A Graph-Based Spatio-Temporal POI Ranking Measure for Pickup and Delivery Platforms

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Abstract

Traditional graph-based ranking models that treat locations as isolated entities often fail to capture the complex spatio-temporal dependencies inherent in pickup and delivery platforms. Regardless of the quality of learning models adopted to predict future demand, their results can be further enhanced by encoding the spatio-temporal graph-based structure of the road network. We define a spatio-temporal graph-based measure for POI ranking, namely ZoneRank, that encodes spatial relationships, mobility flows, and temporal transitions in such platforms. Furthermore, we implement a multi-purpose ridesharing simulator to evaluate the effectiveness of ZoneRank in the context of idle vehicle repositioning.

CCS Concepts

• **Information systems** → **Spatial-temporal systems**.

Keywords

spatio-temporal, ranking, graph, point of interest, repositioning

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1 Introduction

Spatio-temporal Point-of-Interest (POI) is a fundamental problem in spatial computing with applications in urban analytics, location-based services, and fleet management. Traditional graph-based ranking models that treat locations as isolated entities often fail to capture the complex spatio-temporal dependencies inherent in pickup and delivery platforms. In such platforms, the importance of a POI should not only capture its spatial properties, but also the temporally varying pickups and delivery in its spatio-temporal neighboring zones.

Although models for predicting future demand in such platforms exist, such as [7], we argue that regardless of the quality of learning models adopted to predict future demand, the results can be further enhanced by encoding the spatio-temporal graph-based structure of the road network into the quantities predicted. Previous approaches, such as DROP [4] and STARS [1], applied spatial techniques for similar purposes, but do not capture temporal variations of the demand within the network or account for the dynamic changes of these quantities as decisions are made in real-time.

In this work, we propose a spatio-temporal graph-based measure for POI ranking, namely ZoneRank, that encodes spatial relationships, mobility flows, and temporal transitions in such platforms. Thus, allowing for a structured, yet flexible, framework for POI ranking that addresses the needs of real-time decision platforms such as ride-sharing and delivery services. The definition of ZoneRank extends classical ranking methods like PageRank [2] and influence maximization [3] to temporal graphs by incorporating edge decay functions, time-aware node scoring, and online updates.

Furthermore, we evaluate our ranking measure via extensive benchmarks in the context of idle vehicle repositioning in ridesharing platforms, using real traces collected from NYC [6]. Our results confirm the significance of using ZoneRank on ride completion as well as driver participation, with positive effects on customer pickup delays and deadheading.

2 Spatio-Temporal Ranking of Zones

We define ZoneRank as a novel spatial-temporal measure of location popularity and centrality in dynamic pickup and delivery systems, in which the mobility field is represented by an evolving graph, and historical traces of past pickups and deliveries are available for forecasting.

A *dynamic graph* is defined as $G^T = (V, E, W)$, in which the set of vertices V represents the points of interest (POIs) in the road network, and the set of edges E represents the connections, *i.e.*, streets, between these POIs. The weight function, $W : V \times V \times T \rightarrow N$, represents the cost of travel between two adjacent vertices in the network, $(u, v) \in E$, when moving at time step $0 \leq t \leq T$. We assume that anticipated future pickups and deliveries on POI $v \in V$ at time $0 \leq t \leq T$ are made available[1].

The ZoneRank score quantifies the importance of a location at some time t, based on its spatial properties, its predicted anticipated demand, the anticipated demand of its neighboring locations in the future, as well as the anticipated deliveries at its neighboring locations in the past. Inspired by the classic definition of PageRank [2], we define the ZoneRank of a vertex v on the at time t as,

[1]via existing prediction models or statistical estimation.

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$$ZR(v,t) = (1-\delta) + \delta \sum_{u \in adj(v)} \frac{ZR(u, t + dist(v,u)) - Delv(u, t - dist(v,u))}{|adj(v)|}$$

in which $0 < \delta < 1$ is a dampening factor on the effect of spatial neighborhoods on the rank of the vertex, $adj(v)$ refers to the vertices adjacent to v, $dist(u,v)$ refers to the total weight, or time distance, of the shortest path from u to v, and $Delv(u,t)$ refers to the anticipated deliveries at the spatio-temporal point (v,t). The initial values of these ranks are set to the anticipated pickups predicted from historical traces, and then these ranks are repetitively re-computed for each spatio-temporal value $< v, t >$ until the average marginal difference in values from one iteration to the next becomes smaller than some η. This computation can be performed offline since it depends on data computed from the offline phase.

