Evolutionary Computation plus Dynamic Programming for the Bi-Objective Travelling Thief Problem

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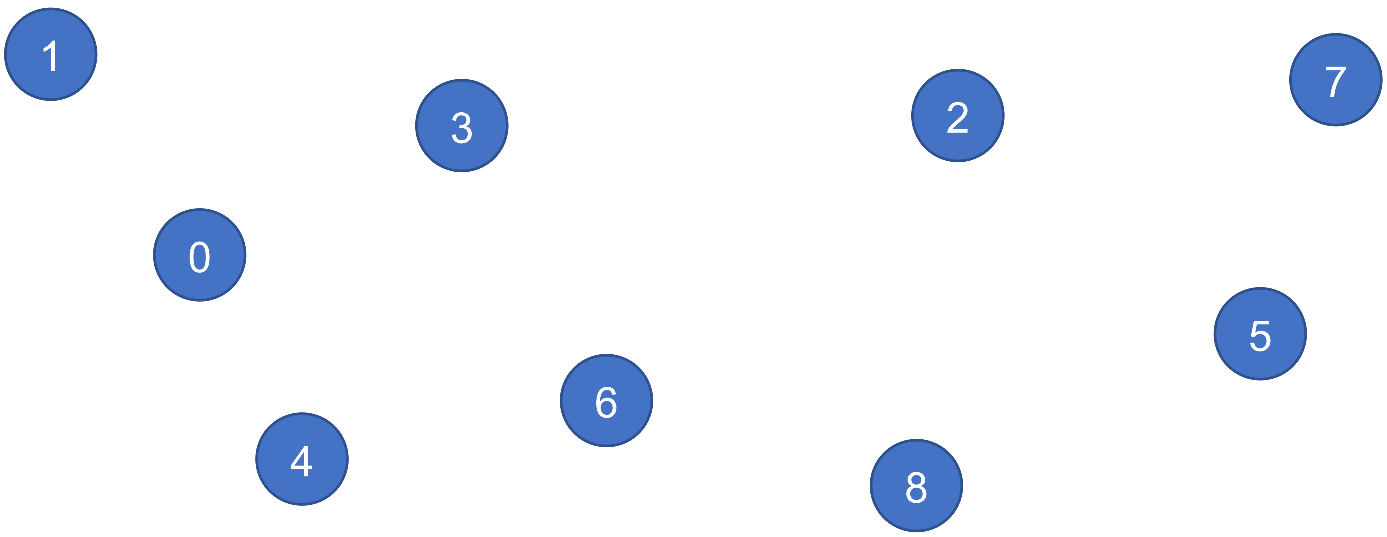
Project page: https://cs.adelaide.edu.au/~optlog/research/ttp.php

Or google “travelling thief Adelaide”

Tuesday, July 17, 10:40-12:20, Conference Room D (3F)

The Travelling Thief Problem (TTP)

Composed of the merging of the Traveling Salesman Problem and the Knapsack Problem



