

Spatial Graph Neural Networks for Accurate Product Demand Prediction

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Abstract: Accurate product demand prediction is critical for enhancing operational efficiency and strategic planning in supply chain management. Traditional forecasting methods, such as time series analysis and regression models, often fall short in capturing the complex spatial dependencies that influence consumer behavior across different geographical regions. This paper explores the application of Spatial Graph Neural Networks (SGNNs) as an innovative approach to address these limitations. SGNNs extend conventional Graph Neural Networks by integrating spatial information into the graph structure, allowing for a more nuanced understanding of how local market conditions, demographic factors, and competitive dynamics impact product demand. Our study demonstrates that SGNNs significantly outperform traditional forecasting techniques by effectively modeling spatial relationships. Comparative analyses reveal the advantages and limitations of SGNNs relative to other machine learning approaches, emphasizing the importance of spatial considerations in demand prediction. Future research directions include refining SGNN methodologies, incorporating diverse data sources, and exploring applications in various domains beyond supply chain management. This work underscores the potential of SGNNs to transform demand forecasting practices across industries, paving the way for more accurate and reliable prediction techniques.

Keywords: Spatial Graph Neural Networks; Product Demand Prediction; Supply Chain Management.

1. Introduction

In the rapidly evolving landscape of supply chain management, accurate product demand prediction has emerged as a critical factor for operational efficiency and strategic planning. Effective demand forecasting enables businesses to optimize inventory levels, reduce costs, and enhance customer satisfaction [1-3]. Traditional methods of demand prediction, such as time series analysis and regression models, have long been employed to forecast future sales based on historical data. These techniques, while foundational, often struggle to account for complex patterns and dependencies inherent in demand data [4-6].

Despite their effectiveness in many scenarios, traditional models typically fail to capture spatial dependencies—an increasingly important factor in demand prediction as consumer behavior becomes more geographically nuanced [7-8]. For instance, demand for a product can vary significantly across different regions due to factors such as local preferences, economic conditions, and competition [9-12]. As such, there is a pressing need for advanced methodologies that can better incorporate spatial relationships into demand forecasting.

Graph Neural Networks represent a paradigm shift in the way relational data is processed and analyzed. Defined as neural networks that operate on graph structures, GNNs leverage the inherent relationships between nodes (entities) to enhance learning and prediction capabilities [13-16]. By capturing the connectivity patterns among nodes, GNNs can effectively model complex interdependencies that traditional methods overlook [17-20]. This ability to handle relational data makes GNNs particularly suitable for applications in various domains, including social networks, molecular chemistry, and transportation networks [21, 22].

Previous scholars proposed an innovative approach using Spatial Graph Neural Networks (SGNN) for product demand prediction in e-commerce [23]. Their method leverages

spatial relationships in online sales data and demonstrates superior performance over traditional statistical and machine learning techniques, offering valuable insights for optimizing online sales strategies.

Spatial Graph Neural Networks extend the capabilities of traditional GNNs by incorporating spatial information into the graph structure. In the context of product demand prediction, spatial graphs can represent products and their relationships with geographical locations, enabling the model to account for the influence of spatial factors on demand [24-26]. The integration of spatial relationships is essential, as demand for products is often influenced by local market conditions, demographic factors, and competitive dynamics, which vary significantly across locations [27-30].

The primary objective of this paper is to explore the application of SGNNs for product demand prediction. By leveraging the strengths of SGNNs, we aim to develop a model that effectively captures spatial dependencies and enhances forecasting accuracy. Additionally, we will compare the performance of SGNNs with traditional demand prediction models and other machine learning approaches, providing insights into the advantages and limitations of each method.

2. Literature Review

Demand prediction techniques have evolved significantly over the years, encompassing a wide range of methodologies. Statistical methods, such as moving averages and exponential smoothing, have traditionally been used for forecasting [31-36]. However, these methods often struggle with non-linear relationships and interactions among variables [37-39]. Machine learning approaches, including decision trees, support vector machines, and ensemble methods, have gained popularity due to their ability to model complex patterns in data [40-48].

