ALICE

Analysis & Learning Iterative Consecutive Executions

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University of Iceland

June 30, 2016

Motivation:

- ⋆ The general goal is to train optimisation algorithms using data.

Contribution:

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

Introduction

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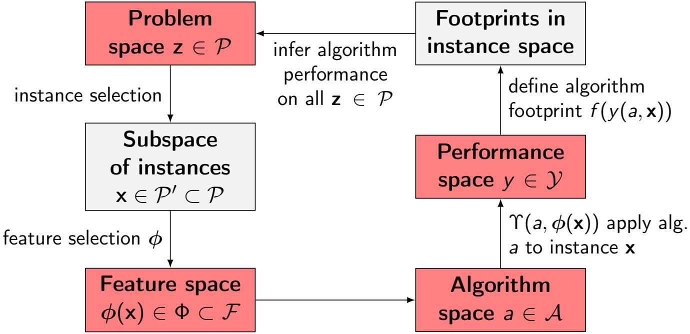
Framework for Algorithm Selection

Overview of Rice (1976)



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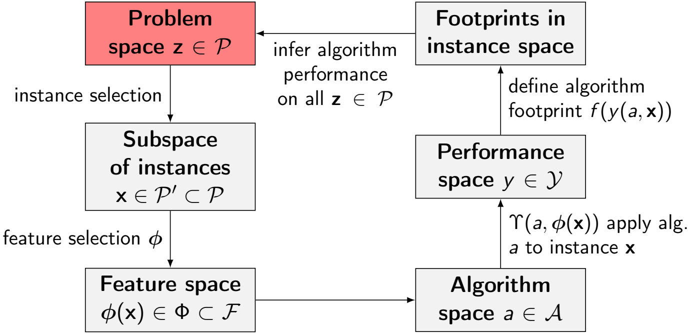

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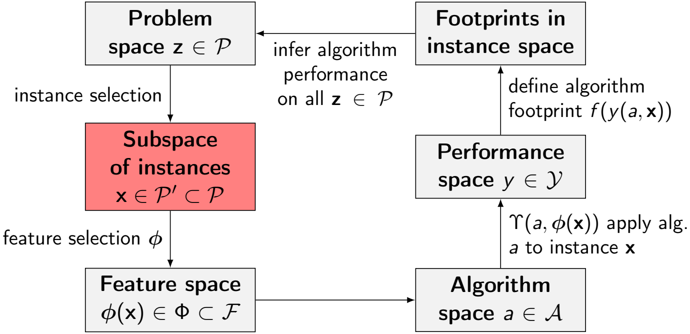

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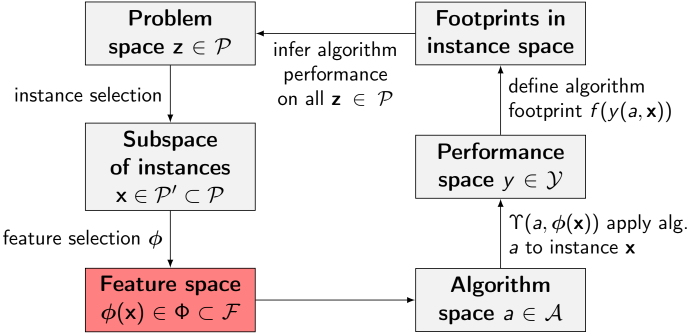

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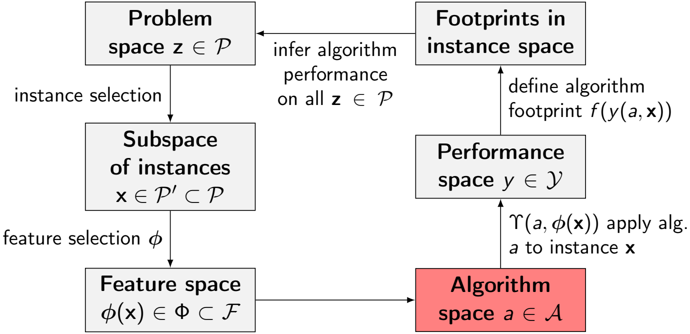

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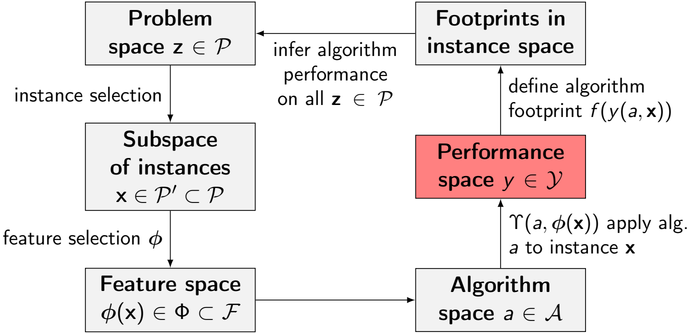

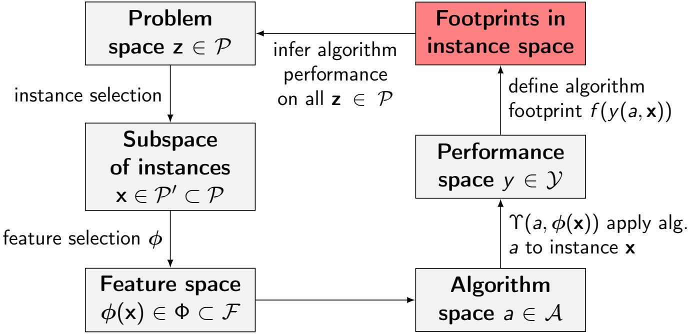

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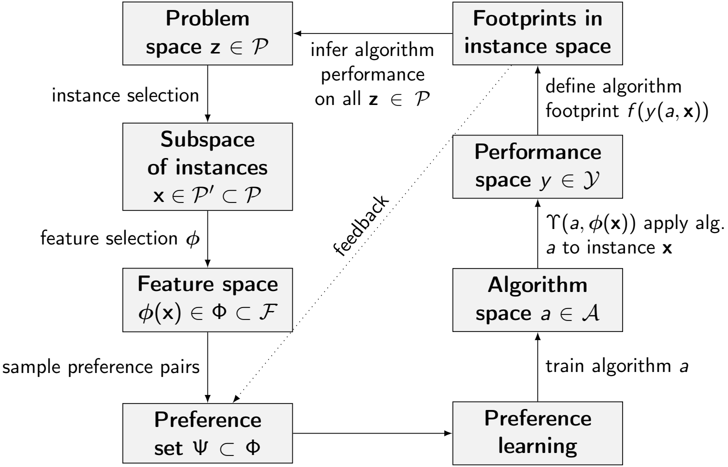

