

Data science: How to leverage data for superior decision making



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Artificial Intelligence



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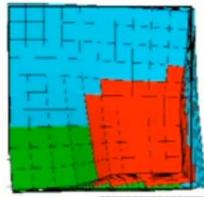
Deep Blue

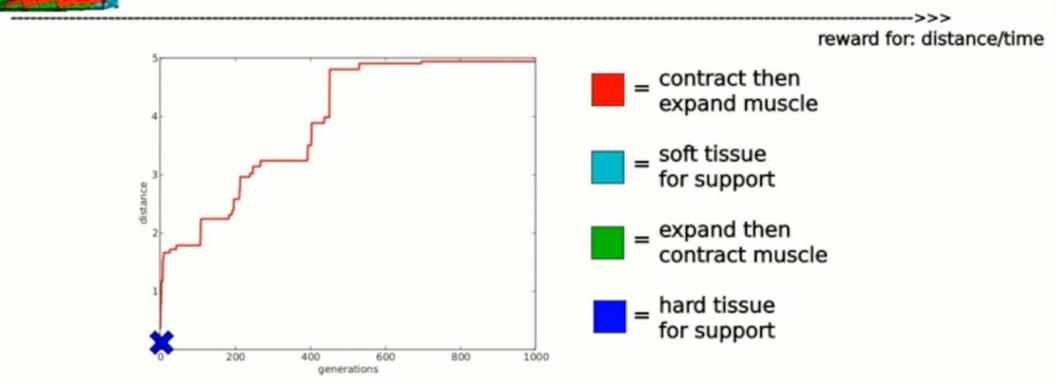
Garry Kasparov





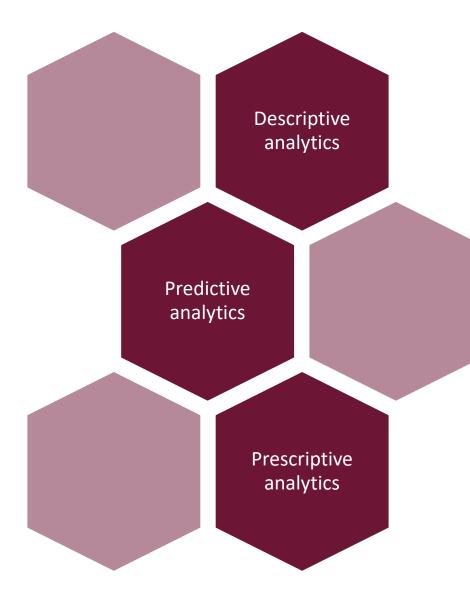






Acknowledgements: Cheney, Nick, Robert MacCurdy, Jeff Clune, and Hod Lipson. "Unshackling evolution: evolving soft robots with multiple materials and a powerful generative encoding." ACM SIGEVOlution 7, no. 1 (2014): 11-23.

