Selection Hyper-Heuristics for Automated Design, Configuration and Selection

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Generation Hyper-Heuristics for Automated Design, Configuration and Selection

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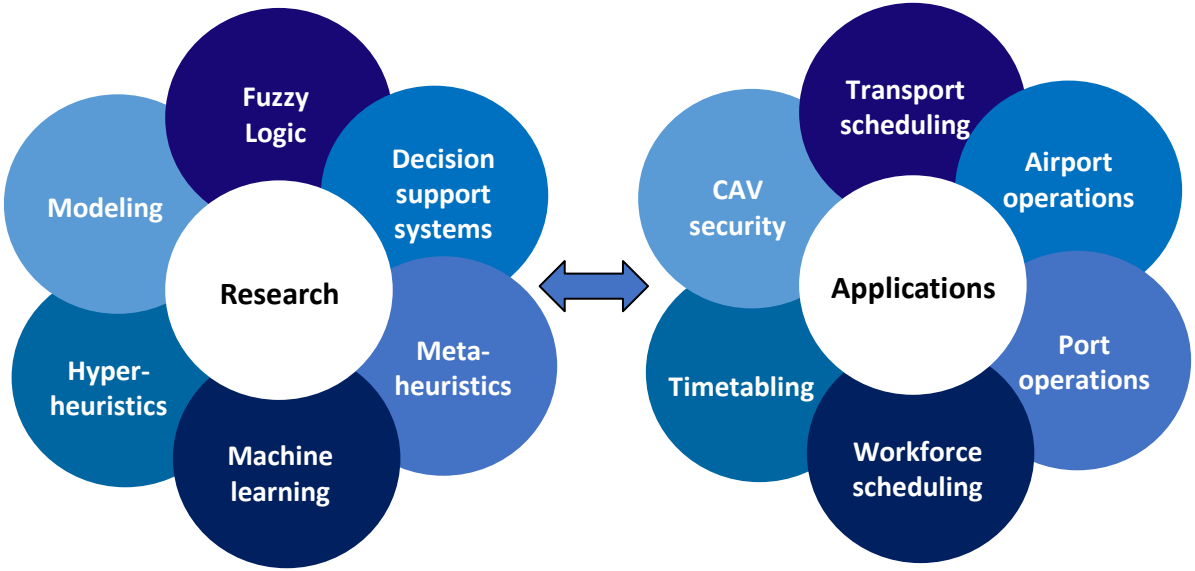