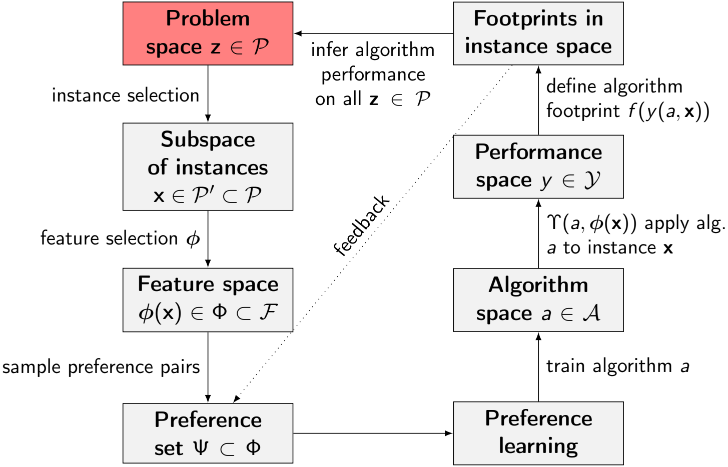
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Framework for Algorithm Learning

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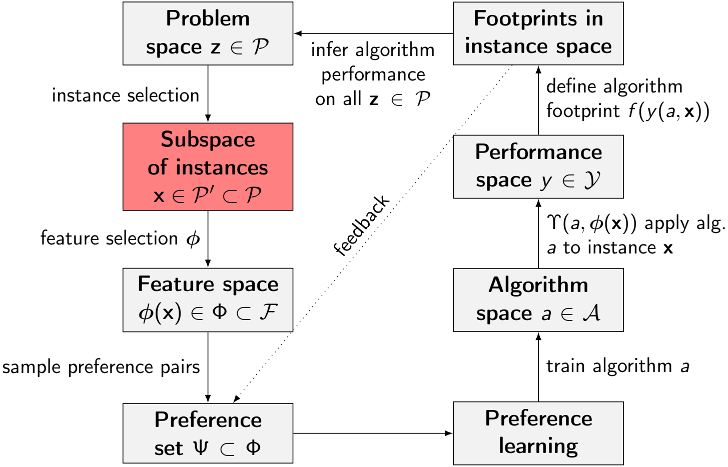

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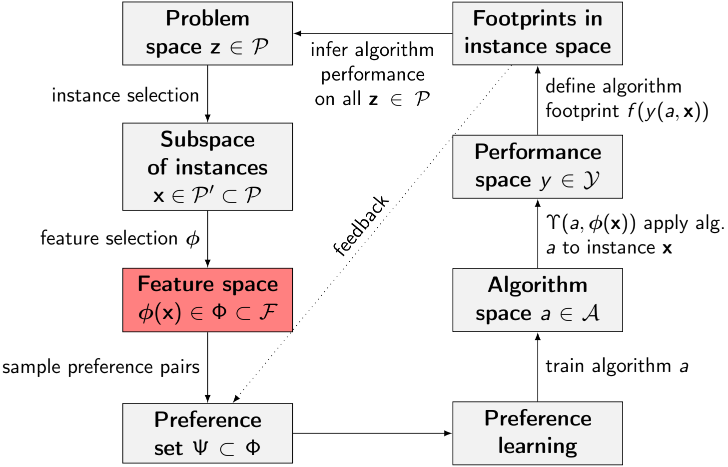

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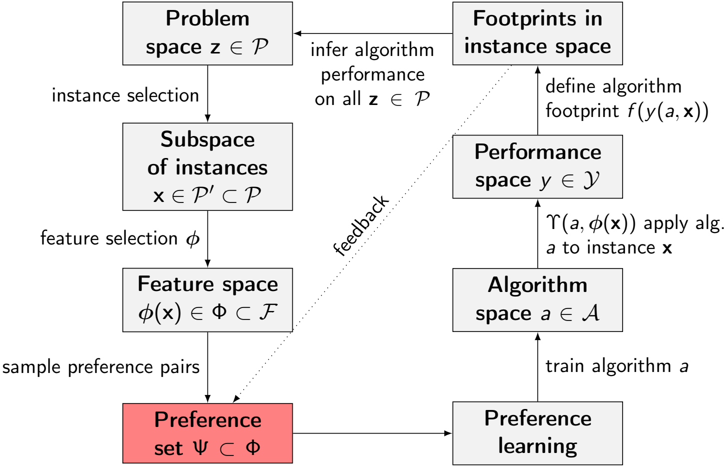

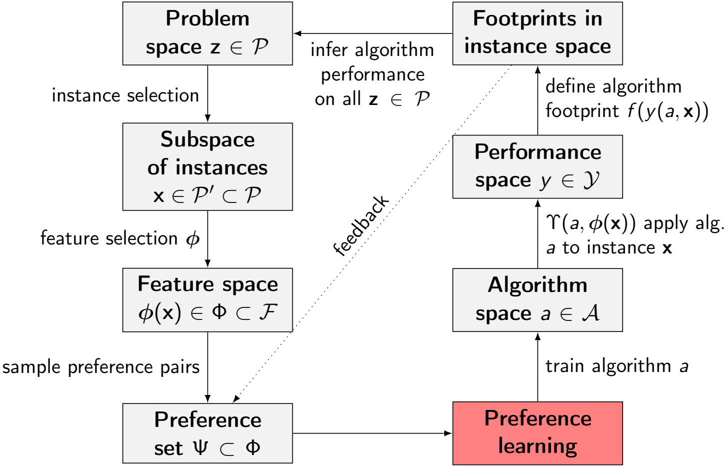

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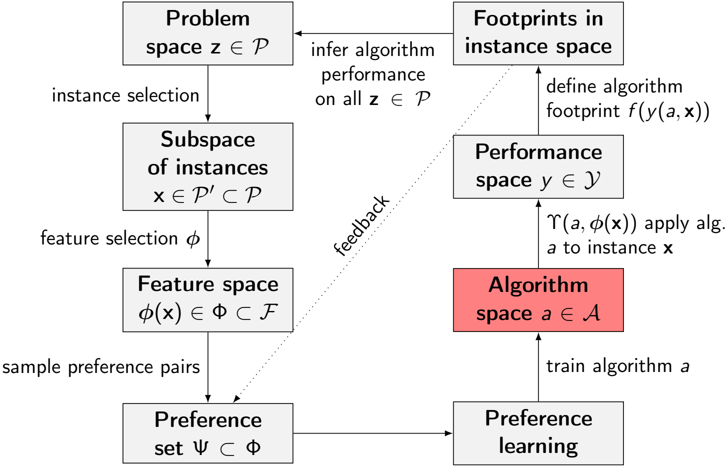

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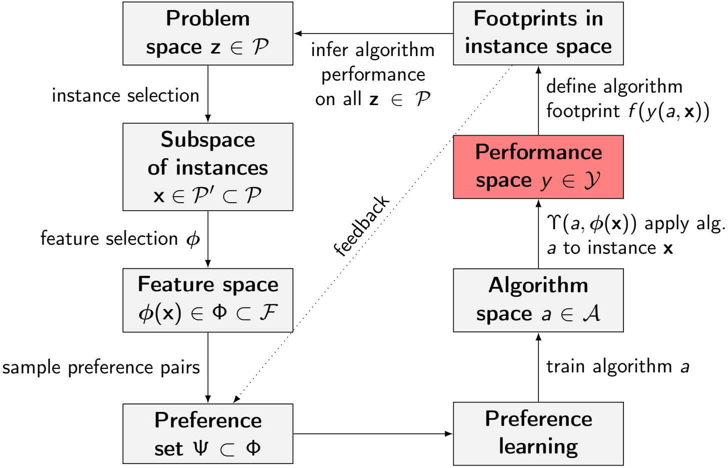

