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Path-Rank: Context Aware Route Selection Using Adaptive Routing Algorithm

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Abstract

The choice of a route by driver to a destination may depend on its distance and travel time, also factor into the driver's decision. Driver's route choice can be context dependent, e.g., varies with respect to time, distance and also it varies from driver to driver. Conventional routing services supports less in context dependent route selection, also they deliver same routes to all drivers. Here the study is to identify context-aware routes for each drivers based on historical trajectories. Ranking paths becomes an increasingly most important functionality in many transportation services, where multiple paths connecting a source-destination pair are offered to drivers. First propose a real training data using enriching method to obtain a dense and expanded set of training paths using historical trajectories. Second, a multi-task learning framework that consider features that take into account both candidate paths and contexts are proposed. Third, propose road network embedding which uses road network topology and context-aware properties to embed the paths into feature vectors. Next, propose a path rank method to generate a compact and diverse set of training paths to enable efficient and effective learning. Finally, propose Adaptive Routing Algorithm to shows that the accuracy results outperforms baseline methods.

Keywords- Path ranking, diversified paths, multi-task learning, road network embedding, graph embedding.

1. INTRODUCTION

Nowadays, transportation becomes pulse of a city. It plays an essential role in people's day-to-day lives. With continued digitization and deployment of sensing technologies, enormous amounts of vehicle trajectory data are collected. This plays an important role in improving the quality of transportation services, like vehicle routing and traffic prediction. Routing becomes the major functionality in vehicular transportation. Using classic routing algorithms like Dijkstra's algorithm, a single optimal path connecting the source and the destination can be identified. Optimal path is the path with least travel cost, e.g., shortest or fastest path. Based on routing service quality study, local drivers repeatedly choose paths which are neither shortest nor fastest, so using classic routing algorithms becomes impracticable in most real world routing scenarios. Existing solutions every often depend on simple heuristics, e.g., ranking paths based on their travel times. Nevertheless, travel times always may not be the most important factor while drivers choose their paths. Also, existing solutions mostly provide same ranking to all drivers ignoring distinct preferences that different drivers have.

In this paper, we propose a context-aware ranking framework PathRank to rank paths in road networks. By considering road network topology and context-aware properties, road network embedding is proposed to embed paths into feature vectors. Using this method, a compact and diverse set of training paths are generated to enable efficient and effective learning. Path-Rank of the contextual path can be found out from the user frequency of the most usable paths by using the Dynamic Frequency Selection Algorithm. The accuracy results from the algorithm outperforms baseline methods.

2. PROPOSED WORK

2.1. RANKING FRAMEWORK

In specific, PathRank models rank the candidate paths as a regression problem. PathRank estimates ranking score for each candidate path using local drivers' trajectories. This in turn rank the candidate paths with respect to their ranking scores. The framework is flexible in which different contextual information can be lodged. Two challenges must be addressed to enable this framework.

Enrich Training Data. We need to formulate the training data to train the model. If a driver used path P to travel from source s to destination d at time t, then it is a proof that driver considered path P as the favourite path over other paths to travel from s to d at time t. Thus, path P carries higher ranking. In the meantime, there exist a huge amount of paths from a source to a destination, thus include all other paths other than P as negative paths. Randomly selecting small subset of such paths may badly affect the effectiveness of training. Selecting a compact and diversified training path set to represent negative training data is little bit challenging. Compact set guarantees training efficiency and diversified set guarantees training effectiveness.

Effective Feature Representations. An input to PathRank is a path means a sequence of vertices in a road network graph. A significant feature space should consider both road network topology and the context-aware properties of road network. A compact and diverse set of training paths are generated to enable efficient and effective learning. Path-Rank of the contextual path can be found out from the user frequency of the most usable paths by using the Dynamic Frequency Selection Algorithm.

2.1.1. Enrich Training Data

Propose an effective method to produce a compact and diversified training path set. We consider user frequency of the most usable paths by using the Dynamic Frequency Selection Algorithm.

Dynamic Routing Algorithms makes routing decisions dynamically based on network condition. It creates the routing table based on network traffic and topology. They use the principle of dynamic routing. Here, the routing paths that are available in dynamic routing tables are restored based on network topology and traffic. They are more frequently used in networks which are exposed to frequent changes and these algorithms can adjust very well to the changes. Here, the Path-Rank of the contextual path can be found out from the user frequency of the most usable paths by using the Dynamic Frequency Selection Algorithm.

2.1.2. Effective Feature Representations

Propose a comprehensive learning framework. This helps us to learn feature representations of paths that capture both topological and context-aware properties. In a road network graph, input is a path which is represented as a sequence of vertices. An unsupervised graph embedding is employed to convert vertices into feature vectors to capture road network topology.

