World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:5, No:6, 2011

Transferring Route Plan over Time

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***Abstract*—**Travelling salesman problem (TSP) is a combinational optimization problem and solution approaches have been applied many real world problems. Pure TSP assumes the cities to visit are fixed in time and thus solutions are created to find shortest path according to these point. But some of the points are canceled to visit in time. If the problem is not time crucial it is not important to determine new routing plan but if the points are changing rapidly and time is necessary do decide a new route plan a new approach should be applied in such cases. We developed a route plan transfer method based on transfer learning and we achieved high performance against determining a new model from scratch in every change.

***Keywords*—**genetic algorithms, transfer learning, travelling salesman problem

I. Introduction

TRAVELLING salesman problem is an NP-hard combinational optimization problem. Problem is finding the shortest path to visit each city once and turn to beginning city between the given cities which pairwise distances are constant and predetermined. TSP has applications like planning, logistic, manufacturing and etc. According to Helsgaun [1] TSP is the most widely used combinational optimization problems in the same category.

Transfer learning is another subject to interest in this work. Train and test is the main principle of supervised machine learning methods. This principle is simply; training a learner with available training data and testing the learned system with similarly distributed test data. However sometimes, in real life this principle doesn't work because distribution of test data and training data may be different. Traditional machine learning techniques requires new labeled data for every distribution change to build new model from scratch but sometimes it may be very hard to find labeled training data or there is limited time for building new model. In such cases transfer learning approaches can be applied. There are two kinds of tasks in transfer learning. One of them is source task which has enough resources like labeled data for training and the other task type is target task which is related to source task but has insufficient resources for traditional machine learning methods. However target task may have resources that can be used in transfer learning like a few labeled data and lot of unlabeled data. Knowledge which achieved from source task also can be used as training resource for target task. Transfer learning is transferring knowledge from related source tasks to target task in order to improve performance of target task in insufficient or absence of labeled training data. The knowledge which transferred between tasks may be weighted instances of source task data, a common feature representation that reduces differences between source and target task or shared parameters or priors. Domain adaptation [2], covariate shift [3] and sample selection bias are also related research areas with transfer learning.

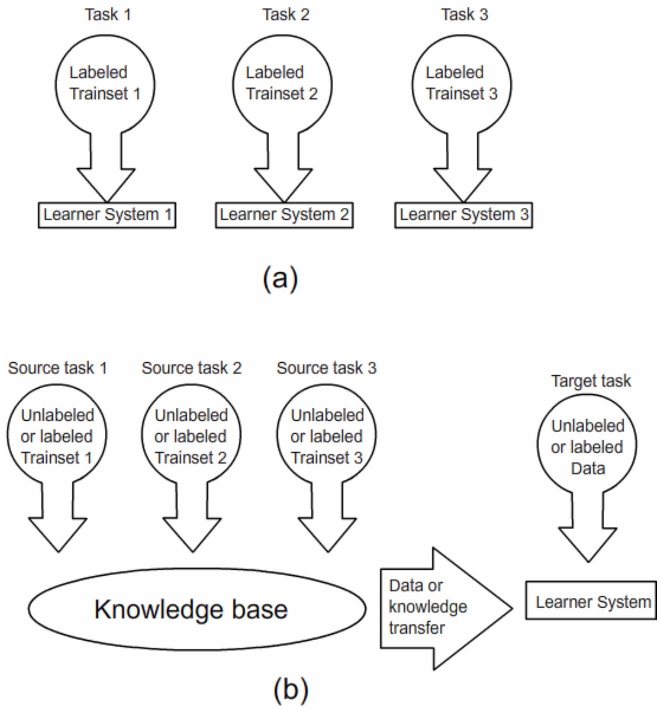

Fig. 1 (a) Traditional supervised machine learning methods and (b) transfer learning methods

However transfer learning is very feasible solution for limited resources or time; transferring knowledge between domains has some problems. The biggest problem of transfer learning is deciding relatedness of source and target tasks. Source task should be related to target task otherwise transfer won't affect even decrease the performance of target task. This side effect is named as negative transfer. Another problem is deciding what to transfer. Acquiring transferable knowledge is hard to build. However reusability of acquired knowledge is a low priority problem in transfer learning it is a need too especially for lifelong learning problems [4]. Working principles of traditional machine learning methods and transfer learning methods are illustrated in figure 1.a and figure 1.b respectively.

Transfer learning problems can be categorized by existence of labeled or unlabeled target task data and source task data. If

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there is some labeled data for target task this type of transfer learning is named inductive transfer learning. If there is no labeled data for target task this situation is named transductive transfer learning and if there is no labeled data for both source and target tasks this is unsupervised transfer learning.