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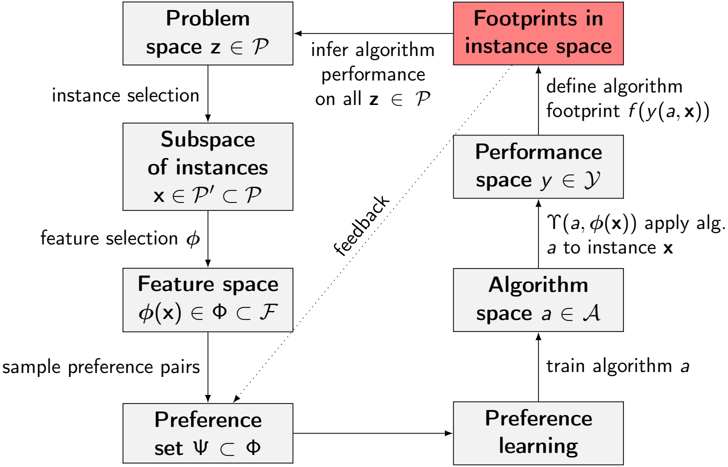

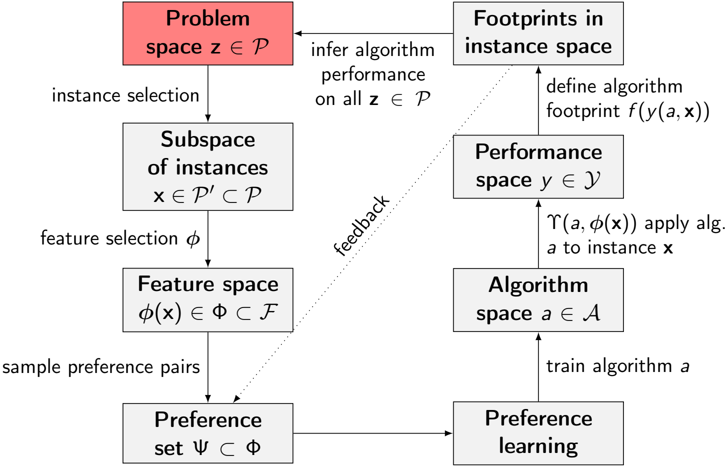
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Mad Hatter Tea-party

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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 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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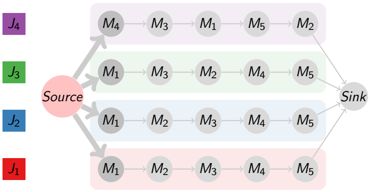


Figure: Disjunctive graph

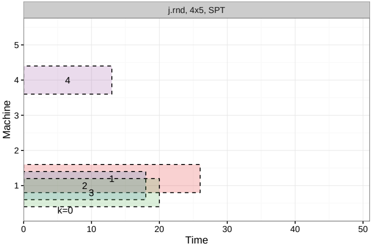
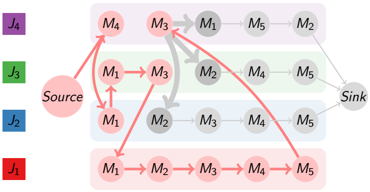


Figure: Gantt chart

Midway: $k = 10$



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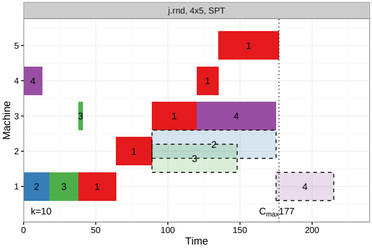
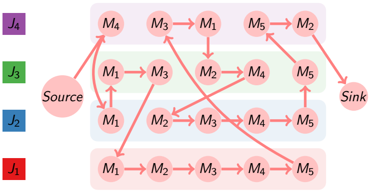


Figure: Gantt chart

Finish: $k = 20$



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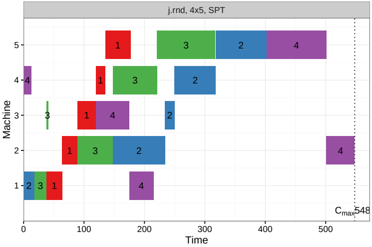

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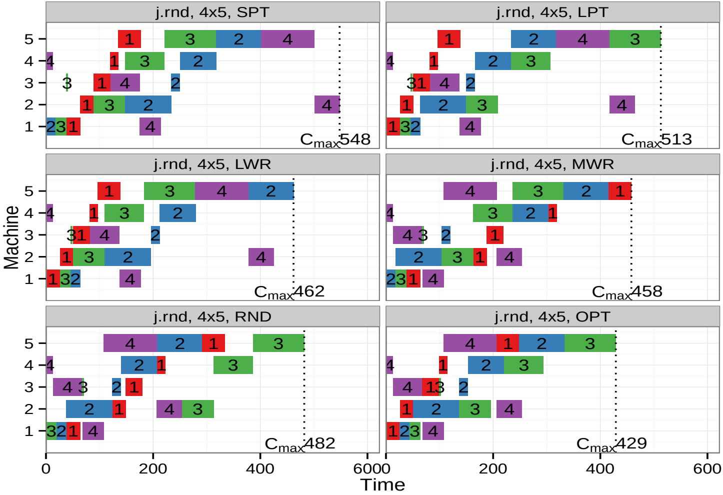
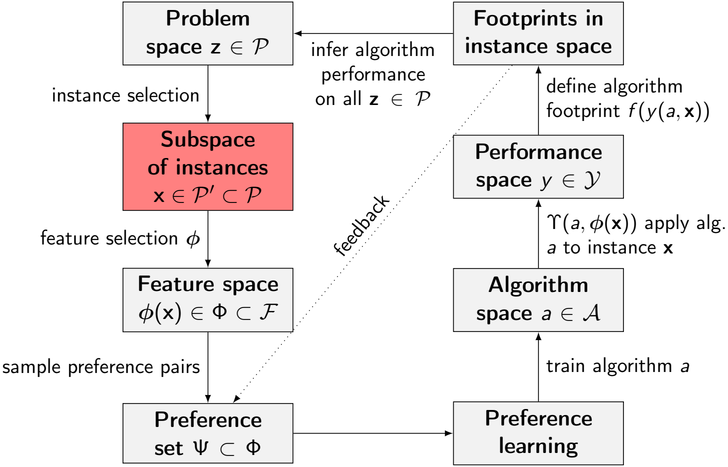


j.rnd, 4x5, SPT
C_{max}548
j.rnd, 4x5, LPT
C_{max}513
j.rnd, 4x5, LWR
C_{max}462
j.rnd, 4x5, MWR
C_{max}458
j.rnd, 4x5, RND
C_{max}482
j.rnd, 4x5, OPT
C_{max}429
Machine
Time
0
200
400
600