Data Science

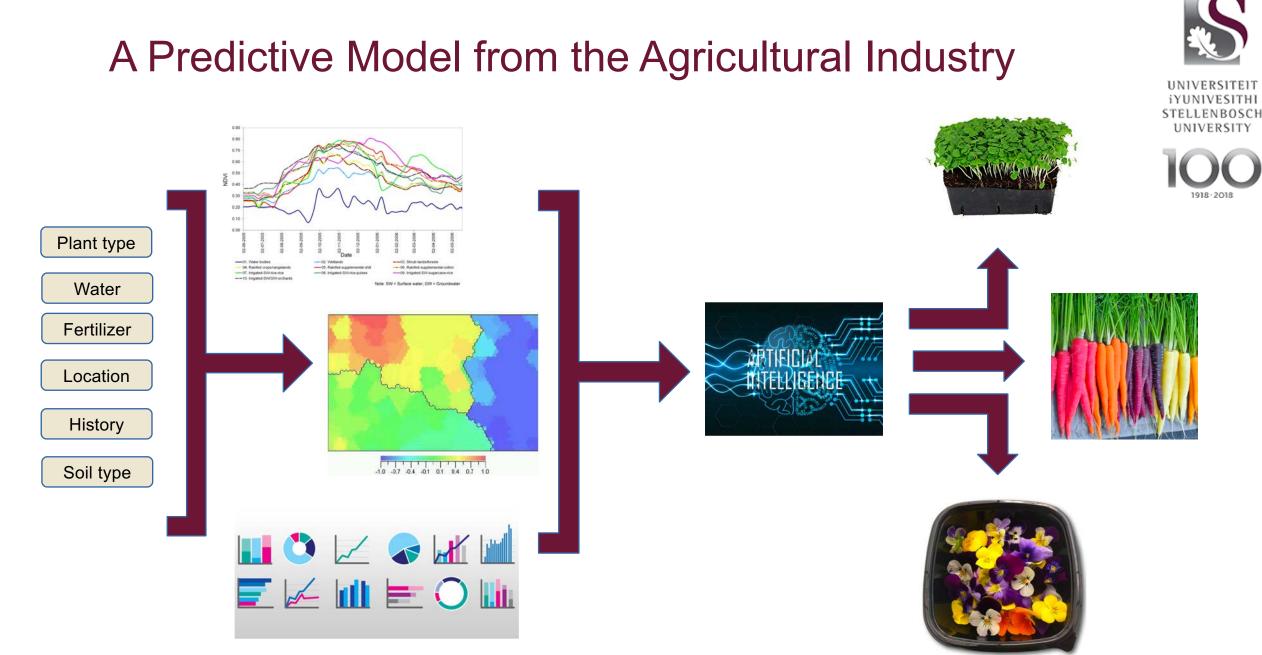






Acknowledgements: Yolandi Le Roux; University of Pretoria

more SLASTICA



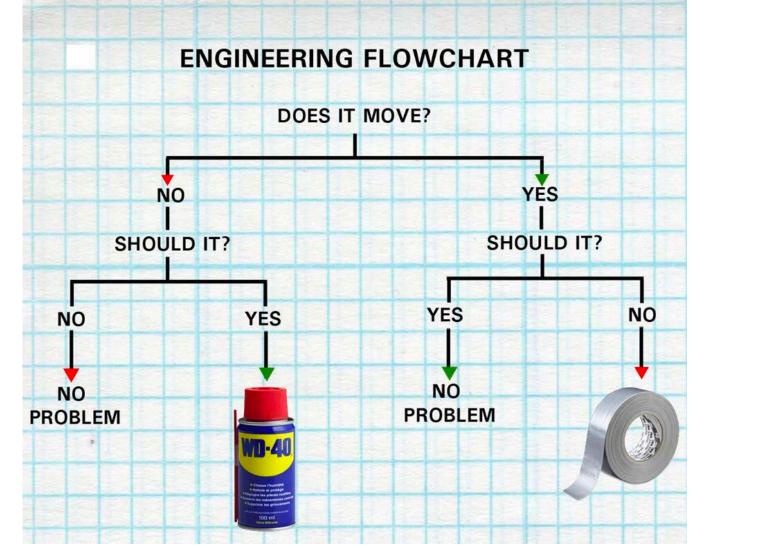
Acknowledgements: Yolandi Le Roux; University of Pretoria



