Forecasting is all we need: Adapting graph neural network methods for a peer-to-peer sharing economy platform

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Abstract – Estimating events in the near future with the help of forecasting techniques is undoubtedly of crucial importance in practice and facilitates decision-making from a management perspective. However, in the context of peer-to-peer (P2P) sharing markets, the evaluation of appropriate forecasting methods is still largely unexplored, especially for submarkets with a heterogenous product assortment and spatio-temporal dynamics. In this study, we investigate this gap and rely on graph neural networks (GNNs) methods from the application domains that are similar in their inherent characteristics to the P2P sharing market. We utilize the next basket prediction techniques, in particular set prediction, and traffic forecasting methods that consider both temporal and spatial aspects. More specifically, we change the evaluation point of set prediction from the user level to the region level and include meteorological variables as inputs to the traffic forecasting algorithm. The adapted models are then applied to the transaction data of a P2P sharing economy platform. We find that the methods work satisfactorily as they capture important patterns in the transaction data, leading to useful product-level predictions for a P2P sharing market.

Keywords— sharing economy, set prediction, spatio-temporal forecasting, P2P forecasting, graph forecasting

I. INTRODUCTION

Forecasting plays a central role in various industries and serves as an important tool for strategic planning and decision-making. In the energy sector, forecasting is an essential tool for estimating the required energy demand, in stock trading, forecasting algorithms are used to find optimal selling points, and in retail, forecasting is used to optimize inventory management. Each industry has its own characteristics that need to be carefully considered in the forecasting process. As a result, advanced methods tailored to specific needs may be of great value to a particular industry, making them less applicable or hardly transferable to other sectors. This is a disadvantage for niche markets or comparatively small markets with very specific characteristics, as they do not receive as much attention. One market that contains aspects of both a niche market and a market with very specific characteristics is the sharing economy.

The sharing economy is an economic concept in which resources are shared and used collaboratively. This means that companies or individuals who own items that they do not use all the time can make them available to others for temporary usage [1]. The items in question are not limited to a specific category but can range from immobile resources such as housing or apartments (e.g., *Airbnb*), means of mobility such as bicycles or scooters (e.g., *Lime*) to everyday goods (e.g., *Fat Llama*) [2]. The positive effects of the sharing economy include optimized product usage and a reduction in purchases, which leads to greater sustainability [3].

Transactions in the sharing economy are temporary in nature and often need to be coordinated via platforms that serve as a meeting point between supply and demand. Entities that have a supply can offer their goods on such marketplaces, while entities that have a demand can find what they are looking for there. It is often assumed that the sharing economy works according to the peer-to-peer (P2P) principle, i.e., that both demand and supply are generated by (private) individuals and not by specialized businesses (e.g., "professional hosts" on Airbnb).

The inclusion of P2P functionality has an impact on spatial and temporal dimensions of the sharing market in comparison to e.g., retail. While retail is usually centralized and dependent on the supply chain, in the sharing economy both demand and supply are decentralized and can only be controlled indirectly via marketing or communication campaigns from a platform's perspective. This means that even if a platform succeeds in attracting supply or demand, this has to happen in the right, decentralized place for both sides. If supply is created for product X in area A, but demand only exists in area B, product X will probably not be rented out as the distances between A and B might be too great. In addition, both supply and demand must be present on the market at the same time, as the absence of the other can demotivate participants from taking part. Thus, both spatial and temporal factors contribute to the complexity of the market.

This study focuses on a company that is very active in a highly dynamic sharing economy market. The company offers a sharing platform that operates on a P2P basis, i.e., entities are responsible for both supply and demand, with products from over 300 categories being offered and rented.

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The basic functioning of a successful sharing transaction is as follows. The entity with the demand (also called the renter) sends the supplying entity (also called the lender) a request specifying the desired time period for the chosen product. The lender then has the option of either accepting or rejecting the request. If the lender accepts the request, the renter can pick up the item at an agreed location, usually at the address where the product is registered on the platform. While this function seems straightforward, we have found that there is still a large gap between supply and demand in this active market, i.e., the regional submarkets differ greatly in terms of both supply and demand from a numerical perspective.