Recurrent neural networks (RNNs) are worthy at modelling sequential information. As path is a sequence of vertices, we employ RNN to model the sequence of feature vectors of vertices in a path. Already, the framework considers road network topology, but still lacks in context-aware properties. These are not captured by classic graph embedding. To accommodate the context-aware properties, we let RNN estimate several values, including a ranking score and also context-aware properties of a path such as Place Id, Place Name, Visiting Time and User-Frequency of the place. Thus it makes the framework to be a multi-task learning framework where the foremost task is to estimate the ranking score that is used for ultimate ranking, and auxiliary tasks make sure to update feature vectors of vertices and also to capture context-aware properties of underlying road network, which finally aid in increasing the accuracy of main task.

This paper provides an end-to-end solution to context-aware path ranking in road networks. First propose a method using which a compact and diverse set of training paths are generated to enable efficient and effective learning. Second, a multi-task learning framework that consider features that take into account both candidate paths and contexts are proposed. Third, propose road network embedding which uses road network topology and context-aware properties to embed the paths into feature vectors. Path-Rank of the contextual path can be found out from the user frequency of the most usable paths by using the Dynamic Frequency

Selection Algorithm. Finally, propose Adaptive Routing Algorithm to shows that the accuracy results outperforms baseline methods.

2.2. PRELIMINARIES

A road network is designed as a directed, weighted graph G = (V,E,D,T,F). Vertex V represents road intersections and Edge E represents the segments of road. Functions D, T, and F represents the travel costs. Function D maps each edge to their length.

A path P = (v1, v2, v3, . . . , vX) which represents a sequence of X vertices and in which two adjacent vertices be connected by an edge in E. We use P.s and P.d to denote the source and the destination of path P.

A trajectory T = (p1, p2, p3, . . ., pY) which represents a sequence of paths that lead to a trip. Each path pi = (location, time) which represents the location of a vehicle at a particular timestamp.

Map matching is just able to map a path to a specific location on an edge in the underlying road network, thus aligning a trajectory T with a path in the underlying road network, denoted as T.P which is known as trajectory paths.

Path Similarities. Several similarity functions are available to calculate similarity between two paths. In this paper, Weighted Jaccard Similarity (see Equation (1)) is used to evaluate the similarity between two paths,

$$\mathrm{sim}(P_1, P_2) = \frac{\sum_{e \in P_1 \cap P_2} G.D(e)}{\sum_{e \in P_1 \cup P_2} G.D(e)}.$$

2.3. PATHRANK

Trajectory paths P are obtained by map matching the given set of historical trajectories. These trajectory paths are then provided into Training Data Enrichment module. Here we generated a well enriched training data set. A compact and diversified set of candidate paths P’ are generated for each trajectory path. Each candidate path connects same source and destination of the trajectory path. For each path P’, similarity score sim(P, P’) is computed as the ground truth ranking score of P’. Output of the training data enrichment module is denoted as {P’, sim(P, P’)} which denotes set of candidate paths and ranking score pair. This is used as input for PathRank.

In the training phase, each input path Pi’ is represented into an appropriate feature space. We propose to use a vertex embedding network which converts each vertex in a path into an appropriate feature vector. Path is a sequence of vertices. After vertex embedding these paths becomes a sequence of feature vectors. This output is then fed into a Recurrent Neural Network (RNN). Added to this, Context Embedding Module embeds additional contextual information such as Place Id, Place Name, Visiting Time and User-Frequency of the place are also converted into feature vectors and fed into RNN. Recurrent neural networks (RNNs) are able to capture dependency for sequential data. RNN is used to model the sequence of feature vectors. Finally RNN outputs an estimated ranking score, as shown in Figure 1. This is compared with ground truth ranking score simi. The main function is to measure the difference between estimated ranking score and ground truth ranking score.

In the testing phase, trained PathRank is used to rank candidate paths. Given context information, source, destination and routing algorithms are able to provide multiple candidate paths. Then, PathRank takes each candidate path as input and provides an estimated ranking score. Finally, the candidate paths are ranked according to estimated ranking scores.

