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

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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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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 $\Pi_i$ is the city at tour position $i$ in tour $\Pi$, and $W_{\Pi_i}$ is the current weight of the knapsack at city $\Pi_i$. 
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 $\tau_\pi$ be a corresponding objective vector for $\bar{P}_\pi$. Then $\tau_\pi$ represents the related Pareto front designated as a DP front for the given tour $\pi$. 

\[ \rho_1 \rightarrow (z_1, w_1), \rho_1 \rightarrow (z_2, w_2), \rho_1 \rightarrow (z_3, w_3), \rho_1 \rightarrow (z_4, w_4), \rho_1 \rightarrow (z_5, w_5) \]
(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
Algorithm 1 Hybrid IBEA Approach

Input: population size $\mu$; limit on the number of generations $\alpha$;

Initialisation:
set the iteration counter $c = 0$;
populate $\bar{\Pi}$ with $\mu$ new tours produced by the TSP solver;

while ($c \leq \alpha$) do
set $c = c + 1$;

Indicator:
run the DP for every tour $\pi \in \bar{\Pi}$ to compute its DP front $\tau_{\pi}$;
apply indicator function $I(\tau_{\pi})$ to calculate the indicator value for every individual tour $\pi \in \bar{\Pi}$;

Survivor Selection:
repeatedly remove the individual with the smallest indicator value from the population $\bar{\Pi}$ until the population size is $\mu$ (ties are broken randomly);

Parent Selection:
apply parent selection procedure to $\bar{\Pi}$ according to the indicator values to choose a set $\Lambda$ of $\lambda$ parent individuals;

Mating:
apply crossover and mutation operators to the parents of $\Lambda$ to obtain a child population $\Lambda'$;
set the new population as $\bar{\Pi} = \bar{\Pi} \cup \Lambda'$;

end while
Indicators

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

Given a tour $\tau_\pi$, and its corresponding solution set $T_\pi$:

- Surface Contribution: number of objective vectors contributed by $T_\pi$
- Hypervolume: volume covered by $T_\pi$ w.r.t $(0,C)$

- Loss of Contribution:
  \[
  LSC(\tau_\pi) = 1 - \frac{SC(\Phi \setminus T_\pi)}{SC(\Phi)}
  \]
  \[
  LHV(\tau_\pi) = 1 - \frac{HV(\Phi \setminus T_\pi)}{HV(\Phi)}
  \]
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)
Make this a pseudo animation with “appear”

Note: bars are sums of log-scaled p-values
Comparison of bi-obj. approaches with single-objective MA2B

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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