While estimating the total weekly number of transactions in a P2P environment works well with traditional forecasting methods such as recurrent neural networks (RNNs) or deep learning models, these methods run into difficulties when it comes to making more granular predictions, such as predictions at the product category level, namely what type of product will be in demand in a particular region over the next few days. The reason for this is that the product assortment consists of many different product categories and each category may have individual, perhaps even sparse, time series components due to trends or seasonality characterized by few data points. Therefore, a forecasting method is needed that is able to make an accurate short-term prediction of item popularity for specific regions, taking into account the specific supply demand in a sub-region. This would be invaluable for marketing purposes such as mobilizing supply for upcoming demand or activating demand.

The sharing economy sector has already been the subject of previous forecasting research. However, the focus has only been on the sub-sectors of accommodation platforms or mobility services to the best of our knowledge. While these areas are of legitimate research interest, they generally contain a relatively homogenous product range. This means that the products have certain features and specifications in common, which makes forecasting easier. Accordingly, the methods developed for these sub-sectors do not provide reasonable solutions for P2P markets with a heterogenous product range.

Our study aims to address the requirement for a short-term product popularity forecasting technique that is capable of making valid predictions at the sub-market level in a P2P sharing environment. We do this by evaluating cross-domain, graph neural networks (GNNs)-based forecasting techniques for their ability to produce an acceptable forecast at the product category level. To explain this, we first outline which forecasting methods have been the focus of research in the context of the sharing economy. We then summarize the forecasting literature from industries that are familiar with either spatio-temporal characteristics or multi-object forecasting. The aim of this step is to identify methods that are potentially suitable for the forecasting problem at hand. We then adapt the selected methods and apply them to the problem of predicting the popularity of items in our P2P market. Finally, we analyse and compare the results to evaluate the suitability of the selected methods for the sharing context. Therefore, our unique contribution lies in the successful application of cross-domain forecasting techniques in the P2P sharing market.

II. RELATED WORK

A. Forecasting in the sharing economy

In the sharing economy, forecasting research has so far heavily aimed at demand or price forecasts for accommodation and shared mobility services.

1) Accommodation services: For accommodation services, research on forecasting methods has largely focused on predicting occupancy or prices. Kuan et al. [4] tested various models such as exponential smoothing, linear regression, neural networks and ARIMA models for their ability to predict daily occupancy. They found that both the regression models and the neural networks performed best overall, while the exact performance depended on the city for which a forecast was to be made. Tang et al. [5] worked on the same problem and found that machine learning methods using boosting regression performed reasonably well. In [6], the abilities of extreme learning machines to predict Airbnb prices were tested in comparison to eXtreme Gradient Boosting (XGBoost), with the former showing a smaller mean squared error as well as a smaller average percentage error. Mahyoub et al. [7] also investigated the capabilities of different machine learning algorithms for predicting Airbnb prices, with random forest regression performing best in their setting.

2) Shared mobility services: In the context of shared mobility services, a considerable amount of research interest is focused on demand forecasting. Both [8] and [9] used Long Short-Term Memory (LSTM) models to estimate demand for car sharing schemes. Alencar et al. [10] also used LSTM in their assessment of car sharing demand, but also considered a number of other methods such as the Prophet model or gradient boosting. Bürgin et al. [11] predicted the demand for a free-floating car sharing service taking into account information about time and space. They also included the interaction between supply and demand in their analysis. In Bai et al. [12], the demand for car sharing services is formulated as a graph. Hierarchical graph convolutional structures are then applied to capture both spatial and temporal characteristics of sharing activities.

B. Cross-domain forecasting methods

In order to find suitable cross-domain methods that can be applied to our P2P sharing market, the literature was searched for areas that are familiar with either predicting multiple objects simultaneously or spatio-temporal properties. This led to the areas of next basket prediction and traffic forecasting.

