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Introduction

Problem Space

Subspace of Instances

Feature Space

Algorithm Space

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Footprints in Instance Space

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Conclusions

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Analysis & Learning Iterative Consecutive Executions

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Introduction

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.

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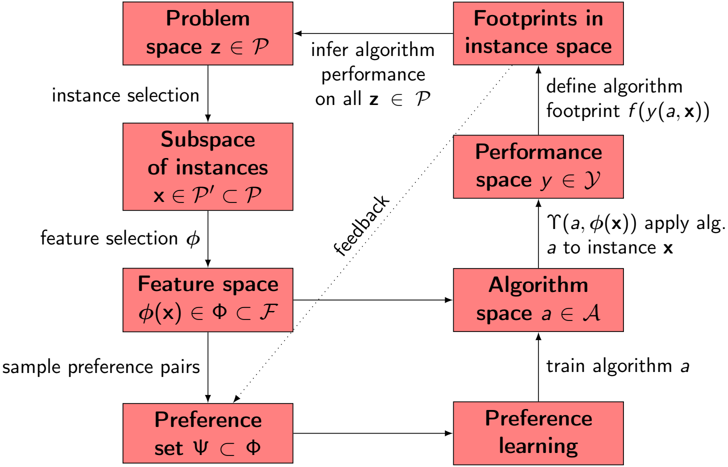


Mad Hatter Tea-party

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 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).

Midway: $k = 10$

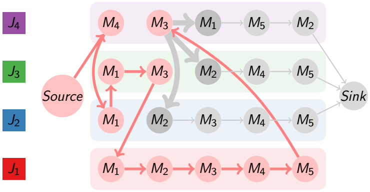


Figure: Disjunctive graph

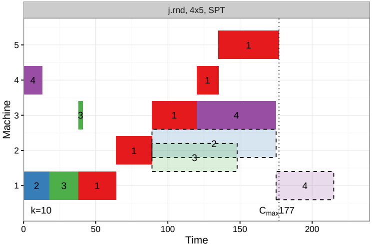
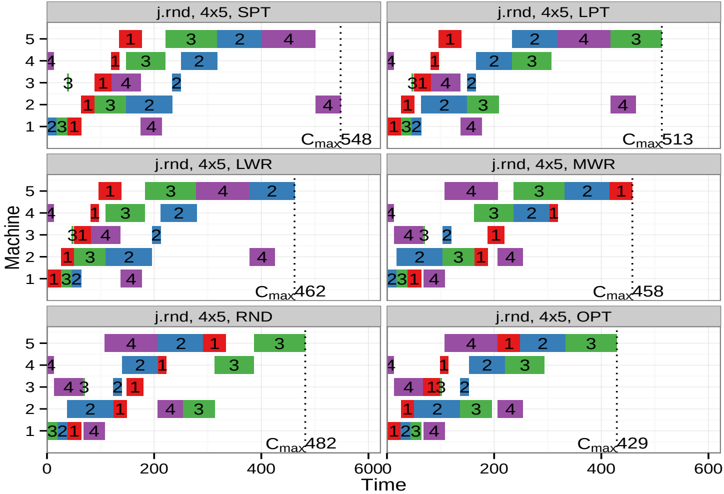


Figure: Gantt chart

Mad Hatter Tea-party

K-solutions



Problem Instance Generators

Based on Watson et al. (2002)

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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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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}

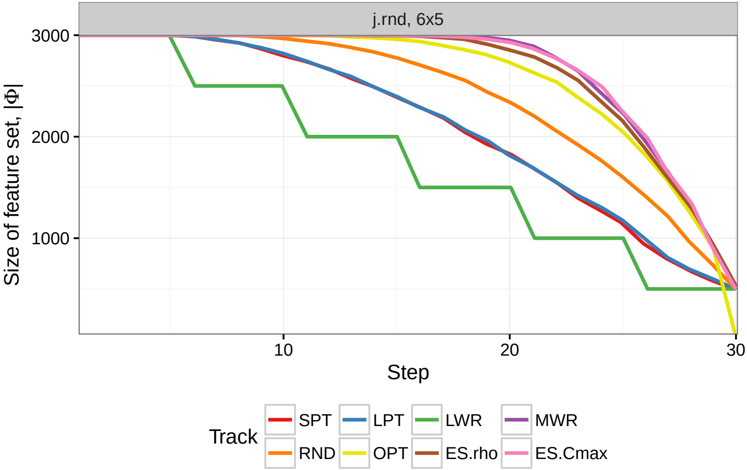
Trajectory Strategies for Φ

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).
- $\star$ ($\Phi^{\mathrm{ES}.\rho}$) the policy obtained by optimising with CMA-ES.
- $\star$ (Φ^{ALL}) union of all of the above.

