Modeling Price Elasticity for Occupancy Prediction in Hotel Dynamic Pricing

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ABSTRACT
Demand estimation plays an important role in dynamic pricing where the optimal price can be obtained via maximizing the revenue based on the demand curve. In online hotel booking platform, the demand or occupancy of rooms varies across room-types and changes over time, and thus it is challenging to get an accurate occupancy estimate. In this paper, we propose a novel hotel demand function that explicitly models the price elasticity of demand for occupancy prediction, and design a price elasticity prediction model to learn the dynamic price elasticity coefficient from a variety of affecting factors. Our model is composed of carefully designed elasticity learning modules to alleviate the endogeneity problem, and trained in a multi-task framework to tackle the data sparseness. We conduct comprehensive experiments on real-world datasets and validate the superiority of our method over the state-of-the-art baselines for both occupancy prediction and dynamic pricing.

CCS CONCEPTS
• Computing methodologies → Neural networks; • Applied computing → Forecasting.

KEYWORDS
Dynamic Pricing, Occupancy Prediction, Price Elasticity

1 INTRODUCTION
Dynamic pricing [4], which determines the optimal prices of products or services based on the dynamic market demands, has received considerable attention in research [1, 6] and industries [2, 14, 16, 21, 24–26]. In online hotel reservation platforms (e.g., booking.com, Fliggy), dynamic pricing is extremely important as similar hotels on the platform compete to share the market demand, and the inventory (i.e., the available rooms) of each hotel is perishable on each day. Thus, a good pricing policy can benefit the matching of supply and demand, and improve the overall revenue. In practice, most pricing strategies recommend an optimal price to maximize the revenue based on a demand curve [4] that depicts the relationship between the selling price and the demand (or particularly referred to as occupancy) at that price.

Regression models are widely adopted in existing works to estimate the dynamic occupancy. For example, Ye et al. [25] use a Gradient Boosting Machine (GBM) [7] to map a set of raw features to an estimated booking probability for Airbnb’s listings. Zhang et al. [26] capitalize on a seq2seq model [17] to predict the future occupancy based on the hotel features and statistics. However, these regression models may suffer from the data sparseness as many rooms only have reservations on certain days while the reservation prices are generally in a narrow range, and endogeneity problem [22] as many features are price dependent (e.g., the feature of historical sales is positively correlated with price). To address this, in this paper, we aim at a more accurate and explainable occupancy prediction approach for dynamic hotel pricing.

Motivation. Our idea is inspired by the concept of “price elasticity” in economics [22]. Particularly, we observe that though price is a significant affecting factor for hotel occupancy (e.g., the more a hotel lowers the price, the higher the occupancy rate), the sensitivity of
occupancy to price change (i.e., price elasticity of demand) could be quite different. On the one hand, the price elasticity of hotels with different characteristics is essentially different, e.g., the occupancy of luxury hotels is less price-sensitive than budget hotels as they have less substitutes in the market place. On the other hand, even for a same hotel room, its price elasticity could be varying across time due to the external factors such as seasonality and market trend. For example, hot spring hotels are less price-sensitive in winter as the demand is seasonal. Moreover, the price elasticity of hotels in a shared market synchronously fluctuates due to the competition among them. For example, discount on a hotel room would drive higher demand for it, and at the same time lead to the lower occupancy for its competitors.

Proposal. Such observations motivate us to explicitly model the price elasticity of demand in occupancy estimation. Specifically, we define the occupancy of a hotel room as a function \( F(P, \beta) \) of its selling price \( P \) and the elasticity coefficient \( \beta \), and propose a price elasticity model (PEM) to learn the dynamic price elasticity coefficients in the occupancy function. Once \( \beta \) is inferred, the optimal price can be easily obtained based on the demand curve \( F(P, \beta) \).

In addition to better modeling the demand dynamics, the elastic demand function brings two other advantages: (1) the price elasticity of rooms are inherently similar to that of hotels they belong to. Thus, the hotel-level reservation data can be used to handle the data sparsity issue and enhance the model training; (2) the features affecting \( \beta \) are less dependent on price but more relevant to the room characteristics and external influences. Thus, it is promising to alleviate the endogeneity problem with proper model design.