1) Next basket prediction: Next basket prediction is thematically rooted in recommender systems and aims to predict the user's next shopping basket, i.e., based on a certain order history, which items will be purchased together next. This aspect has been addressed from different perspectives in the literature. Qiu et al. [7] adopted a customer-centric approach and developed a two-stage prediction framework to separately model the customer's motivation and product preference characteristics. In this way, the model, which consists of collaborative filtering, a Bayesian discrete choice model and a heat model, was able to learn the preferences of individual users and estimate the next N products a customer would buy. Van Maasakkers et al. [13] also focused their analysis on maintaining the individuality of products and customers and chose a gated recurrent unit (GRU) architecture to capture customer tastes, repeat purchases and product co-occurrences.

A different approach was taken by Sun et al. [14]. Instead of treating the sequential purchases of items at an individual level, they grouped the items into multi-level temporal sets. To then predict these temporal sets, a transformer model was developed to learn the item-level patterns, and another transformer model was developed to capture the set-level representation. In a next step, the temporal dependencies of both sets and items were learned by a third module adapted from the transformer architecture, so that finally a gating mechanism could be used to predict the next set by combining the different connections and temporal relations between items and sets.

Yu et al. [15] also proposed an integrated method based on set prediction: Instead of using multiple steps to capture the relationship between individual items and sets, they reformulated this problem by constructing set-level co-occurrence graphs while learning dynamic relationships through an attention-based module. To discover the patterns in specific sequences, a gated updating mechanism was applied.

Although both [14] and [15] were not explicitly developed for the next basket prediction, both evaluated the methods on different online shopping datasets and showed that the methods significantly outperform the baseline and state-of-the-art methods.

2) Traffic forecasting: Shared mobility services and traffic forecasting are closely linked thematically. Shared mobility services focus on the perspective of a specific service provider, whereas traffic forecasting takes all traffic into account, including public and private transport.

The focus of research in the field of traffic forecasting has recently shifted from classical static methods or time series analysis to convolutional neural networks (CNNs) or RNNs to GNNs [16]. In particular, various model architectures or extensions have been researched for GNNs. In [17], a recurrent graph convolutional neural network for traffic forecasting was developed in which the road network is represented as a graph. Similarly, a residual recurrent graph neural work was proposed in [18], which can capture both spatial dependencies and temporal information. Other models that are able to analyse traffic problems either in terms of spatial, temporal or both dependencies were analysed and summarized in the review by Bui et al. [19].

However, research in the field of traffic forecasting is not limited to GNNs that can incorporate spatial or temporal information into their estimates. It extends the analysis further by including external factors such as events. An example of event-aware forecasting that also considers spatio-temporal features was provided by Wang et al. [20]. Their proposed model is based on a spatio-temporal network augmented by a heterogenous mobility information network and a memory-enhanced dynamic filter generator. The latter is responsible to for capturing multimodal information as part of the forecasting consideration in their case information about events that happen take place in a specific time window. By applying such a model architecture, they showed superior prediction results for three mobility datasets compared to ten other models.

III. *Methodology*

A. Dataset

For this study, an anonymized database excerpt from the aforementioned company was provided. The excerpt included sharing transactions with a start date between 01 January 2020 and 30 June 2022 and contained over 22’500 unique rental transactions for more than 350 product categories by 2’901 unique renters. The full variable description is shown in Table I.

Table I. Variables in the Dataset

Variables	Description
Transaction ID	Unique ID per day and renter
Status	Categorical information about whether the rental transaction is pending, cancelled, successfully completed, etc.
Object ID	Unique ID of the object being rented
Product	Indicates the product category to which an object / item belongs. *
Booking date	Date on which the sharing transaction was initiated
Transaction start	Start date of the rental transaction
Transaction end	End date of the rental transaction
Location of product	The postal code under which the product is registered
Location of lender	Indication of the postal code where the lender is located
Locality of renter	Indication of the postal code where the renter resides

*: For reasons of conciseness, we do not use the term “product category” in the following and use “product” instead.

A preliminary analysis of the data shows that a transaction consists of 1.09 items on average (SD = 0.37), meaning renters rent one item per time they use the sharing platform and not multiple ones. Furthermore, the average number of transactions per renter is 7.76 (SD = 16.83) for the analysed period from January 2020 to June 2022.