Methods which used in transfer learning are generally based on transferring one of three following knowledge source:

- Instance transfer: This is transferring or weighting training data instances of source task for target task.
- Feature representation transfer: Selecting good feature representation to reduce difference between source and target task is named feature representation transfer. After selecting a suitable feature representation this shared model trained with all available labeled data.
- Parameter transfer: This is predicting shared parameters or priors between source and target tasks.

II. Related work

A. Travelling salesman:

There are two main approaches for TSP, one of them exact algorithms for example Dantzig et al. has developed a method to solve large size TSPs, Balas and Christofids [6] developed restricted Lagrangean relaxation based on the assignment problem method to solve asymmetric TSP problems and Grötschel and Holland [7] developed a cutting plane procedure to solve symmetric TSP up to 1000 cities. Because of exact algorithms can solve a small set of problems, heuristic and probabilistic methods are attracted more attention. We especially focused on meta heuristic algorithms like tabu search [8], neural networks [9] and of course genetic algorithms [10, 11, 12].

B. Transfer Learning

There are several area which transfer learning methods applied to and several machine learning techniques which modified for transfer learning. Recently there are growing works on using transfer learning for natural language processing. In this area transfer learning provides huge performance gains for classifiers which have poor or no training data via knowledge transfer from related domain by rich resources, for example [13, 14, 15].

Another interesting area which transfer learning is adopted is reinforcement learning for example skill transfer [16], action schema transfer [17] and control knowledge transfer [18]. Transfer learning methods are developed based on many main machine learning techniques like neural networks [19, 20, 21], Markov logic networks [22], hidden Markov model [23] and these transfer learning techniques are applied to text categorization [24], web page classification [25], indoor wi-fi localization [26] and lifelong robot learning [27] problems. Also in our early study [30] we showed how to use genetic algorithms for transfer learning. Even transfer learning is applied for some computer vision problems like sign language [28] and image classification [29].

III. Transferring Route Plan

The simplest form of TSP, assumes that cities are given in the beginning of the problem and salesman must visit all the cities, but in real life these conditions may change. For example roads to some cities may be closed, or a new salesman may take over some of the cities. So when some of the cities are canceled to visit by salesman, traditional methods start from scratch to make a new route plan. But in a time crucial task it is very important to determine new plan as quick as possible. In such a situation instead of making a new plan from scratch, some suitable information from old plan may be helpful. We developed a genetic algorithm based transfer learning method which is a modified and improved version of our early work for transfer learning in genetic algorithms [30]. Method creates a solution pool while making a plan for current cities. If cities are changed then it tries to find a suitable plan for new cities by evaluating each solution in solution pool. Flowchart of the proposed genetic transfer learning algorithm is illustrated in figure 2. Source task is represents the classical TSP and target task represents the task when some of the cities are not need to be visit anymore.

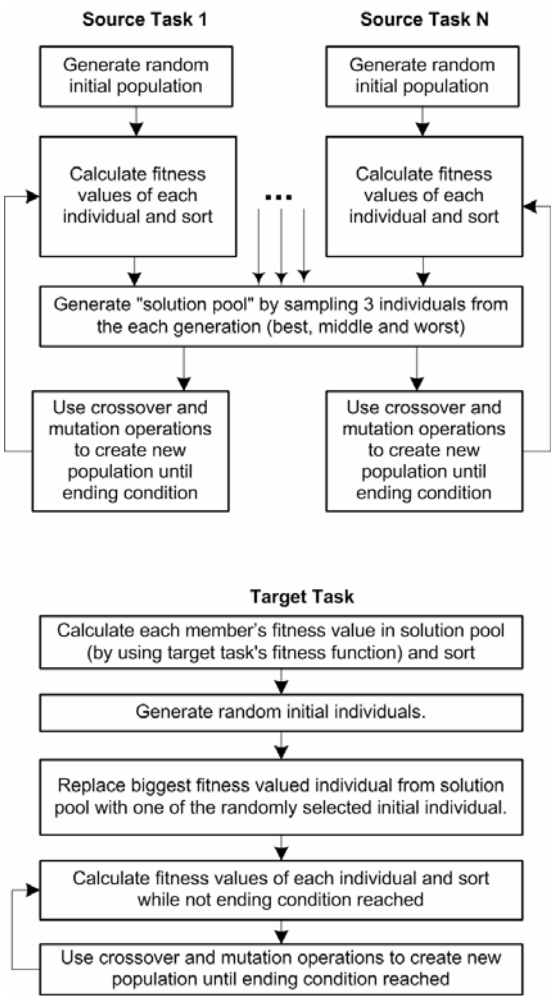

Fig. 2 Flowchart of the genetic transfer learning.

