ALICE

Analysis & Learning Iterative Consecutive Executions

Helga Ingimundardóttir

University of Iceland

June 30, 2016

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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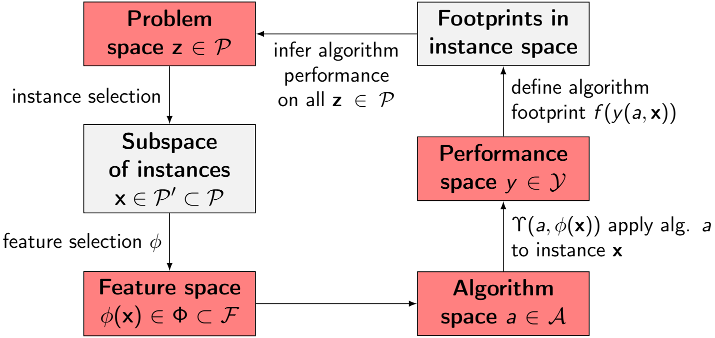
Framework for Algorithm Learning



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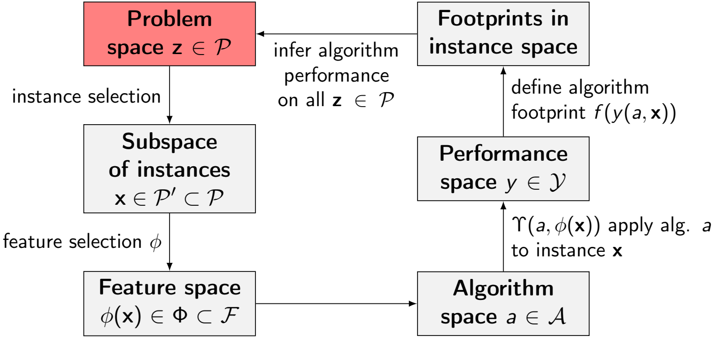

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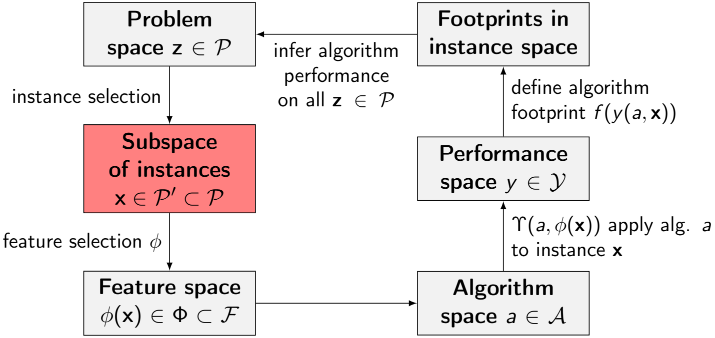

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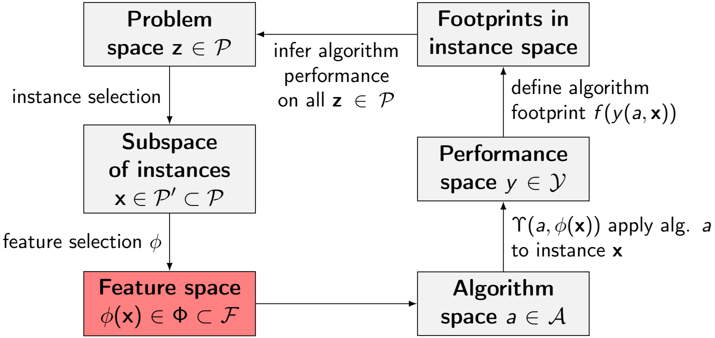

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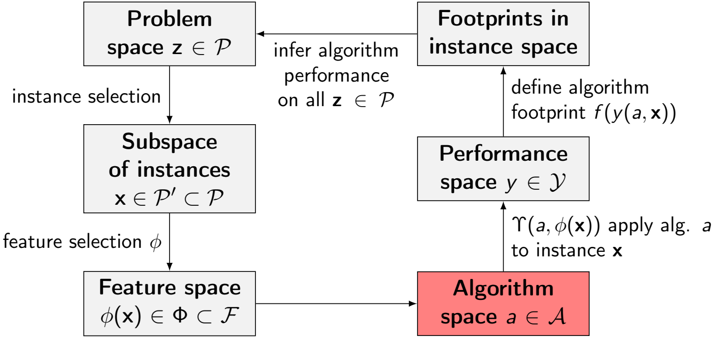

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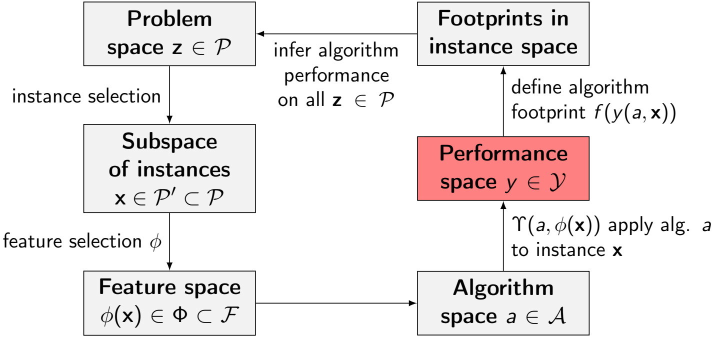

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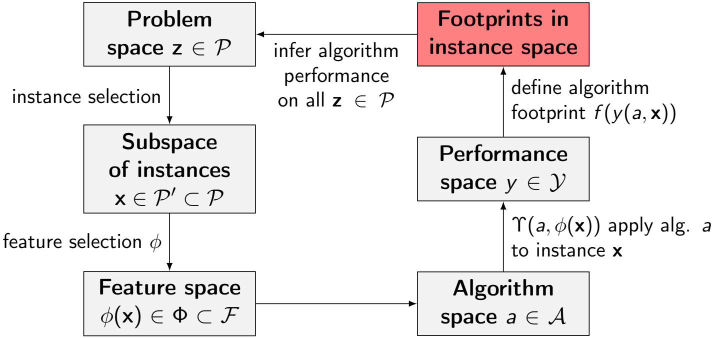

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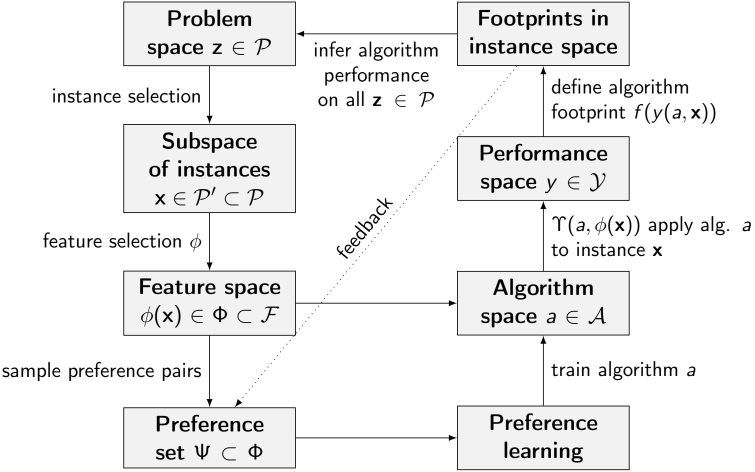