The number of total daily sharing transactions is subject to seasonal fluctuations with the highest values between April and July (Fig. 1). Table II shows significant Spearman correlation values between the total number of rentals per day and the selected product rentals per day. Nevertheless, Fig. 2 shows that each individual product can exhibit different seasonal patterns compared to the trend shown in Fig. 1.

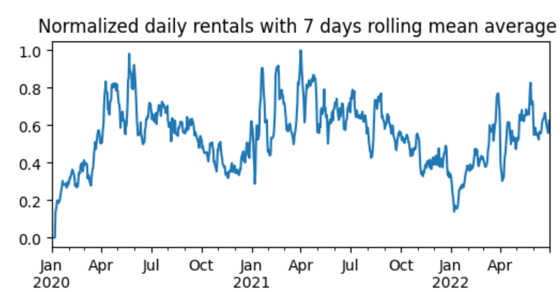

Fig. 1. Normalized daily rentals with rolling 7-day average.

TABLE II. SPEARMAN'S RHO OF TOTAL RENTALS PER DAY WITH RENTALS AT PRODUCT LEVEL PER DAY

	Product 1	Product 2	Product 7
Total number of rentals	-0.229*	0.517*	0.511*

*: The correlation is significant at the level of 0.01

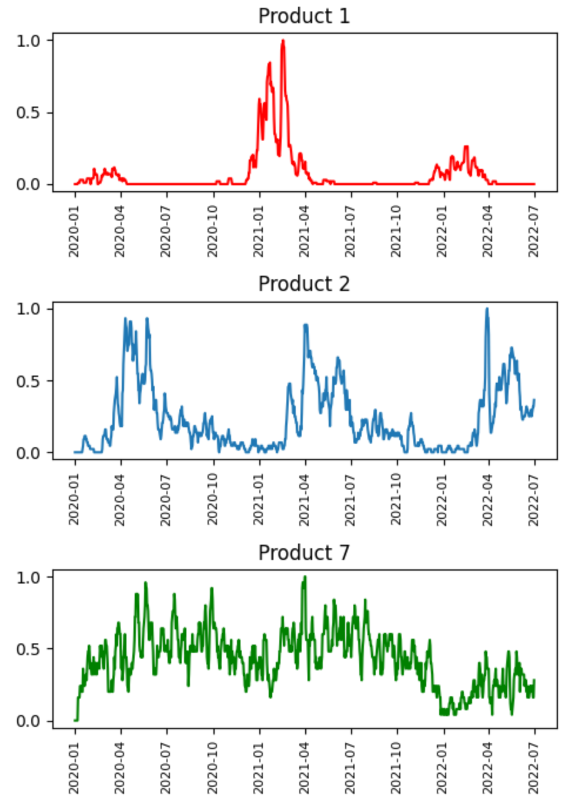

Fig. 2. Normalized daily rentals of the three most popular items with a rolling 7-day average. Each product shows its own pattern in terms of seasonality and trend. The anonymisation of the products is based on the index number and does not reflect the popularity of the products.

B. Extended Features

The dataset provided was extended with meteorological information for the sharing market within the period of interest. It was taken from the national weather service and included daily information on sunshine duration [hour], precipitation [mm], average wind speed [km/h], snow amount [mm] and average temperature [°C]. To reduce complexity, the meteorological data was clustered into eight groups using the *K*-means clustering and under consideration of based on the Silhouette score and the Davies-Bouldin score (Fig. 3).

Meteorological data were included as an extended feature because our preliminary models aiming at predicting the total number of daily transactions showed better performance when meteorological information was included as a covariate. The correlation between the meteorological data and the total number of sharing transactions per day remained significant, e.g., Pearson coefficients were found for temperature ($r = 0.391, p > .001$) and hours of sunshine ($r = 0.365, p > .001$).

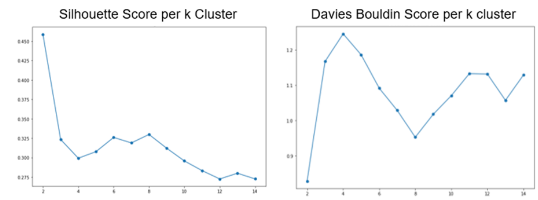

Fig. 3. Cluster metrics of *K* clusters for -*K* ranging from 2 to 14. Both the Silhouette score and the Davies-Bouldin score suggest 8 as the optimal number of clusters.