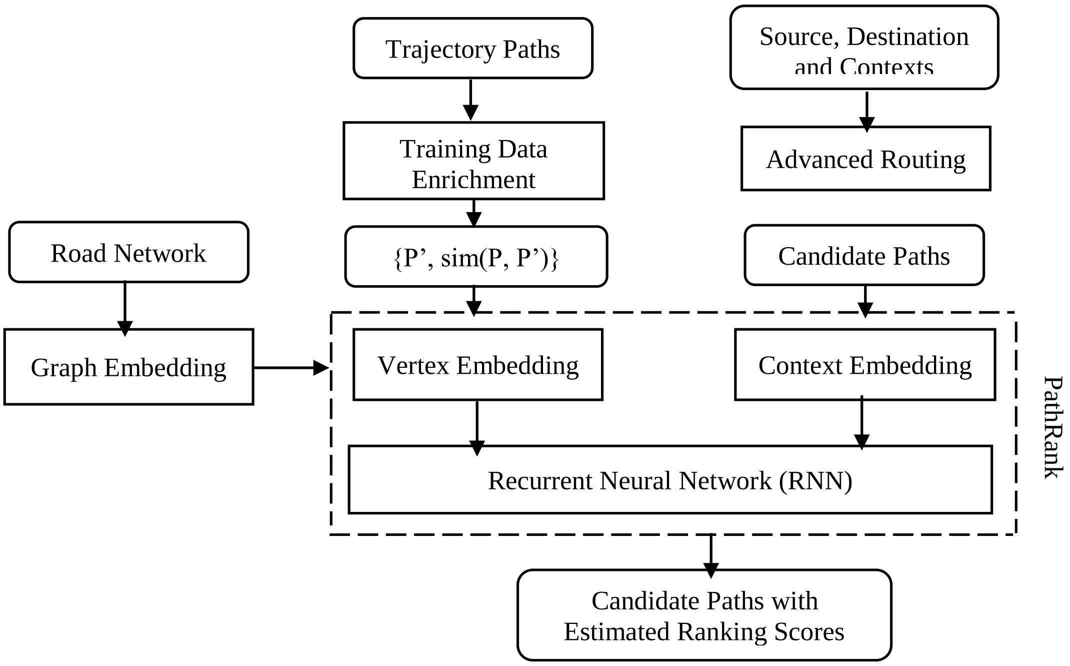

Figure 1. PathRank Framework

2.4. PATHRANK FRAMEWORKS

Different Variants of PathRank are considered,

1. PR-B: Vertex Embedding just employs Embedding Matrix B. Ignores Graph Topology.
2. PR-A1: Vertex Embedding employs Graph Embedding which considers Graph Topology. Here the Vertex Embedding is static.
3. PR-A2: similar to PR-A1 model. Graph Embedding is used and Vertex Embedding is dynamic which is updated during training.
4. PR-A2-Mx: Similar to PR-A2 model. Graph Embedding is used and Vertex Embedding is dynamic updated during training. Added to this, Multi-task learning is used which considers spatial properties.
5. PR-CA: Advanced framework PRC with both Contextual Embedding and Multi-Task learning.
6. PR-AR-CA: Advanced framework PRC with both Contextual Embedding and Multi-Task learning using Adaptive Routing.

For all frameworks PR-A1, PR-A2, PR-A2-Mx, PR-CA and PR-AR-CA that use graph embedding, we take node2vec as the graph embedding method. Node2vec is a basic random walk based graph embedding method. This outperforms alternative methods such as DeepWalk and LINE. When new enhanced unsupervised graph embedding method becomes available, it can be easily incorporated into PathRank to replace node2vec.

2.5. EVALUATION METRICS

Accuracy of the proposed PathRank framework can be assessed by calculating Mean Absolute Error (MAE). This metric is used to measure how accurate the estimated ranking scores with respect to ground truth ranking scores. Smaller MAE value means higher accuracy.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|x_i - \hat{x}_i|;$$

x_i and $\hat{x}_i$ represent ground truth ranking score and estimated ranking score.
n represents total number of estimations.

3. EXPERIMENT RESULTS

3.1.PERFORMANCE ANALYSIS

Performance of the similarity models are compared to consider different variations of Path Rank.

Table 1 and Figure 2. shows the comparison.

Table 1. Comparison of Various PathRank Frameworks Similarity Accuracy

Methods	Average MAE Value
PR-A1	0.0776
PR-A2	0.0710
PR-A2-M1	0.0680
PR-A2-M2	0.0809
PR-A2-M3	0.0695
PR-CA-M3	0.0611
PR-AR-CA-M3	**0.0169**