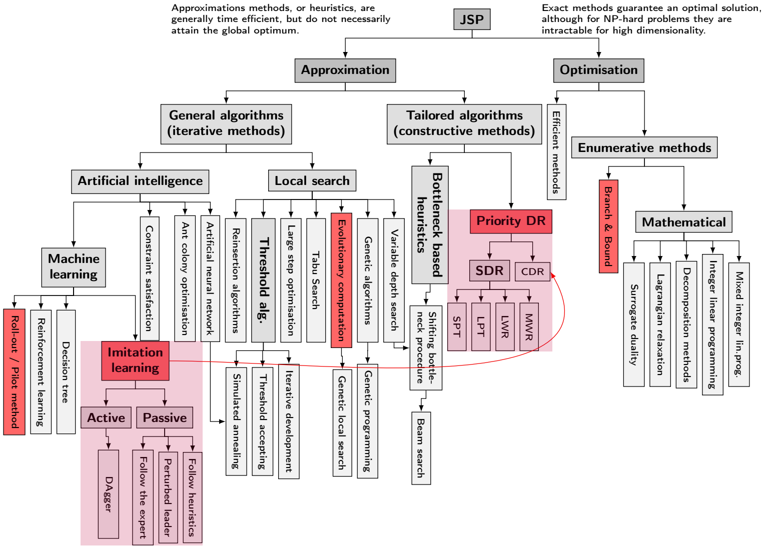
Sampled Size of $|\Phi(k)|$

6×5, $N_{train} = 500$



Various Methods for Solving JSP

Based on Jain and Meeran (1999)



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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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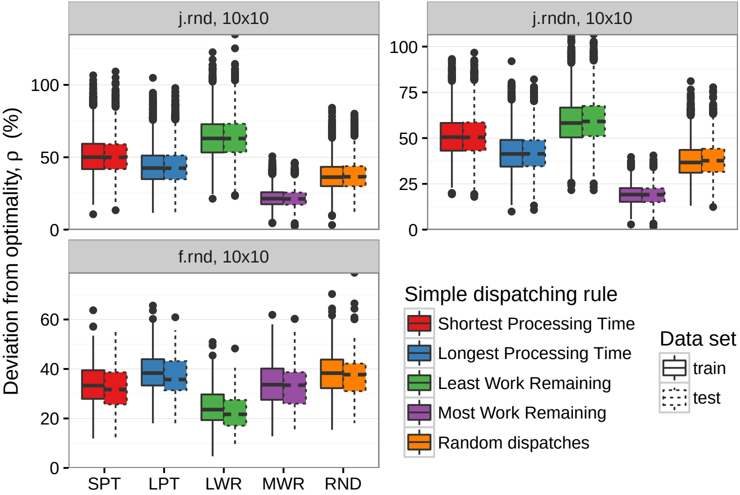
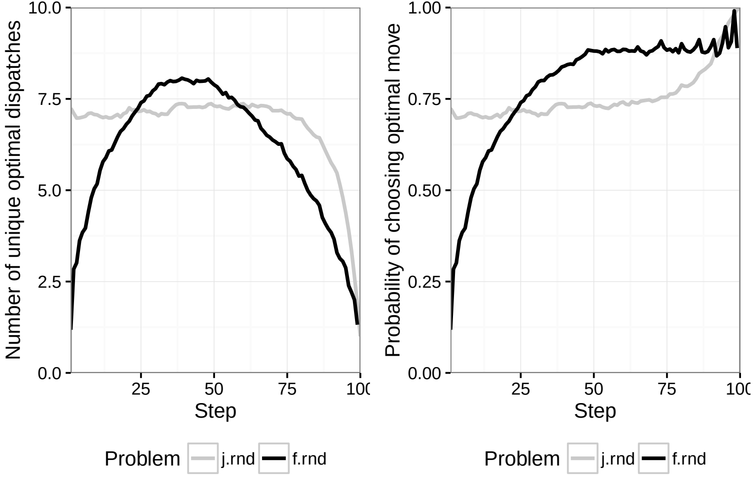