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Decision Trees

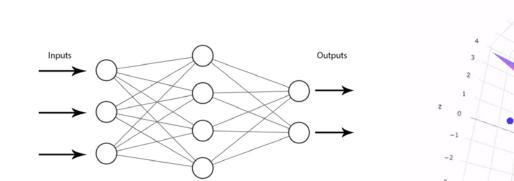


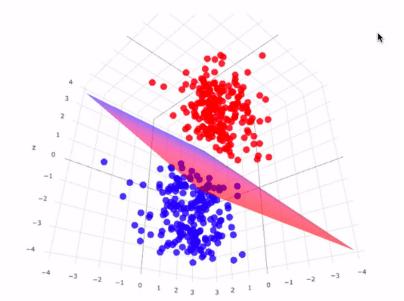


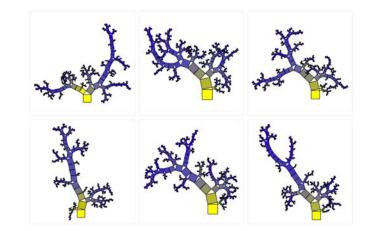
More Algorithms











Classifier Type	Algorithm	Accuracy
Bayesian	Bayes Net	40.89%
	Naïve Bayes	36.89%
	Naïve Bayes Updateable	36.89%
Functions	Logistic	35.15%
	Multi layer Perception	55.92%
	Simple Logistic	33.79%
	SMO	38.34%
Lazy	IBK	93.90%
	Star	90.16%
	LWL	30.51%
Meta	Attribute Selected Classifier	81.79%
	Bagging	73.59%
	Classification Via Regression	74.59%
	Filtered Classifier	61.11%
	Iterative Classifier Optimiser	44.72%
	Logit Boost	44.72%
	Multi Class Classifier	34.15%
	Random Committee	94.17%
	Randomizable Filtered Classifier	94.17%
	Random Sub Space	68.49%
Rules	Decision Table	63.48%
	JRip	68.76%
	Part	88.25%
Trees	Hoeffding Tree	36.16%
	J48	87.70%
	LMT	88.98%
	Random Forest	94.17%
	Random Tree	93.90%
	REP Tree	63.39%

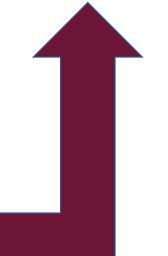
Results



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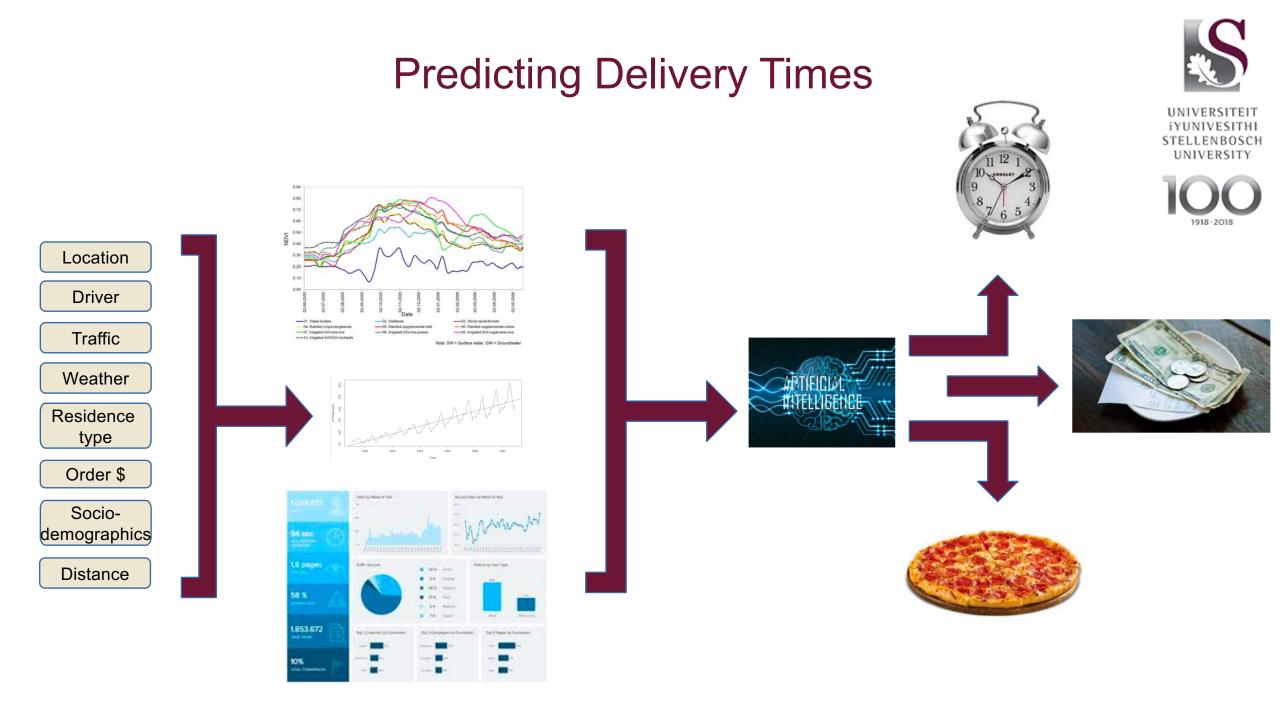
100

