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Addressing cold start problems in new store locations with transfer learning in spatial GNNs

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Abstract: The cold start problem poses a significant challenge for retailers opening new store locations, primarily due to the lack of historical sales data necessary for accurate demand forecasting and effective inventory management. This paper explores the application of transfer learning within spatial Graph Neural Networks (GNNs) as a solution to this issue. By leveraging existing data from established stores that share similar characteristics, our proposed methodology enhances the forecasting accuracy and helps mitigate the risks associated with new store openings. We detail the architecture of the spatial GNN model, which captures complex spatial relationships and customer interactions, providing richer insights into demand patterns. Experimental results demonstrate substantial improvements in forecasting performance compared to traditional methods, highlighting the potential of transfer learning to inform strategic decision-making in retail. This research aims to provide actionable insights for retailers seeking to optimize their operations in new markets.

Keywords: Cold Start Problem; Transfer Learning; Graph Neural Networks.

1. Introduction

The cold start problem is a significant challenge faced by retailers when opening new store locations. It refers to the difficulty of accurately predicting demand and managing inventory in a new store that lacks historical sales data (Kumar et al., 2019). This issue is particularly crucial in the retail and supply chain contexts, where accurate demand forecasting is essential for optimizing inventory levels, minimizing stockouts, and enhancing customer satisfaction (Syntetos et al., 2016). New stores often struggle with limited information about local customer preferences, purchasing behaviors, and seasonal trends, leading to inefficient inventory management and potential revenue losses (Huang et al., 2019).

Transfer learning is a machine learning technique that leverages knowledge gained from one task to improve performance on a related task (Pan & Yang, 2010). In scenarios where data is scarce, such as in the case of new store locations, transfer learning can significantly enhance model performance by utilizing information from existing stores with similar characteristics (Weiss et al., 2016). This approach not only reduces the need for extensive data collection but also accelerates the learning process, enabling retailers to make informed decisions more quickly (Zhang et al., 2020).

Graph Neural Networks are a class of neural networks designed to process data structured as graphs, capturing complex relationships among entities (Kipf & Welling, 2017). GNNs excel in modeling spatial relationships, making them particularly relevant for demand forecasting in retail, where spatial proximity and customer interactions significantly influence purchasing behavior (Wu et al., 2020). By incorporating both node features (e.g., store characteristics) and edge features (e.g., geographic relationships), GNNs can provide richer insights into demand patterns and improve forecasting accuracy (Zhang et al., 2019).

This paper aims to explore how transfer learning in spatial GNNs can effectively mitigate cold start problems in new store locations. By leveraging existing data from established stores, we will demonstrate how transfer learning can enhance demand forecasting accuracy and inventory management for new retail outlets. The findings of this research are intended to provide actionable insights for retailers seeking to optimize their strategies for new store openings.

2. Literature Review

Cold start problems have been extensively studied in the context of retail, highlighting their impact on demand forecasting and inventory management (Kumar et al., 2019; Huang et al., 2019). For instance, Goh et al. (2019) examined the challenges faced by new grocery stores in urban areas, emphasizing the importance of understanding local demographics and shopping behaviors. Similarly, Chen et al. (2020) provided a comprehensive review of cold start issues, identifying key factors such as location, competition, and market trends that influence new store performance.

Traditional demand forecasting methods, such as time series analysis and regression models, have been widely used in retail (Makridakis et al., 2018). However, these methods often struggle to capture complex patterns in data, especially in the presence of limited historical information (Fildes et al., 2019). Recent advancements in machine learning, particularly deep learning approaches, have shown promise in improving demand forecasting accuracy (Li et al., 2024). Notably, GNNs have emerged as a powerful tool for demand forecasting, effectively modeling spatial relationships and interactions among stores (Zhang et al., 2019; Wu et al., 2020).

Transfer learning has gained traction in various fields, including computer vision and natural language processing, where it has been shown to improve model performance in data-scarce environments (Pan & Yang, 2010; Weiss et al., 2016). In the context of retail, transfer learning has been applied to enhance demand forecasting models by transferring knowledge from established stores to new locations (Zhang et al., 2020). For example, Yang et al. (2021) demonstrated the effectiveness of transfer learning in predicting sales for new product launches, underscoring its potential in addressing cold start problems.