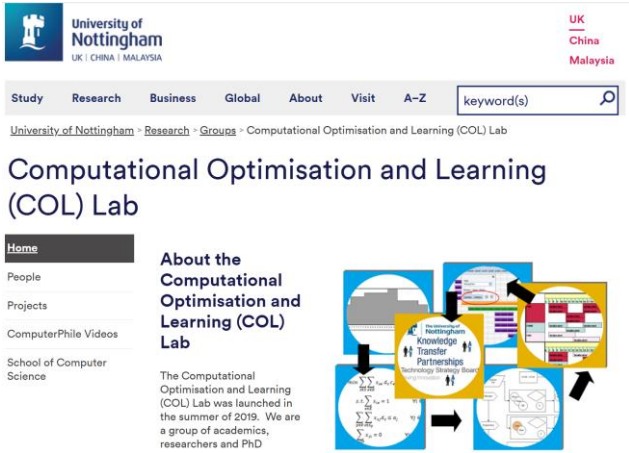

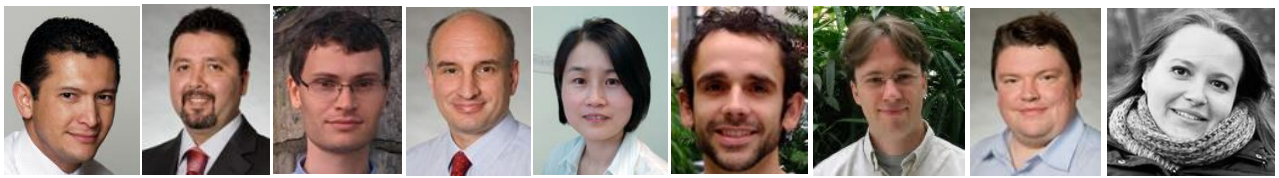

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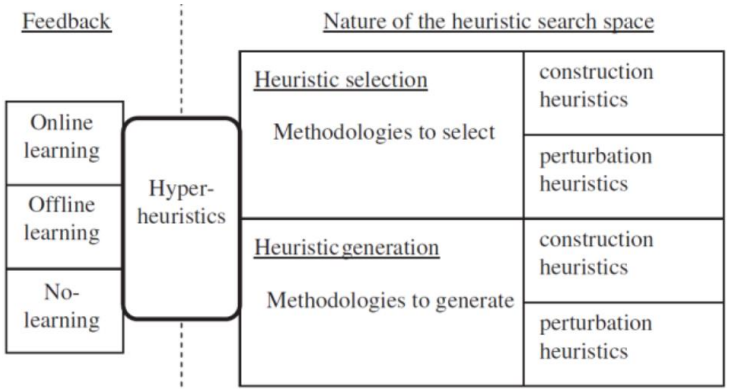
Automated Algorithm Design (AutoDes) with Hyper-heuristics



Automated Algorithm Design (AutoDes)

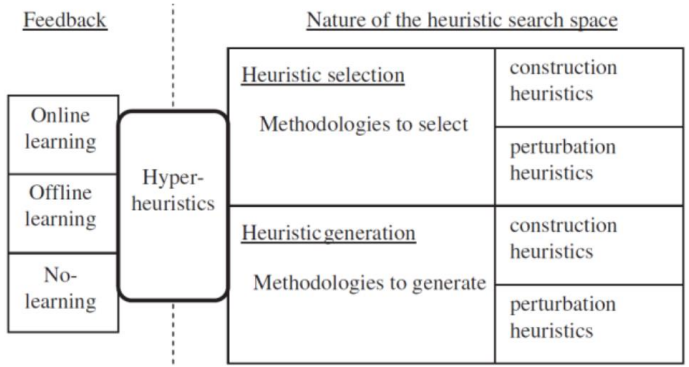
- Decisions to make when designing algorithms
  - Algorithm specific decisions
    - Simulated annealing; Tabu search; Variable neighbourhood search
    - Genetic algorithms; Estimation of distribution algorithm
    - Swarm Intelligence
    - Heuristics / operators
    - And some more …

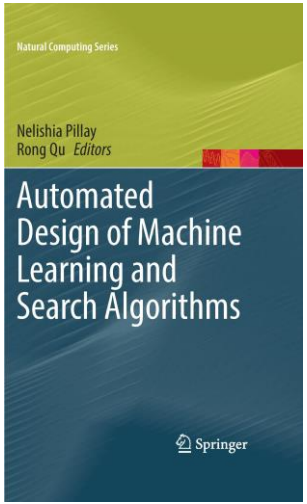
Automated Algorithm Design (AutoDes)

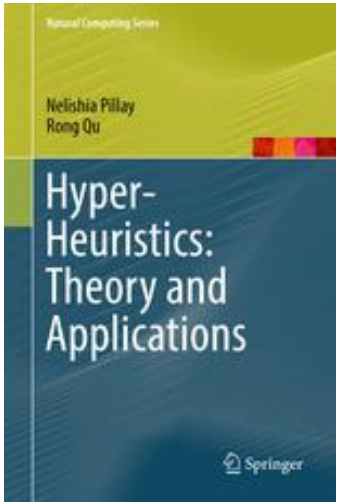
- Decisions to make when designing algorithms
  - Problem specific decisions
    - Operators
    - Solution representation
    - Evaluation function
  - General decisions
    - Initialisation
    - Stopping condition
    - Acceptance criteria

Automated Algorithm Design (AutoDes)

- Recent / advanced research developments
  - Integration of other computational intelligence techniques
    - Hybridisation of evolutionary and local search algorithms
    - Machine learning and optimisation
    - Data-driven optimisation
    - Hyper-heuristics
    - And many more …