Deep learning models, particularly recurrent neural networks and long short-term memory networks, have shown

promise in capturing temporal dependencies in time series data [49-53]. However, these models often overlook the spatial aspects of demand, which can lead to suboptimal predictions in scenarios where geographic factors play a significant role [54].

The historical development of Graph Neural Networks can be traced back to early work on neural networks for graph-structured data [55]. Since then, several key architectures have emerged, including Graph Convolutional Networks [56], Graph Attention Networks [57], and GraphSAGE [58]. These architectures have been designed to effectively aggregate information from neighboring nodes and learn representations that capture the structural properties of graphs.

Recent research has begun to explore the applications of GNNs in demand prediction, particularly in the context of supply chain management [59, 60]. Several studies have demonstrated the effectiveness of GNNs in capturing relational data for forecasting purposes, highlighting their potential to improve prediction accuracy and provide insights into demand patterns [61-65]. However, there are still gaps in the literature related to the integration of spatial considerations into GNN-based demand prediction models. Specifically, there is a need for further exploration of how spatial relationships can be effectively represented and utilized within SGNN frameworks [66-69].

3. Methodology

3.1. Problem Formulation

Demand prediction is a critical aspect of supply chain management, influencing inventory control, production planning, and customer satisfaction. In this research, we define the demand prediction problem within a spatial context, recognizing that product demand is not only influenced by temporal factors but also significantly shaped by spatial relationships among products and locations. The goal is to predict future demand for products at various locations using spatial graph neural networks.

To achieve this, we utilize a diverse set of data sources. Sales data is collected from retail transactions, encompassing information such as product IDs, transaction timestamps, quantities sold, and locations of sales. Geographic information systems data is also integrated, providing spatial attributes such as proximity to suppliers, population density, and regional economic indicators. By combining these datasets, we can create a comprehensive view of the factors influencing product demand across different locations.

3.2. Spatial Graph Construction

The construction of the spatial graph is a pivotal step in our methodology. In this context, nodes represent products and locations, while edges denote the relationships between them. For instance, an edge can be established between a product and a location if the product is sold at that location. Additionally, we consider spatial relationships by incorporating geographical proximity.

To define the edges quantitatively, we employ distance metrics such as Euclidean distance or Haversine distance for geographical coordinates. We also create adjacency matrices that reflect the connectivity of nodes based on both product-location relationships and spatial proximity. This adjacency matrix serves as the foundation for our SGNN, allowing the model to learn from both the relational and spatial characteristics of the data.

3.3. SGNN Architecture

The proposed SGNN architecture builds upon established graph neural network frameworks while incorporating specific adaptations for spatial data. The architecture consists of several key components:

a. **Input Layer:** This layer takes in the features of nodes, which may include product attributes (e.g., category, price) and location attributes (e.g., demographic information, historical demand).

b. **Graph Convolutional Layers:** These layers perform convolutions over the graph, allowing the model to aggregate information from neighboring nodes. The convolutional operation is modified to account for spatial relationships, ensuring that spatially close nodes have a more significant influence on each other.

c. **Pooling Layers:** To reduce dimensionality and capture essential features, pooling layers are employed. These layers summarize information from multiple nodes, facilitating the learning of higher-level representations.

d. **Activation Functions:** Non-linear activation functions such as ReLU (Rectified Linear Unit) are utilized to introduce non-linearity into the model, enhancing its capacity to learn complex patterns.

e. **Output Layer:** The final layer generates demand predictions for each product at each location. The output can be tailored to provide point estimates or probabilistic forecasts, depending on the specific requirements of the demand prediction task.

f. **Optimization Techniques:** We employ optimization algorithms such as Adam or RMSprop to minimize the loss function, typically using Mean Squared Error for regression tasks. Regularization techniques, such as dropout, are also implemented to prevent overfitting.

3.4. Training and Evaluation

The dataset is divided into three subsets: training, validation, and test sets. The training set is used to fit the SGNN model, while the validation set helps tune hyperparameters and prevent overfitting. The test set is reserved for evaluating the model's performance on unseen data.

Performance metrics are crucial for assessing the effectiveness of demand predictions. We utilize several metrics, including:

- **Root Mean Square Error:** This metric provides a measure of the average error in predictions, with an emphasis on larger errors.