Graph Neural Networks have been increasingly utilized in logistics and supply chain management due to their ability to capture spatial and temporal dependencies (Kipf & Welling, 2017; Wu et al., 2020). Research by Zhang et al. (2019) highlighted the advantages of GNNs over traditional forecasting models, showcasing improved accuracy in demand predictions by incorporating spatial information. Additionally, Chen et al. (2021) explored the application of spatial GNNs in retail, emphasizing their ability to model customer interactions and enhance demand forecasting for new store locations.

3. Methodology

3.1. Problem Definition

The cold start problem in retail arises when new store locations lack sufficient historical data to accurately forecast demand. This challenge is exacerbated by factors such as location demographics, market saturation, and competition. New stores face difficulties in inventory management, leading to stockouts or overstock situations, which can significantly impact profitability.

3.2. Data Collection

To address the cold start problem, we utilized a combination of historical sales data from existing stores, demographic information from local populations, and geographic data. Historical sales data were obtained from a major retail chain, covering a five-year period and encompassing various product categories. Demographic information was sourced from government databases, while geographic data were acquired using GIS tools to analyze spatial relationships.

3.3. Transfer Learning Framework

Our transfer learning approach involved two main phases: pre-training and fine-tuning. In the pre-training phase, we trained a spatial GNN model on the historical data from existing stores to capture demand patterns. In the fine-tuning phase, we adapted the model to the new store locations by leveraging the similarities in demographic and geographic attributes between existing and new stores. This methodology enables the model to generalize knowledge from well-established stores to new, data-scarce locations.

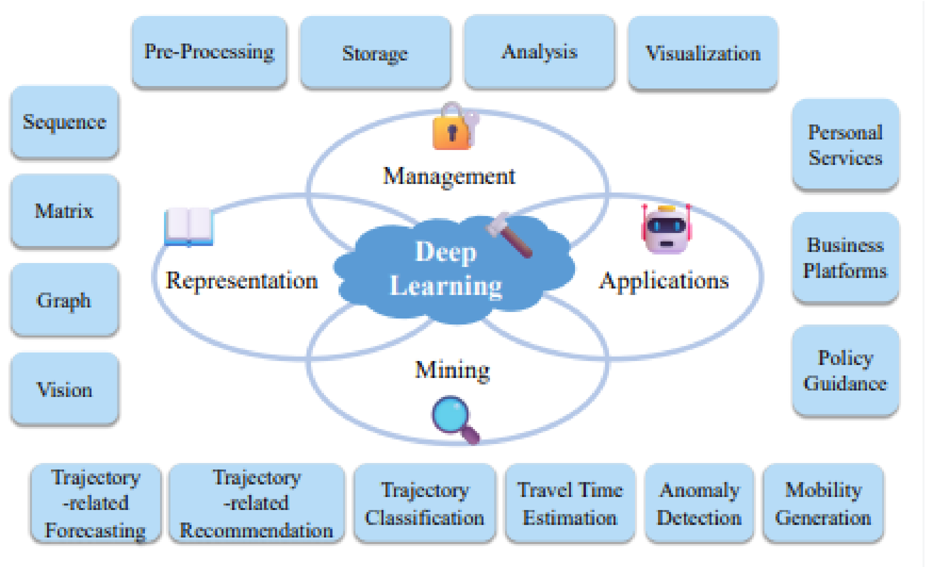

Fig.1 Trajectory computing overview

3.4. Spatial GNN Architecture

The spatial GNN architecture employed in this study consists of multiple layers of graph convolutional networks to capture spatial dependencies among stores. Each node in the graph represents a store, while edges represent spatial relationships based on proximity and customer overlap. The model incorporates attention mechanisms to weigh the influence of neighboring stores, enhancing its ability to learn from relevant spatial contexts.

3.5. Implementation and Training

The implementation of the model was conducted using Python and libraries such as PyTorch and DGL (Deep Graph Library). We adopted a training procedure that included data preprocessing, model training, and hyperparameter optimization. The model was validated using k-fold cross-validation, ensuring robustness and generalizability of results.