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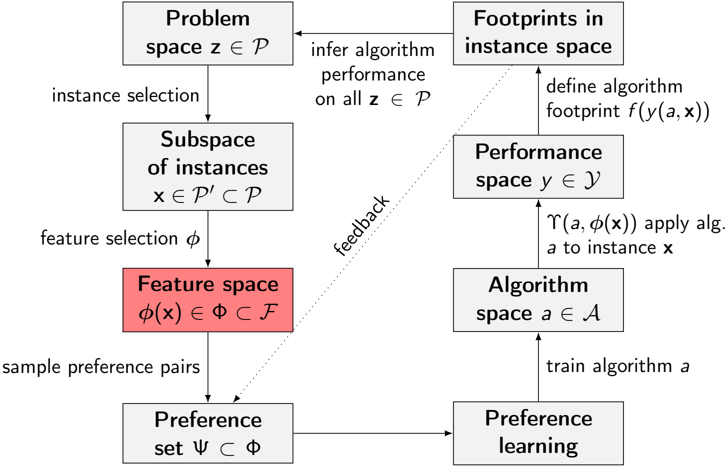
	name	size ($n \times m$)	N_{train}	N_{test}	note
JSP	$\mathcal{P}^{6\times5}_{j.rnd}$	6×5	500	500	random
	$\mathcal{P}^{6\times5}_{j.rndn}$	6×5	500	500	random-narrow
	$\mathcal{P}^{6\times5}_{j.rnd,J_1}$	6×5	500	500	random with job variation
	$\mathcal{P}^{6\times5}_{j.rnd,M_1}$	6×5	500	500	random with 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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Feature Space

for job-shop

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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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).
- $\star$ (Φ^{LWR}) least work remaining (LWR).
- $\star$ (Φ^{MWR}) most work remaining (MWR).
- $\star$ (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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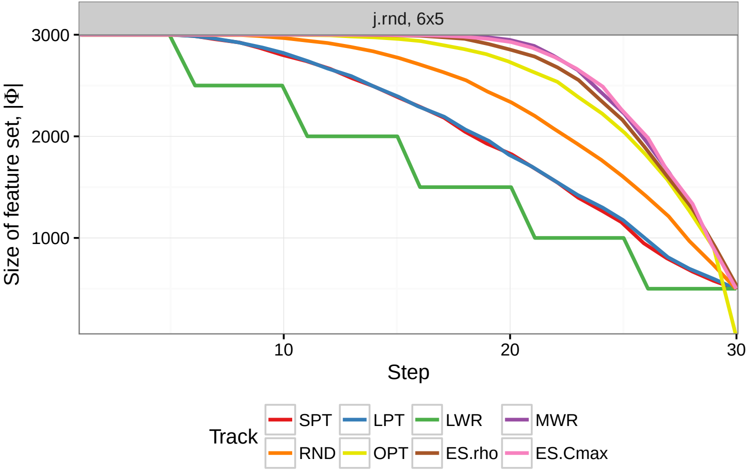
- $\star$ (Φ^{ALL}) union of all of the above.

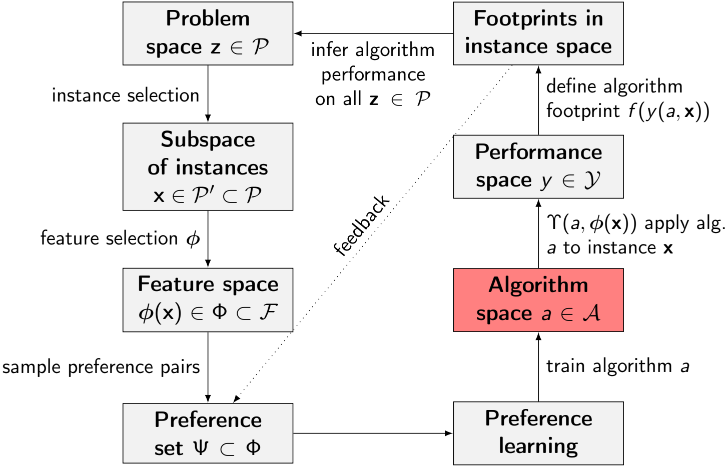
Sampled Size of $|\Phi(k)|$

6×5, $N_{train} = 500$



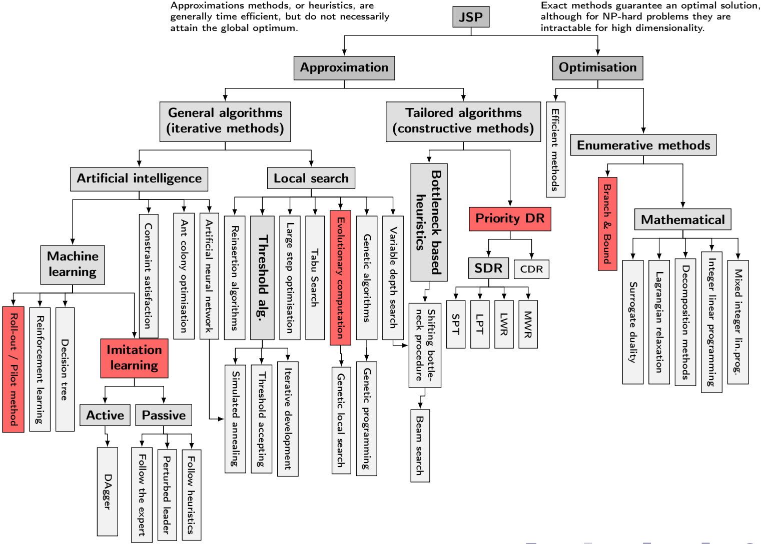
Framework for Algorithm Learning

Outline



Various Methods for Solving JSP

Based on Jain and Meeran (1999)



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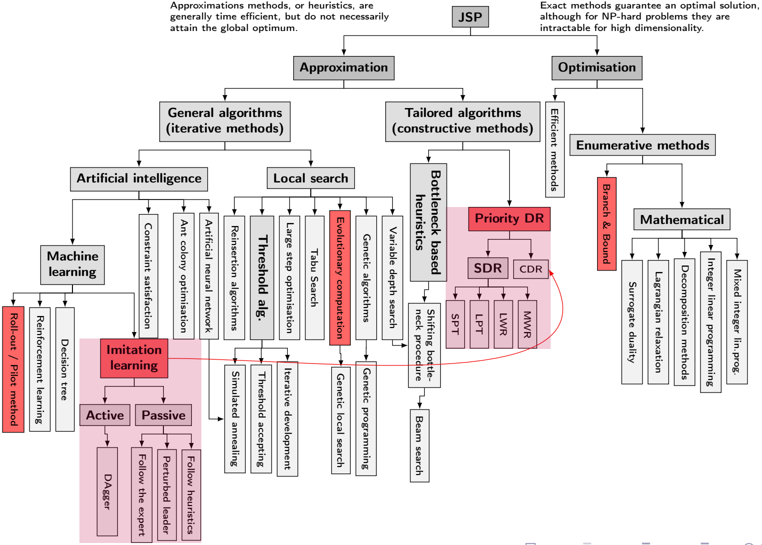

