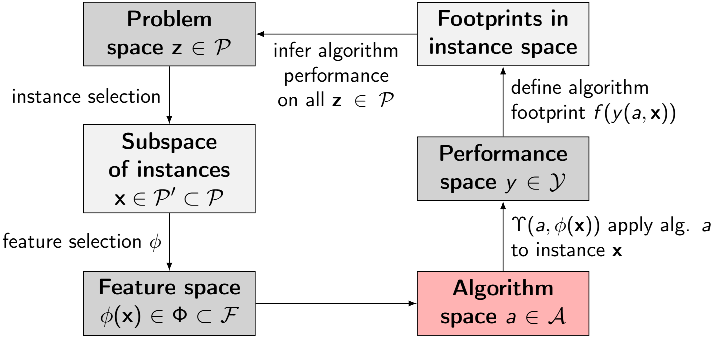

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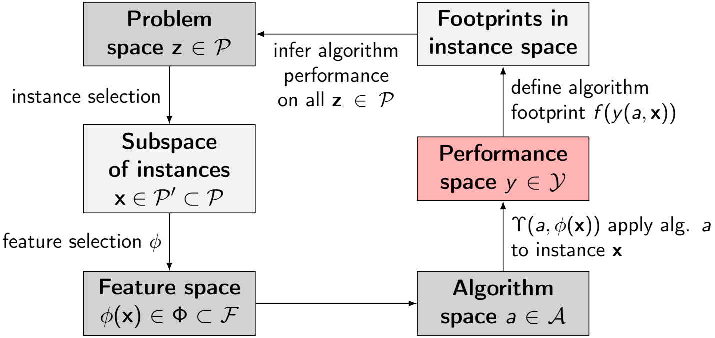

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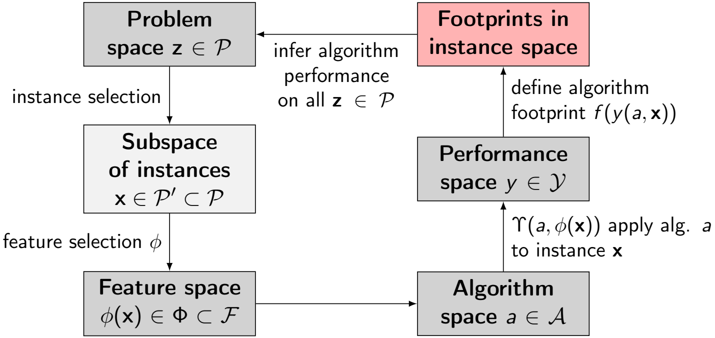

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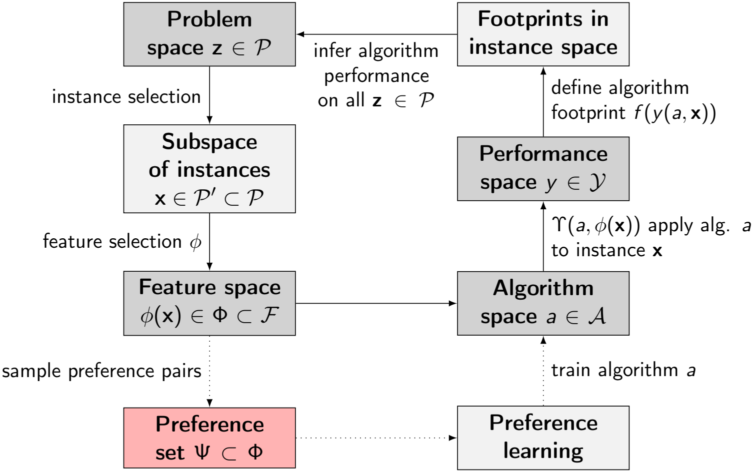

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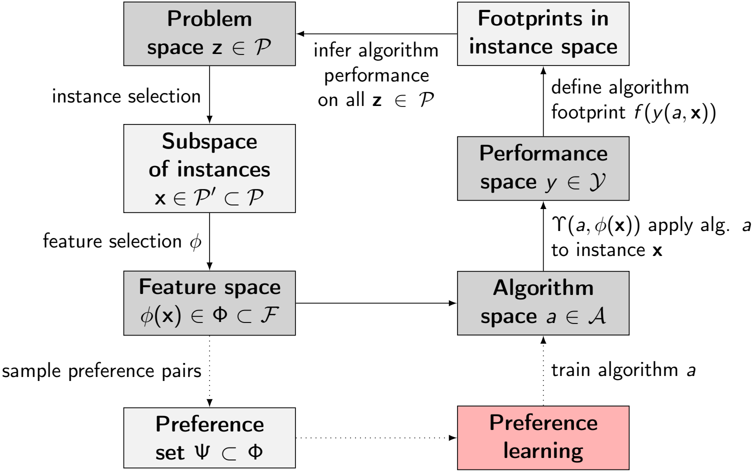