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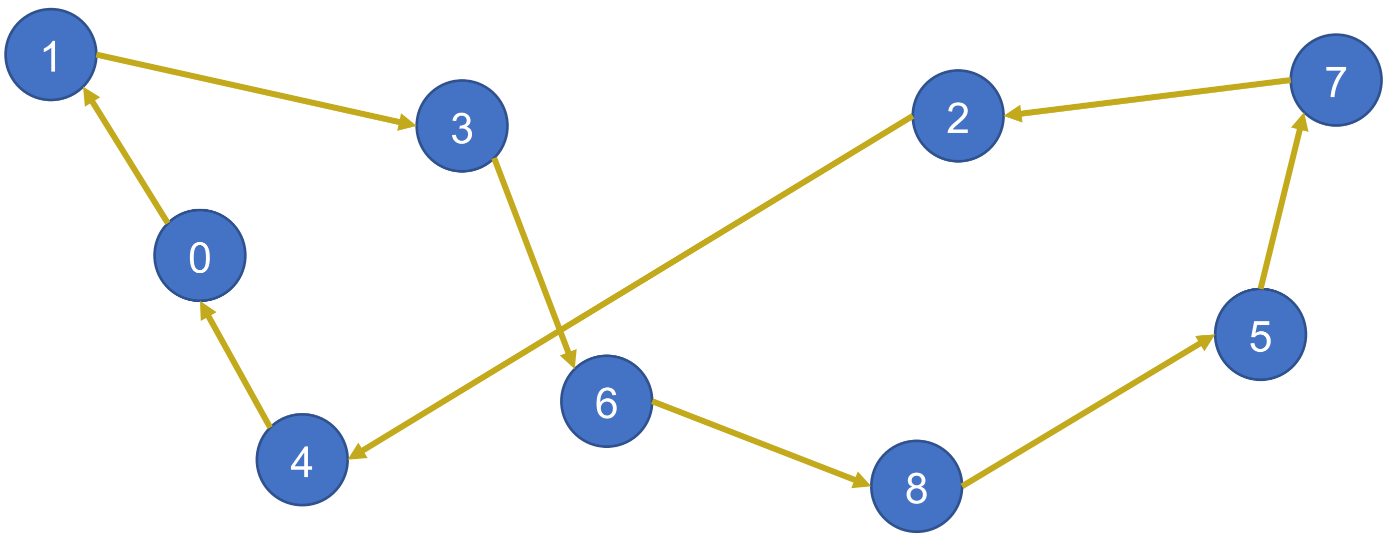

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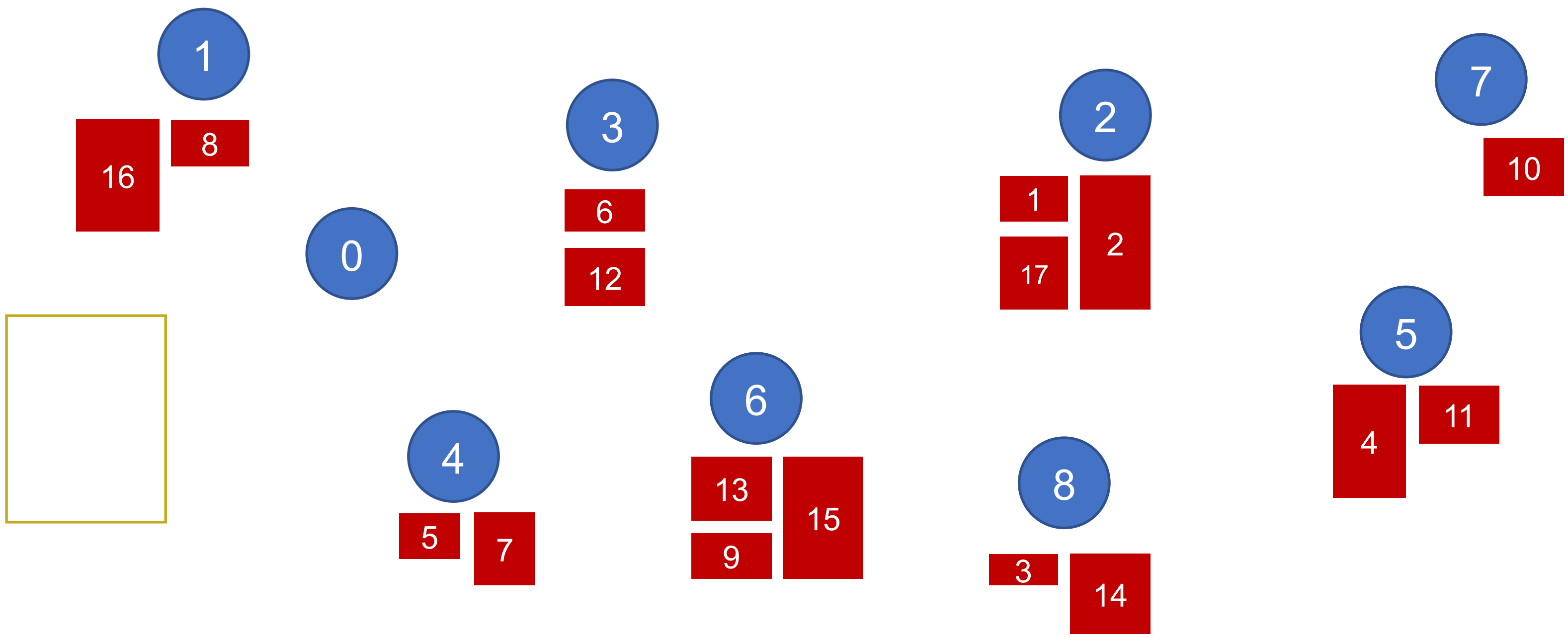