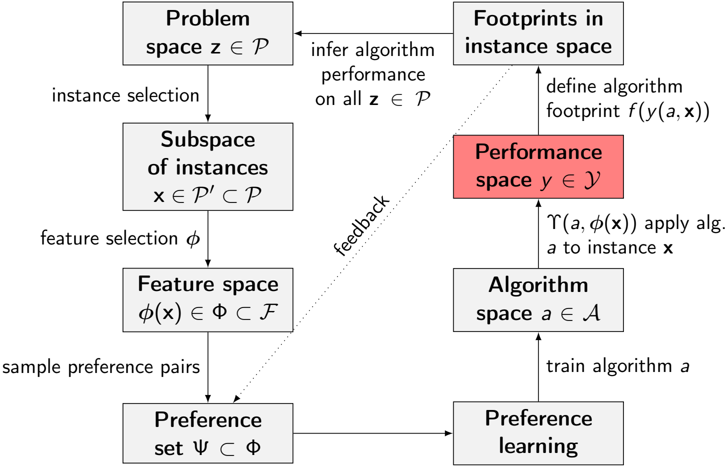

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Footprints in instance space
infer algorithm performance on all $\mathbf{z} \in \mathcal{P}$
instance selection
Subspace of instances $\mathbf{x} \in \mathcal{P}' \subset \mathcal{P}$
define algorithm footprint $f(y(a, \mathbf{x}))$
Performance space $y \in \mathcal{Y}$
feedback
feature selection ϕ
$\Upsilon(a, \phi(\mathbf{x}))$ apply alg. a to instance $\mathbf{x}$
Feature space $\phi(\mathbf{x}) \in \Phi \subset \mathcal{F}$
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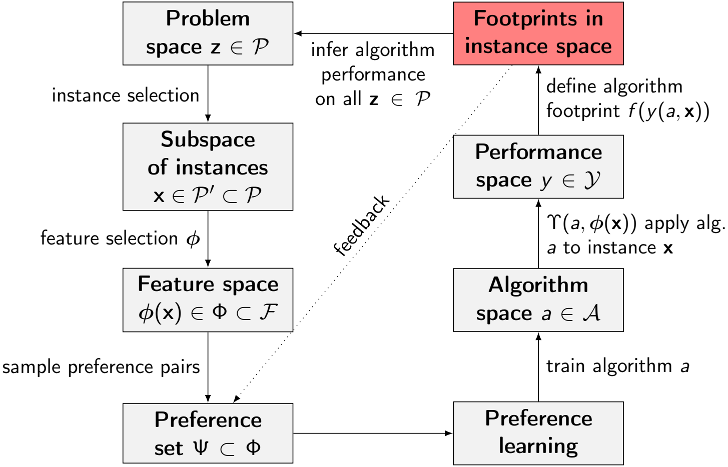
train algorithm a
Preference set $\Psi \subset \Phi$
Preference learning

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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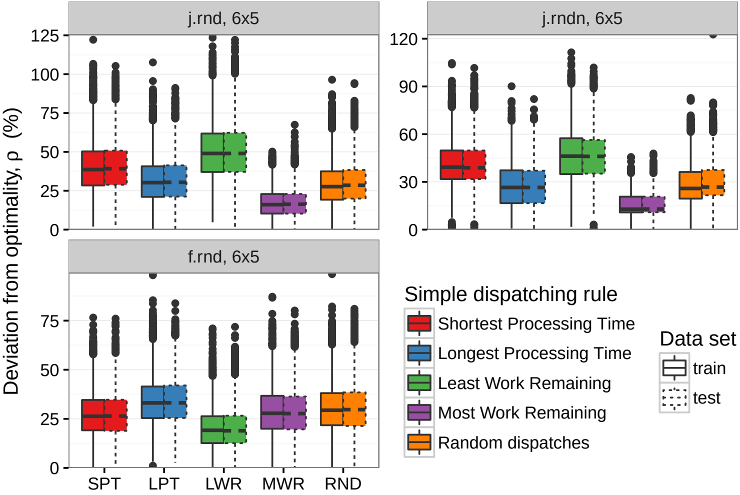
Deviation from Optimality

ρ



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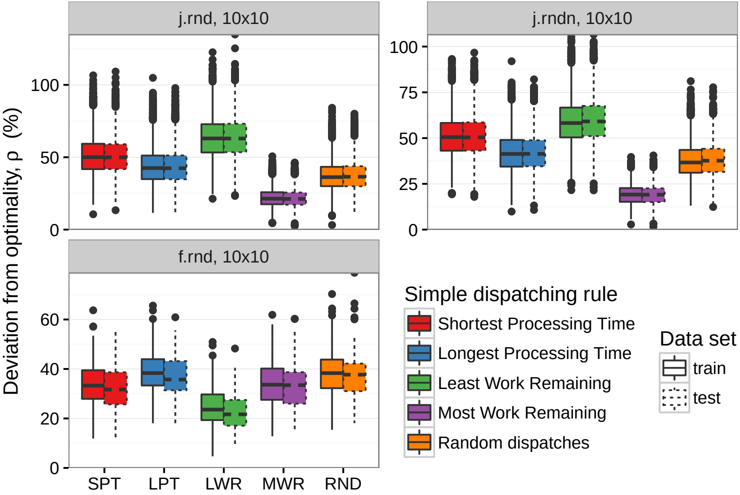
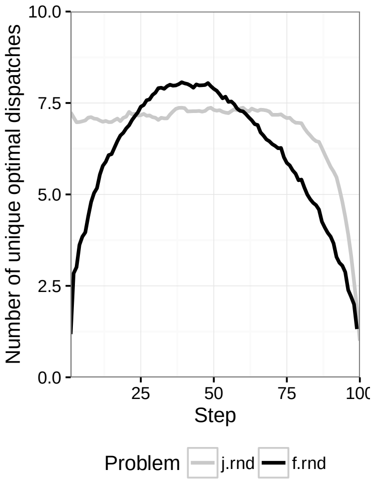
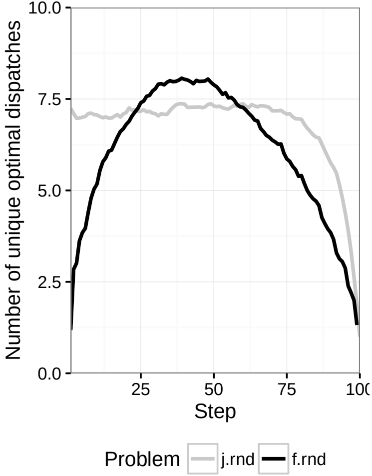