IV. Experimental Settings

We created a source task with 100 cities and 3 different target tasks by deleting some of the cities from source task. There are different metric measurement techniques for calculating distance between cities like Manhattan distance which calculates distance by the sum of the differences of their x and y coordinates, maximum metric which assign maximum of differences of the x and y coordinates and Euclidean distance which uses Euclidean distance of the cities using x and y coordinate. We used Euclidean distance in equation 1 as the metric.

$$D=\sum_{i=1}^{n-1}\sqrt{(x_i-x_{i+1})^2+(y_i-y_{i+1})^2}+\sqrt{(x_n-x_0)^2+(y_n-y_0)^2} \quad (1)$$

Performance comparisons are made for target tasks with two different graphics. One of the graphic represents the performance when target task begin from scratch and the other one represents the performance when target task transfers knowledge from the source task. We used genetic algorithms to make the route plan. We coded the sequence of the cities to genes and evaluated the fitness of the gene by calculating the travel distance of the coded cities. Since traditional crossover and mutation operations can't be used we used order crossover operator proposed by Davis [31] and inverse mutation operator.

Source task which created the solution pool has 100 cities. Figure 3, 4 and 5 illustrates performance of target tasks which have different city counts.

TABLE I
Solution pool fitness evaluation algorithm.

```
SL: Length of the genes in solution pool
Take a solution "S" from solution pool.
j=0;
For i=0 to SL do
Begin
   Read i.th string of S and assign it to R
   If Taget task includes the R then
   begin
      Set j.th string of the gene as R
      j=j+1
   End
End
```

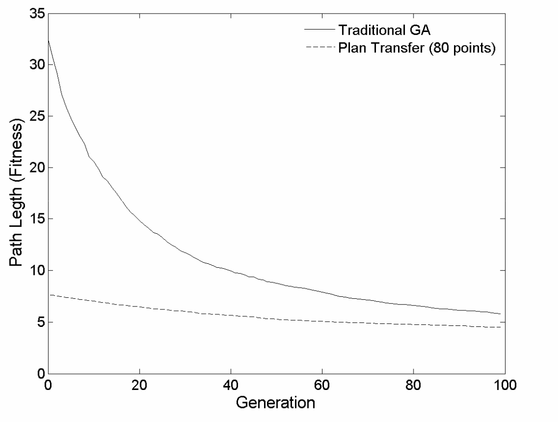

Fig. 3 Performance comparisons for target task which has 80 cities.

Because of solutions in solution pool are not equal size with the target tasks, solutions are evaluated by the algorithm in table 1, assuming that target task has the same distances between cities and has less cities than source task.

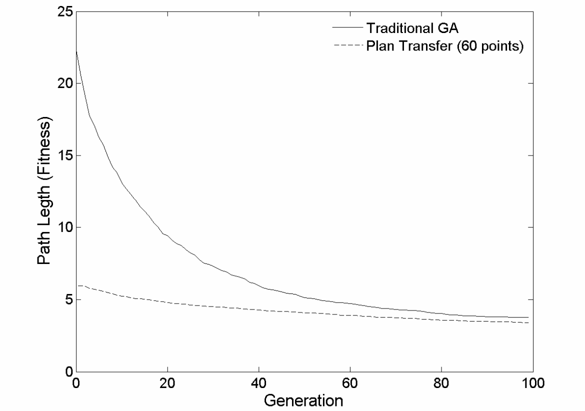

Fig. 4 Performance comparisons for target task which has 60 cities

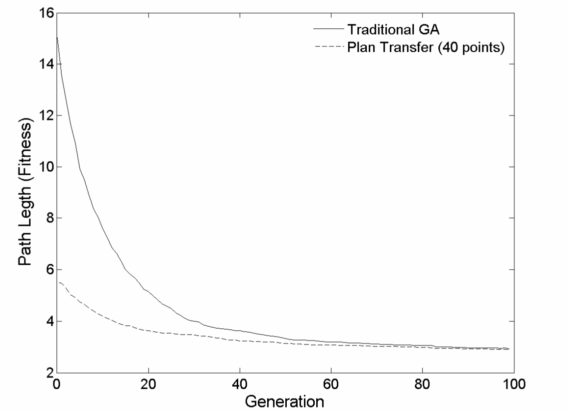

Fig. 5 Performance comparisons for target task which has 40 cities

V. Conclusions

We developed a method for quickly changing TSP, based on transfer learning. Experimental result showed that proposed method is very beneficial when compared to traditional methods when there is a source task to transfer knowledge from. For future work method can be improved to meet for other changing conditions for example adding new cities, changing pairwise distances, etc.

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