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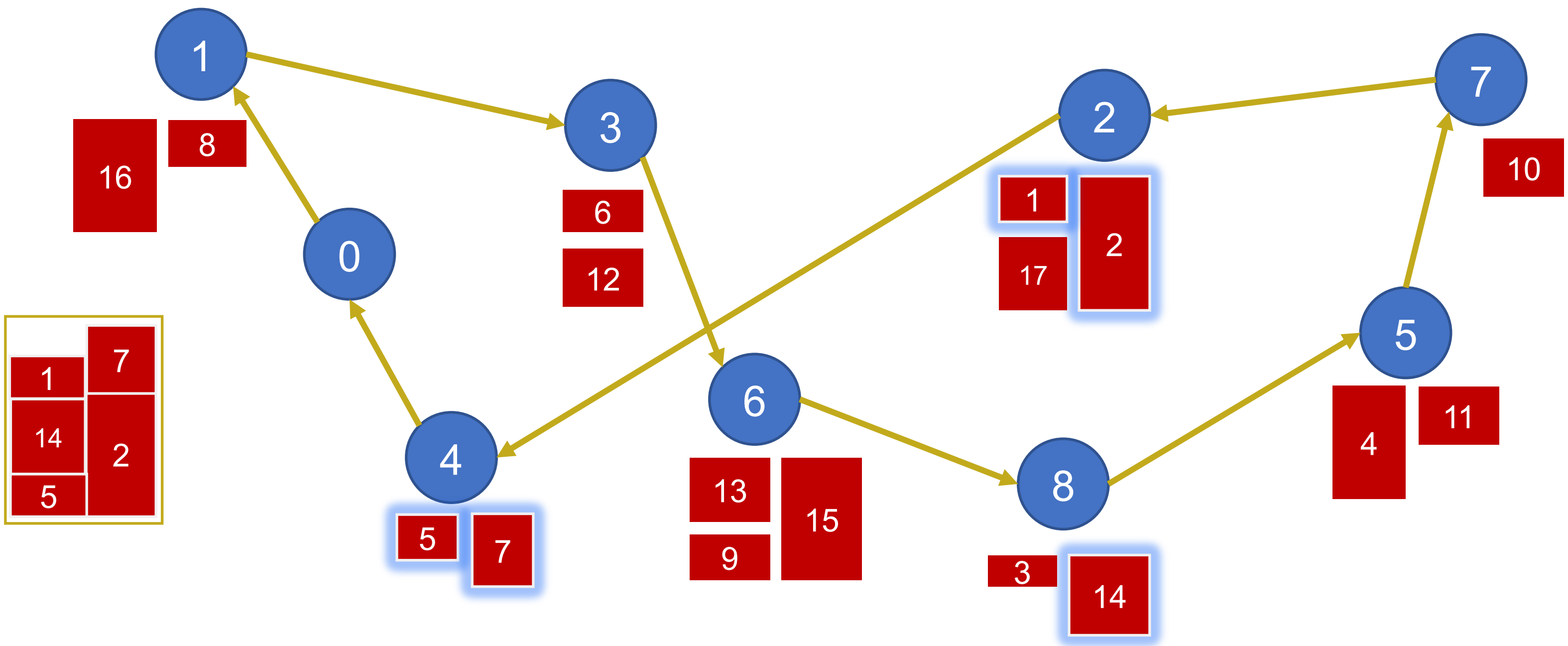


THE TRAVELING THIEF PROBLEM (TTP)

Goal: Visit each city exactly once, maximising the total profit P such that the total weight does not exceed the knapsack capacity W, where P is defined as:

$$P = \sum_{i=1}^{m} p_i x_i - R \sum_{i=1}^{n} t_{i,i+1}$$

where $x_i = \{1|0\}$ depending on whether the item i is picked $\{1\}$ or not $\{0\}$, and $t_{i,j}$ is defined as:

$$t_{i,j} = \frac{d(\Pi_i, \Pi_j)}{v_{max} - W_{\Pi_i}\left(\frac{v_{max} - v_{min}}{W}\right)}$$

where Π_i is the city at tour position i in tour Π, and W_{Π_i} is the current weight of the knapsack at city Π_i.