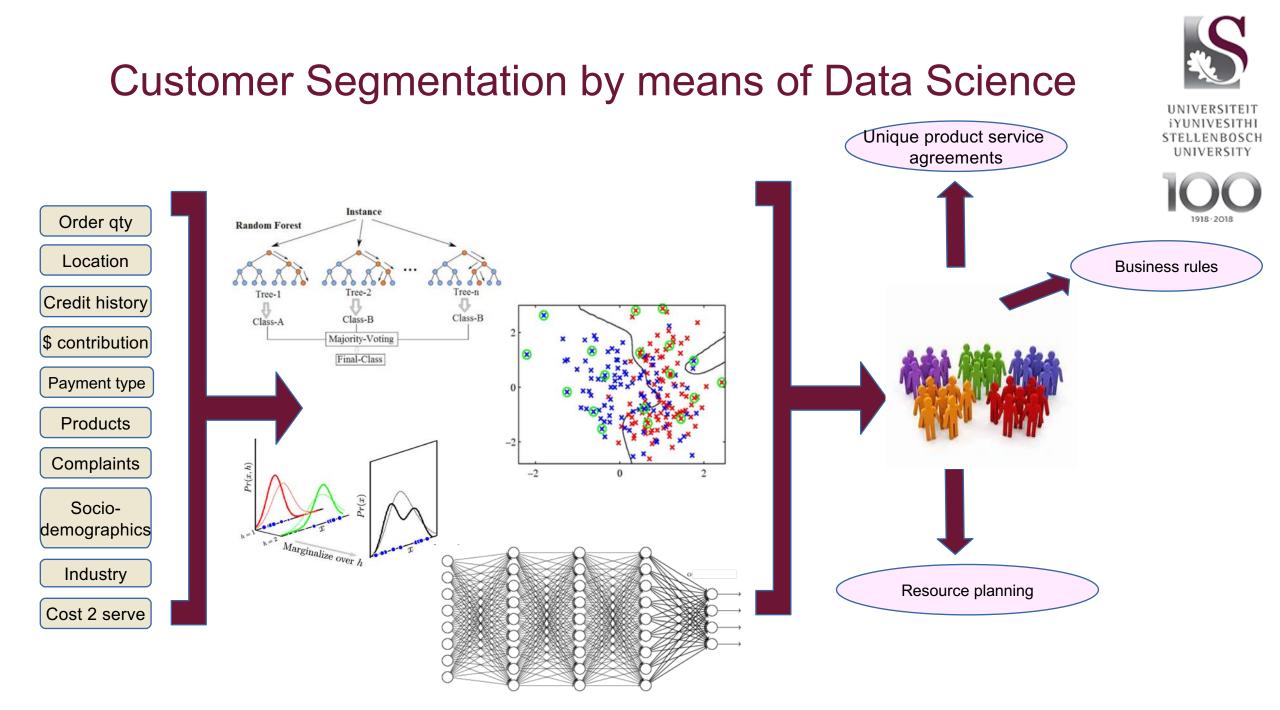
94% accuracy obtained with a random forest algorithm





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Other Projects

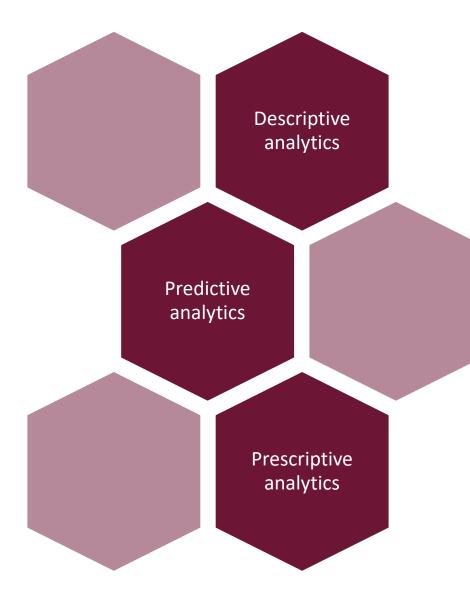
- Developing a recommender system for a wellness program
- Predicting port delays from wind, wave and other data
- Predicting manufacturing system quality
- Predicting energy requirements in the hospitality industry