Specifically, we comprehensively examine the features affecting the price elasticity, and identify three orthogonal groups of factors: competitive factors (i.e., the influence of competitive hotels in a same market), temporal factors (i.e., the effect of hotel popularity and market trend), and characteristic factors (i.e., the effect of basic features). We develop a competitiveness representation module and a multi-sequence fusion module to capture the competitive factors and the temporal factors, and attentively integrate them for occupancy prediction. Our model is trained in a multi-task learning framework using hotel occupancy prediction task to assist room occupancy prediction, to handle the data sparsity issue.

Contributions. Our contributions are three-fold. (1) We propose a novel elastic demand function that utilizes the price elasticity of demand to enhance the occupancy estimation for hotel dynamic pricing. (2) We develop a multi-task price elasticity learning framework that tackles the data sparsity of room-level occupancy with the assistance of hotel-level occupancy prediction, and alleviate the endogeneity problem with carefully designed modules. (3) Extensive experiments on two real-world datasets validate the superiority of our method for both occupancy prediction and dynamic pricing.

2 APPROACH

In this section, we define a novel demand function in hotel dynamic pricing, and present the proposed price elasticity learning model.

2.1 Elastic Demand Function

In online hotel booking platform, a typical hotel provides multiple types of rooms for reservation on each day. The demand or occupancy of rooms varies across room-types (e.g., luxury rooms, economic rooms) and changes over time (e.g., weekday, weekend).

To forecast the occupancy \( O^t_r \) of a room type \( r \) on a specific night \( t \), as motivated in Sect. 1, we propose to model \( O^t_r \) as a function of the selling price \( P^t_r \) and a price elasticity coefficient \( \beta^t_r \). We now concretely define the demand function based on two intuitions: (1) changes in \( O^t_r \) are inversely related to changes in \( P^t_r \) (e.g., demand usually falls when price rises); (2) how much \( O^t_r \) changes is regulated by the price elasticity coefficient \( \beta^t_r \). Therefore, we can formalize the demand function in a concise yet effective way as

\[
O^t_r = \bar{O}_r \cdot (P^t_r/\bar{P}_r)^{-\beta^t_r},
\]

where \( \bar{O}_r \) and \( \bar{P}_r \) are the constant benchmark occupancy and price, respectively, e.g., the average occupancy or price in one week.

Therefore, \( \beta^t_r \) is the key to the success of occupancy prediction. Once \( \beta^t_r \) is inferred, we can simply sample a set of prices \( P^t_r \) in a reasonable range to calculate the corresponding \( O^t_r \), and the optimal price is the one that maximizes the expected revenue

\[
P^t_r^{\star} = \arg\max_{P^t_r} (P^t_r - \bar{P}_r) \cdot O^t_r,
\]

where \( \bar{P}_r \) is the cost price of room type \( r \).

2.2 Price Elasticity Prediction Model

We now present the Price Elasticity prediction Model (PEM) to learn the price elasticity coefficient \( \beta^t_r \) in Eq. (1). We identify three types of factors affecting the price elasticity in the hotel industry: (1) **Competitive factors** such as the price and quality of competitors. Hotels that have better quality than its competitors are less price-elastic. (2) **Temporal factors** such as events, seasonality, popularity. The price elasticity of a room is time-varying due to the seasonality, or change of its popularity. (3) **Characteristic factors** such as hotel star, location and business district. Hotels with different characteristics naturally have different price elasticity.

Our PEM model is designed to leverage all these factors for dynamic demand learning. As shown in Fig. 1, PEM is developed in a multi-task learning framework that simultaneously predicts the price elasticity coefficient \( \beta^t_r \) of a room \( r \), and the price elasticity coefficient \( \beta^h_t \) of its belonging hotel \( h \) at night \( t \). For each prediction task, the input contains the aforementioned features, as well as the contextual features such as real-time price, holiday-or-not information. To alleviate the endogeneity problem, the basic features of location, hotel star etc. and contextual features are transformed into low-dimensional representations through an embedding layer, while the other features related to competitive factors and temporal factors are respectively processed with two sub-modules: Competitiveness Representation Module (CRM) and Multi-Sequence Fusion Module (MSFM), elaborated in the following subsections.

2.2.1 Competitiveness Representation Module. As discussed, the price elasticity of rooms in a shared market synchronously fluctuates due to the competition among them. To model this pattern, we propose the CRM module (Fig. 1(b)) to learn the competitiveness of each selling price among a group of similar/competing rooms.