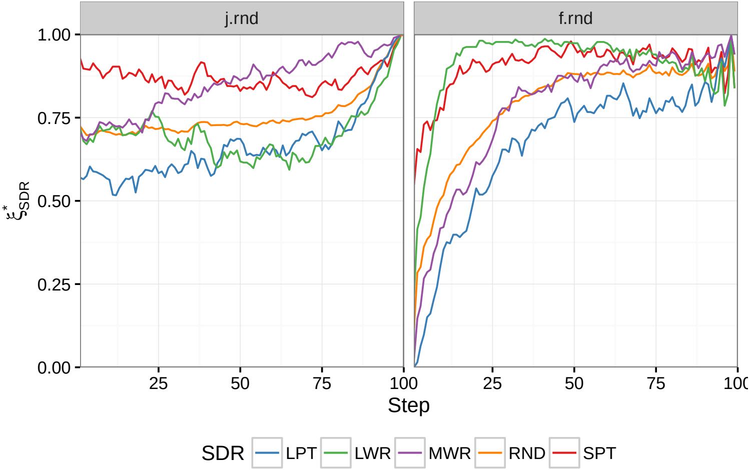
Making Optimal Decisions

$\xi_{\pi}^{\star}$



Probability of SDR Being Optimal

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



Blended Dispatching Rules

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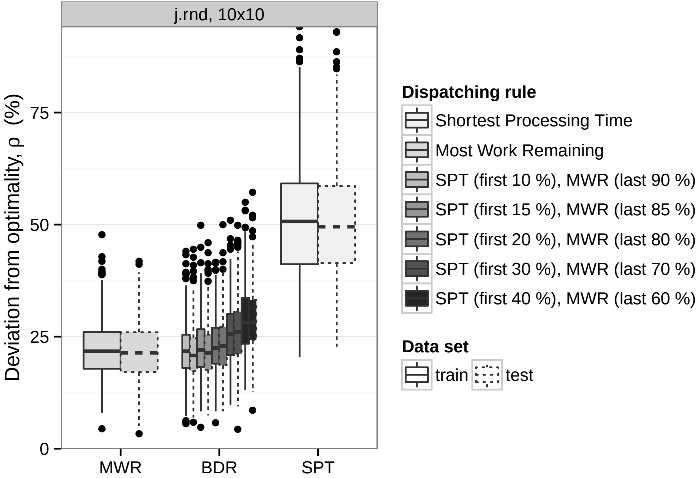
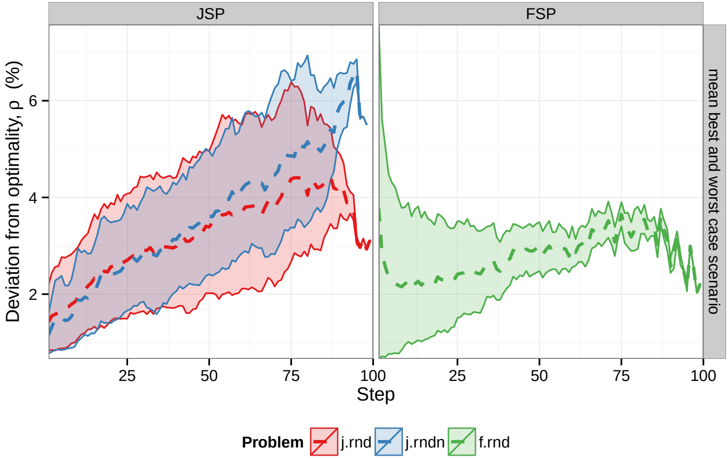


Impact of Sub-optimal Decision

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



Probability of SDR Being Optimal

$\xi_{\langle \mathrm{SDR} \rangle}$

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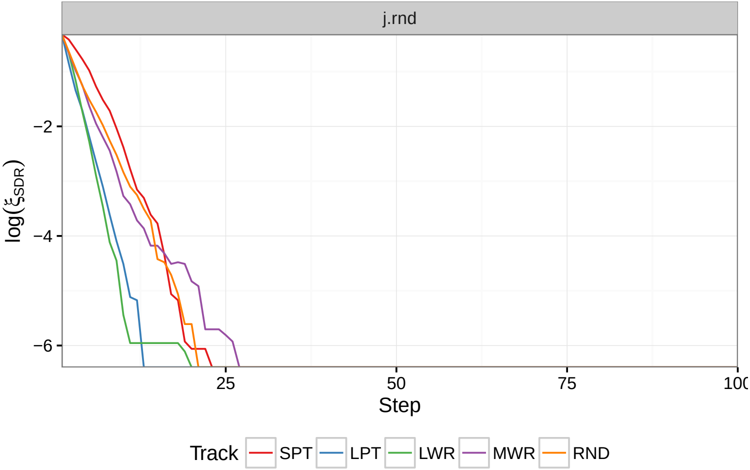