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Data Science

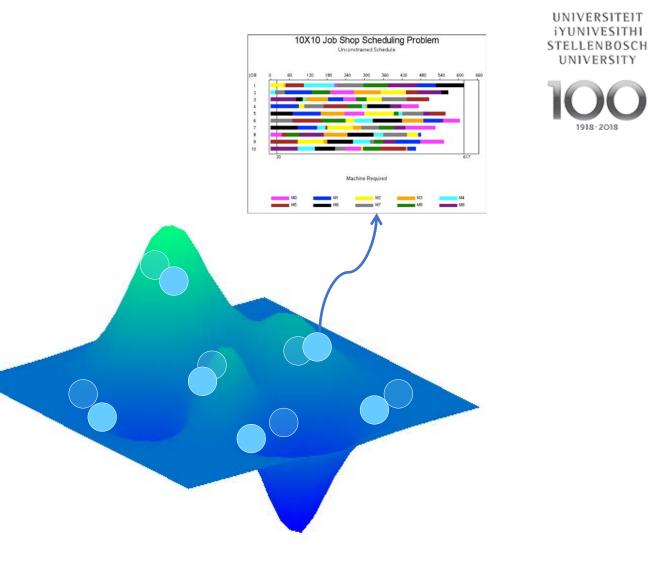






Prescriptive Analytics





- Objective function
 - Decision variables
- Constraints





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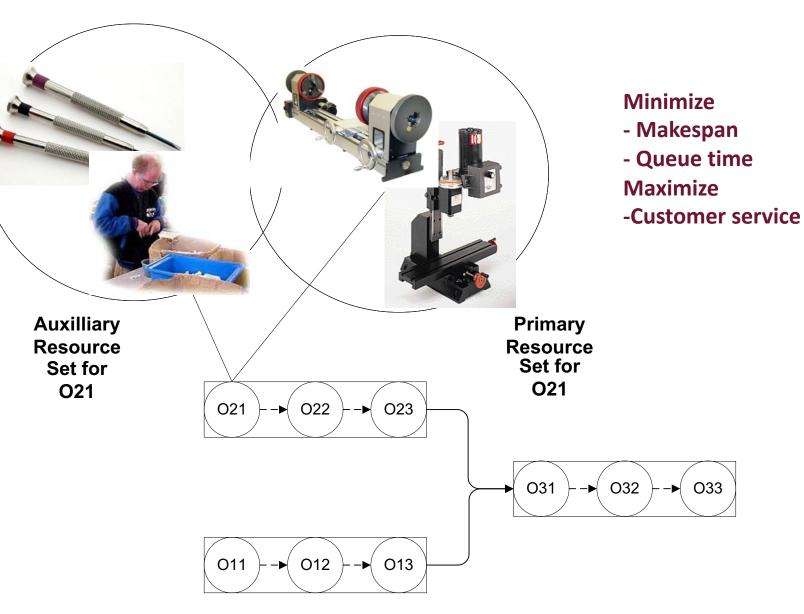