C. Methods

We selected one model each that is thematically rooted in next basket prediction and spatio-temporal forecasting to predict item popularities in our P2P sharing data. In particular, we chose GNNs approaches based on [15] and [20] because they are able to express the complexity of sharing transactions in terms of networks by additionally considering spatio-temporal aspects. Moreover, these methods can understand the concept of collective item sets and thus provide a framework for analysing the relationships between sharing transactions at both item and set levels.

We do not use baseline results generated by classical time series or deep learning models. The reason for this is that the models tested performed poorly under the given settings for most of the product categories considered. Consequently, the results derived by these classical methods could not provide any meaningful reference values.

1) Set prediction model:

a) Problem formulation: We reformulate the problem of next basket prediction to utilize the model's capabilities in the sharing context. In [15], the algorithm is able to capture the temporal dynamics of shopping behaviour considering the co-occurrence of items in sets. However, spatial features are not explicitly considered in the algorithm. Therefore, we consider the sets from a spatial perspective and interpret the "user" in our case as a spatial entity. For a selected geographic region *r* within the platform's market, the past transactions within this area, i.e., the number of transactions and the product rented, can be compared with the purchases made by shoppers. Thus, let $\mathbb{r} = \{r_1, \dots r_n\}$ be the collection of *n* regions and $\mathbb{p} = \{p_1, \dots p_m\}$ the collection of *m* products, a set *S* corresponds to the collection of products, $S \subset \mathbb{p}$. For given past sharing transactions in a region $r_i \in \mathbb{r}$, expressed as a sequence of sets, the goal is to forecast the next possible set, whereas *w* are trainable parameters.

$$\hat{s}_i^{T+1} = f(s_i^1, s_i^2, \dots, s_i^T, w) \quad (1)$$

b) Model architecture: A model architecture based on [15] is used (Fig. 4). For a collection of sets, we first train a weighted graph convolutional network on dynamic graphs such that the weights of the network represent the co-occurrence of set elements. We then exchange information between the individual elements within these graphs to capture relevant properties between the elements to gain a general understanding of the dynamics of the relationships.

These steps are summarised as "element relationship learning" in Fig. 4.

To learn about temporal dynamics, i.e., to understand the relationship between the elements and their set representations over time, temporal dependency learning is applied. To this end, a self-attention-based mechanism is used to analyse the past sets of a given geographic region and generate the so-called "dynamic representation" in Fig. 4. The information contained in the existing sets serves as the basis for predicting the next set. In addition, there could be information beyond the sharing market that could be shared between different regions. This information is shown in Fig. 4 as a "static representation". Then, a gated component decides which information from the dynamic and static representation is important by calculating the "updated representation". Finally, a prediction layer in the form of a sigmoid function calculates the set of items for the next periods for a geographic region.

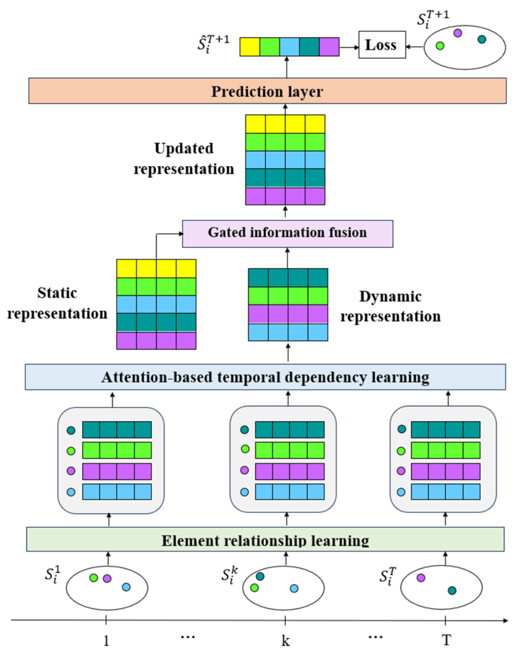

Fig. 4. Framework of the set prediction model. Adapted from [15]

c) Data preparation: We consider sharing transactions between 01.01.2020 to 30.06.2022 for major cities, whereas we define a major city as contributing to at least 120 transactions in the study period. We also filter the dataset by the 36 most popular items during this period to reduce noise.