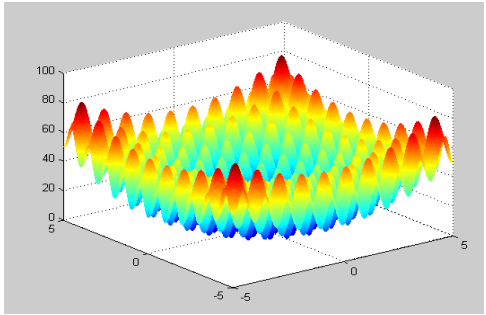


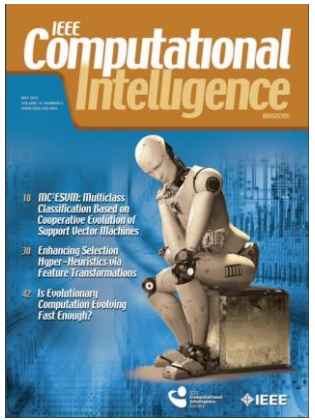




Automated Algorithm Design (AutoDes)

- Recent / advanced research developments
  - Automated algorithm design, w.r.t. decision space (of algorithm design) [Qu20]
    - Automated composition: components of algorithms
    - Automated configuration: parameter selection/setting
    - Automated selection: given algorithms





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Automated Algorithm Design (AutoDes)

- Search space: parameter configurations of target algorithms
- Objective: To automatically configure parameters of pre-defined target algorithms offline against a given set of training instances
  - Target algorithms: stochastic local search [Pag19], multi-objective evolutionary algorithms [Lop12]
  - Parameters: numerical, categorical
  - COPs: TSP, VRP, flowshop scheduling problems
- Platforms: automatically search for the configuration of parameter space for target algorithms
  - ParamILS[1]: [Hut09]
  - F-Race/I-Race[2]: [Bir10]

1. http://www.cs.ubc.ca/labs/beta/Projects/ParamILS/
2. http://iridia.ulb.ac.be/irace/

Automated Algorithm Design (AutoDes)

- Search space: a family/portfolio of algorithms/solvers
- Objective: according to the grouping/clustering of a set of training instances against certain features, to automatically select from the given target algorithms offline
  - Target algorithms: evolutionary algorithms [Aka17], solvers [Liu19]
  - COPs: TSP, function optimisation

- Platforms
  - Population-based Algorithm Portfolios (PAP): [Tan14]
  - Hydra: [Xu10]

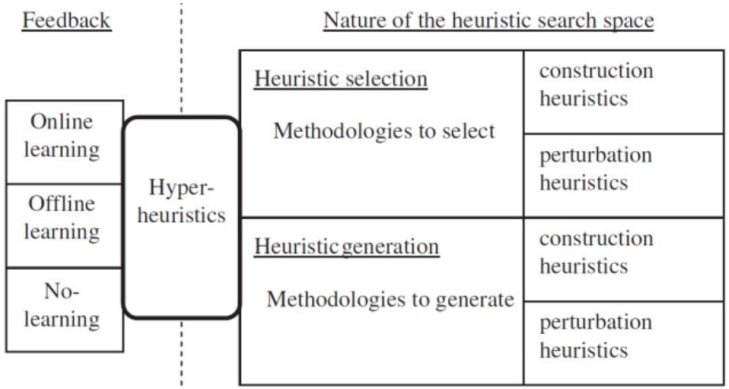
Automated Algorithm Design (AutoDes)

- Search space: a set of basic building blocks/components of algorithms
- Objective: To automatically compose new algorithms online by searching for the best composition of components for solving the given problem instances online
  - Target algorithms: evolutionary algorithms [Bez14], general new algorithms, i.e. hyper-heuristics [Bur13,Pil18]
  - COPs: timetabling, NRP, TSP, job shop scheduling, VRP

- Platforms:
  - HyFlex: [Bur11]
  - EvoHyp: timetabling, NRP, TSP, VRP, etc. [Pil17]

AutoDes – Hyper-heuristics

- "A high-level approach that, given a particular problem instance and a number of low-level heuristics, can select and apply an appropriate low-level heuristic at each decision point" [Bur13]
- Objective: to find
  - the right high-level method or sequence of easy-to-implement low-level heuristics in a given situation, rather than trying to solve the problem directly
  - an adequate combination of the provided components to effectively solve the given problem(s)
- Platforms:
  - HyFlex: [Bur11]
  - EvoHyp: timetabling, NRP, TSP, VRP, etc. [Pil17]