The Bi-Objective TTP

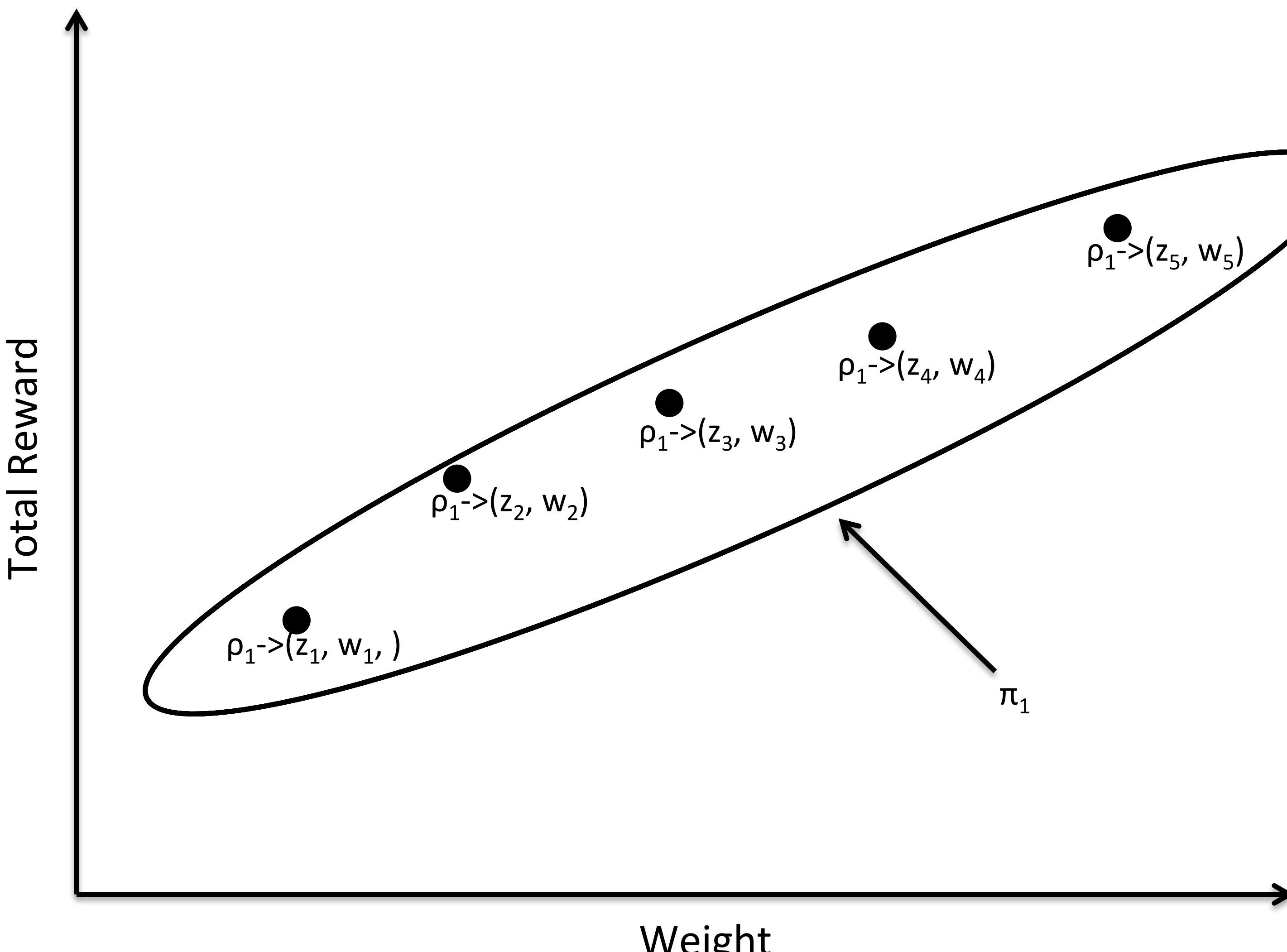
a natural extension:
maximise the reward for a given weight of collected items, or determine the least weight subject to bounds imposed on the reward