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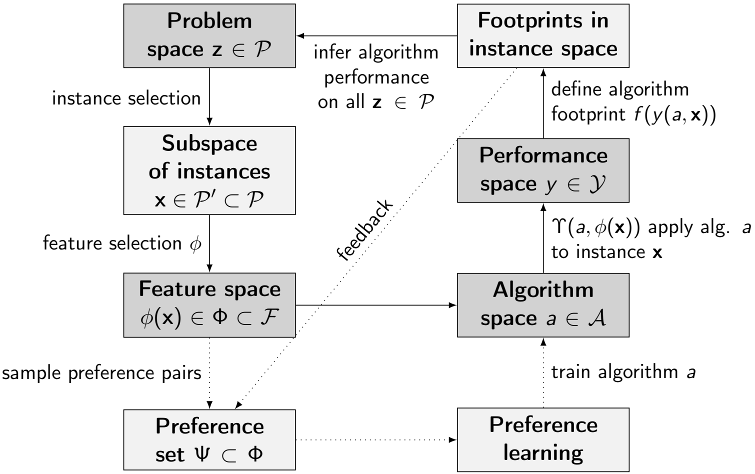

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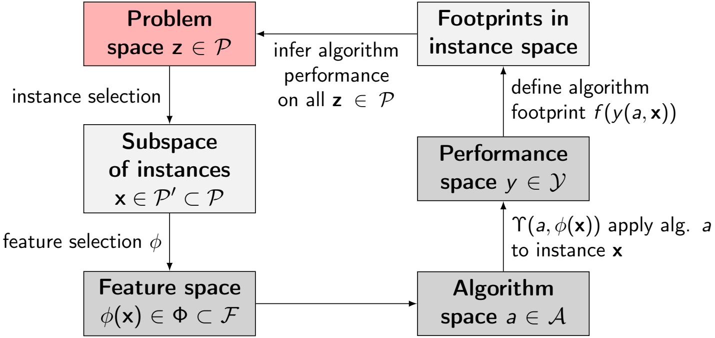


Job Shop Scheduling (JSP)

Simple job-shop is where n jobs are scheduled on a set of m machines, subject to constraints:

- ⋆ each job must follow a predefined machine order,
- ⋆ that a machine can handle at most one job at a time.

Objective: schedule the jobs so as to minimise the maximum completion time, i.e., makespan, $C_{\max}$.

Dispatching rules

Dispatching rules (DR) are consecutive executions found by:

- ⋆ Starting with an empty schedule and adding on one operation at a time.
- ⋆ When a machine is free the DR inspects the available jobs and selects the one with the highest priority.
- ⋆ Complete schedule consists of $\ell = n \cdot m$ sequential dispatches.
- ⋆ At each dispatch k, features $\phi(k)$ for the temporal schedule are calculated.

Mad Hatter tea-party (definition)

The attending guests:

J_1) Alice
J_2) March Hare
J_3) Dormouse
J_4) Mad Hatter.

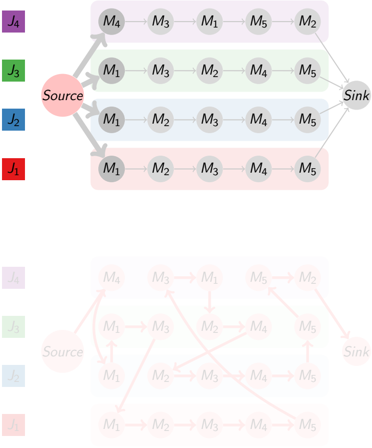
They all have to:

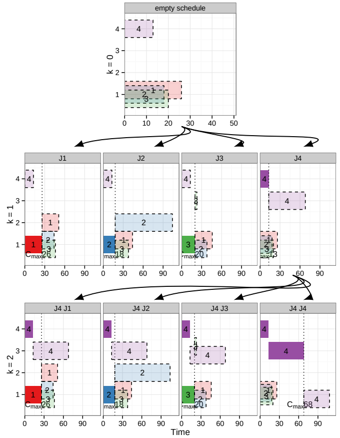
M_1) have wine or pour tea
M_2) spread butter
M_3) get a haircut
M_4) check the time of the broken watch
M_5) say what they mean.

This can be considered as is a typical 4×5 job-shop, where:

- ⋆ our guests are the jobs
- ⋆ their tasks are the machines
- ⋆ objective is to minimise $C_{\max}$ (when Alice can leave).

Mad Hatter tea-party (action states)





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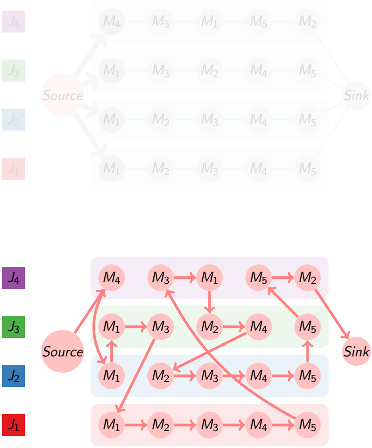