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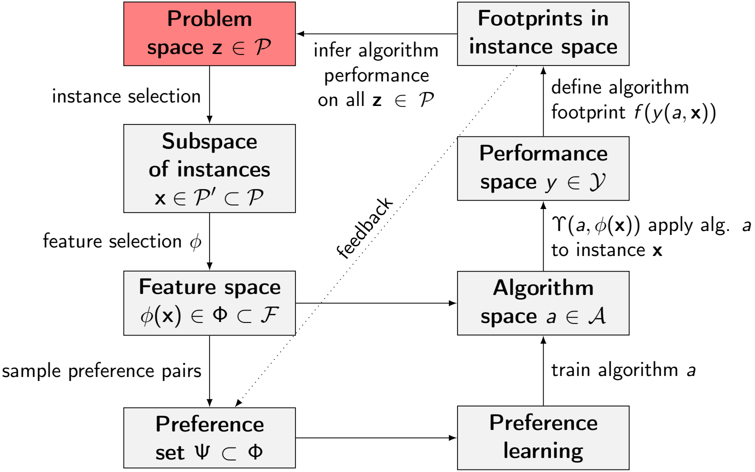

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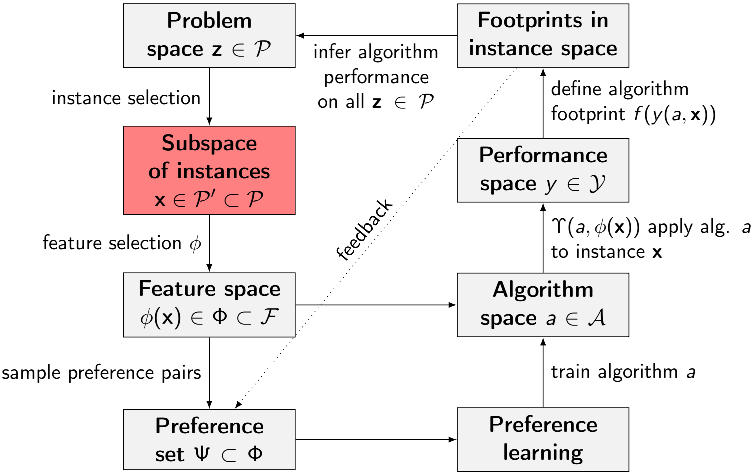

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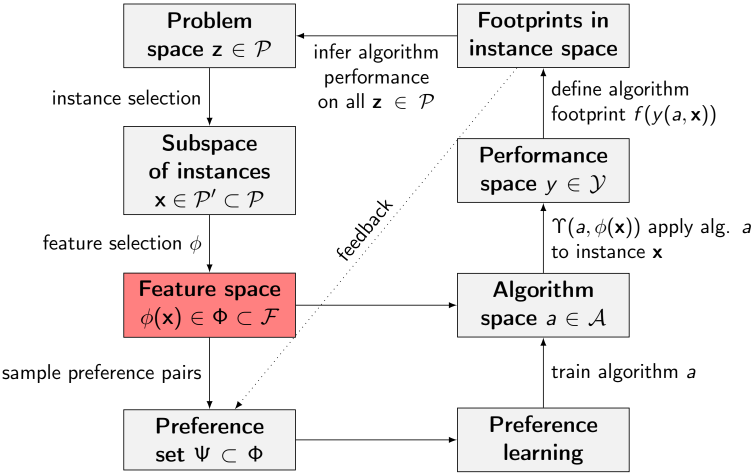

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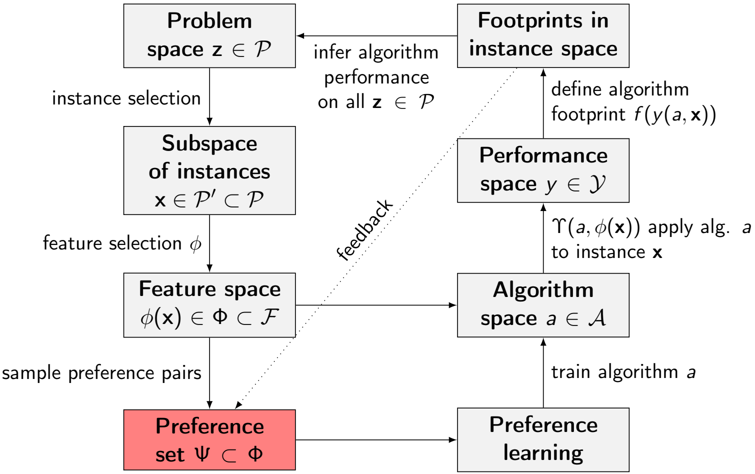

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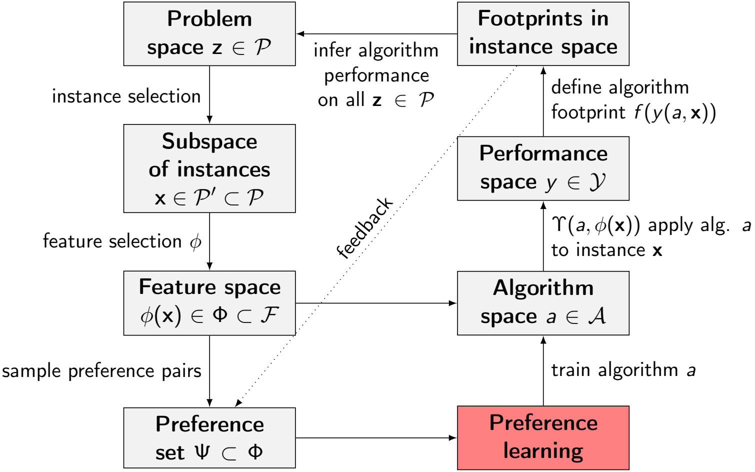

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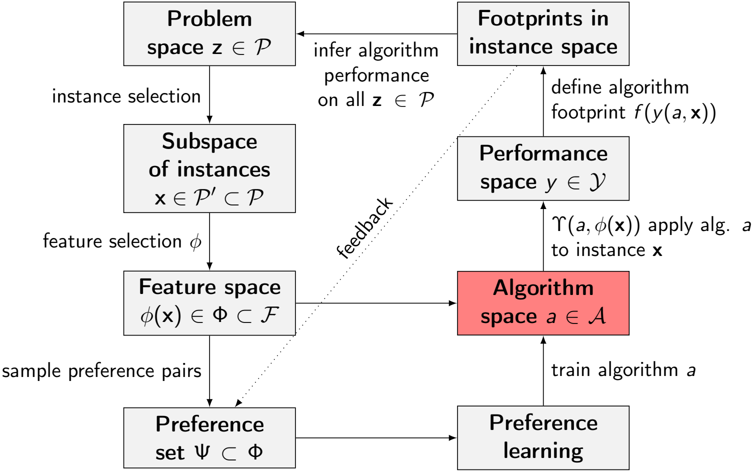