This dataset is then divided into contiguous blocks of seven days each, resulting in 131 blocks. For each of the cities under consideration, a time-series of length 131 is created, which contains the set of items in demand in that location over the seven-days period.

Finally, the processed data is split 7:1:2 into train, validation, and test. We perform the split twice: once along the temporal axis to see if the model can predict future sets for regions from past sets. The other time we split along the spatial axis, i.e., meaning certain cities are only included in train, while other regions are only included in test. In this way, we evaluate the generalization capabilities of the model: once whether it is able to learn from the past, and once whether it is able to learn from other regions.

d) Evaluation: Three metrics are used to evaluate the performance of the set prediction model for the prediction of product demand on a monthly basis: Recall, Personal Hit Ratio (PHR) and Normalized Discounted Cumulative Gain (NDCG). Recall measures whether all items of interest for a region r_i have been found. This is done by diving the intersection of true (s) and predicted ($\hat{s}$) items over the size of the ground truth set.

$$\text{Recall@K}(r_i) = \frac{|\hat{s}_i \cap s_i|}{|s_i|} \quad (2)$$

[15]PHR is calculated using the ratio of regions r whose predicted sets contain the ground truth items:

$$\text{PHR@K} = \sum_{i=1}^{N'} \frac{g(|\hat{s}_i \cap s_i|)}{N'} \quad (3)$$

where g(x) returns 1 if x ≥ 0 and N' is the number of test samples.

NDCG is a measure of the quality of the ranking, in which the order of the elements in a list is taken into account. Mathematically, this is represented as follows:

$$\text{NDCG@K}(r_i) = \frac{\sum_{k=1}^{K} \frac{\partial(\hat{s}_i^k, s_i)}{\log_2(k+1)}}{\sum_{k=1}^{\min(K,|s_i|)} \frac{1}{\log_2(k+1)}} \quad (4)$$

whereas $\partial(\hat{s}_i^k, s_i)$ returns 1 when an element ($\hat{s}_i^k$) is in a set s_i, otherwise 0 [15].

2) Event-aware spatio-temporal forecasting model:

a) Problem formulation: We adopt the model proposed in [20] by changing the prediction target from heterogenous mobility behaviour in a traffic environment to heterogenous sharing transactions within a P2P sharing market. Moreover, in addition to temporal information, we also treat meteorological data in the form of cluster information as covariates.

Given that sharing transactions are organized into sets of time windows of equal length $\mathbb{t} = \{t_1, \dots t_n\}$, regions $\mathbb{r} = \{r_1, \dots r_n\}$ are discretized and the assumption that there are m different products $\mathbb{p} = \{p_1, \dots p_m\}$. We can form a sharing transaction tensor $\mathcal{Y} \in \mathbb{R}^{t \times r \times c}$, where $c = 2 \cdot p$ and represents both the demand and the supply for the products. Given q-step consecutive observations Y in $\mathcal{Y}$, expressed as $(Y_{t-q+1}, \dots Y_t)$ whereas $Y \in \mathbb{R}^{r \times c}$, the goal is to predict the next u steps $(\hat{Y}_{t+1}, \dots, \hat{Y}_{t+u})$, using the information contained in the auxiliary covariates w that describe both weather-related and temporal aspects.

b) Model architecture: Based on [21], the event-aware spatio-temporal forecasting model shown in Fig. 5 [20]receives two inputs: The sharing transactions expressed over the network and the meteorological and the temporal information as optional covariates. The network consists of a set of nodes that include entities such as locations and products of the sharing transactions. The edges are defined as the relationships between them, e.g., city-to-city, item-to-item, and city-to-item. The covariates are fused stepwise. The integrated data is applied to a spatio-temporal network, which is a combination of a graph convolutional network (GCN) and an RNN to process the spatial dependencies through a graph-aware functionality and the temporal dependencies in a recurrent form [20]. We also use a memory-augmented dynamic filter generation to dynamically generate filters that utilize relevant features over time.