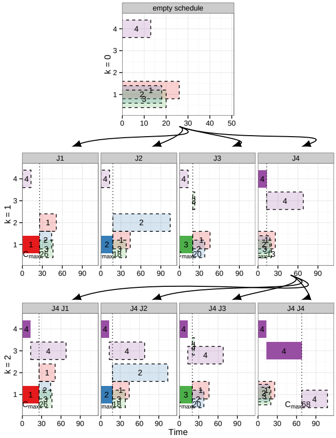

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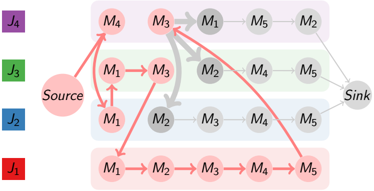
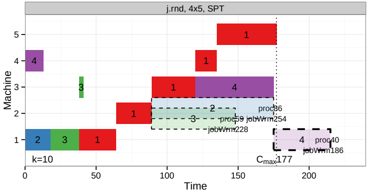
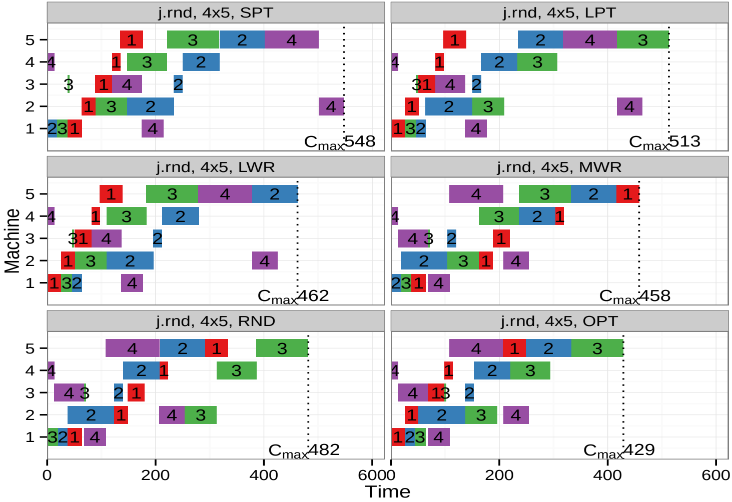




Mad Hatter tea-party (SDRs)



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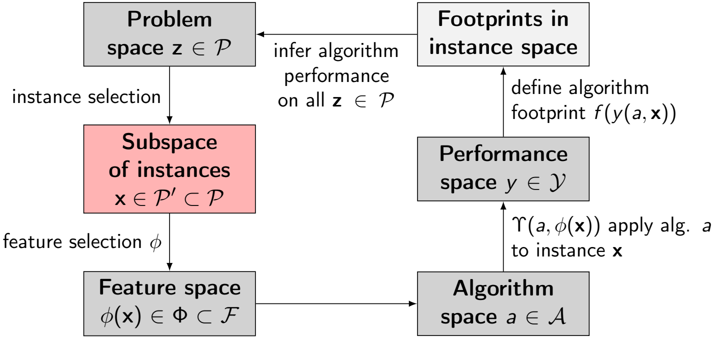

Problem instance generators

	name	size ($n \times m$)	N_{train}	N_{test}	note
JSP	$\mathcal{P}_{j.rnd}^{6\times5}$	6×5	500	500	random
	$\mathcal{P}_{j.rndn}^{6\times5}$	6×5	500	500	random-narrow
	$\mathcal{P}_{j.rnd,J_1}^{6\times5}$	6×5	500	500	random with job variation
	$\mathcal{P}_{j.rnd,M_1}^{6\times5}$	6×5	500	500	random with machine variation
	$\mathcal{P}_{j.rnd}^{10\times10}$	10×10	300	200	random
	$\mathcal{P}_{j.rndn}^{10\times10}$	10×10	300	200	random-narrow
	$\mathcal{P}_{j.rnd,J_1}^{10\times10}$	10×10	300	200	random with job variation
	$\mathcal{P}_{j.rnd,M_1}^{10\times10}$	10×10	300	200	random with machine variation
	$\mathcal{P}_{JSP.ORLIB}$	various	–	82	various
FSP	$\mathcal{P}_{f.rnd}^{6\times5}$	6×5	500	500	random
	$\mathcal{P}_{f.rndn}^{6\times5}$	6×5	500	500	random-narrow
	$\mathcal{P}_{f.jc}^{6\times5}$	6×5	500	500	job-correlated
	$\mathcal{P}_{f.mc}^{6\times5}$	6×5	500	500	machine-correlated
	$\mathcal{P}_{f.mxc}^{6\times5}$	6×5	500	500	mixed-correlation
	$\mathcal{P}_{f.rnd}^{10\times10}$	10×10	300	200	random
	$\mathcal{P}_{FPS.ORLIB}$	various	–	31	various

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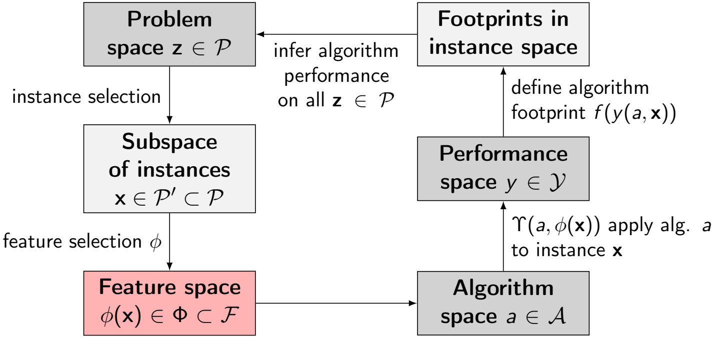

Features for JSP

job	ϕ_1	job processing time
	ϕ_2	job start-time
	ϕ_3	job end-time
	ϕ_4	job arrival time
	ϕ_5	time job had to wait
	ϕ_6	total processing time for job
	ϕ_7	total work remaining for job
	ϕ_8	number of assigned operations for job
machine	ϕ_9	when machine is next free
	ϕ_{10}	total processing time for machine
	ϕ_{11}	total work remaining for machine
	ϕ_{12}	number of assigned operations for machine
	ϕ_{13}	change in idle time by assignment
	ϕ_{14}	total idle time for machine
	ϕ_{15}	total idle time for all machines
	ϕ_{16}	current makespan
final makespan	ϕ_{17}	final makespan using SPT
	ϕ_{18}	final makespan using LPT
	ϕ_{19}	final makespan using LWR
	ϕ_{20}	final makespan using MWR
	ϕ_{RND}	final makespans using 100 random rollouts
	ϕ_{21}	mean for ϕ_{RND}
	ϕ_{22}	standard deviation for ϕ_{RND}
	ϕ_{23}	minimum value for ϕ_{RND}
	ϕ_{24}	maximum value for ϕ_{RND}