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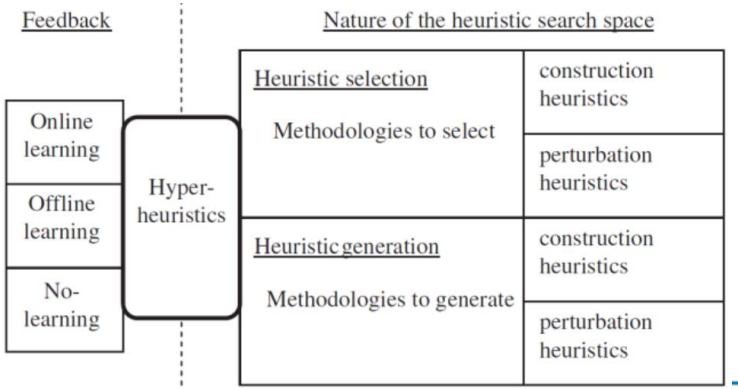
AutoDes – Selection Hyper-heuristics

- Low level heuristics: Constructive
  - Build solutions incrementally
  - Education timetabling (graph coloring), production scheduling (dispatching rules)
  - Bin packing (heuristic rules), workforce scheduling (resource selection)
  - Constraint satisfaction (variable ordering), VRP (both constructive and perturbative)

  - Research issues
    - Two search spaces
    - Landscape analysis on heuristic space



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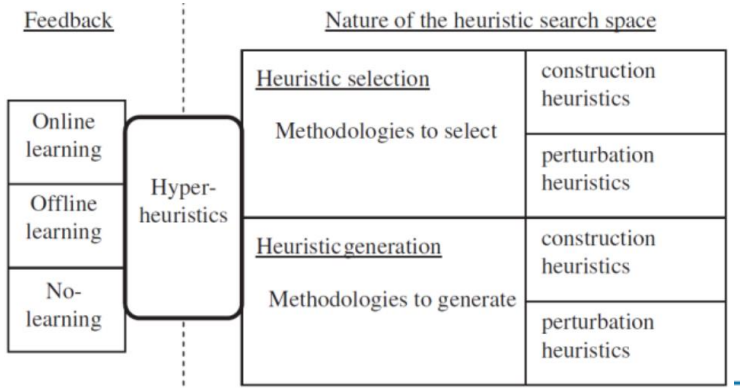
AutoDes – Selection Hyper-heuristics

- Low level heuristics: Perturbative
  - Improves candidate solutions
  - Heuristic selection, acceptance criteria
- Research issues
  - Online learning
  - Reinforcement learning
- Cross Domain Heuristic Challenge (CHeSc)
- HyFlex



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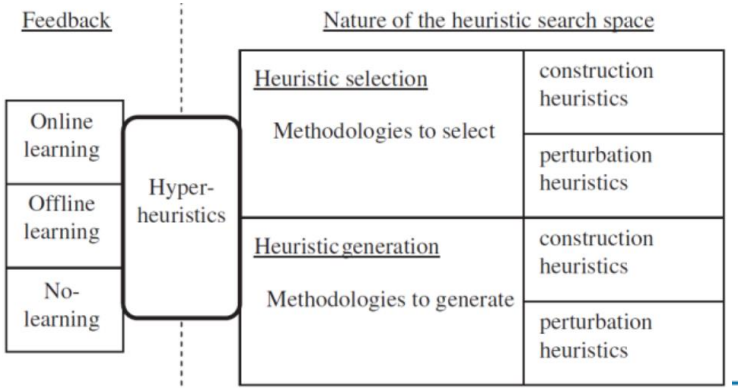
AutoDes – Selection Hyper-heuristics

- Learning to select an appropriate / elite set of low-level heuristics / components
  - Online learning
    - Different low level heuristics effective at different stages
    - Step-by-step reduction during the search, snapshot performance
  - Offline learning
    - Evaluation of collective / accumulative performance
    - Statistical analysis, landscape probing