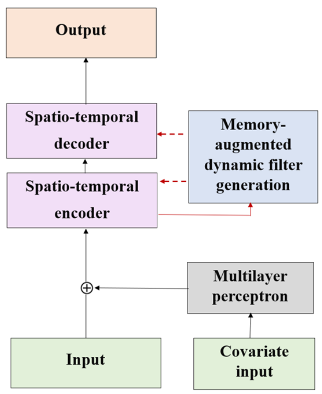

Fig. 5. Simplified framework of the weather-aware spatio-temporal forecasting model. Adapted from [20]

c) Data preparation: Given the sparse data and noise in our dataset, we only consider sharing transaction in 10 major cities in Switzerland. Furthermore, as with the set prediction, we focus on 36 products with the most transactions. Finally, we perform a smoothing of the number of sharing transactions by calculating a cumulative transaction count over a week, starting from the analysed day. Although smoothing results in the model not learning the exact transaction counts, it helps to reduce the fluctuation of transactions between days and better capture the trends in the market.

For the covariates, the clustered weather information is smoothed over a week, starting with the analysed day. We therefore consider the prevailing weather for that week. Both the temporal and meteorological conditions are then one-hot encoded as auxiliary input sequence.

Again, we split the data 7:1:2 into train, validation, and test.

d) Evaluation: We only include the ten largest cities and the 36 products with the most transactions in the analysis. To analyse how important the inclusion of meteorological data is for the predictive performance of the model, we trained the model once with and once without the covariate. The model is evaluated by comparing the predicted product demand with the actual values for the period of the next eight consecutive days. The metric is the Root Mean Squared Error (RMSE). In addition, the correlation between the sequences of the predicted and actual values is calculated.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{5}$$

IV. *Results and Discussion*

A. Set prediction model

Overall, the set prediction model works promisingly for predicting the set of next products in demand. However, the performance of the model differs depending on whether the training data is split along the spatial and temporal dimension.

On the one hand, when the data is split along the spatial dimension, the model can predict the future transactions in the market better when the prediction is made in terms of large top-k items, e.g., $k > 15$. When predicting small top-k items, the model performance can still improve its performance. This applies to both test conditions, i.e. for when the model was trained with the largest city included in train set (Fig. 6) as well was when this was not the case (Fig. 7): All three metrics indicate suboptimal performance for all three data splits (train, validate, test).

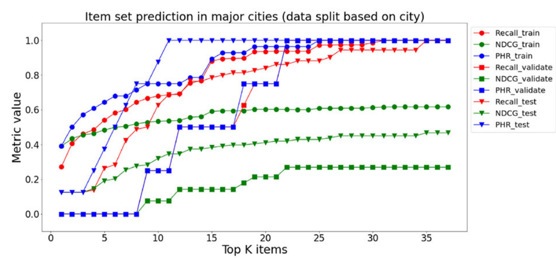

Fig. 6. Evaluation of the set prediction model from a spatial perspective with the largest city in the train

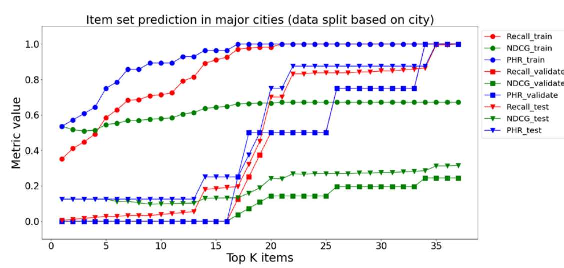

Fig. 7. Evaluation of the set prediction model from a spatial perspective with the largest city in the test

Differences between these two approaches are hereby seen when considering the relationship between set size k and the slope of the error metrics: Whereas the model trained on a dataset that included the largest city shows constant improvement with a growing k, this happens for the model without the inclusion of the largest market in the train dataset in an erratic fashion.

In contrast, evaluating the model's performance when trained on temporally split data, we see a notable and immediate improvement across most error metrics when testing for small k's.