Operation 6

Operation 7

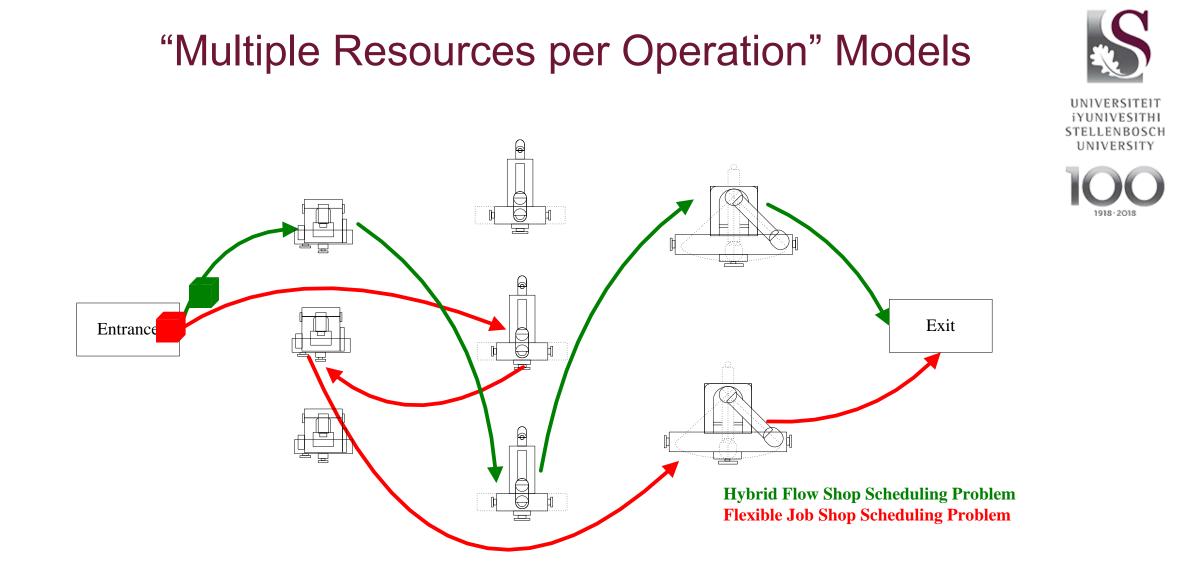
Resources	Time (Days)													
	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	Operation 1			Ο	perati	on 3		Operation 4						
2	Operation 2													
3							Operation 4							
4	Оре	eratio	n 1											

Scheduling









Optimization Literature Example



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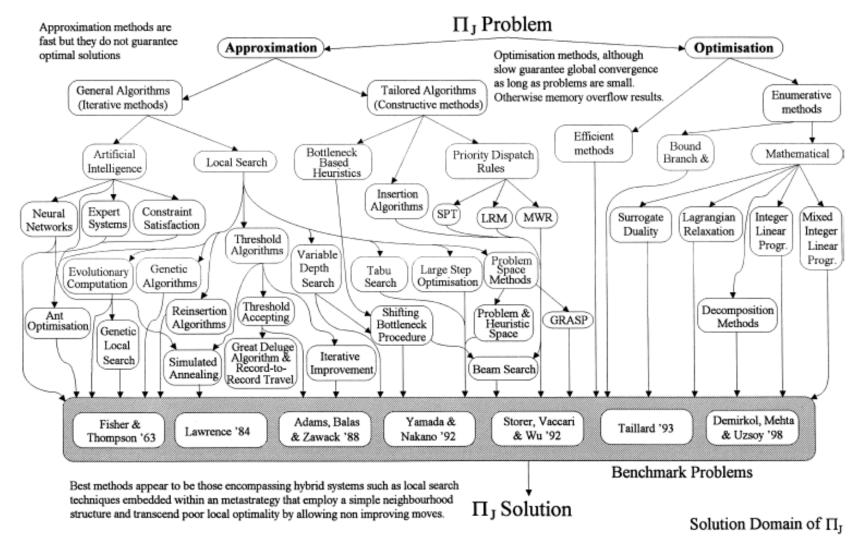


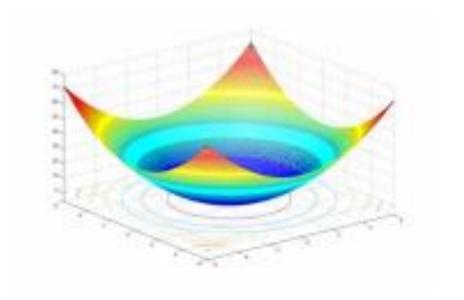


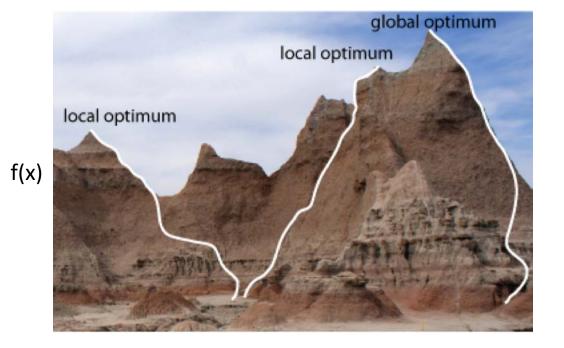
Fig. 1. The phases of Π_J research.

The Local Search Algorithm



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Х

Source: http://community.asdlib.org/imageandvideoexchangeforum/



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But why do we have to pick one algorithm?