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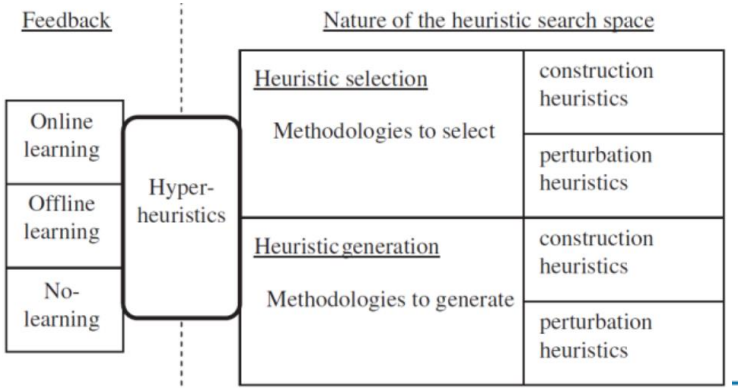
AutoDes – Selection Hyper-heuristics

- Learning to select / compose low-level heuristics / components
  - Online learning
    - Select / predict the most suitable low level heuristics based on their performance during the search
    - Reinforcement learning: Markov chain / models, choice function
    - States: problem-specific features, general / problem independent features
  - Offline learning
    - Choose low-level heuristics or acceptance criteria based on offline training
    - Classification models, logistic regression, neural networks, apprenticeship learning, etc.



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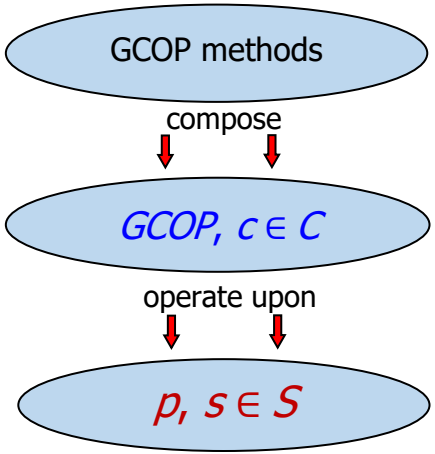
Modelling and Learning in Automated Algorithm Composition

AutoDes – The GCOP Model

- General Combinatorial Optimisation Problem
  - Decision variables: algorithmic components ***a***
- GCOP methods
  - Search for algorithmic components ***a***
    to find algorithmic compositions ***c*** in an algorithm space ***C***
    c match direct solutions ***s*** in the solution space *S* for ***p***
  - Automated algorithm composition

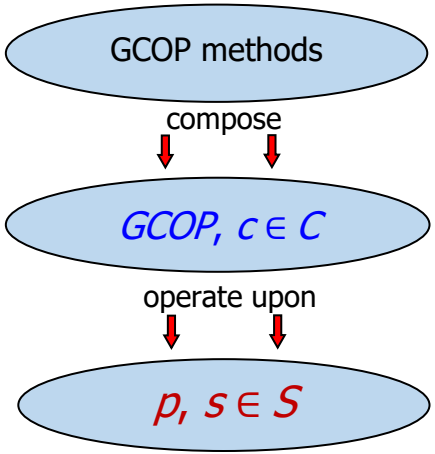


	GCOP Space *C*	Solution space *S*
Encoding	Compositions c upon $a \in A$	Direct solutions $s \in S$ on p
Upper Bound	Depends on |A| and parameters of $a \in A$	Depends on the number of variables in s for p
Operator	Any methods composing a into c	Search operators on $s \in S$
Objective Function	Performance of c that produces s	Solution quality of $s \in S$ for p

AutoDes – The GCOP Model

- The algorithmic compositions ***c*** ∈ ***C*** are measured by objective function *F(c)* → *R*
  The direct solutions ***s*** ∈ ***S*** are measured by objective function *f(s)* → *R*
- *s* are obtained using *c, i.e. c* → *s*
  Let matching function ***M***: *f(s)* → *F(c)*
- The objective of GCOP: to find optimal *c**

$$F(c^*|c^* \rightarrow s^*) \leftarrow f(s^*) = \mathbf{min}(f(s))$$



AutoDes – The GCOP Model

- Modelling of VRP and NRP algorithms

$a \in A_{1.0}$	a **in GCOP for solving NRP** $h1_w$: selection criteria such as the cost of constraint violations, shift type balance, etc.
$o_{chg}(k,h1_w,h1_b)$	*change shift*: use $h1_b$ to change the shift type of k nurses chosen by $h1_w$.
$o^{bw}_{xchg}(k,k,h1_w)$	*swap shifts*: swap k shifts between two nurses chosen by $h1_w$.
$o_{rr}(k,h1_w,h1_b)$	*ruin and recreate*: use $h1_b$ to reassign all k shifts of a set of nurses chosen by $h1_w$.