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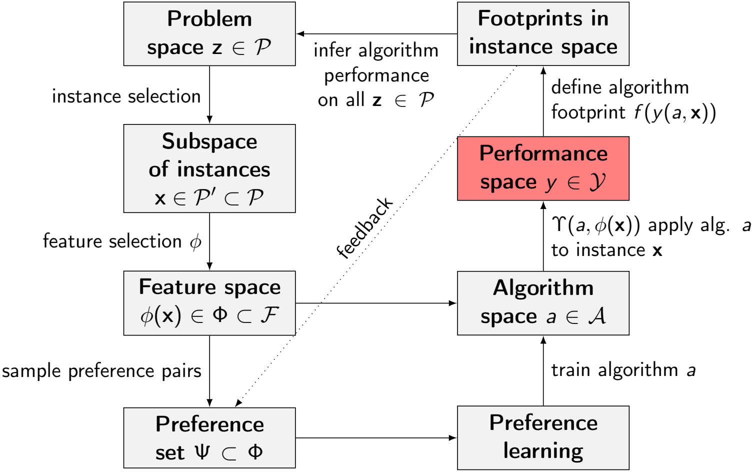

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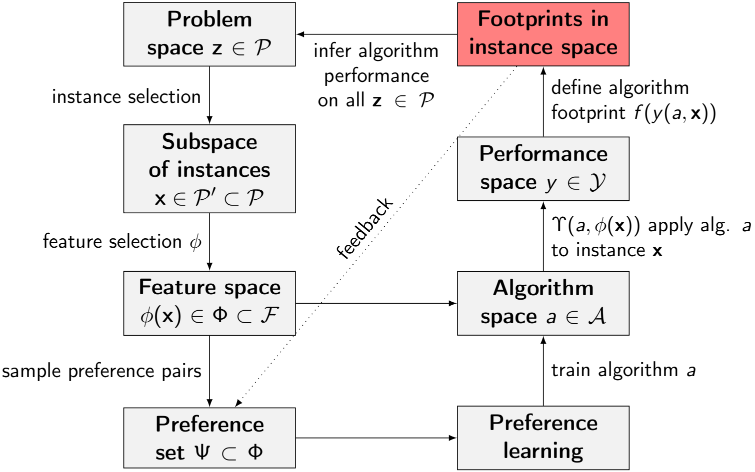

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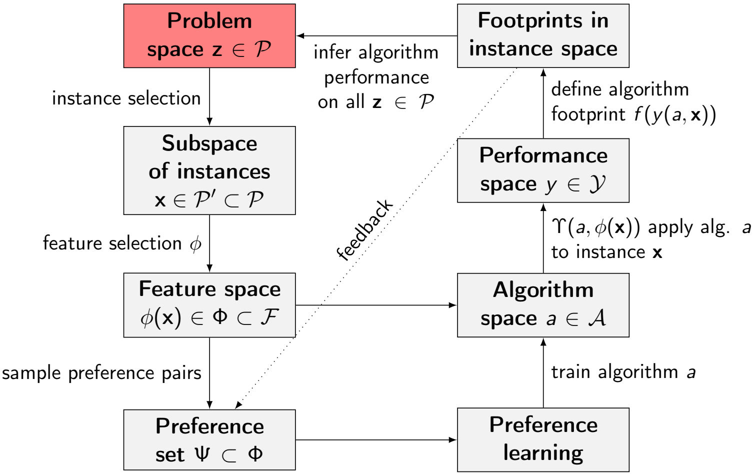

Mad Hatter tea-party (definition)

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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).

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Mad Hatter tea-party (k-solutions)

Start: $k = 0$

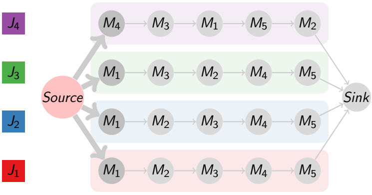

Figure: Disjunctive graph

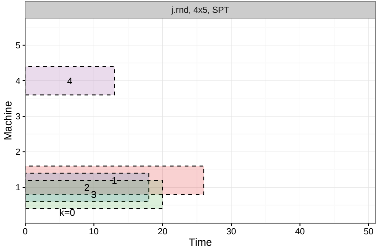

Figure: Gantt chart

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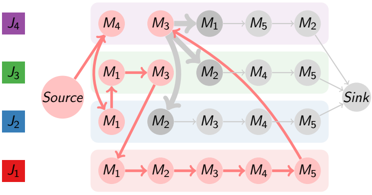
Midway: $k = 10$



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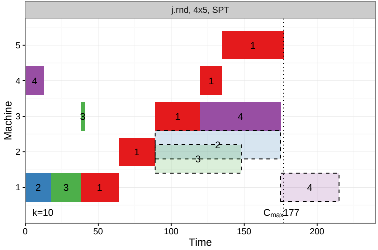
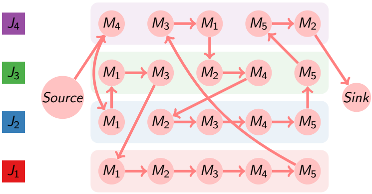


Figure: Gantt chart

Mad Hatter tea-party (k-solutions)

Finish: $k = 20$



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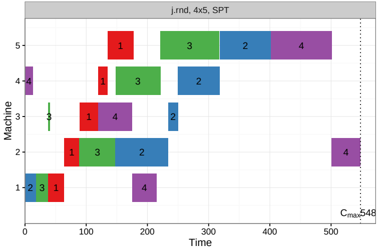

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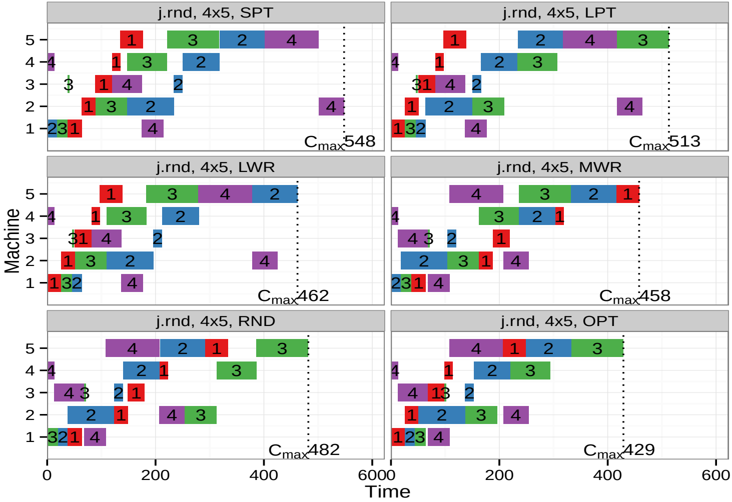

