Machine Learning-Based Demand Predictions for Shared Mobility Services

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***Abstract*—Precise predictions of future demand in shared mobility services could help to facilitate the rapid growth of fleets and support the urgently required mobility transformation. We, therefore, aim to combine recent advances in the deep learning domain to develop a spatial-temporal neural network model to predict shared mobility demand. To build and test our model, we employ real-world data that we collect from numerous shared mobility services around the world.**

I. Introduction

The probably most important challenge for governments, businesses, and individuals is to mitigate climate change. Setting the course for a sustainable future is especially important in the mobility sector. Already today, people in cities around the globe are suffering from air pollution and other traffic-related problems like congestion and noise.

Shared mobility is an emerging alternative to individual transport and could be one of the driving forces behind the urgently required mobility transformation. The main idea is that individuals no longer own their personal vehicles, but instead have on-demand access to vehicles (e.g., cars, bicycles, scooters or mopeds) from shared mobility providers [1]. Especially if the services are operated with electric vehicles, the problems outlined above could be addressed collectively.

However, as a result of the rapidly growing fleets, providers of modern services are facing existential challenges. At the same time, the services must be designed to be environmentally friendly, customer-friendly, economical, and in cooperation with public authorities. For planning and efficient operation, precise predictions of future mobility demand are required. Shared mobility demand prediction, however, can be considered as a challenging task, especially due to the complex spatial-temporal dependencies resulting from the free-floating provision of vehicles without fixed stations.

II. Related Work

The task of predicting shared mobility demand can be considered as a time series forecasting problem. Recently models from the deep learning domain started to emerge and outperform traditional statistical approaches. Most current models are based on recurrent neural networks (RNNs) (e.g., [2]) for temporal modeling, convolutional neural networks (CNNs) for spatial modeling (e.g., [3]), or a combination of both (e.g., [4]). The most common limitation is that these models are restricted to Euclidean data. Accordingly, the operating area is represented as a regular grid where demand is aggregated on the level of equally-sized regions. For operational tasks, however, this partitioning strategy limits the spatial decision basis for fleet providers.

Only recently, researchers started to examine methods from the emerging area of graph convolutional networks (GCNs) (e.g., [5]). GCNs are neural networks designed to process irregularly structured data defined on graphs [6]. However, graph-based models have only been barely examined in the context of shared mobility demand prediction, especially with respect to free-floating services.

The main goal of our work is to develop a model to predict shared mobility demand. In particular, we aim to provide fleet operators with a decision support tool to optimize operational tasks and thereby meet policies, enhance user satisfaction, and increase revenues.

III. Demand Prediction Problem

Dependencies that have to be considered when predicting shared mobility demand can be categorized into temporal dependencies (dependence on previous time steps), spatial dependencies (dependence on both distant and nearby surroundings), and external dependencies (dependence on externalities like weather or events). To formalize the prediction problem, we split the operating area into a set of arbitrarily shaped regions $\mathcal{R} = \{r_0, r_1, ..., r_K\}$. At time step t the demand (i.e. the number of rented vehicles) in region r_k can be denoted D_t^k. Furthermore, external data that is available for each region and/or time step is denoted as Π (e.g., weather data). The problem of shared mobility demand prediction can then be considered as a spatial-temporal time series forecasting problem and defined as follows: given the historical demand and external data, how is the future demand at $t+1, t+2, ..., t+T$ for all regions $r \in \mathcal{R}$.

IV. Methodology

A. Data collection

To build and evaluate our model, we collected shared mobility data from numerous cities around the world. The data includes different services with cars, bikes, scooters, and mopeds. Depending on the service, the data covers a period of three to twelve months but is continuously extended. To collect the data, we developed a web crawler that records vehicle positions every minute. From these positions, we

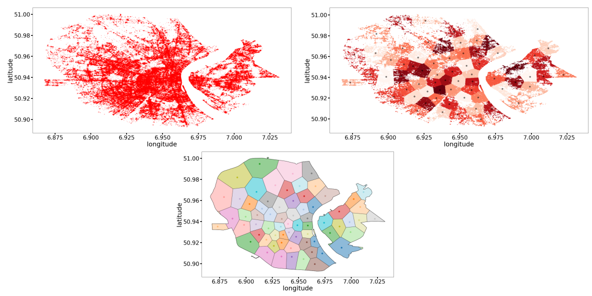

Fig. 1. Spatial Partitioning Approach for the example of Cologne (Germany)

extract trip data by searching for temporal gaps where vehicles disappeared from the map.

B. Spatial Partitioning

As outlined before, the partitioning of operating areas based on a regular grid introduces spatial limitations. We, therefore, follow a different approach which consists of two steps. In particular, we use the k-means algorithm in the first step to cluster trip starts and ends. The obtained cluster centroids are then used as input for the Voronoi tesselation, which creates irregular regions within the operating area. The underlying idea is to partition the operating area into demand-based regions.

C. Multigraph Creation

We represent the operating area as an undirected, weighted graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}, \mathcal{A}\}$. with $\mathcal{V}$ being a set of vertices, $\mathcal{E}$ being a set of edges and $\mathcal{A}$ denoting a multidimensional weighted adjacency matrix. The demand, then, can be defined as a signal on this graph. Within the multigraph, one vertex represents one region. The weights in $\mathcal{A}$ are specified by different graph views. An example are the distance and elevation views that are given by the inverse distance respectively elevation between the regions.

D. Spatial-temporal Modeling

Considering the graph-based approach, the above-mentioned prediction problem can be further formalized as follows:

$$f([D_{t-T_x+1}, ..., D_t], \Pi, \mathcal{G}) = [D_{t+1}, ..., D_{t+T_y}] \tag{1}$$

Consequently, the task is to learn a function $f(\cdot)$ which maps the input demand sequence to the output demand sequence.

To address the complex spatial-temporal dependencies when predicting shared mobility demand, we combine recent advances from the deep learning domain. Instead of limiting input data to be defined in the Euclidean space, the proposed model processes graph-structured sequence data. We, therefore, modify the graph convolutional recurrent network (GCRN) introduced by [7] to fuse RNNs and GCNs. In particular, the recurrent component is a long short-term memory network [8] that captures short- and long-term temporal dependencies. Simultaneously, the convolutional component captures spatial dependencies and applies a first-order approximation of localized spectral graph filters [9]. To further address additional impact factors, the convolution is modified to process a multigraph with different graph views representing various spatial dependencies. Furthermore, an encoder-decoder architecture [10] allows predicting multiple future time steps at once and to include additional external data.

V. Conclusion

Predictions of future shared mobility demand provide a basis to support the sustainable operation of large-scale shared mobility services. The proposed model could be used by fleet operators as a decision support tool. First tests on bike sharing data from two German cities show that our model outperforms traditional statistical approaches. In the next steps we will finish and optimize the Tensorflow implementation of our model and conduct extensive performance tests on real-world data by including benchmarks with state-of-the-art deep learning models. In follow-up research, we also plan to develop software that visualize the model predictions, e.g. a dashboard for cities.

Poster Presentation

We would like to present our research at ICT4S to show how machine learning can be used to predict shared mobility demand. A special focus would be the emerging field of graph-based neural networks. Additional insights would be provided in the context of collecting and preprocessing large-scale shared mobility data sets. To foster discussion we would elaborate on experiences from using shared mobility services and potential impact factors on usage. Additionally, potential applications of demand predictions for operators, public authorities, and users could be discussed.

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