To identify the competing groups, we cluster the rooms based on their basic features such as location, hotel star, and business district, with \( K \)-means clustering algorithm (\( K \) equals to the number of

\[1\]We describe these modules in the context of room-level prediction task while for group-level task we only explain the difference.
patterns are then concatenated as the final temporal vector pooling operation, to exploit the underlying local patterns for all booking prices, of room-type daily clicks, sequence of daily searches, and sequence of historical price elasticity. The input of this module consists of the sequence of model is designed to model the temporal factors that affect the hotel-price graph.

If \( P \) i.e. \( \sum_{i=1}^{m} \delta \) is the average of price (or sum of occupancy) over all rooms, we construct the overall loss by combining the room-level prediction loss \( H_8(O^r_{t+1}, \hat{O}_{t+1}) \) and hotel-level loss \( H_8(O^h_{t+1}, \hat{O}^h_{t+1}) \): 

\[
\mathcal{L} = \lambda \sum_{i=1}^{n} H_8(O^r_{t+1}, \hat{O}_{t+1}) + (1 - \lambda) \sum_{j=1}^{m} H_8(O^h_{t+1}, \hat{O}^h_{t+1}), \tag{3}
\]

where \( \lambda \) is a hyper-parameter to balance two tasks, and each prediction loss \( H_8(y, \hat{y}) \) is defined as the huber loss [10] with hyperparameter \( \delta \in \mathbb{R}^+ \):

\[
H_8(y, \hat{y}) = \begin{cases} 
\frac{1}{2} (y - \hat{y})^2, & \text{if } |y - \hat{y}| \leq \delta; \\
\delta (y - \hat{y}) - \frac{1}{2} \delta^2, & \text{otherwise.} 
\end{cases} \tag{4}
\]

### 3 EXPERIMENTS

In this section, we conduct extensive experiments on two real-world datasets to evaluate our method.

#### 3.1 Experimental Settings

##### 3.1.1 Datasets

As there is no public dataset for hotel pricing, we construct the datasets, Dataset-H and Dataset-L, based on the hotel reservation data at Fliggy in a high-booking season from 2020.12.17 to 2021.01.23 and a low-booking season from 2021.03.11 to 2022.04.17, respectively. In each dataset, the reservations in the

![Figure 1: The proposed PEM model for price elasticity prediction.](image-url)
first 30 days are employed as the training set to predict the occupancy and suggest price for the next 7 days. The details of the datasets are summarized in Table 1.

| Datasets | Training | Testing |
|----------|----------|---------|
| Dataset-H | 12,727 | 16,676 |
| Dataset-L | 11,555 | 14,801 |

3.1.2 Baselines. We compare PEM with the following baselines.

**Occupancy prediction approaches.** (1) *Seasonal Autoregressive Integrated Moving Average (SARIMA)* [20] combines autoregressive model with moving average to model time series exhibiting seasonality. (2) *DeepFM+Seq2seq* [26] is a sequence learning model for occupancy prediction which integrates DeepFM and Seq2Seq model to learn the interaction among different features in the sequence and regress the future occupancy. (3) *DeepAR [15]* is a probabilistic time series forecasting method based on auto-regressive recurrent network. (4) *TFT [11]* combines recurrent layers with self-attention layers [19] to learn temporal relationships at different scales.

**Dynamic pricing approaches.** (1) *DNN-based pricing* [26] adopts a DNN model to regress the optimal price from the input features. (2) *Airbnb pricing* [25] uses a customized regression model to suggest the price w.r.t the booking probability for Airbnb listing-nights.

### 4 IMPLEMENTATION DETAILS

Our proposed PEM model contains two fully-connected layers with 256 and 128 units, respectively. The embedding size of all features is set to 16. The multi-sequence fusion model contains three convolution kernels (sizes: 64, 128, 64) and a two-layer Bi-GRU module (number of units: 64, 32). For training, the batch size is set to 512, dropout rate is 0.2, $\delta = 1.0$ and $\lambda = 0.9$. For SARIMA, we adopt the x13-auto-arima version [8] of the algorithm. The neural network used in DeepAR and TFT is one-layer LSTM [9] with 40 and 16 hidden cells respectively, number of heads in the multi-head attention layer of TFT is set to 2. The regression module of Airbnb is a three-layer MLP (number of hidden nodes: 128, 32, 1).