- **Mean Absolute Error:** This metric captures the average absolute difference between predicted and actual demand, providing a straightforward interpretation of prediction accuracy.

- **Accuracy:** For categorical predictions (e.g., whether demand will exceed a certain threshold), accuracy is employed to evaluate the model's performance.

Baseline models, including traditional time series models like ARIMA and machine learning approaches such as Random Forest and traditional neural networks, are also implemented for comparison. This allows us to benchmark the performance of the SGNN model against conventional methods.

4. Experiments

4.1. Experimental Setup

The experiments are conducted in a controlled computational environment utilizing frameworks such as TensorFlow and PyTorch for model implementation. The SGNN model is trained on a GPU to leverage parallel processing capabilities, which significantly speeds up the

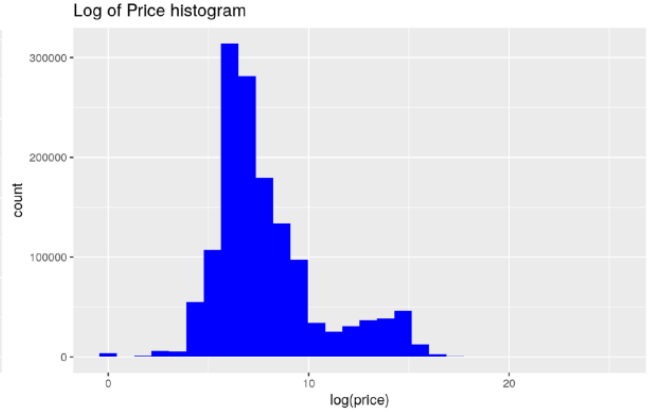
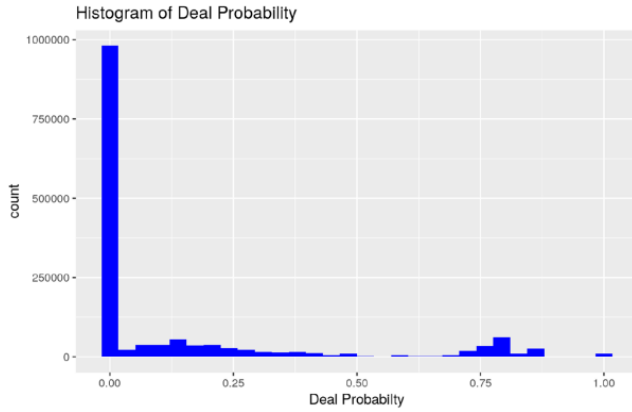


Figure 1. The distribution histogram for the deal probability and log of price over each value range.

4.2. Results from Baseline Models

Before evaluating the SGNN model, we analyze the performance of the baseline models. The results indicate that traditional methods, such as ARIMA, provide reasonable forecasts for time series data but often fail to capture the spatial dependencies inherent in the dataset. Similarly, machine learning approaches like Random Forest demonstrate competitive performance, yet they do not leverage the relational structure of the data effectively.

The insights gained from these baseline results highlight the limitations of conventional approaches in accurately predicting demand in a spatial context. This sets the stage for the introduction of the SGNN model, which aims to address these shortcomings.

4.3. Results from SGNN

The results from the SGNN model demonstrate a significant improvement in demand prediction accuracy compared to baseline models. The SGNN achieves lower RMSE and MAE scores, indicating that it effectively captures both temporal and spatial dependencies in the data.

Additionally, we conduct experiments to analyze the model's performance with varying spatial features. By systematically including and excluding specific spatial attributes, we observe how these features impact the overall prediction accuracy. The findings suggest that incorporating spatial relationships enhances the model's ability to generalize across different locations, leading to more accurate forecasts.

4.4. Visualization of Results

To facilitate a better understanding of the model's performance, we visualize the demand predictions against actual demand using graphical representations. These visualizations highlight the SGNN's ability to closely track actual demand patterns, showcasing its effectiveness in capturing fluctuations and trends.

Moreover, we create spatial heatmaps to illustrate the distribution of predicted demand across various regions and products. These visualizations provide valuable insights for

training process, especially for large datasets.