- Objective one: profit P as defined before
- Objective two: total accumulated weight

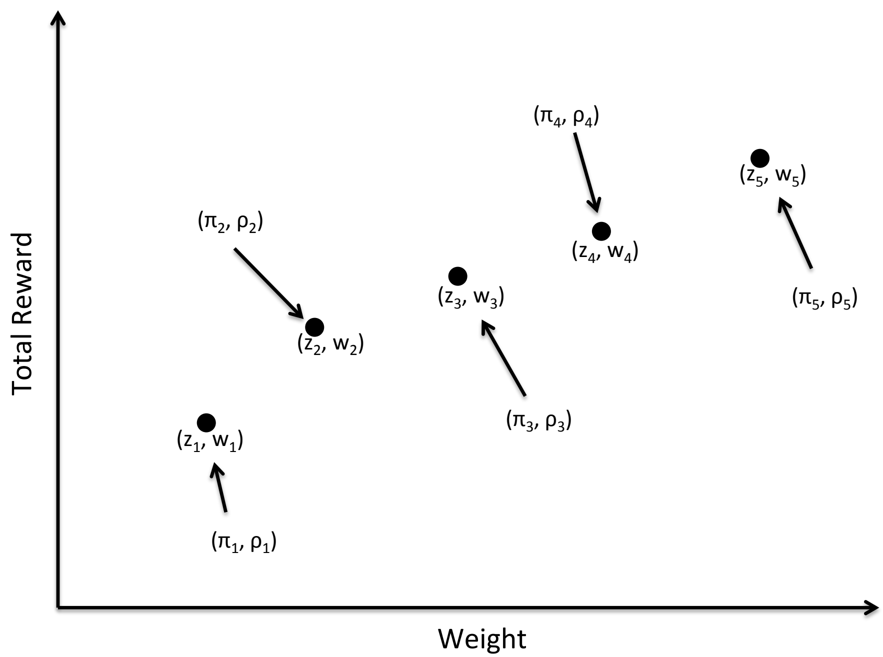
Packing-While-Travelling (PWT)

- …

Definition 3.1. Let τ_π be a corresponding objective vector for $\bar{P}_\pi$. Then τ_π represents the related Pareto front designated as a *DP front* for the given tour π.

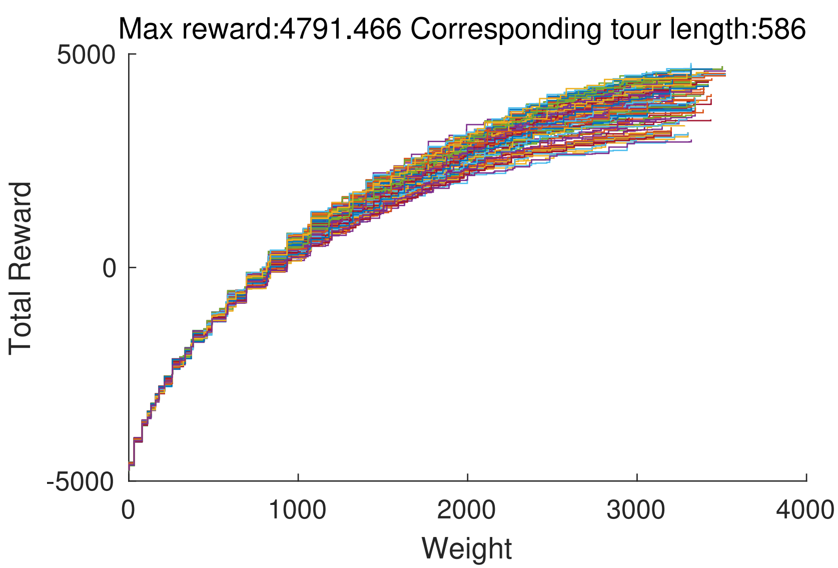


(the “natural” approach would be the following)