ALICE

Helga

Trajectory strategies for Φ

Following the policy:

- (Φ^{OPT}) expert $\pi_\star$.
- ($\Phi^{ES.\rho}$) the policy obtained by optimising with CMA-ES.
- (Φ^{SPT}) shortest processing time (SPT).
- (Φ^{LPT}) longest processing time (LPT).
- (Φ^{LWR}) least work remaining (LWR).
- (Φ^{MWR}) most work remaining (MWR).
- (Φ^{RND}) random policy (RND).
- (Φ^{ALL}) union of all of the above.

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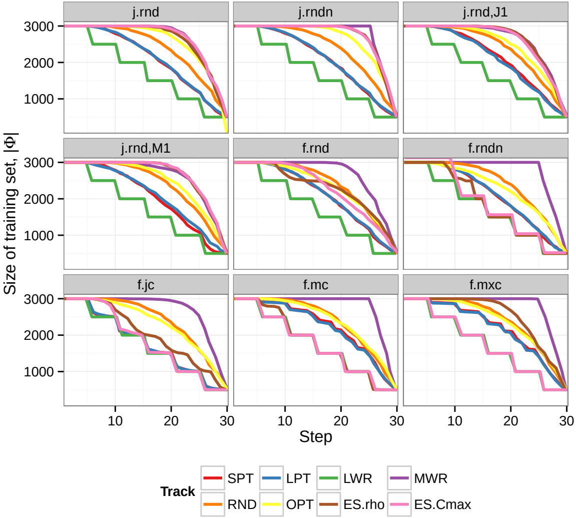
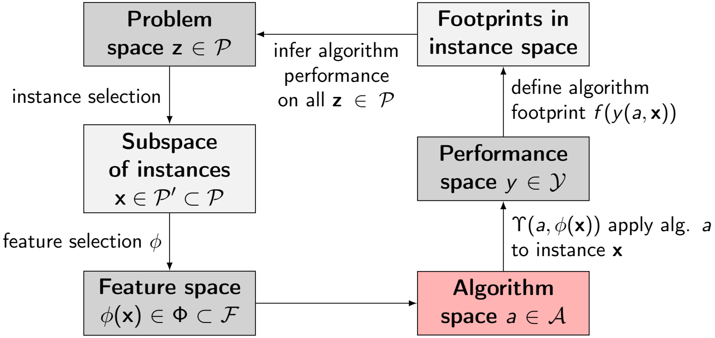
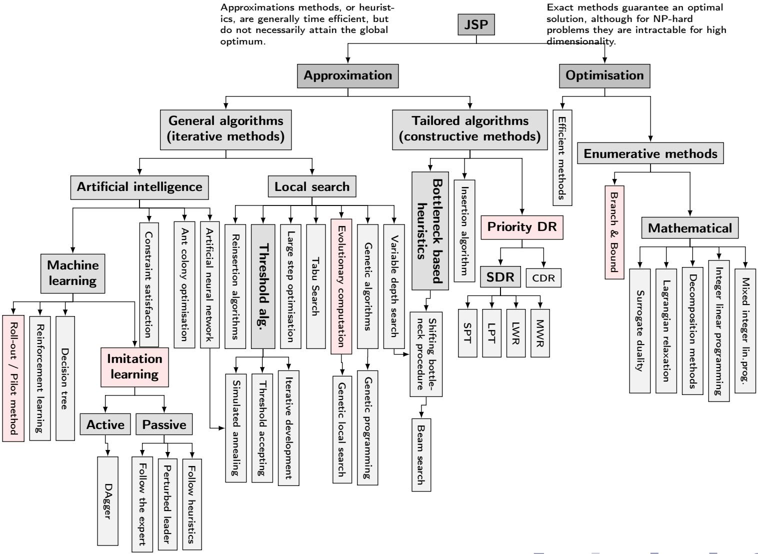
Sampled size of $|\Phi|$ $(6 \times 5, N_{train} = 500)$



Framework for Algorithm Learning



Various Methods for Solving JSP



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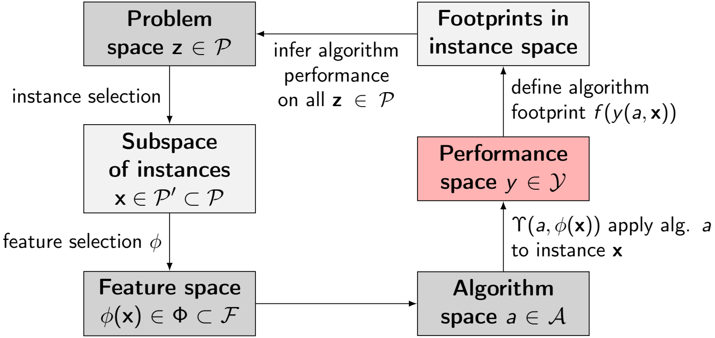

Performance measure

Performance of policy π compared with its optimal makespan, found using an expert policy, $\pi_\star$, is the following loss function:

$$\rho = \frac{C_{\max}^{\pi} - C_{\max}^{\pi_\star}}{C_{\max}^{\pi_\star}} \cdot 100\%$$

The goal is to minimise this discrepancy between predicted value and true outcome.