Hyperparameter tuning is a critical aspect of the experimental setup. We employ techniques such as grid search and random search to identify optimal hyperparameter values, including learning rates, batch sizes, and the number of layers in the SGNN architecture. Cross-validation is also used to ensure that the model's performance is robust and not overly dependent on a specific training set.

businesses, enabling them to identify high-demand areas and optimize inventory allocation accordingly.

5. Discussion

5.1. Interpretation of Results

The results obtained from the SGNN model provide compelling evidence of its effectiveness for demand prediction in a spatial context. The model's architecture, which leverages both spatial and relational data, allows it to outperform traditional methods significantly. By capturing the complex interactions between products and locations, the SGNN can make more informed predictions, thereby enhancing decision-making in supply chain management.

The comparison of SGNN performance against baseline models reveals that while traditional methods can provide reasonable forecasts, they often overlook critical spatial dependencies. In contrast, the SGNN's ability to integrate spatial features leads to improved accuracy and reliability in demand predictions.

5.2. Implications for Practice

The findings of this study have significant implications for businesses seeking to improve their demand forecasting capabilities. By adopting SGNNs, organizations can enhance their understanding of demand patterns, leading to better inventory management, optimized supply chain operations, and increased customer satisfaction.

Furthermore, the integration of SGNNs into existing supply chain management systems can facilitate real-time demand forecasting, enabling businesses to respond swiftly to changing market conditions. This adaptability is crucial in today's dynamic business environment, where consumer preferences and external factors can shift rapidly.

5.3. Limitations of the Study

Despite the promising results, this study is not without limitations. The data used for training the SGNN model may have inherent biases or gaps, which could impact the model's performance. Additionally, assumptions made during the

spatial graph construction process may not fully capture the complexity of real-world relationships.

Challenges faced during model training and evaluation, such as computational resource constraints and overfitting,

also warrant consideration. Future research should aim to address these limitations by exploring larger and more diverse datasets, as well as refining the spatial graph construction methods.