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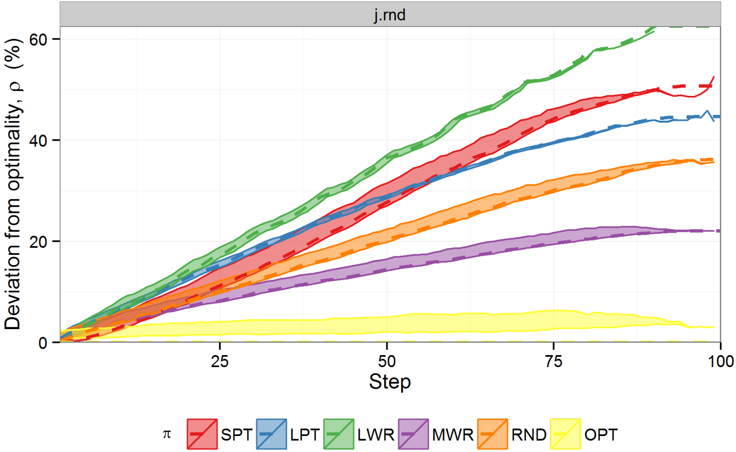

Generating Training Data

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.

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

6×5, $N_{train} = 500$

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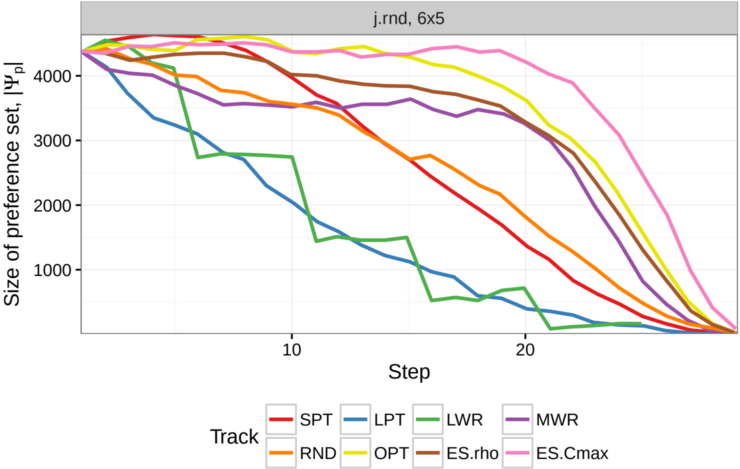
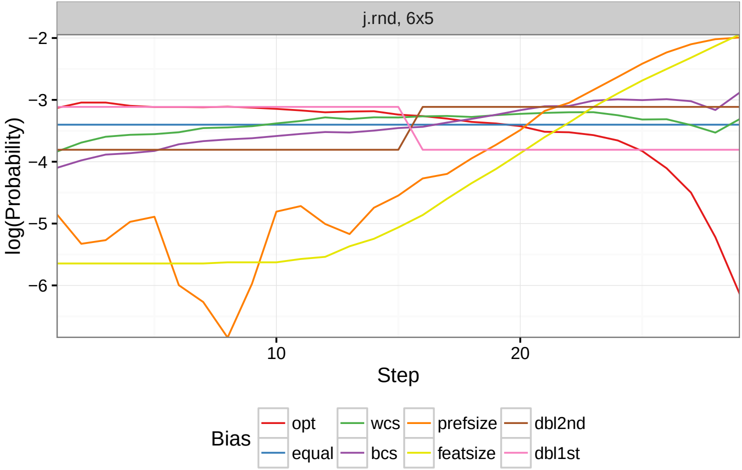


Stepwise Bias Strategies

6×5, $N_{train} = 500$



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:

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

optimised w.r.t. $\mathbf{w}$ based on training data Ψ

- ⋆ Note: Limitations in approximation function to capture the complex dynamics incorporated in optimal trajectories.

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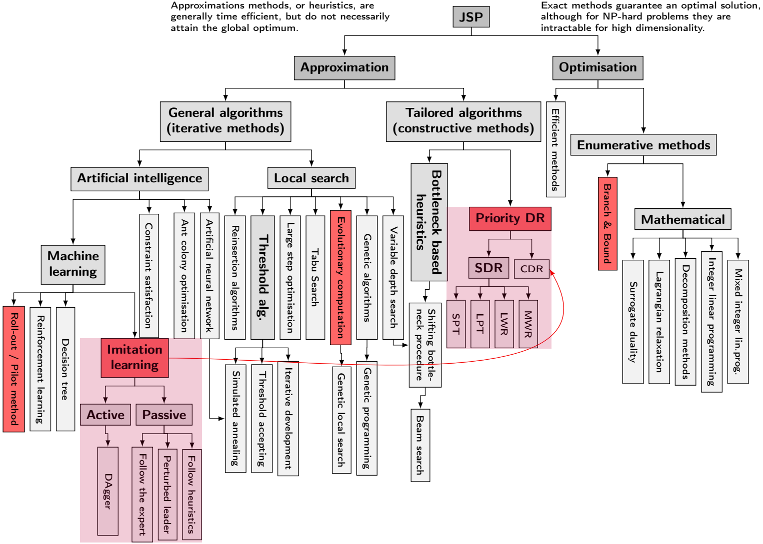