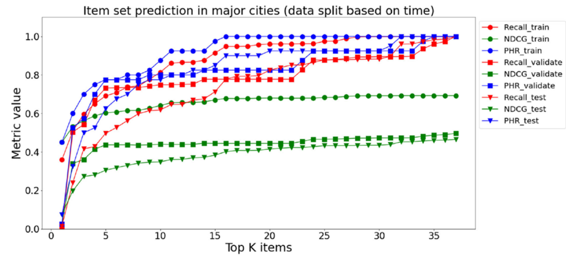

Fig. 8. Evaluation from a temporal perspective

We thus argue that the set prediction model can perform reasonably accurate forecasts for the P2P sharing market. Whereas the model is limitedly able to learn generalized patterns by only seeing certain submarkets in train, it is crucial to acknowledge that the regional submarkets in the data differ greatly in their market dynamics. Hence, even though model performance is not as good in Fig. 6 and Fig. 7 compared to Fig. 8, we consider the results adequate given the deliberate bias within the train data.

Furthermore, set prediction can generalize future behaviour based on past patterns, as expressed by the comparatively good recall and PHR metrics for train, validate and test in Fig. 8.

B. *Event-aware spatio-temporal forecasting model*

Analysing the weather-aware spatio-temporal forecasting model under the aspect of correlation between predicted and true number of rentals, two things become apparent [Table III]. For one, correlation is consistently high but steadily decreases. This seems to be reasonable, as predictions become less reliable in the longer term. Secondly, the model without the inclusion of the meteorological covariate has higher correlation values than the model with throughout the entire predicted time span of eight days.

TABLE III. PEARSON R BETWEEN GROUND TRUTH AND PREDICTION

Day to forecast:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
With covariate	0.95*	0.90*	0.86*	0.81*	0.77*	0.72*	0.68*	0.64*
Without covariate	0.95*	0.91*	0.87*	0.85*	0.83*	0.80*	0.78*	0.76*

*: The correlation is significant at the level of 0.01

However, when considering model performance via RMSE, we do not necessarily see the same result for the models with ("w") and the models without ("o") covariate: For most of the products, we see a better performance in train and test of the first day of forecast. Whereas this effect in general deteriorates over the prediction horizon of eight days, depending on the product, we find in both train and test sets occurrences where prediction under inclusion of meteorological information yielded a lower error for the eight day.

Fig. 9. Forecast accuracy for train and test sets as reported by RMSE for one day ahead (upper half; in orange / red) and eight days ahead forecast (lower half; in blue / purple).

For these reasons, we assert that the weather-aware spatio-temporal network can work with the sharing transaction data and capture certain pattern of the eight following days to be predicted. The combination of correlation and RMSE analysis shows that the inclusion of weather conditions in the forecast model can improve the forecast accuracy of sharing transactions. However, the benefit deteriorates, is product-dependent, and can be counteracted by noise if the forecast is produced for a longer period.

V. CONCLUSION

In this study, we adapted two GNNs methods, set prediction and weather-aware spatio-temporal forecasting, and applied them to predict the demand of products in a P2P sharing economy market. The challenges in this prediction task are that the transactions of items are influenced by spatial and temporal factors and the products are heterogeneously demanded and supplied in the market. Nonetheless, we have shown that both methods are capable of producing usable forecasts under consideration of regional dynamics regarding supply, demand, and product availability. The GNNs hereby convince in different points:

We presented for the set prediction algorithm to deliver meaningful results and show hereby that even when sets are defined on a different level than per user, the model is applicable. Moreover, we saw that the algorithm is able to make generalization under two different training scenarios. Whereas the algorithm is not able to include frequency in its forecast, it is able to provide insights into upcoming demand in a binary form per month.

Our second model hereby works as a complement by making numerical predictions that express the trend behaviour for every product. It is able to make such predictions on a day-level. Additionally, we showed that weather-dependent information can improve prediction quality. In general, the weather-aware spatio-temporal network provides a new way to incorporate weather into prediction algorithms, which can be used to predict upcoming sharing transactions for specific items in interested cities.

Future work should extend our analysis by also integrating data points we did not include or investigate the effects of model or hyperparameter tuning. This should be done to analyse the influence of the quality of input data on our findings as well as elaborate on the importance of model set up.

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