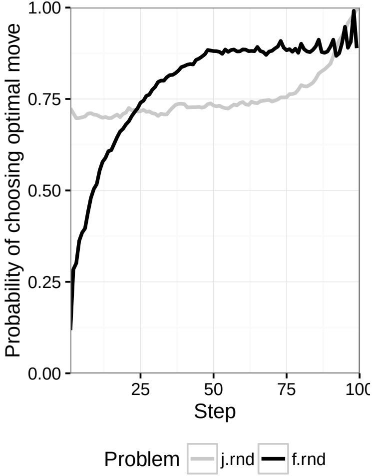
Making Optimal Decisions

$\xi_\pi^\star$





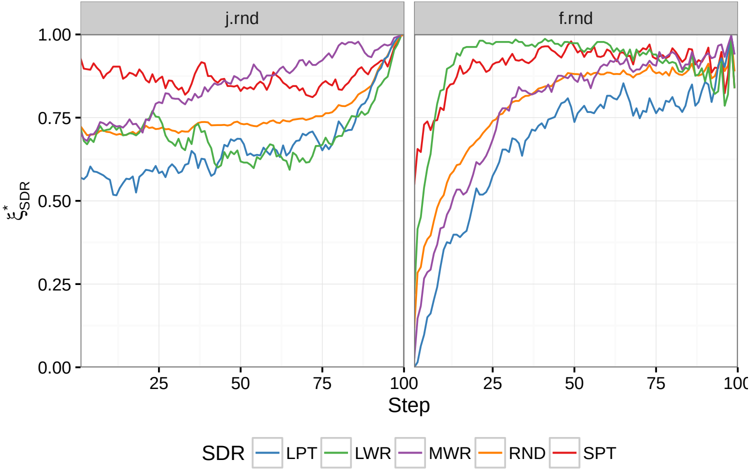
Number of unique optimal dispatches
10.0
7.5
5.0
2.5
0.0
25
50
75
100
Step
Problem
j.rnd
f.rnd

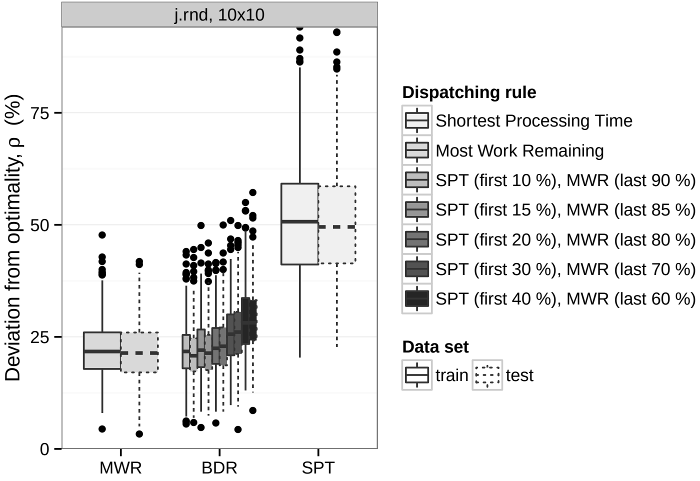


Probability of choosing optimal move
1.00
0.75
0.50
0.25
0.00
25
50
75
100
Step
Problem
j.rnd
f.rnd

Probability of SDR Being Optimal

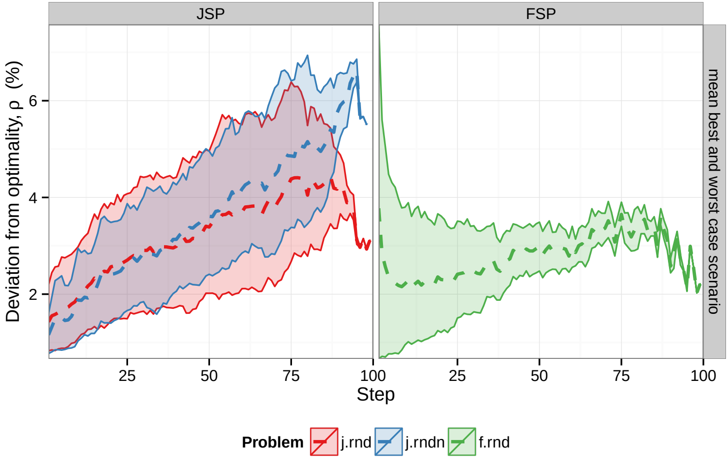
$\xi^{\star}_{\langle \mathrm{SDR} \rangle}$

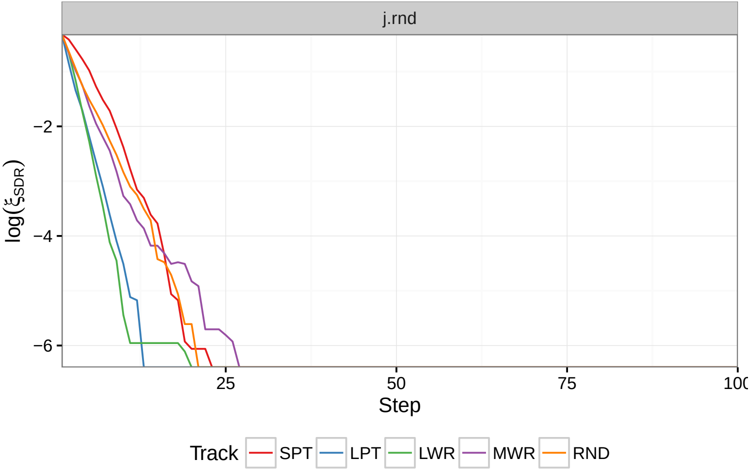



j.rnd, 10x10
Deviation from optimality, ρ (%)
0
25
50
75
MWR
BDR
SPT
Dispatching rule
Shortest Processing Time
Most Work Remaining
SPT (first 10 %), MWR (last 90 %)
SPT (first 15 %), MWR (last 85 %)
SPT (first 20 %), MWR (last 80 %)
SPT (first 30 %), MWR (last 70 %)
SPT (first 40 %), MWR (last 60 %)
Data set
train
test