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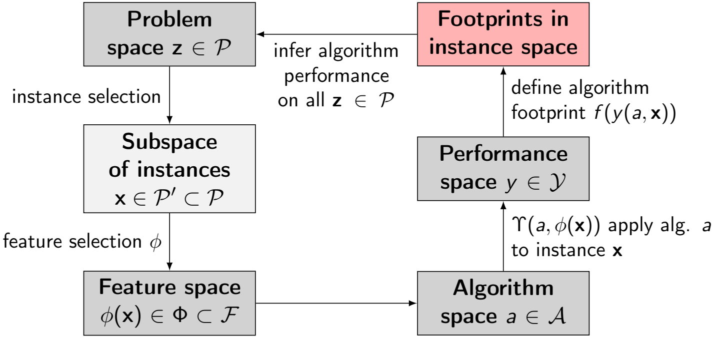
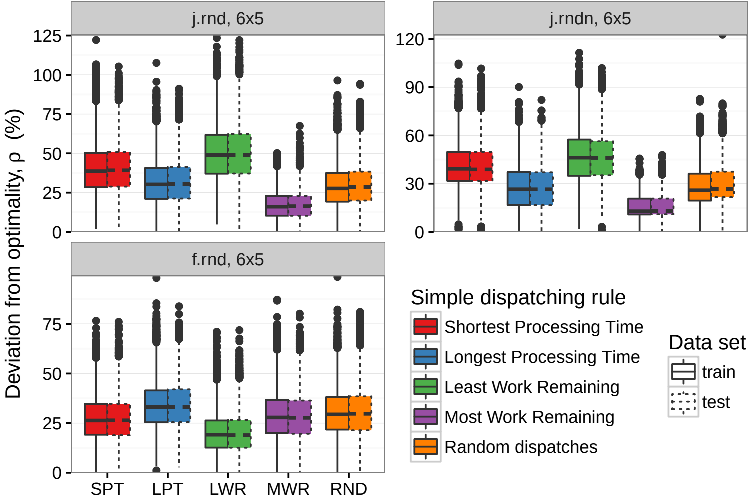


Deviation from optimality, ρ



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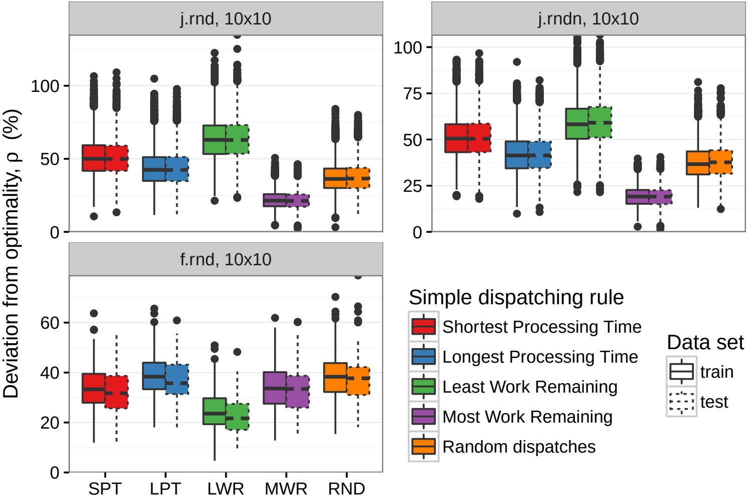
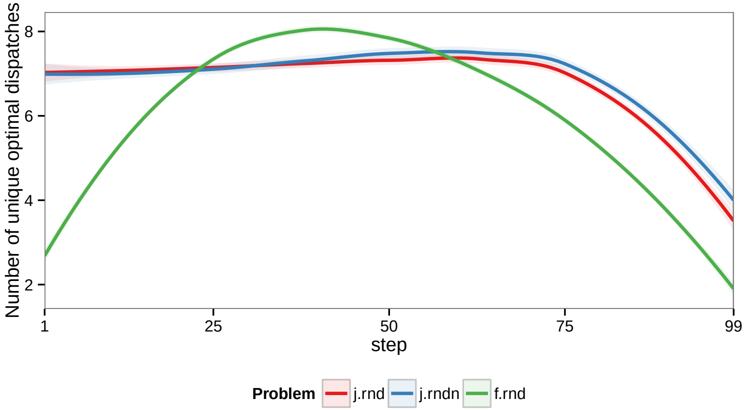


Making optimal decisions, $\xi_\pi^\star$



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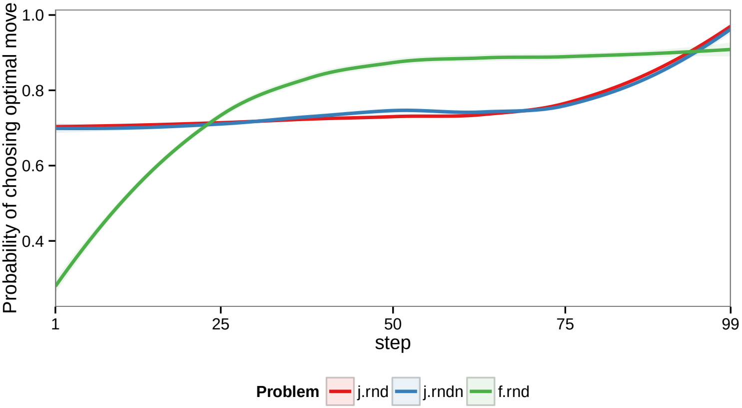