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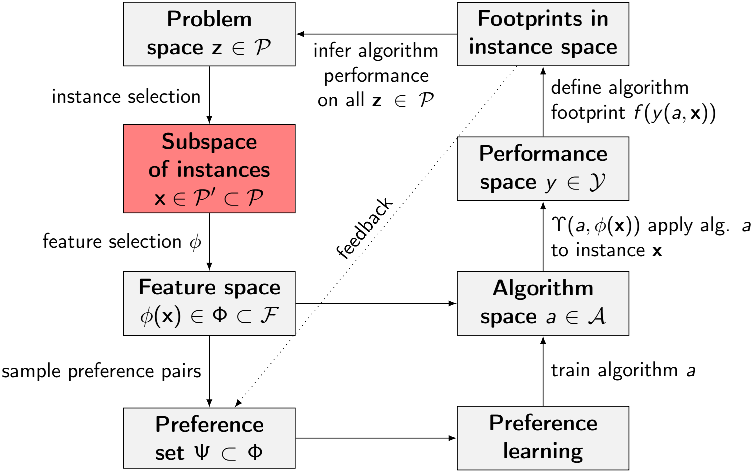

Problem instance generators

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

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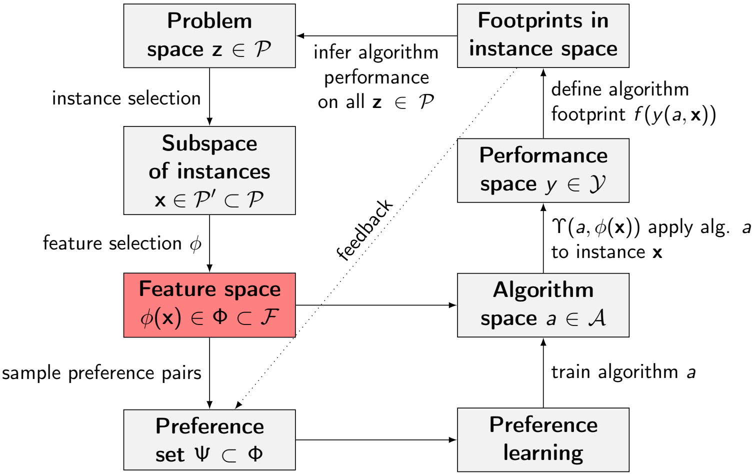

Features for JSP

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}

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machine	ϕ_9	when machine is next free
	ϕ_{10}	total processing time for machine
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Trajectory strategies for Φ

Following the policy:

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

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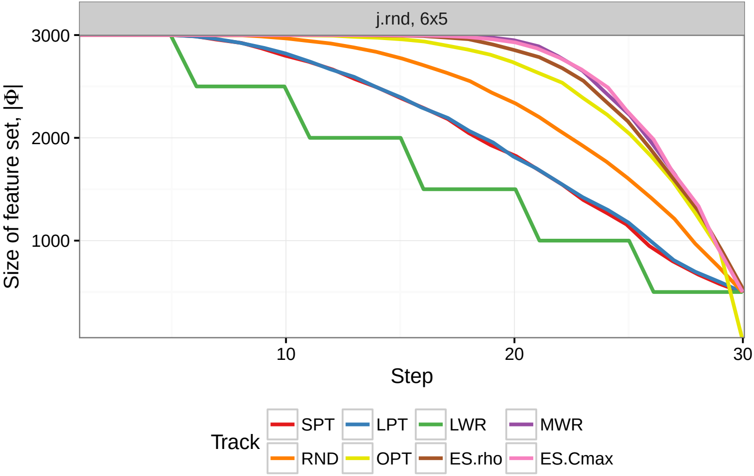
Sampled size of $|\Phi(k)|$

$(6 \times 5, N_{train} = 500)$



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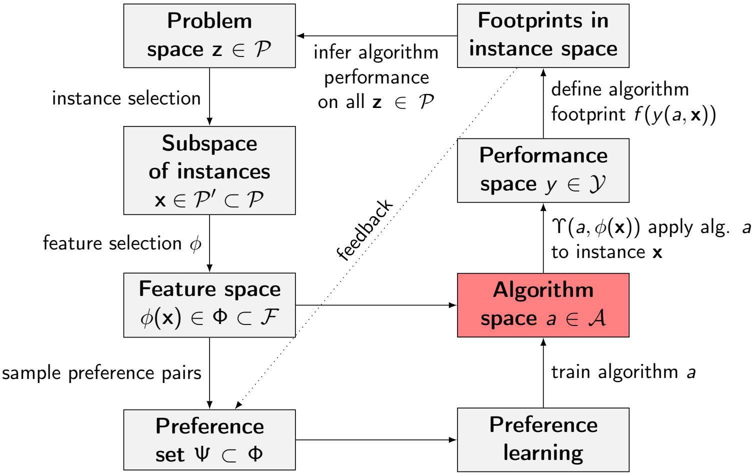
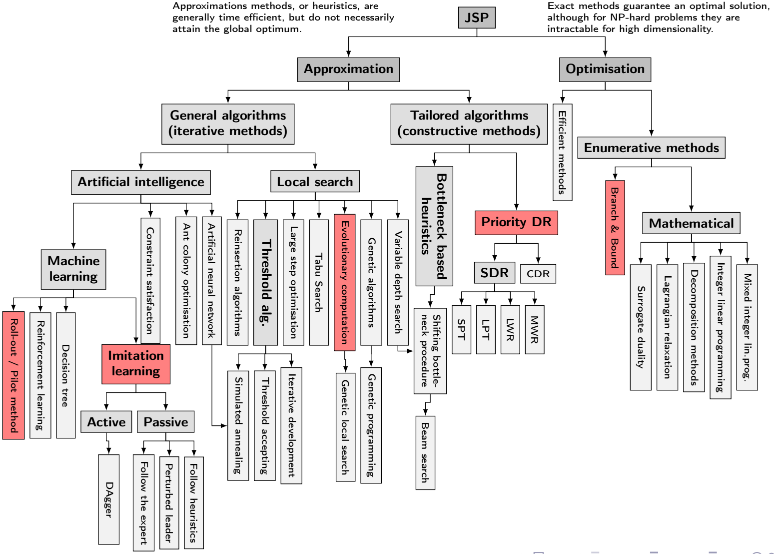