	$a \in A_{1.0}$ **in GCOP for VRP** $h1_w$, $h1_b$: selection criteria/heuristics
$o_{ins}(k,h1_w,h1_b)$	*greedy*, *insertion* [30]: insert k nodes chosen by $h1_w$ to a route chosen by $h1_b$.
$o_{chg}(k,h1_w,h1_b)$	*shift* [31]: use $h1_b$ to change k nodes selected by $h1_w$.
$o_{xchg}(k,m,h1_w)$	*k-opt* [31], *interchange*, *Van Breedam* [32]: swap k and m nodes selected by $h1_w$.
$o_{xo}(k,m,h2_b)$	*crossover*: exchange sub-routes of k and m nodes between two solutions chosen by $h2_b$.
$o_{rr}(k,h1_w,h1_b)$	*destroy and repair*: remove k nodes chosen by $h1_w$, and re-assign them using $h1_b$.

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AutoDes – The Framework

- General Search Framework [Yi22]
  - Automated Algorithm Composition

TABLE I
COMPONENTS WITHIN THE GENERAL SEARCH FRAMEWORK

Component	Criteria
Initialization	random, problem-specific heuristics
Selection for evolution	probability-based operators, deterministic operators
Evolution	mutation, crossover
Selection for replacement	comma-selection, plus-selection
Termination	time, convergence

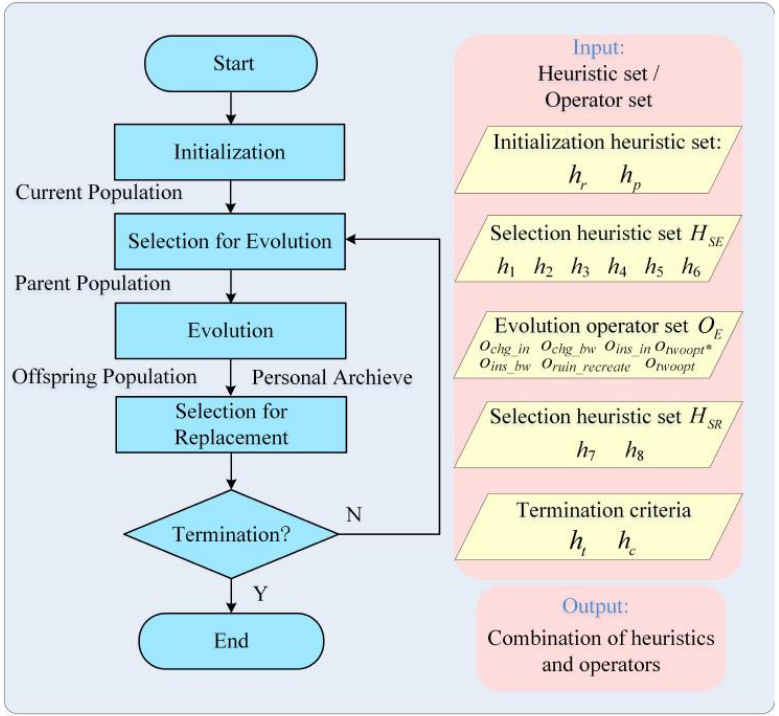


Fig. 1. General search framework

AutoDes – The Framework

- Learning on automated algorithm composition [Men22]