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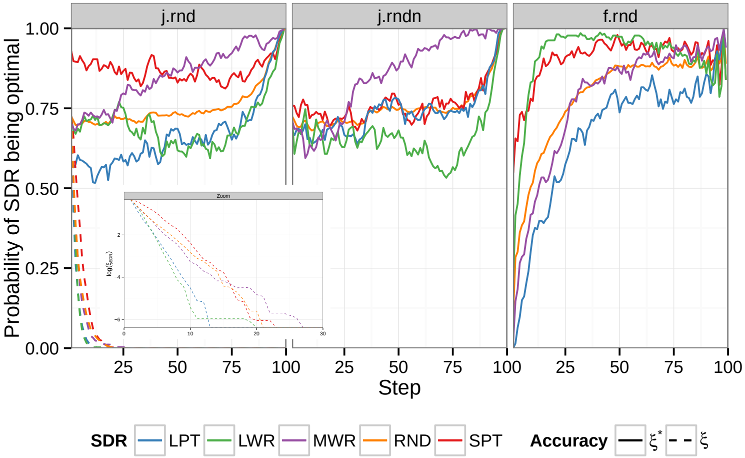
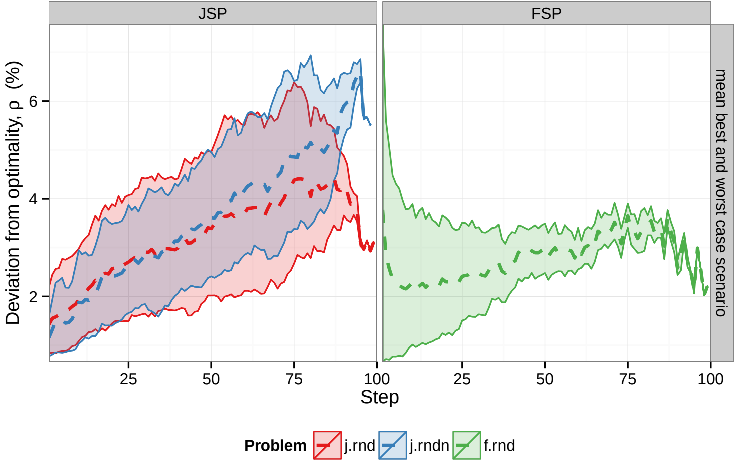


Impact of suboptimal decision, $\{\zeta^\star_{\min}, \zeta^\star_{\max}\}$



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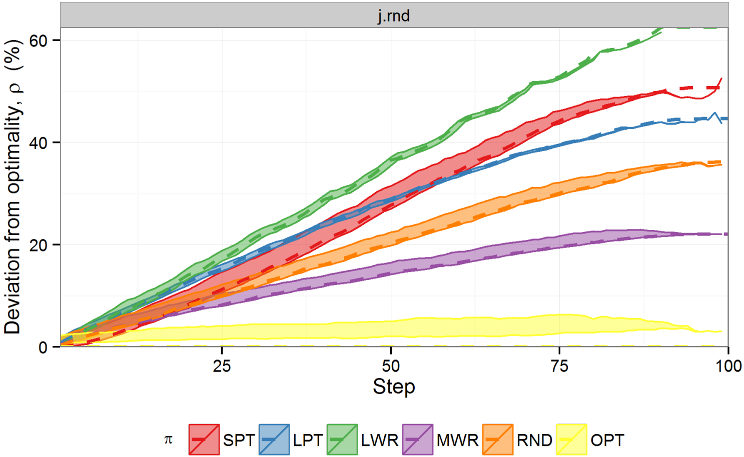
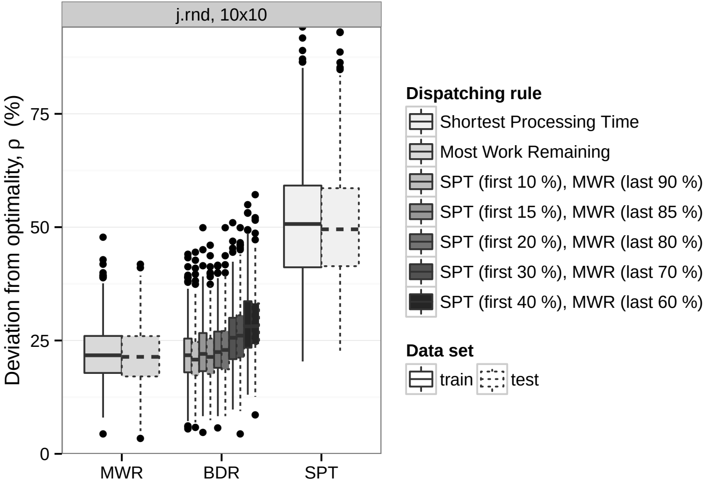


Blended dispatching rule



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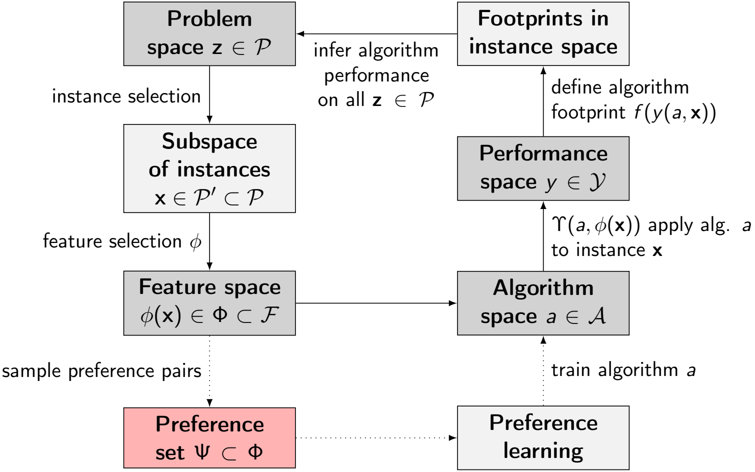