#### 4.1 Performance Comparison

##### 4.1.1 Evaluation metrics. We adopt two common metrics MAPE and WMAPE [3, 18] for the evaluation of occupancy prediction. For the evaluation of pricing strategy, we adopt the same metrics employed in hotel dynamic pricing [25, 26]: PDR, PDP, PIR, PIP and BR. The detailed description of these metrics can be referred to [26]. Generally, BR measures the closeness between the suggested prices and the booked prices, and the other four metrics measure the profit improvement at the suggested prices. In practice, there should be trade-offs for these metrics to increase the overall revenue of the platform and to maintain business trust from hoteliers.

##### 4.1.2 Results and analysis. The comparison of occupancy prediction and dynamic pricing are shown in Tables 2 and 3, respectively. For occupancy prediction, PEM achieves the best performance in terms of both metrics, which validates the effectiveness of our elastic demand function and the price elasticity prediction model for occupancy forecasting. For dynamic pricing, we observe: (1) PEM significantly outperforms DNN and Airbnb on the first four metrics related to revenue improvement. (2) The BR value of PEM is approaching DNN and Airbnb which are designed to directly regress the booking prices. However, for these baselines, the improvement in BR is obtained at the expense of much worse profit gains. In contrast, our PEM model achieves the best trade-offs among these metrics, demonstrating the effectiveness of our pricing strategy with elastic demand function.

#### 4.2 Ablation Study

We conduct an ablation study to investigate the contribution of each key module and loss. We compare PEM with three variants: 1) PEM-C: without competitiveness representation module; 2) PEM-M: without multi-sequence fusion module; 3) PEM-L: without hotel-level occupancy prediction task. The experimental results illustrated in Table 4 verify that all the components and losses are essential, among which the multi-sequence fusion module contributes the most. Specifically, on Dataset-H, the accuracy of PEM-C, PEM-M and PEM-L in WMAPE drops by 2.4%, 2.7%, 1.3% respectively.

#### 5 CONCLUSIONS

In this paper, we propose a novel elastic demand function that captures the price elasticity of demand in hotel occupancy prediction. We develop a price elasticity prediction model (PEM) with a competitive representation module and a multi-sequence fusion model to learn the dynamic price elasticity from a complex set of affecting factors. Moreover, a multi-task framework consisting of rooms- and hotel-level occupancy prediction tasks is introduced to PEM to alleviate the data sparsity issue. Extensive experiments on real-world datasets show that PEM outperforms other state-of-the-art methods for both occupancy prediction and dynamic pricing. PEM model has been successfully deployed at Fliggy and shown good performance in online hotel booking services.

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| Method | Dataset-H | Dataset-L |
|--------|------------|------------|
| SARIMA | 28.56 | 38.51 |
| DeepFM+Seq2seq | 28.72 | 39.75 |
| DeepAR | 28.11 | 39.78 |
| TFT | 27.96 | 39.22 |
| PEM | 27.88 | 39.03 |

| Method | Dataset-H | Dataset-L |
|--------|------------|------------|
| MAPE   | WMAPE     | MAPE   | WMAPE     |
| SARIMA | 28.56 | 40.03 | 30.51 | 41.10 |
| DeepFM+Seq2seq | 28.72 | 39.75 | 30.22 | 41.13 |
| DeepAR | 28.11 | 39.78 | 30.24 | 40.86 |
| TFT | 27.96 | 39.22 | 30.03 | 40.37 |
| PEM | 27.88 | 39.03 | 29.86 | 40.21 |

### Table 2: Evaluation on occupancy prediction (in percent).

| Method | Dataset-H | Dataset-L |
|--------|------------|------------|
| PDR   | PDP       | PIR      | PIP      | BR      |
| DNN   | 54.2     | 53.7     | 27.6     | 28.1     | 7.8  |
| Airbnb | 54.8     | 50.3     | 27.0     | 27.8     | 8.1  |
| PEM   | 56.3     | 55.5     | 30.1     | 30.8     | 8.5  |

| Method | Dataset-H | Dataset-L |
|--------|------------|------------|
| PDR   | PDP       | PIR      | PIP      | BR      |
| DNN   | 60.6     | 59.4     | 35.9     | 37.6     | 3.6  |
| Airbnb | 61.3     | 60.5     | 37.9     | 38.8     | 6.0  |

### Table 3: Evaluation on pricing strategy (in percent).

| Method | Dataset-H | Dataset-L |
|--------|------------|------------|
| PEM-C  | 29.01     | 40.15     |
| PEM-M  | 46.18     | 52.32     |
| PEM-L  | 28.39     | 39.81     |
| PEM    | 27.88     | 39.03     |
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