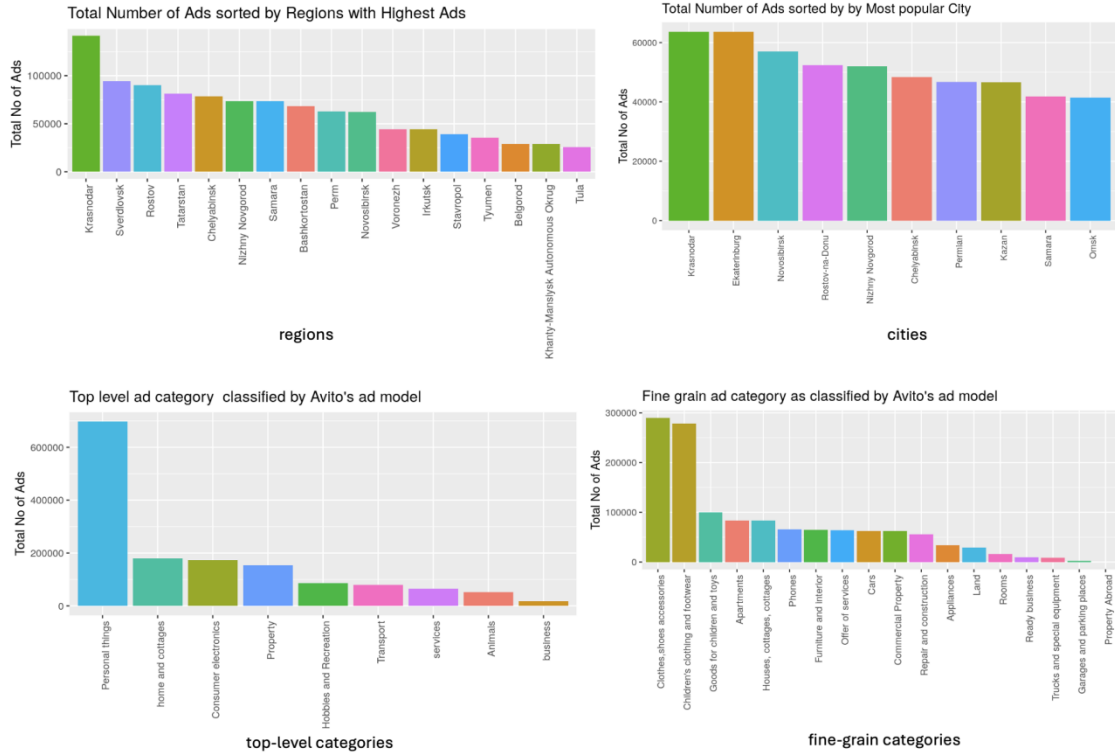


Figure 2. The distribution histogram for the region, city, top-level category, and fine-grain category, correspondingly

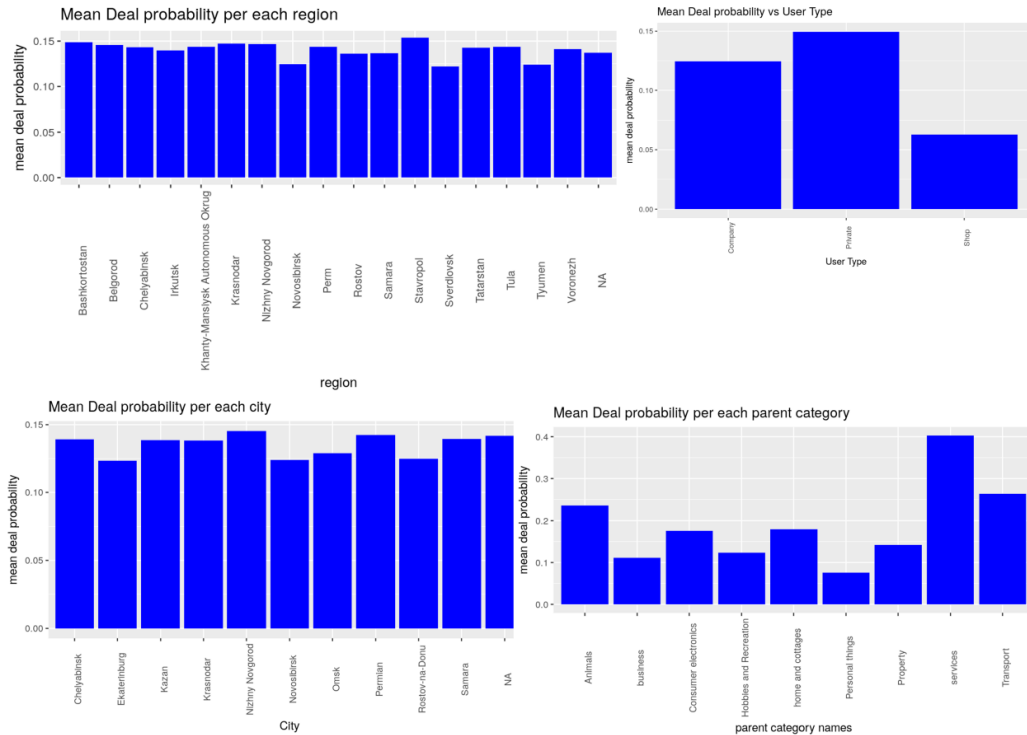


Figure 3. The histograms for mean deal probability in each group of corresponding variables, including region, user type, city, and parent category

6. Conclusion

In summary, this study demonstrates the effectiveness of spatial graph neural networks for product demand prediction. By leveraging the spatial relationships between products and locations, the SGNN model significantly outperforms

traditional forecasting methods. The results highlight the importance of considering spatial dependencies in demand prediction, paving the way for more accurate and reliable forecasting techniques.

Future research should focus on enhancing the SGNN model and methodology. Potential avenues for exploration

include the incorporation of additional data sources, such as social media sentiment analysis or economic indicators, to further enrich the demand prediction process. Additionally, refining the spatial graph construction techniques and exploring advanced architectures may yield even greater improvements in prediction accuracy.

The exploration of SGNNs in different domains beyond supply chain management, such as urban planning or transportation, could also provide valuable insights and broaden the applicability of this methodology. Ultimately, the advancement of SGNNs holds promise for transforming demand prediction practices across various industries.

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