Why can't we let the algorithm pick the algorithm?



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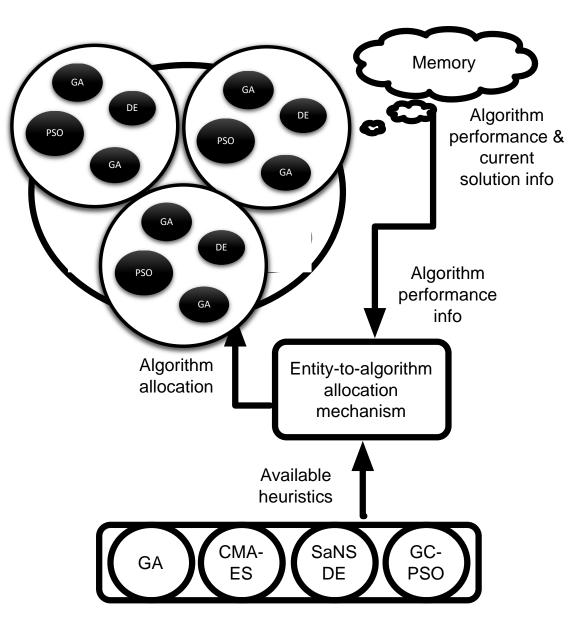
- 24 algorithm variations
- 60 diverse problems

. . .