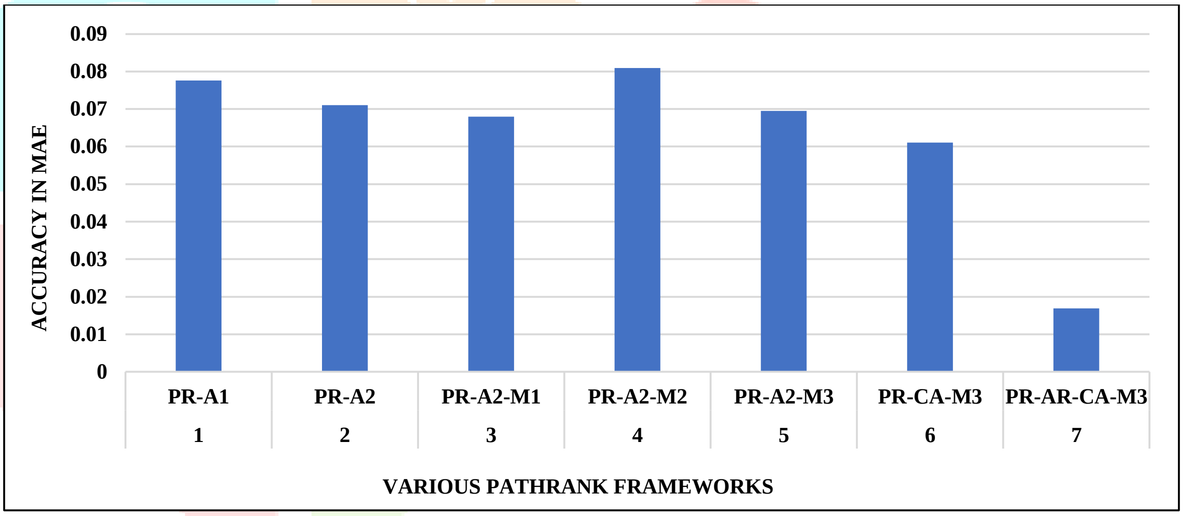

Figure 2. Accuracy Comparison in various PathRank Frameworks

The similarity comparison with the baseline methods shows that the contextual information contributes to improve the overall accuracy. Ranking obtained by the proposed framework PR-AR-CA outperforms all baselines. Table 2. and Figure 3. shows the comparison. Our design on path representation which captures both road network topology and context properties are effective.

Table 2. Comparison of Category Similarity Accuracy

Methods	Average MAE Value
LR	0.2640
LASSO	0.2876
SVR	0.2390
DT	0.2516
DTA	0.2686
LSTM	0.2682
PR-CA	0.0611
PR-AR-CA	**0.0169**

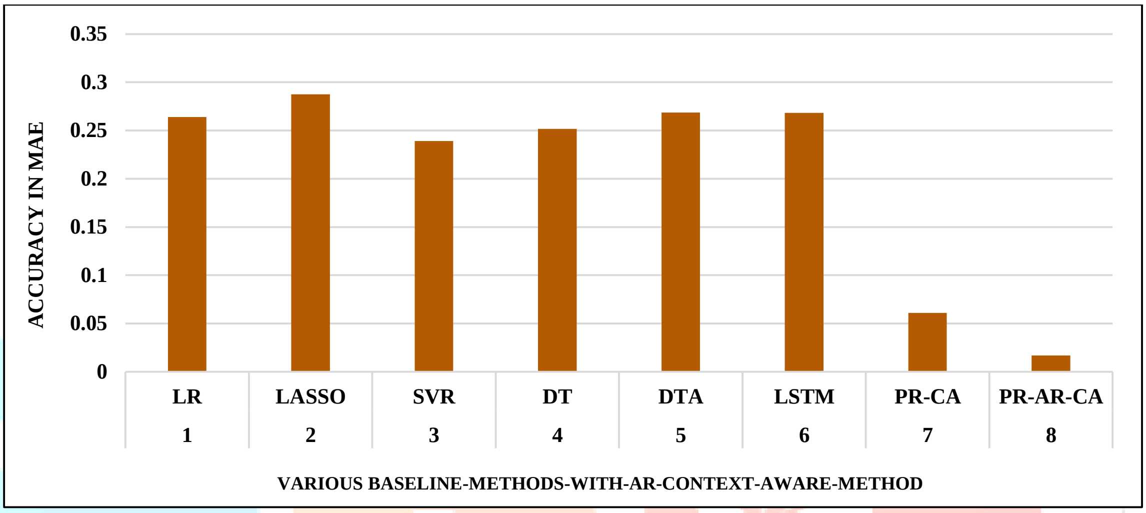

Figure 3. Accuracy Comparison of various baseline methods with AR-CONTEXT-AWARE Method

4. CONCLUSION

This proposed model is a context-aware, multitask learning framework useful to rank paths in road networks. It is an effective method used to generate compact and diverse set of training paths to enable efficient and effective learning. This multi-task learning framework enable road network embedding that take into account both candidate paths and contexts properties. One of the adaptive routing algorithm, together with the learned road network embedding, is employed to estimate the ranking scores to eventually enable ranking paths. In addition, a temporal graph is proposed to embed temporal contexts.

5. FUTURE WORK

The results from this proposed system suggest that user specific Path Rank models still have a potential to achieve personalized ranking. This system may outperform the Path Rank model trained on all trajectories in PR-CA with adaptive routing. In future, plan to explore attention mechanisms on driver feature vectors to achieve the Path Rank model trained on all trajectories. It is of interest to exploit different means, to further improve the ranking quality of Path Rank. Also, interest to explore in parallel computing to improve efficiency.

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