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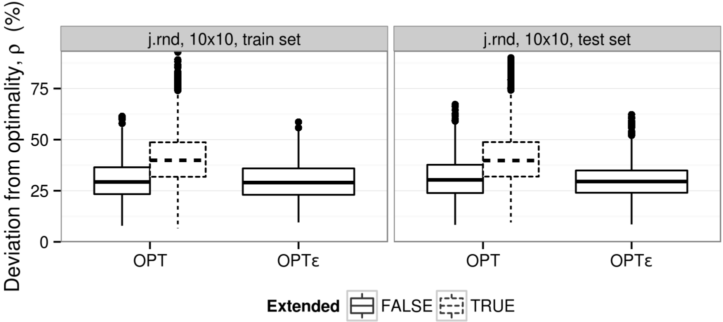
Passive imitation learning (single pass):

- ⋆ Prediction with expert advice, $\pi_\star$
- ⋆ Follow the perturbed leader (OPTϵ)
- ⋆ Follow a heuristic (e.g. SDRs).



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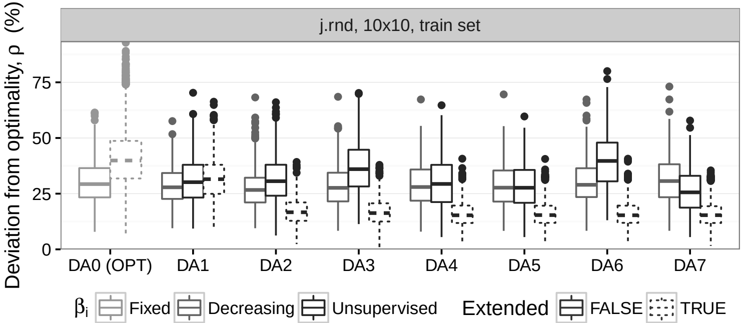
Active imitation learning (iterative):

- ⋆ 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.



Deviation from Optimality

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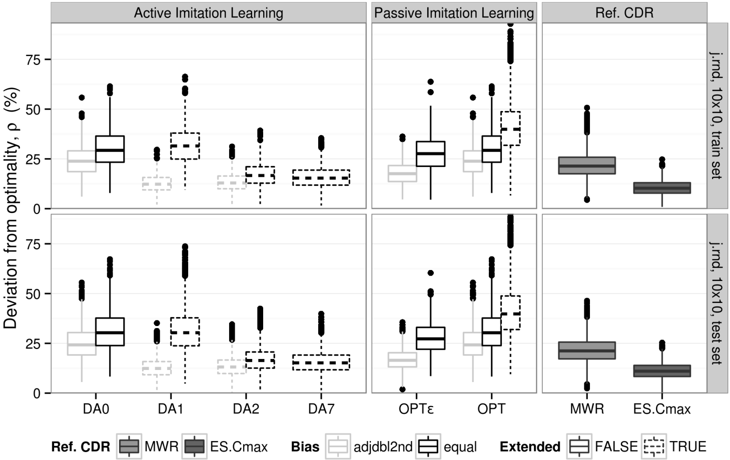

Using ALICE Framework I

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.
  - ⋆ Stepwise bias is needed to balance time dependent Ψ_p in order to create time independent models.

It is non intuitive how to go about collecting training data.

Using ALICE Framework II

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.

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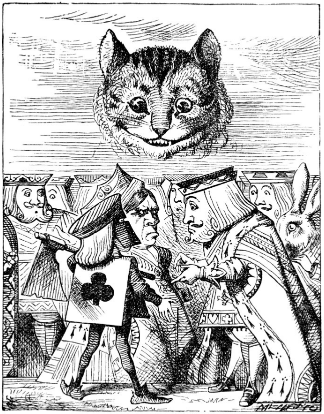
- Prof. Michèle Sebag, Université Paris-Sud.



Illustrations: Sir John Tenniel (1820–1914)

Thank You for Your Attention

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Supplementary material:

- Shiny application
- Github.