Impact of Sub-optimal Decision

$\{\zeta^{\star}_{\min}, \zeta^{\star}_{\max}\}$

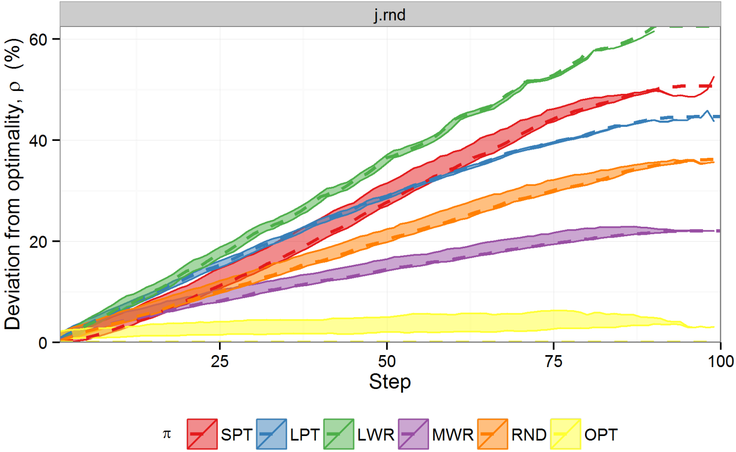


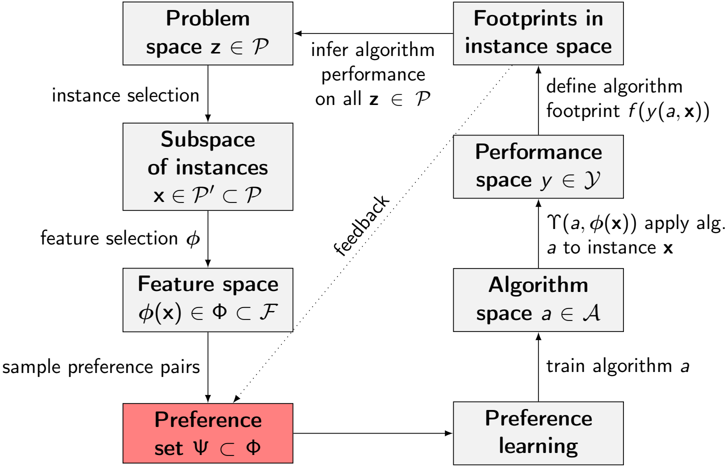


j.rnd
log(ξSDR)
−2
−4
−6
25
50
75
100
Step
Track
SPT
LPT
LWR
MWR
RND

Impact of Sub-optimal Decision

$\{\zeta^{\pi}_{\min}, \zeta^{\pi}_{\max}\}$





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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.

Generating Training Data

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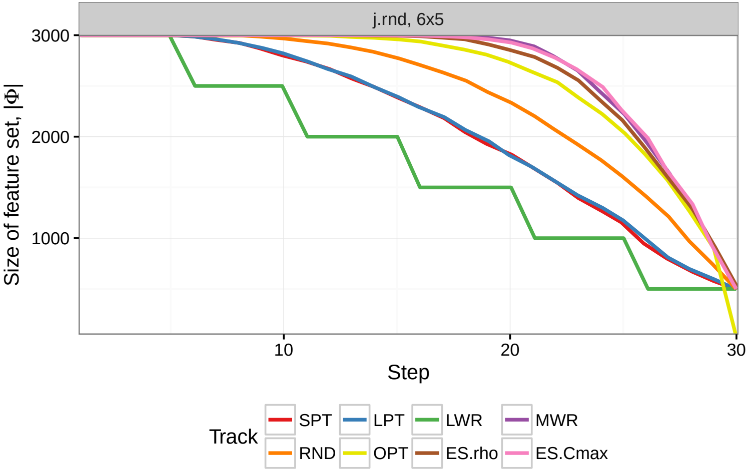

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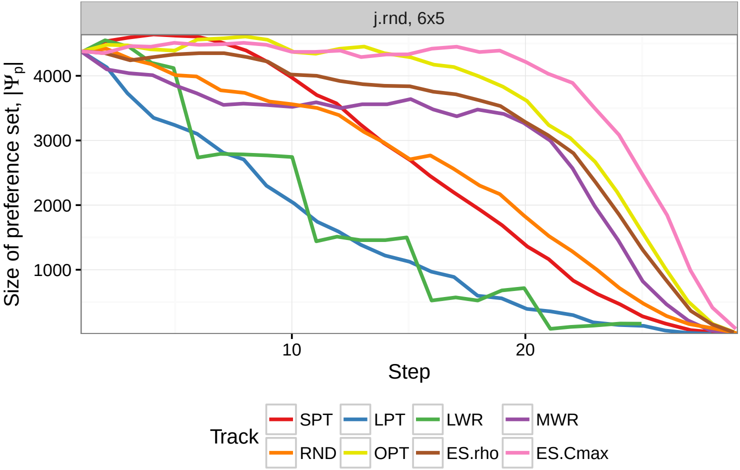
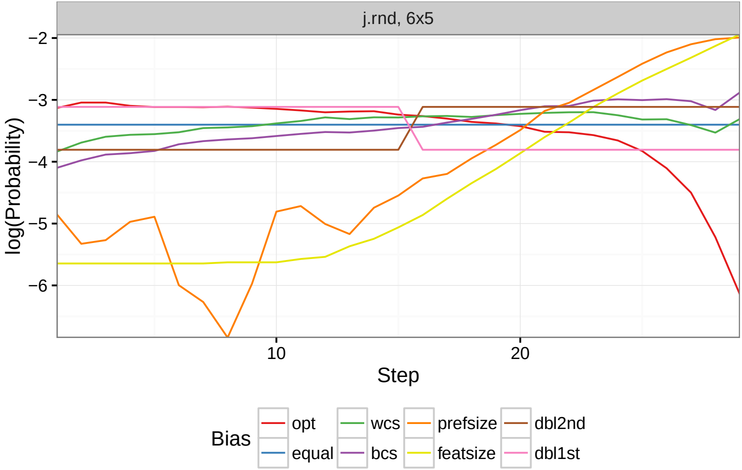
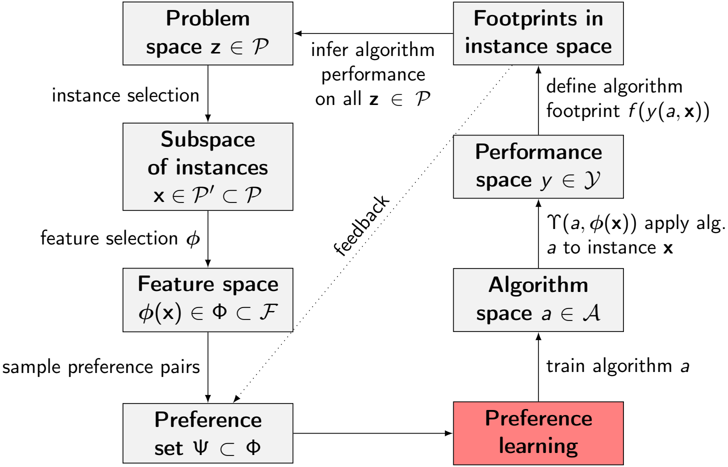




j.rnd, 6x5
log(Probability)
−2
−3
−4
−5
−6
10
20
Step
Bias
opt
equal
wcs
bcs
prefsize
featsize
dbl2nd
dbl1st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Ordinal Regression