Generating training data

ALICE framework for creating dispatching rules:

- ⋆ Linear classification to identify good dispatches, from worse ones.
- ⋆ Generate feature set, $\Phi \subset \mathcal{F}$, both from
  - ⋆ optimal solutions, ϕ^o
  - ⋆ suboptimal solutions, ϕ^s

  by exploring various trajectories within the feature-space (where $\phi^o, \phi^s \in \mathcal{F}$).
- ⋆ Sample Φ to create training set Ψ with rank pairs:
  - ⋆ optimal decision, $(\mathbf{z}^o, y_o) = (\phi^o - \phi^s, +1)$
  - ⋆ suboptimal decision, $(\mathbf{z}^s, y_s) = (\phi^s - \phi^o, -1)$

  using different ranking schemes (where $\mathbf{z}^o, \mathbf{z}^s \in \Psi$)
- ⋆ Sample Ψ using stepwise bias for time independent policy.

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Ranking schemes for Ψ

Sampling rankings of available jobs where where $r_1 > r_2 > \cdots > r_{n'}$ $(n' \leq n)$ with respect to:

- Ψ_b all opt rankings r_1 vs. all possible subopt rankings r_i, $i \in \{2, ..., n'\}$
- Ψ_f full subsequent rankings, i.e., all combinations of r_i and r_{i+1} for all $i \in \{1, ..., n'\}$.
- Ψ_p partial subsequent rankings, similar to Ψ_f except if there are more than one operation with the same rank, only one is needed to be compared to subsequent rank $(\Psi_p \subset \Psi_f)$.
- Ψ_a union of all of the above.

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- Ψ_b all opt rankings r_1 vs. all possible subopt rankings r_i, $i \in \{2, ..., n'\}$
- Ψ_f full subsequent rankings, i.e., all combinations of r_i and r_{i+1} for all $i \in \{1, ..., n'\}$.
- Ψ_p partial subsequent rankings, similar to Ψ_f except if there are more than one operation with the same rank, only one is needed to be compared to subsequent rank $(\Psi_p \subset \Psi_f)$.
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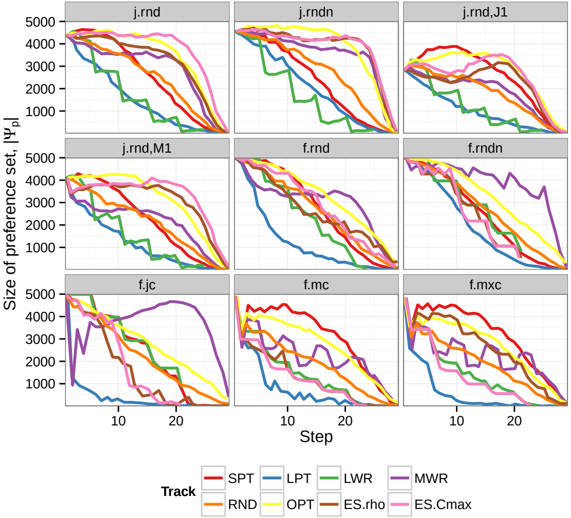
Sampled size of $|\Psi|$ $(6 \times 5, N_{train} = 500)$



Stepwise bias for sampling Ψ

Sampling stepwise bias for preference pairs:

- $\star$ (equal) equal probability.
- $\star$ (opt) inverse optimality for random dispatches – $1 - \xi^{\star}_{\text{RND}}$.
- $\star$ (bcs) best case scenario for mean ρ – $\zeta^{\star}_{\min}$.
- $\star$ (wcs) worst case scenario for mean ρ – $\zeta^{\star}_{\max}$.
- $\star$ (featsize) inversely proportional to $|\Phi^{\text{OPT}}|$
- $\star$ (prefsize) inversely proportional to $|\Psi_p^{\text{OPT}}|$
- $\star$ (dbl1st) twice as much weight on the first half of the dispatches.
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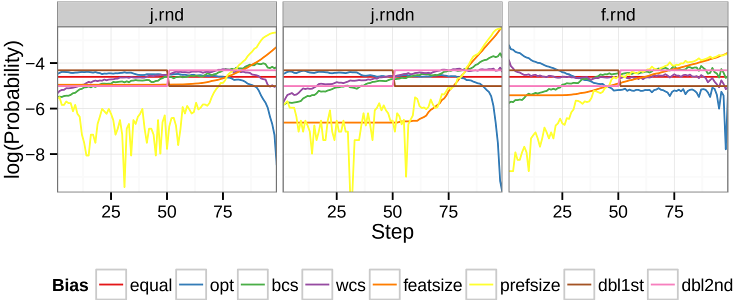
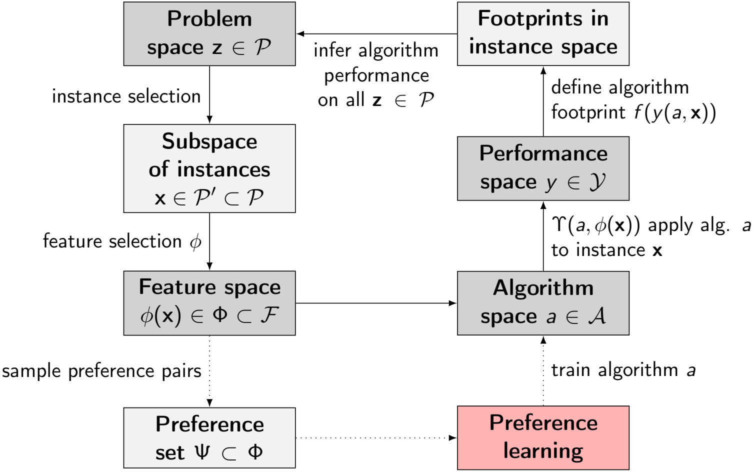