Solving the Bi-Obj. TTP

- Many single-objective TTP heuristics take a good TSP tour as a starting point. What does this mean here?
- TSP solvers; CONCORDE (CON), ACO, LKH and LKH2



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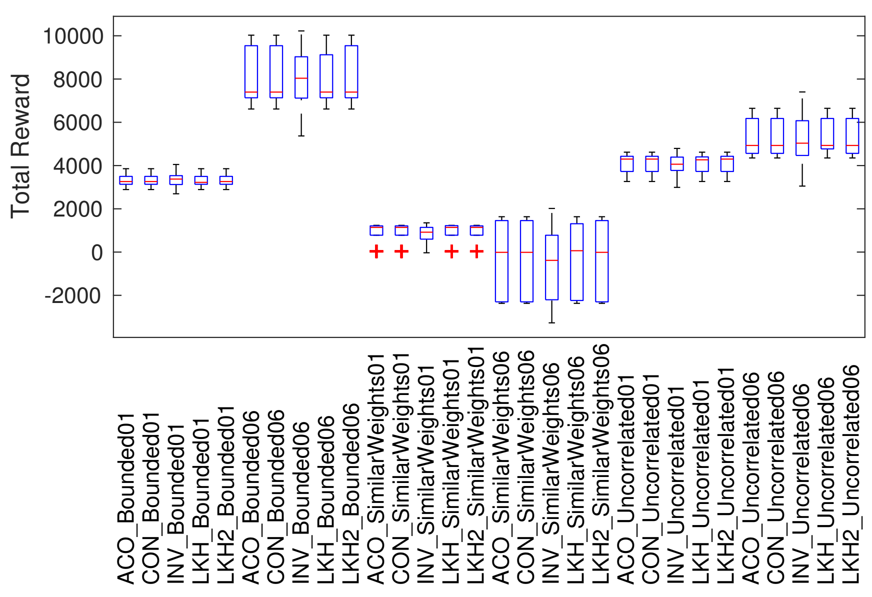


Algorithm 1 Hybrid IBEA Approach

Input: population size μ; limit on the number of generations α;
Initialisation:
set the iteration counter $c = 0$;
populate $\overline{\Pi}$ with μ new tours produced by the TSP solver;
while $(c \leq \alpha)$ **do**
  set $c = c + 1$;
  Indicator:
  run the DP for every tour $\pi \in \overline{\Pi}$ to compute its DP front τ_π;
  apply indicator function $\mathcal{I}(\tau_\pi)$ to calculate the indicator value for every individual tour $\pi \in \overline{\Pi}$;
  Survivor Selection:
  repeatedly remove the individual with the smallest indicator value from the population $\overline{\Pi}$ until the population size is μ (ties are broken randomly);
  Parent Selection:
  apply parent selection procedure to $\overline{\Pi}$ according to the indicator values to choose a set Λ of λ parent individuals;
  Mating:
  apply crossover and mutation operators to the parents of Λ to obtain a child population Λ';
  set the new population as $\overline{\Pi} = \overline{\Pi} \cup \Lambda'$;
end while

Indicators

Def 3.2: Given q different DP fronts, let ϕ denote a set of possible unique solution points derived by $\tau_1 .. \tau_q$. Then ω is a Pareto front formed by the points of ϕ and ω is named as the surface of ϕ.

Given a tour τ_π, and its corresponding solution set T_π:

- Surface Contribution: number of objective vectors contributed by T_π
- Hypervolume: volume covered by T_π w.r.t (0,C)
- Loss of Contribution:

$$LSC(\tau_\pi) = 1 - SC(\Phi \setminus T_\pi)$$

$$LHV(\tau_\pi) = 1 - \frac{HV(\Phi \setminus T_\pi)}{HV(\Phi)}$$

Parent Selection Mechanisms

- Rank-Based Selection (RBS), Fitness-Proportionate Selection (FPS), Tournament Selection (TS), Arbitrary Selection (AS), Uniformly-at-Random Selection (UAR)