Various Methods for Solving JSP



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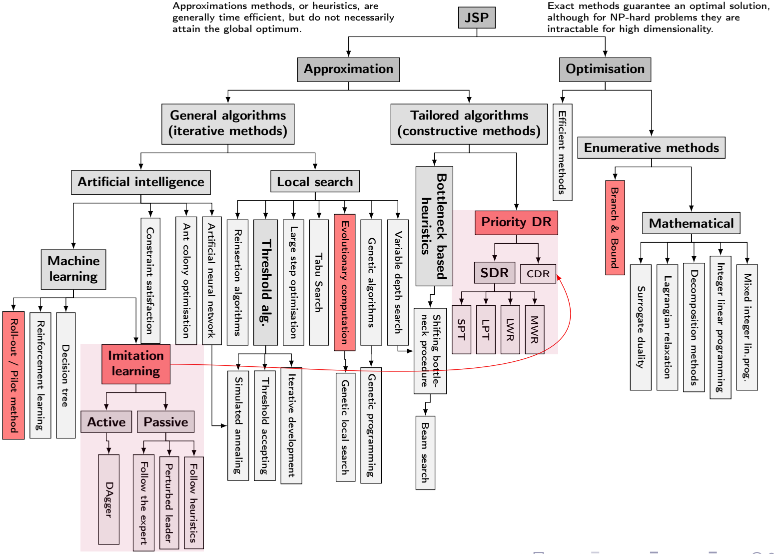

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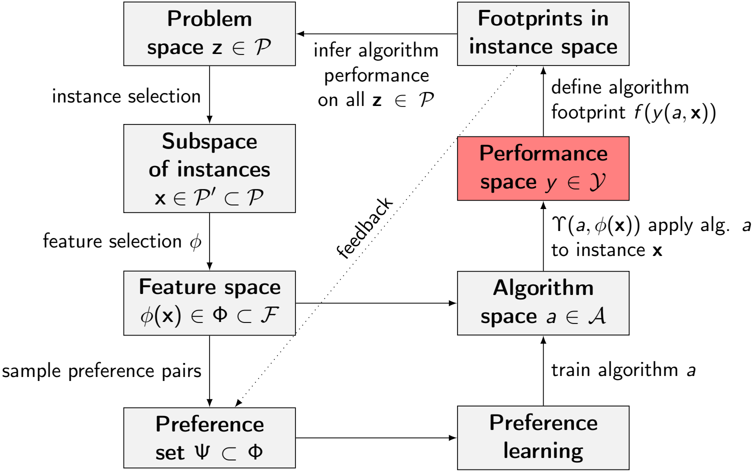

Performance measure

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

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

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

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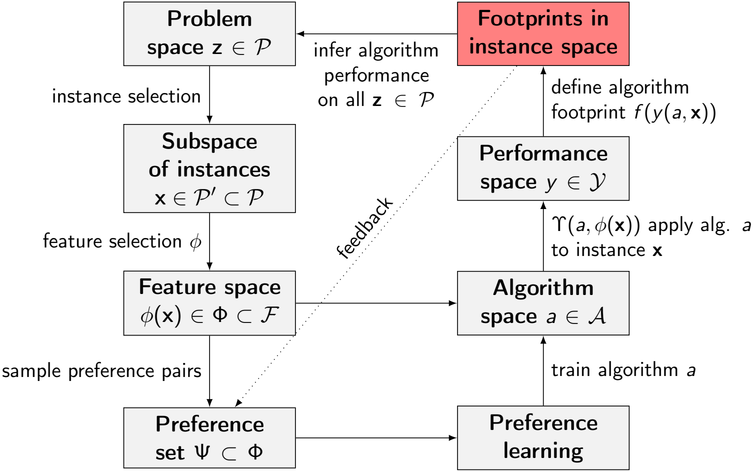
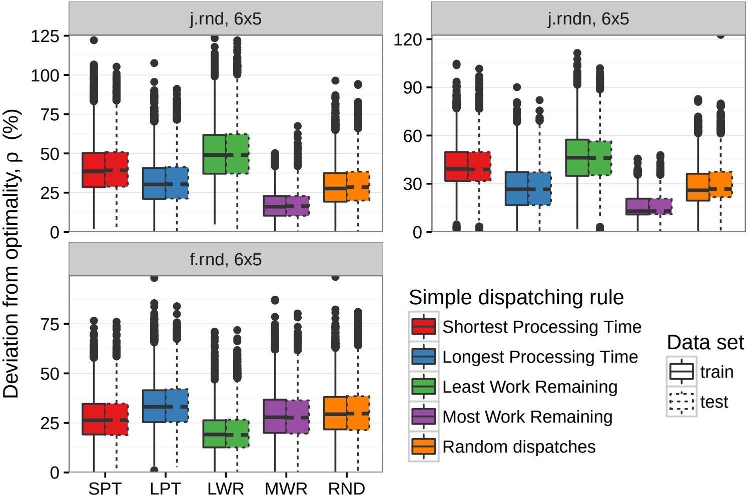


Deviation from optimality, ρ



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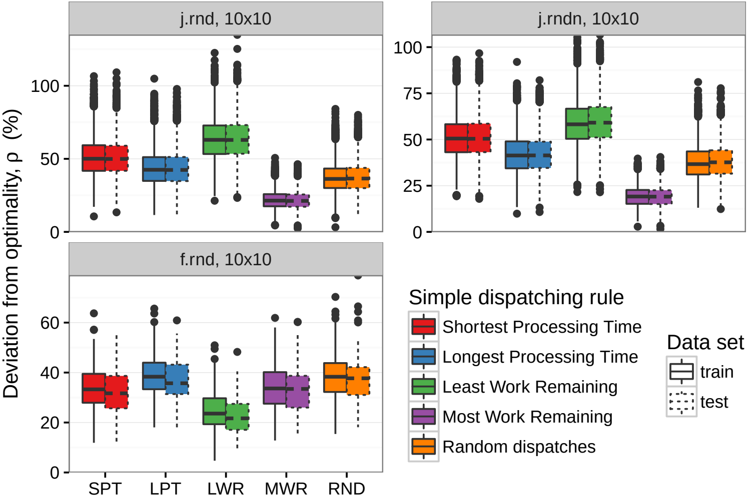
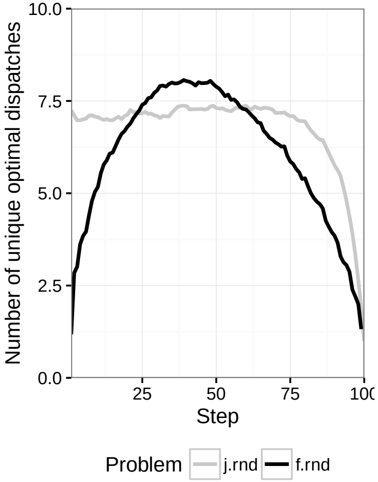