Framework for Algorithm Learning



Ordinal Regression

Preference learning:

- ⋆ Mapping of points to ranks: $\{h(\cdot) : \Phi \mapsto Y\}$ where

$$\phi_o \succ \phi_s \quad \Longleftrightarrow \quad h(\phi_o) > h(\phi_s)$$

- ⋆ The preference is defined by a linear function:

$$h(\phi) = \sum_{i=1}^{d} w_i \phi$$

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Passive imitation learning (single pass):

- ⋆ Prediction with expert advice, $\pi_\star$ – Gurobi
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Active imitation learning (iterative):

- ⋆ Dataset Aggregation (DAgger)

$$\pi_i = \beta_i \pi_\star + (1 - \beta_i)\hat{\pi}_{i-1}$$

where $\hat{\pi}_{i-1}$ is the previous learned model, and $\hat{\pi}_i$ learns on

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Require: $T \geq 1$

procedure DAgger($\pi_\star, \Phi^{\text{IL}0}, T$)

  $\hat{\pi}_0 \leftarrow$ Train($\Phi^{\text{IL}0}$) ▷ initial model, iff $\Phi^{\text{IL}0} = \Phi^{\text{OPT}}$

  for $i \leftarrow 1$ **to** T **do** ▷ at each imitation learning iteration

    Let $\pi_i = \beta_i \pi_\star + (1 - \beta_i)\hat{\pi}_{i-1}$

    Sample a K-solution using π_i ▷ IL($i, \hat{\pi}_{i-1}, \pi_\star$)

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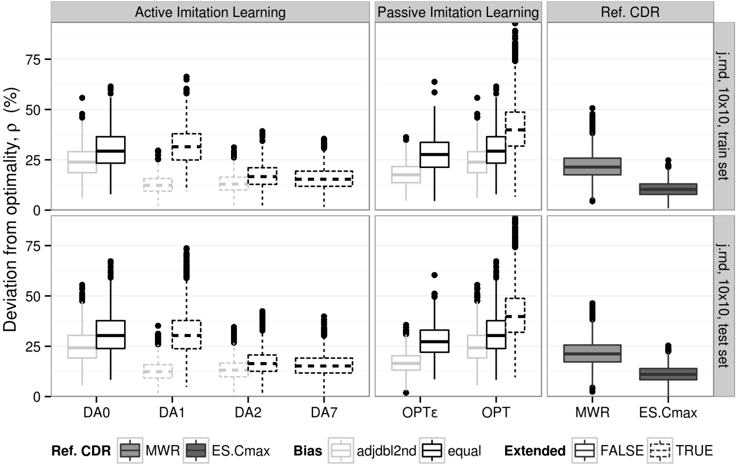
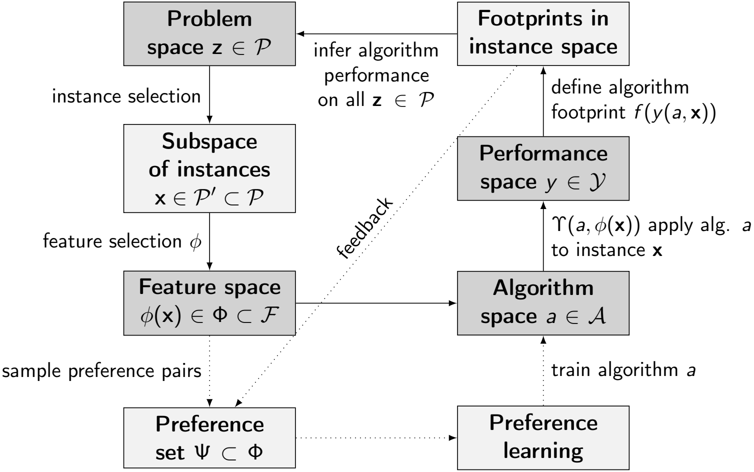


Framework for Algorithm Learning



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- ⋆ Learning optimal trajectories predominant in literature. Study showed Φ^{OPT} can result in insufficient knowledge.
- ⋆ Following sub-optimal deterministic policies, yet labelling with an optimal solver, improves the guiding policy.
- ⋆ In sequential decision making, all future observations are dependent on previous operations. Active update procedure using DAgger ensures sample states the learned model is likely to encounter is integrated to $\Psi_p^{\mathrm{DA}i}$.
- ⋆ Instead of reusing same problem instances, extend the training set with new instances for quicker convergence of DAgger.

Future work

Main conclusions:

- ⋆ .

Thank you for your attention

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Supplementary material:

- ⋆ Shiny application
- ⋆ Github.