Can Route Planning be Smarter with Transfer Optimization?

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ABSTRACT

We aim to showcase the benefit of transfer optimization for route planning problems by illustrating how the solution accuracy of travelling salesman problem instances can be enhanced via autonomous and positive transfer of knowledge from related source problems that have been encountered previously. Our approach is able to achieve better solution accuracy by exploiting useful past experiences at runtime, based on a source-target similarity measure learned online.

CCS CONCEPTS

Computing methodologies → Mixture models

KEYWORDS

transfer optimization, evolutionary algorithms, route planning

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1 INTRODUCTION

Transfer optimization [1] is an emerging research topic that offers a new perspective to leverage on potentially useful knowledge from past problem-solving experiences. Recent studies [1, 2] have shown that knowledge transfer from related problems can enhance evolutionary optimization performance, but the focus is mainly on continuous optimization problems. Moreover, since practitioners usually do not have prior knowledge about the relationship between previously optimized source problems and the current target problem of interest, one of the most challenging issues is then to reduce the threat of negative transfer (which may arise from transferring knowledge in a random fashion). Motivated by these circumstances, here we explore the possibility of enhancing the solution accuracy of route planning (i.e. combinatorial optimization) problems by autonomous and positive transfer of knowledge from related source problems. We consider travelling salesman problem (TSP) instances in this paper.

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2 OUR APPROACH

Our approach assumes that a knowledge base containing high quality information from previously encountered source combinatorial problems is available. Such information represents the knowledge extracted and stored as edge histogram models [3] $p_1(\boldsymbol{x})$, ..., $p_{K-1}(\boldsymbol{x})$ (i.e. discrete source probabilistic models). Relevant knowledge can be transferred from the source models at runtime to enhance the search performance when solving a new target optimization problem. Positive transfer of knowledge is achieved by using an optimal configuration of source models and the target model $p'_K(\boldsymbol{x})$ to build an optimal target mixture model $p_K(\boldsymbol{x})$, which is mathematically expressed as follows:

$$p_K(\boldsymbol{x}) = \sum_{k=1}^{K-1} w_k \cdot p_k(\boldsymbol{x}) + w_K \cdot p'_K(\boldsymbol{x}), \tag{1}$$

where w_1, ..., w_{K-1} are the optimal source-target similarity values, w_K is the mixture coefficient of the original target model, and $\sum_{k=1}^{K} w_k = 1$.

The optimal value of w_k's is the learned source-target similarity measure which automatically determines the extent of knowledge transfer from each source model. To learn the optimal configuration of w_k's, a mathematical program in terms of a *log-likelihood function* must be solved as follows [2]:

$$\text{Maximize} \quad \log L = \sum_{i=1}^{N} \log \sum_{k=1}^{K} w_k \, \varphi_k(\boldsymbol{x}_i), \tag{2}$$

where N is the target population size, and $\varphi_k(\boldsymbol{x}_i)$ is the $(i,k)^{\text{th}}$ entry of an $N \times K$ matrix representing the likelihood of the k^{th} model on the i^{th} individual in the target population.

We name this approach as the probabilistic model-based transfer evolutionary algorithm (PMTEA). PMTEA consists of two components: (i) a standard genetic algorithm (GA), and (ii) a probabilistic model-based sequential transfer procedure that is activated periodically according to a *transfer interval* parameter. The required inputs of PMTEA are a new target optimization problem with objective function f_K, a knowledge base containing source probabilistic models and a transfer interval Δ. The algorithm begins by randomly generating an initial population of solutions encoded in permutation representation. All individuals are evaluated using f_K, and domain generalization is performed on all source models to match the dimensionality of the target problem. While mod $(t, \Delta) \neq 0$, a standard GA runs by applying crossover and/or mutation operators on the selected parent population to create the offspring population.

When mod $(t, \Delta) = 0$, the sequential transfer procedure is activated and the $p_K(\boldsymbol{x})$ is built by learning the optimal w_k's online according to (1) and (2) respectively. In contrast to the standard GA, the offspring population is generated by sampling solutions from $p_K(\boldsymbol{x})$, hence facilitates positive transfer of relevant knowledge from the source problems. Subsequently, the new population for the next generation is selected based on elitist selection. The entire evolutionary process is repeated until specified stopping condition(s) are met.

3 EXPERIMENTS

We use TSP instances from [5] as target problems. The source problems are generated from the respective target problem by randomly removing a number of nodes. All source problems are pre-optimized using standard GA, and the source models are built using the final population containing the optimum solution. The transfer interval is set to Δ=5 for PMTEA. The stopping condition is set to 500 consecutive generations without change in the population's best fitness. For all GA search, the crossover rate is set to p_c = 0.5 and the mutation rate is set to p_m = 0.2, while edge recombination crossover and displacement mutation operators are used. All population sizes are set to N = 300.

We compare PMTEA to a no-transfer variant of PMTEA (NT-PMTEA) as well as to conventional EAs without knowledge transfer, such as the standard GA [4] and the edge histogram-based sampling algorithm (EHBSA) [3]. Table 1 shows the mean and standard deviation values achieved by all considered algorithms over 30 independent runs. We can see that PMTEA consistently achieved better solution accuracy than the other algorithms. We attribute this observation to the positive transfer of knowledge that PMTEA enables by controlling the extent of knowledge transfer based on a source-target similarity measure $0 \leq w_k \leq 1$ learned online. In Fig. 1, we illustrate the similarity measure learning trends in PMTEA for the case of TSP100. We can deduce that the higher values of w_k learned in the early stage of evolutionary search has enabled positive knowledge transfer from TSP95 that led to better solution accuracy of TSP100.

Table 1: Experimental Results

Algorithms	Mean ± std of L_2-Metric ($\times 10^3$)		
	Target: TSP100 Source: TSP95	Target: TSP150 Source: TSP130	Target: TSP200 Source: TSP190
PMTEA	21.205 ± 0.36	29.497 ± 1.18	34.603 ± 0.44
NT-PMTEA	22.522 ± 1.01	31.702 ± 1.23	38.617 ± 1.66
GA	22.493 ± 0.68	30.895 ± 1.31	37.124 ± 1.79
EHBSA	24.894 ± 0.84	39.302 ± 1.10	58.590 ± 1.75

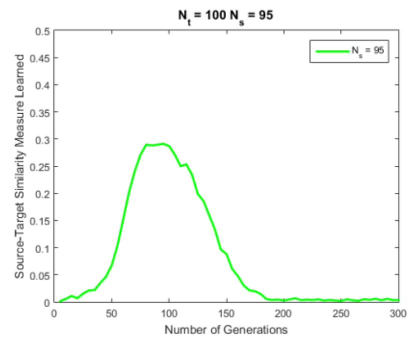

Figure 1: The learning of w_k in PMTEA.

4 CONCLUSION

We have verified that route planning problems can benefit from past problem-solving experiences via transfer optimization. Our transfer optimization approach is capable of enhancing the solution accuracy of new target problems by automatically promoting positive transfer of knowledge from related source problems based on a source-target similarity measure learned online. In future, it would be interesting to affirm the benefits of our approach for a wider variety of combinatorial optimization problems, including real-world instances.

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