Making optimal decisions, $\xi_\pi^\star$



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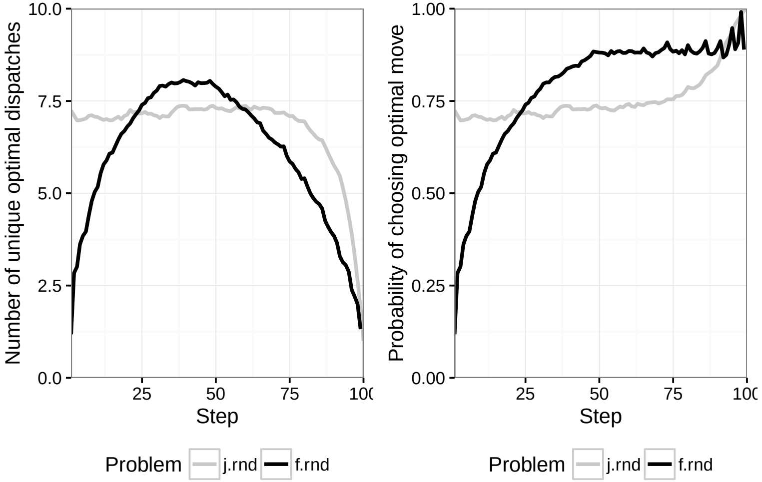
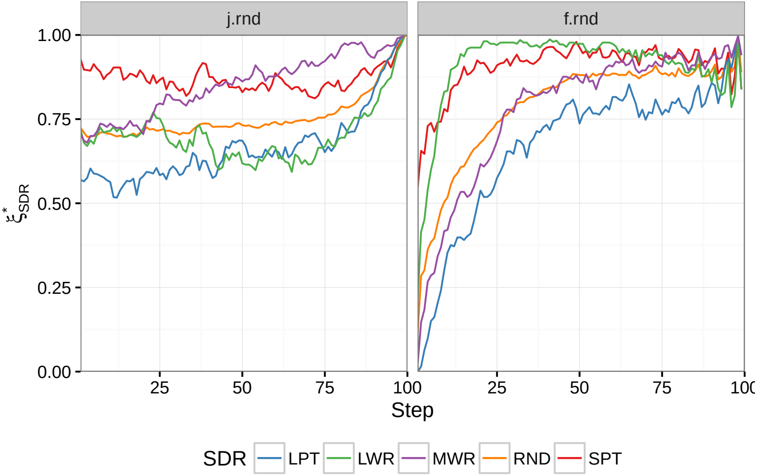
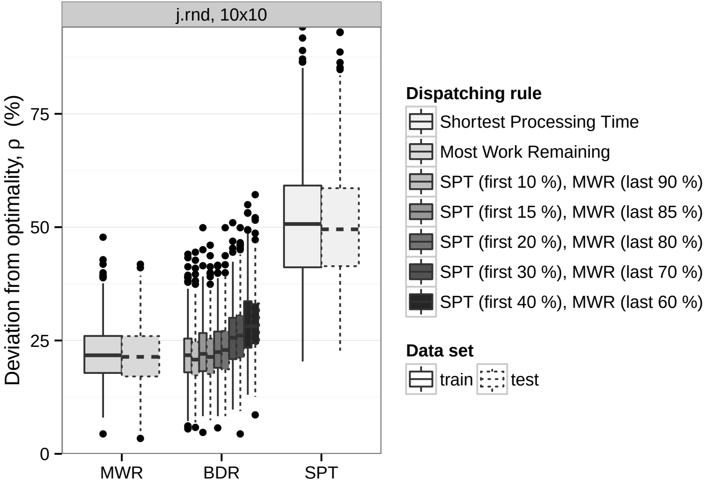


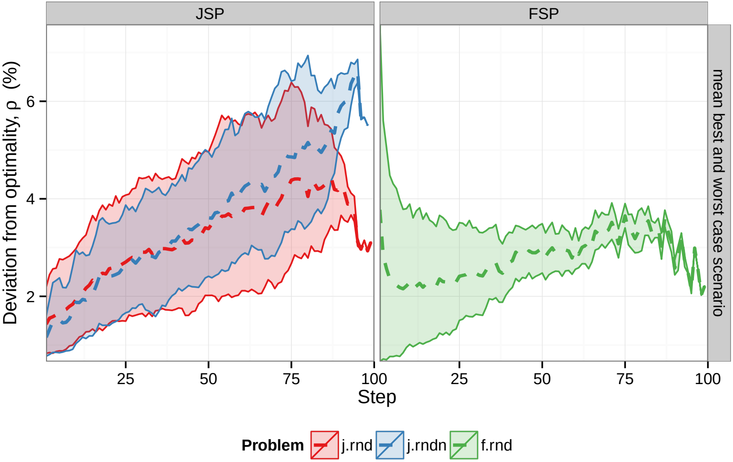
Probability of SDR being optimal, $\xi^{\star}_{\langle \text{SDR} \rangle}$



Blended dispatching rule



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



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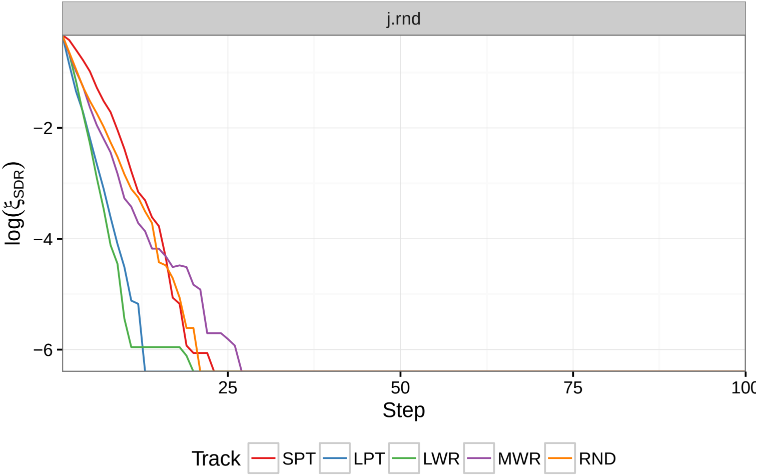