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:

$$h(\phi) = \langle \mathbf{w} \cdot \phi \rangle$$

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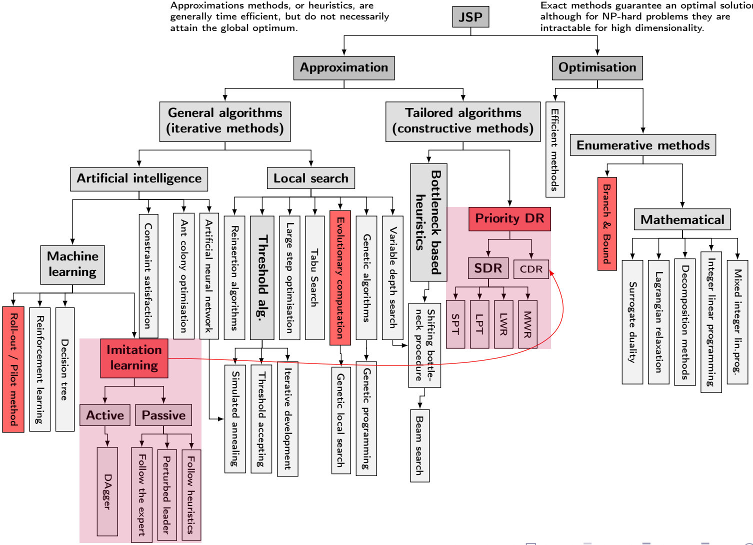
Based on Jain and Meeran (1999)

Approximations methods, or heuristics, are generally time efficient, but do not necessarily attain the global optimum.

Exact methods guarantee an optimal solution, although for NP-hard problems they are intractable for high dimensionality.



Passive imitation learning (single pass):

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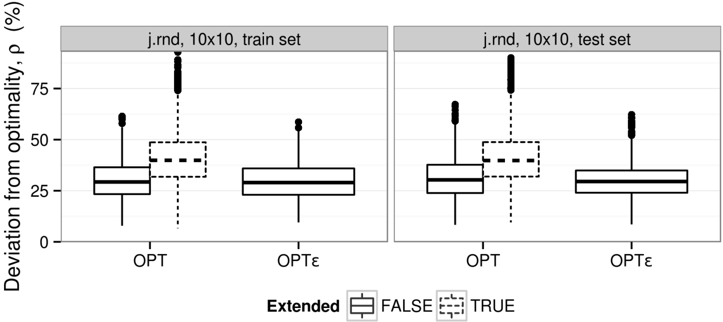

Active imitation learning (iterative):

- 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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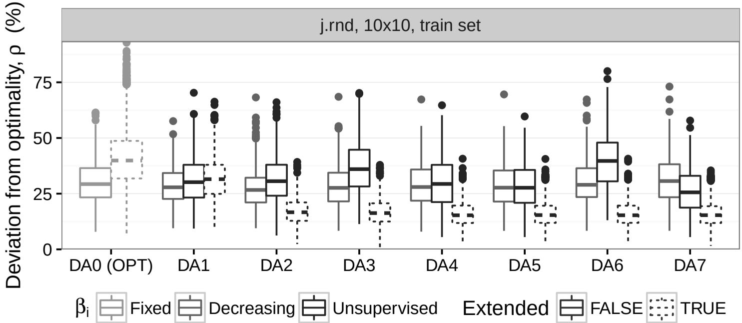
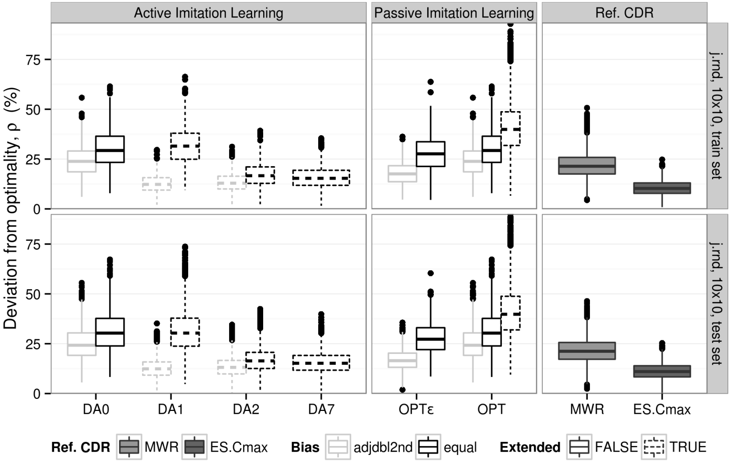


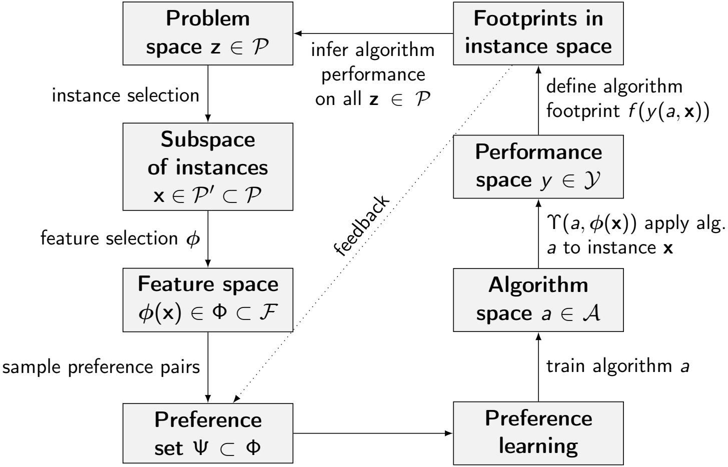
Deviation from Optimality

ρ



Framework for Algorithm Learning

Overview of Rice (1976)



The thesis introduces 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.
- Define features to grasp the essence of visited k-solutions
- Success is highly dependent on the preference pairs introduced to the system:
  - Ψ_p reduces the preference set without loss of performance.
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Continued from prev. slide:

- ⋆ 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.
- ⋆ Active update procedure using DAgger ensures sample states the learned model is likely to encounter is integrated to $\Psi_p^{\text{DA}i}$.
- ⋆ Instead of reusing the same problem instances, extend the training set with new instances for quicker convergence of DAgger.
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Using ALICE Framework II

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Continued from prev. slide:

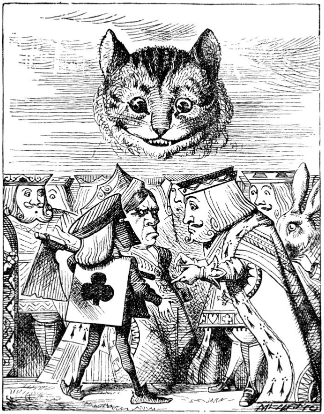
- ⋆ Learning optimal trajectories predominant in literature. Study showed Φ^{OPT} can result in insufficient knowledge.
- ⋆ Following sub-optimal deterministic policies, yet labelling with an optimal solver, improves the guiding policy.
- ⋆ Active update procedure using DAgger ensures sample states the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

Acknowledgements

Funding: University of Iceland's Research Fund.

Doctoral committee:

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



Illustrations: Sir John Tenniel (1820–1914)

Thank You for Your Attention

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Supplementary material:

- ⋆ Shiny application
- ⋆ Github.