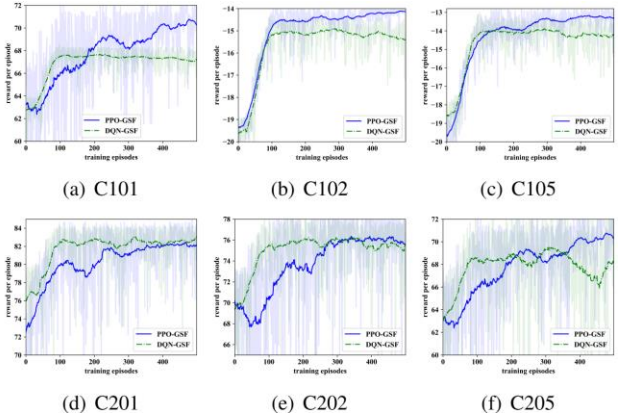


Figure 1: The M_{IP} updated during six iterations

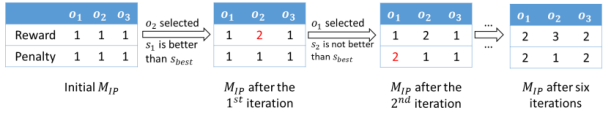
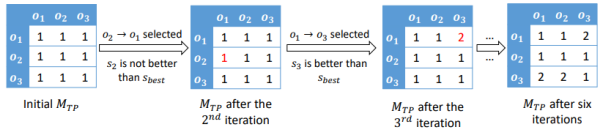
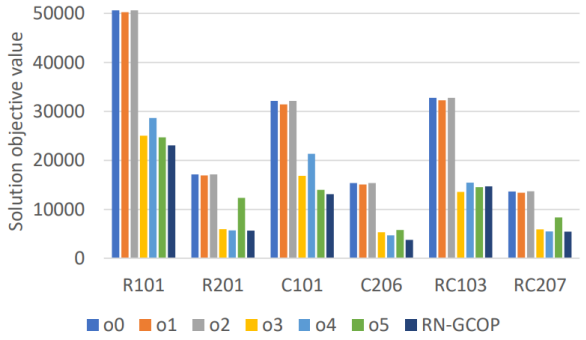


Figure 2: The M_{TP} updated during six iterations





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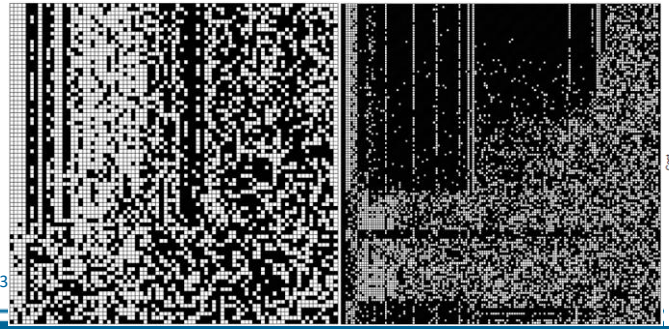
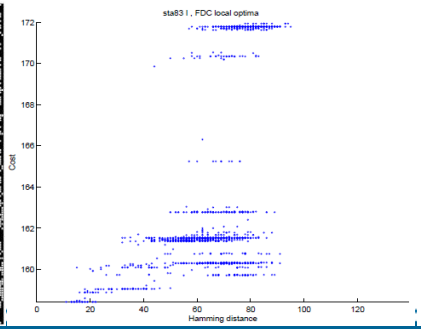
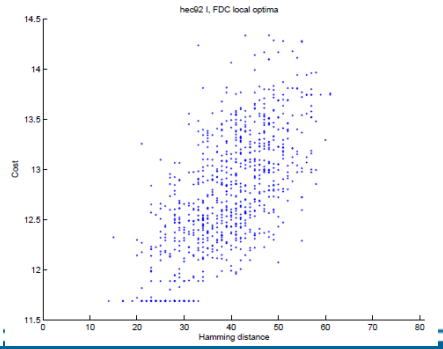
AutoDes – Fundamental Issues

- Within unified algorithm design framework
  - Learning on heuristic / components compositions
  - Search space and landscape analysis of high level heuristic compositions *c*
    - High level heuristic compositions *c:* one-dimensional string
    - Easy to measure distances / differences: simpler solution encoding
    - Distribution of costs for local optimal *c*
    - Fitness distance correlation (*fdc*) of local to global optimum







AutoDes – Future Research

- Theory
  - Modelling and standardisation of algorithm design
  - General framework / platforms
  - Search space / landscape analysis
  - Common problem representation / encoding
- Machine learning + optimisation
  - Hidden patterns / new knowledge
  - Reusability and interpretability

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