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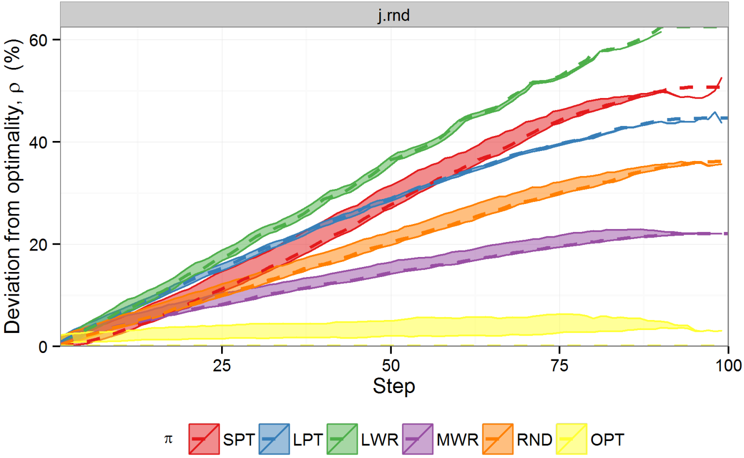
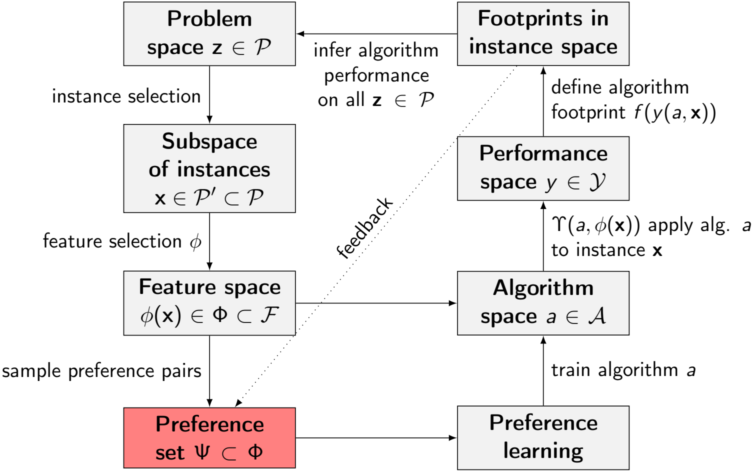


Framework for Algorithm Learning



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:
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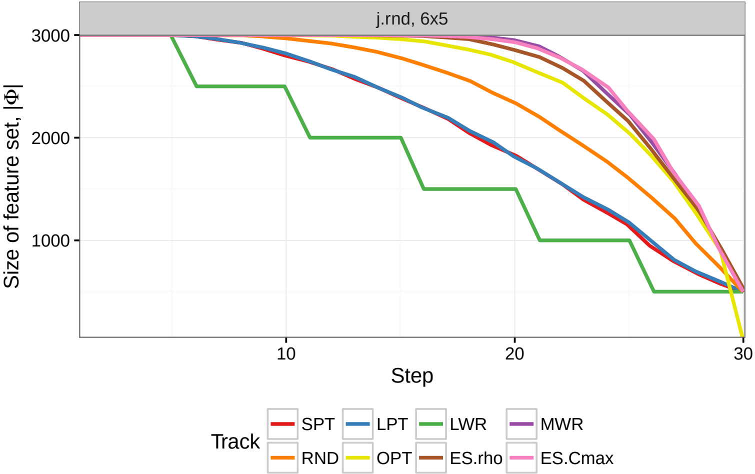
Sampled size of $|\Phi(k)|$

$(6 \times 5, N_{train} = 500)$



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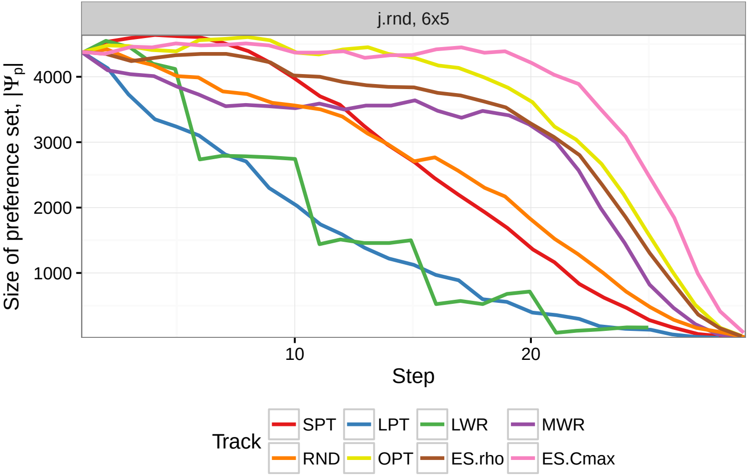

Stepwise bias strategies
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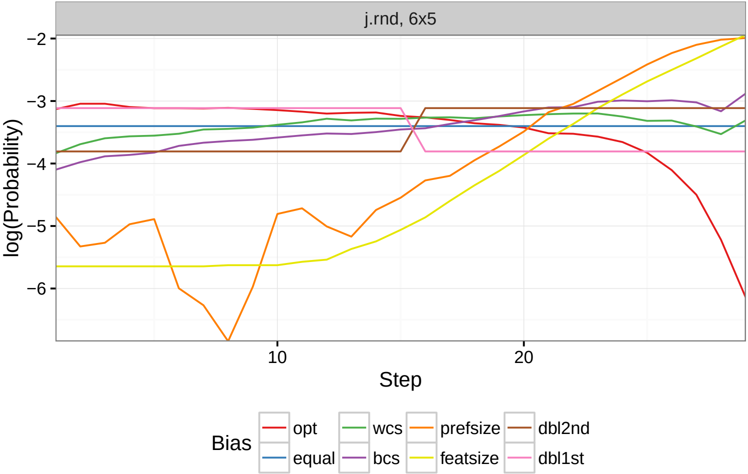
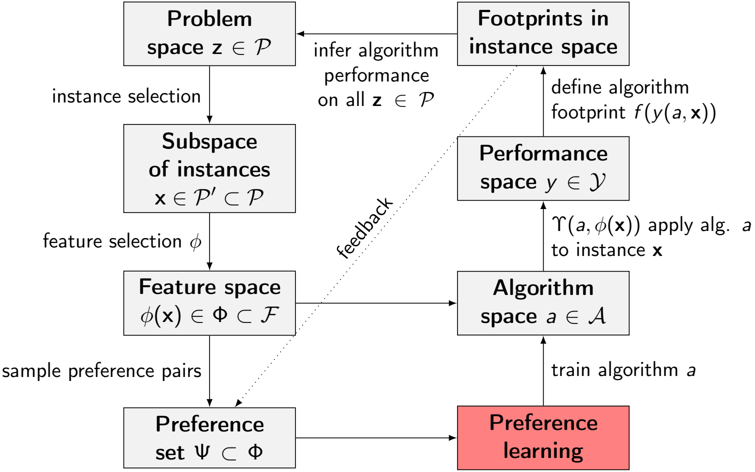


Framework for Algorithm Learning



Preference learning:

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

$$\phi_o \succ \phi_s \iff h(\phi_o) > h(\phi_s)$$

- ⋆ The preference is defined by a linear function:

$$h(\phi) = \langle w_i \cdot \phi \rangle$$

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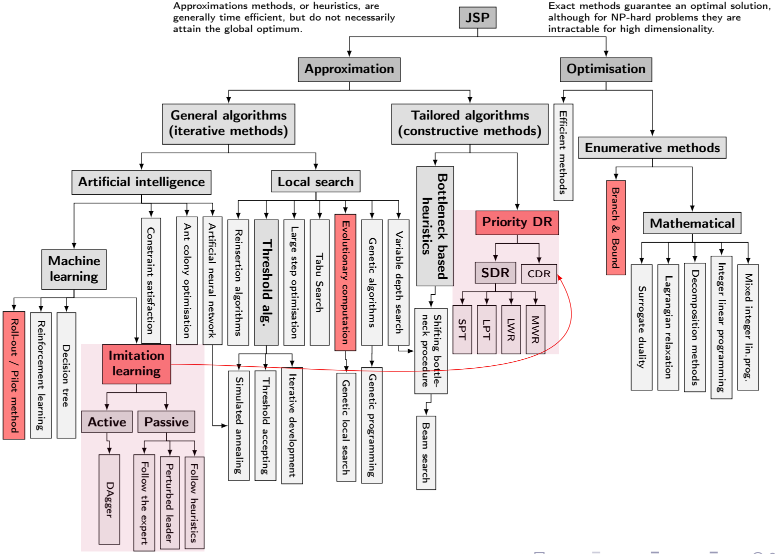
Various Methods for Solving JSP



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Passive imitation learning (single pass):

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- Follow the perturbed leader (OPTϵ)
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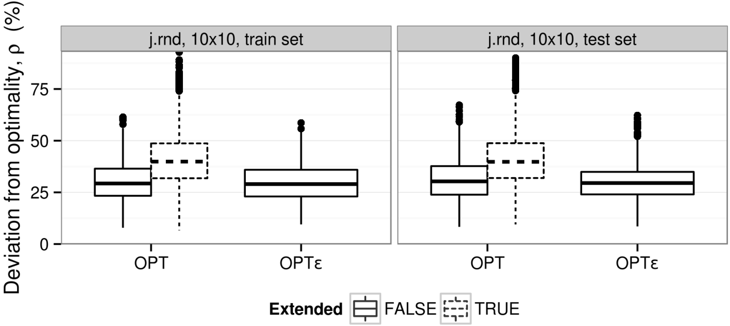

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Active imitation learning (iterative):

- 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 aggregated dataset of all previous iterations.

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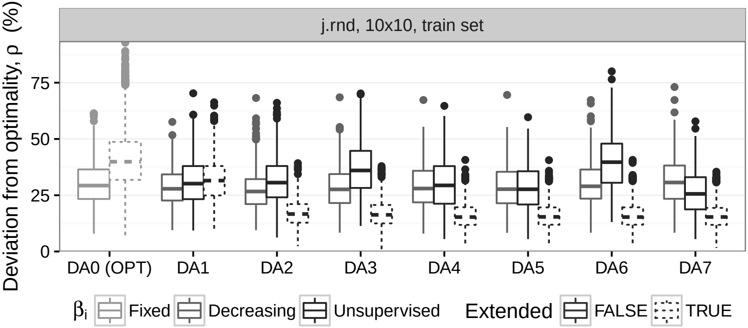

Deviation from optimality, ρ

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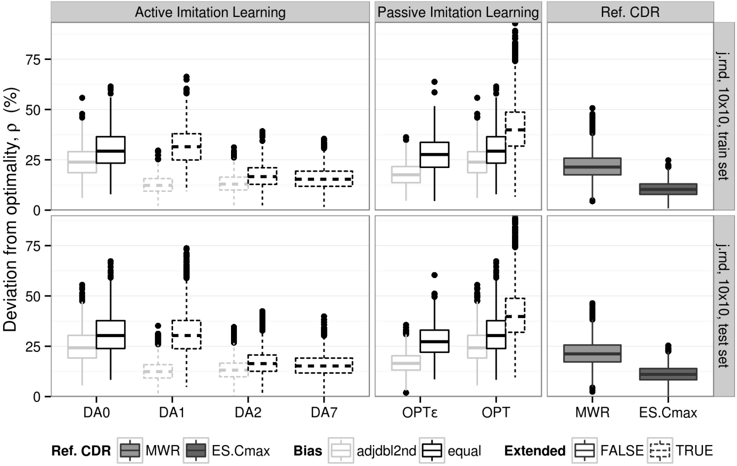

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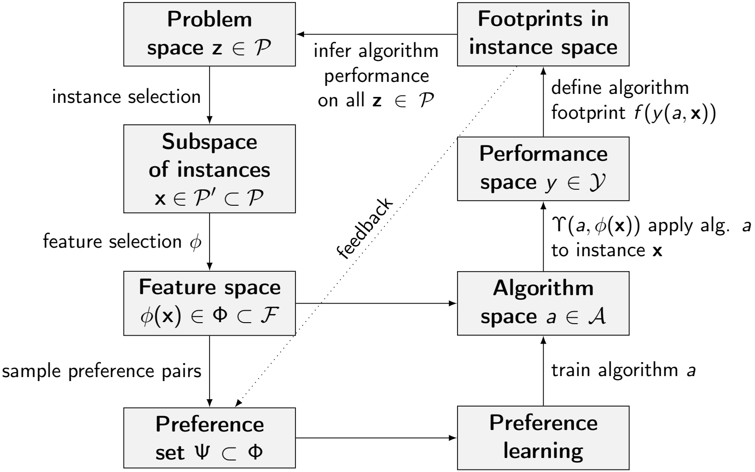

Using Analysis & Learning Iterative Consecutive Executions framework I

The thesis introduced a framework for learning (linear) composite priority dispatching rule – using job-shop as a case-study – with the following guidelines:

- For a given problem domain, use a suitable problem generator to train and test on.
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It is non intuitive how to go about collecting training data.

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Using Analysis & Learning Iterative Consecutive Executions framework II

Continued from prev. slide:

- ⋆ Learning optimal trajectories predominant in literature. Study showed Φ^{OPT} can result in insufficient knowledge.
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Acknowledgements

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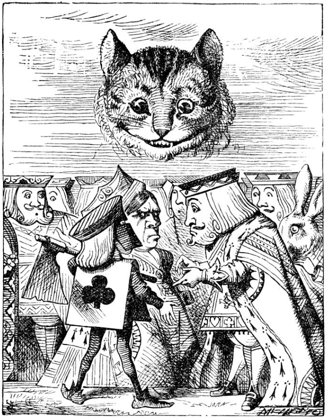
- ⋆ Prof. Tómas Philip Rúnarsson, University of Iceland (advisor).
- ⋆ Prof. Gunnar Stefánsson, University of Iceland.
- ⋆ Prof. Michèle Sebag, Université Paris-Sud.



Thank you for your attention

Questions?

Helga Ingimundardóttir
`hei2@hi.is`

Supplementary material:

- ⋆ Shiny application
- ⋆ Github.