3 Performance Evaluation

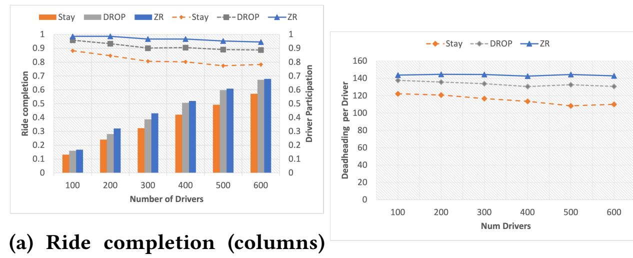
We implemented an agent-based discrete event simulator with benchmarks from real ride traces to evaluate the effect of POI ranking on idle driver repositioning. The results reported below are a subset of a much larger set of evaluations and all of them are measured as an average of 10 executions, in which only the randomized positioning of the drivers at the beginning of the simulation vary.

Datasets. For this project, we run our experiments using historical ride data traces obtained from NYC TLC Yellow Taxi Data [6]. For evaluation purposes against the state-of-the-art algorithms [8], we focus our experiments on the data from January through June 2016, using the data for the first few months as historical records and the data from June evaluation purposes (10000 rides). Moreover, we use the Uber H3 library to partition the NYC graph into 99 hexagonal regions [5].

Baseline Algorithms. We compare the Stay-in-Place (Stay) algorithm, in which the driver chooses to roam around the same zone when idle, and the DROP repositioning algorithm [8], in which a destination is chosen in a weighted random model based on PoI ranks, and drivers follow the shortest routes to that recommended destination. When using DROP, we compare between their original scoring model and our defined ZoneRank measure. Future work will be sure to include additional algorithms for broader validation.

Effect of driver coverage in congested areas. In the first set of experiments, we randomly sample 1000 rides with pickups in a temporal range of **60** minutes and scatter a varying number of drivers on the road. We expect to see all repositioning algorithms to improve in overall ride completion as the number of drivers increase, with stay-in-place performing the worst, as confirmed by the column plots in Figure 1a. We note that the improvement in ride completion when using ZoneRank is not very significant due to the temporal constraints set in the simulation setup. The significant result lies in the consistently higher driver participation rate (line plots in Figure 1a), regardless of driver coverage, with minimal increased deadheading (Figure 1b). In a real system, this indicates more vehicles in the platform actively picking up and dropping off customers, reducing idling emissions.

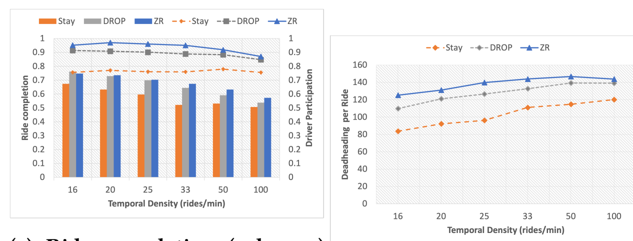
Effect of ride frequency in congested areas. In the second set of experiments, we fix the number of drivers and simulation



(a) Ride completion (columns) and driver participation (lines). **(b) Average deadheading per ride.**

Figure 1: ZoneRank allows for better repositioning of idle vehicles leading to higher driver participation rate with minimal increased deadheading.

time, and increase the frequency of ride requests incoming to the system. As the rides increase in frequency, ZoneRank outperforms the other metric as shown in Figure 2, with consistently higher driver participation and minimal increased deadheading.



(a) Ride completion (columns) and driver participation (lines). **(b) Average deadheading per ride.**

Figure 2: As the frequency of rides increases, ZoneRank outperforms other metrics as it leads drivers closer to zones with anticipated pickups.

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