• 24 000 hrs of processing time

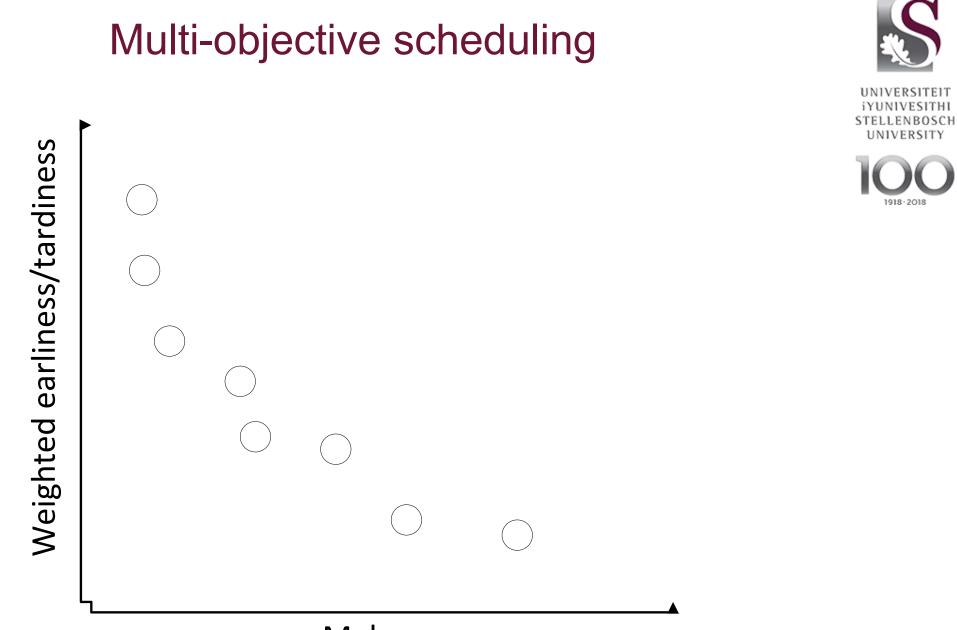


The HMHH scheduling algorithm





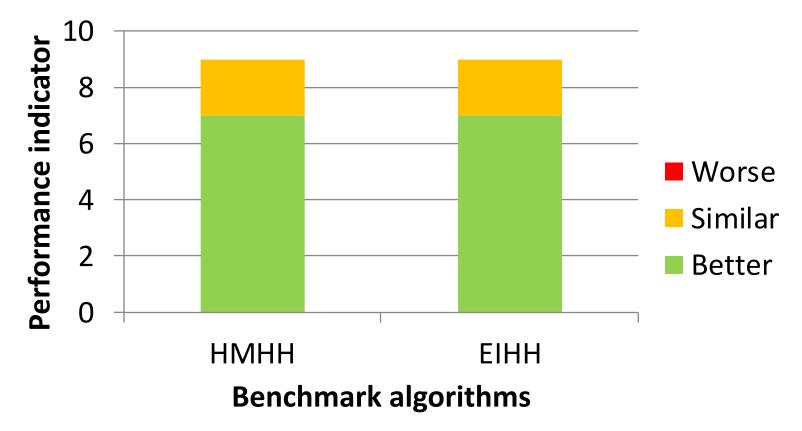




Makespan

Results interpretation

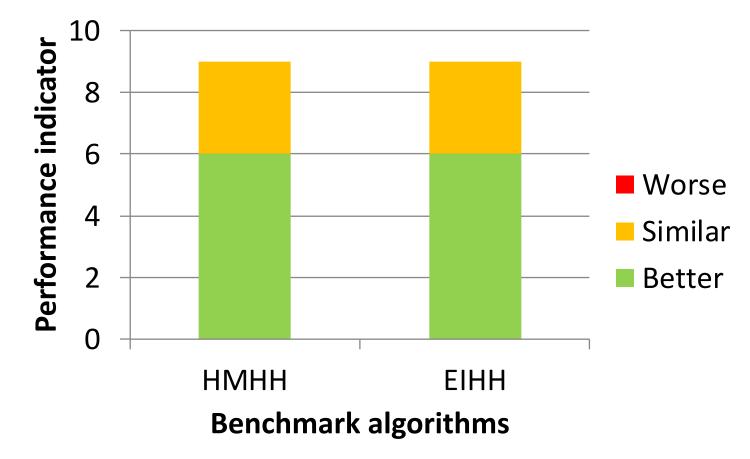
S-metric vs constituent algorithms





Results interpretation

Extent vs constituent algorithms





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 68% improvement when compared with state-ofthe-art algorithms

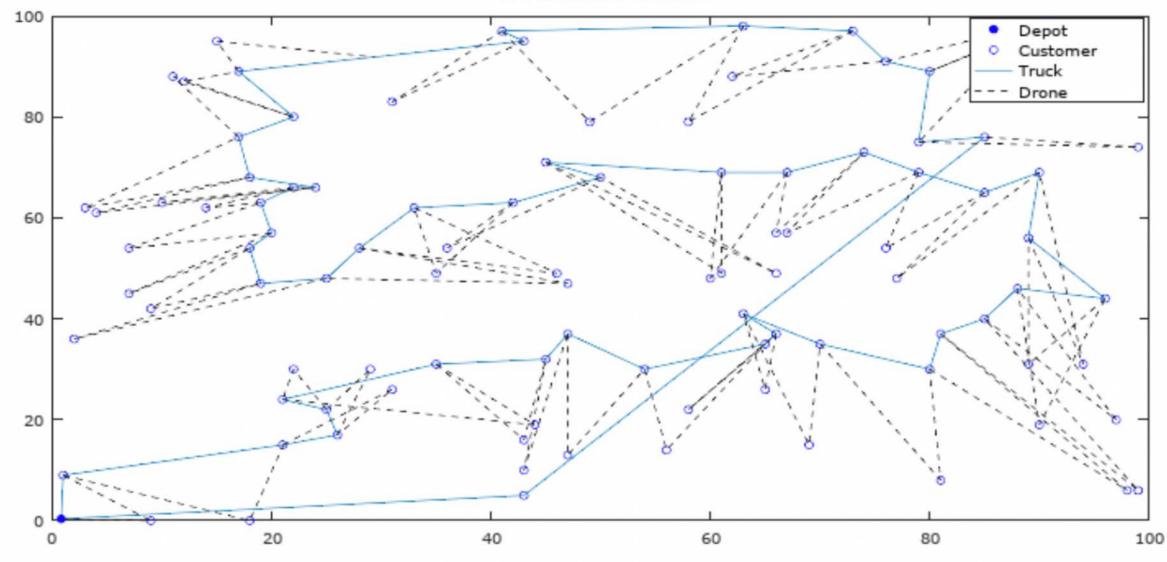
Impact

• At 40 hrs per design experiment and eliminating 5 experimental designs, you save 220 development hours per algorithm application



Preliminary Results

A Truck and a Drone



Acknowledgements: Tsietsi Moremi





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