Crossover and Mutation Operators

- TSP-only: multi-point crossover, 2-opt mutation, jump

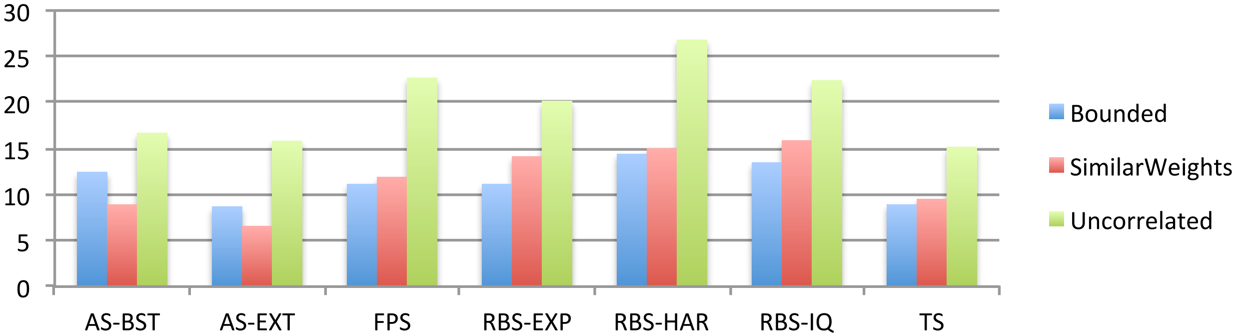
Experimental Study

- 2 indicators X 8 parent selection strategies
- TTP instances from the classes eil51, eil76, eil101; three knapsack types

Assessment

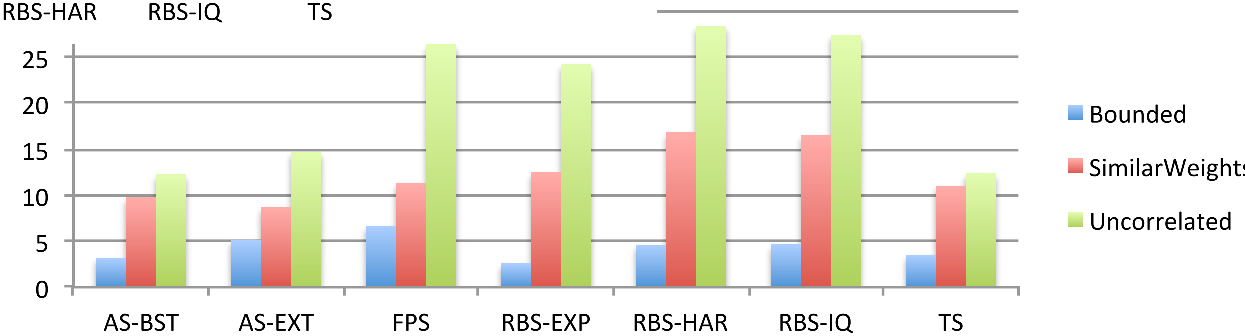
- 30 repetitions, Welch’s t-test with UAR as a baseline (like the Student's t-test, but more reliable when the two samples have unequal variances and unequal sample sizes)

Loss Hypervolume



hypervolume

total reward



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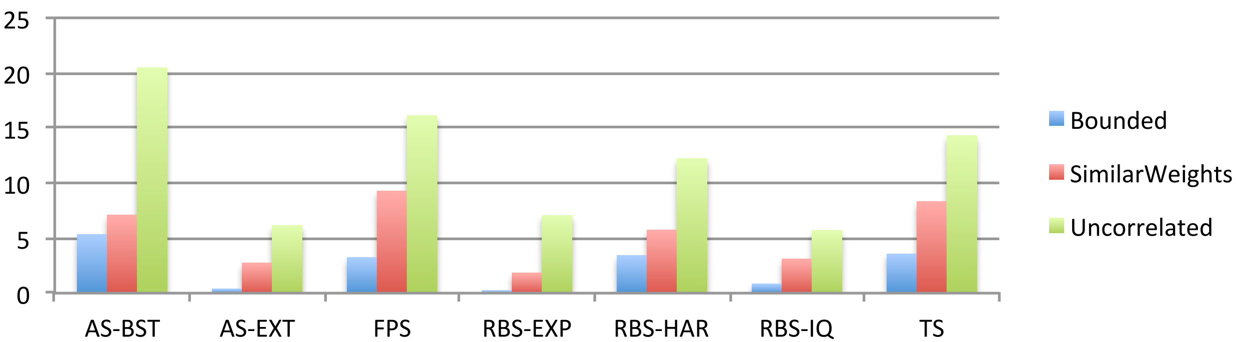
Loss Surface Contribution



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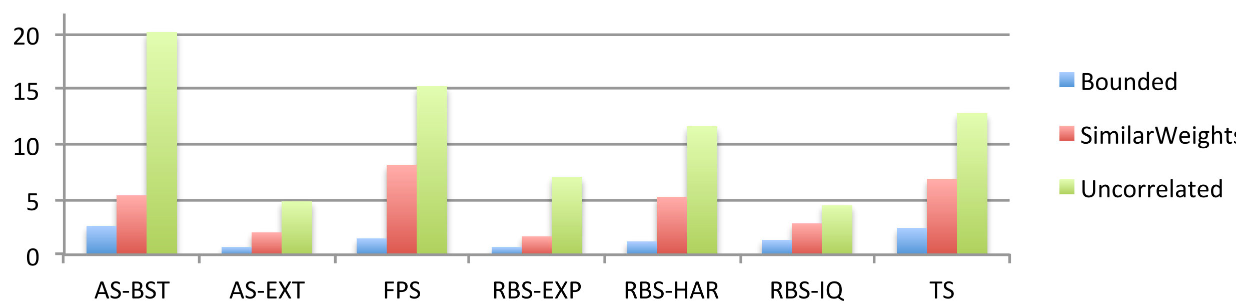

Note: bars are sums of log-scaled p-values

Comparison of bi-obj. approaches with single-objective MA2B

MA2B by El Yafrani and Ahiod [GECCO'16]

Fitness-Proportionate Selection
Loss of Hypervolume
Loss of Surface Contribution

MA2B				
		Mean	Max	SD
eil51_n50	Uncorrelated	2805.000	2855	27.814
	SimilarWeights	1416.348	1460	47.906
	Bounded	4057.652	4105	25.841
eil76_n75	Uncorrelated	5275.067	5423	78.138
	SimilarWeights	1398.867	1502	55.448
	Bounded	3849.067	4109	139.742
eil101_n100	Uncorrelated	3339.600	3789	388.360
	SimilarWeights	2215.500	2483	235.905
	Bounded	4949.000	5137	139.285

FPS LHV				
		Mean	Max	SD
eil51_n50	Uncorrelated	2828.728	2854.543	15.357
	SimilarWeights	1413.044	1459.953	17.780
	Bounded	4229.149	4230.997	10.118
eil76_n75	Uncorrelated	5445.624	5514.666	58.992
	SimilarWeights	1477.680	1513.404	24.494
	Bounded	4042.449	4108.760	38.805
eil101_n100	Uncorrelated	3620.844	3943.425	222.815
	SimilarWeights	2431.907	2482.462	52.265
	Bounded	5094.246	5233.513	65.267

FPS LSC				
		Mean	Max	SD
eil51_n50	Uncorrelated	2810.509	2832.496	18.076
	SimilarWeights	1426.135	1459.953	21.990
	Bounded	4231.299	4241.199	1.881
eil76_n75	Uncorrelated	5392.575	5514.666	73.029
	SimilarWeights	1474.803	1513.404	21.346
	Bounded	4054.815	4102.167	21.440
eil101_n100	Uncorrelated	3664.369	3846.172	124.994
	SimilarWeights	2436.374	2482.462	49.731
	Bounded	5067.070	5233.513	55.587

Summary

- Bi-Objective TTP: profit vs. weight
- Dynamic programming provides provably optimal trade-off fronts for a given tour
- Indicator-based EA with a population of tours: with ”loss of surface contribution” and “loss of hypervolume”
- Best bi-objective approaches beat single-objective state-of-the-art