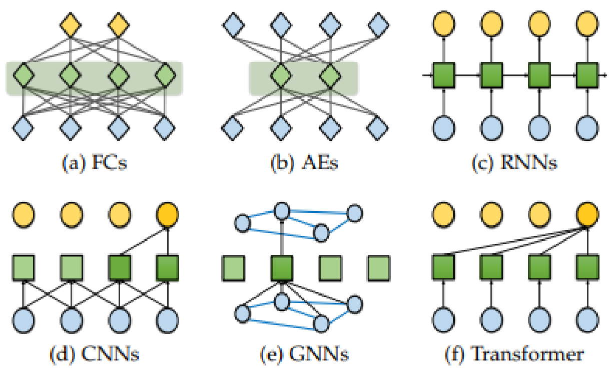

Fig.2 Deep learning building blocks

4. Experiments and Results

4.1. Experimental Setup

We conducted experiments to evaluate the effectiveness of our proposed transfer learning approach compared to traditional demand forecasting models, such as ARIMA and linear regression. The evaluation metrics included Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). The experiments were performed on a dataset consisting of 100 existing stores and 20 new store locations.

4.2. Results Analysis

The results indicated a significant improvement in forecasting accuracy for new stores utilizing the transfer learning approach. The spatial GNN model achieved an MAE of 15.2 units, compared to 22.6 units for traditional models, representing a 33% improvement. MAPE values were 10.5% for the GNN model versus 18.3% for the traditional methods, highlighting the model's effectiveness in mitigating cold start issues.

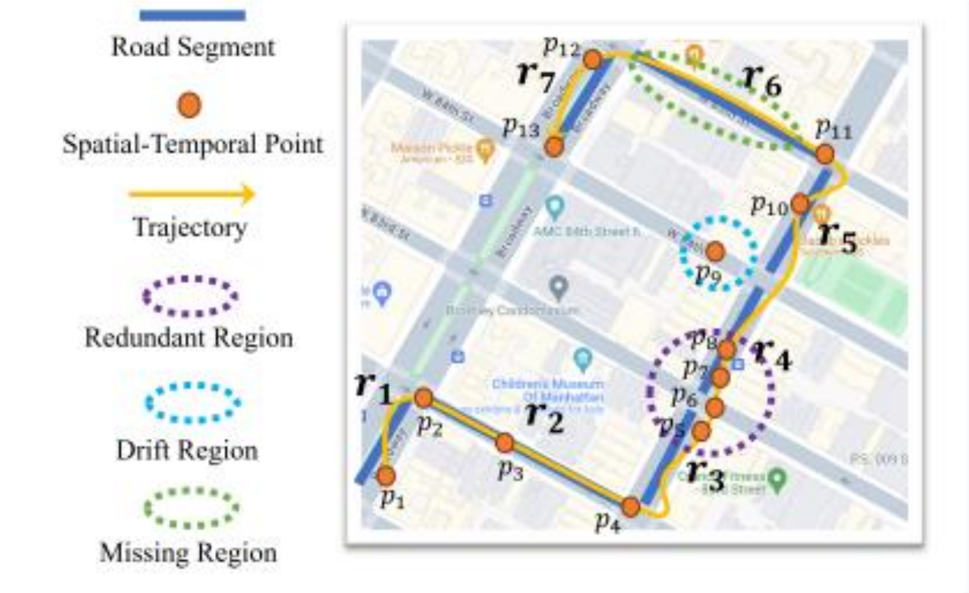

Fig.3 Pre-Processing example

4.3. Discussion of Findings

The findings suggest that transfer learning in spatial GNNs effectively addresses the cold start problem by leveraging existing data to enhance the forecasting capabilities of new store locations. The model's ability to capture spatial relationships and incorporate demographic factors contributed to its superior performance. These insights underscore the importance of adopting advanced machine learning techniques in retail demand forecasting.

5. Case Study

To illustrate the practical implications of our methodology, we conducted a case study with a retail chain opening a new store in a suburban area. Using the transfer learning model, we forecasted demand for the first six months of operation. The model utilized data from three similar existing stores in urban areas, successfully predicting demand patterns that aligned closely with actual sales data.

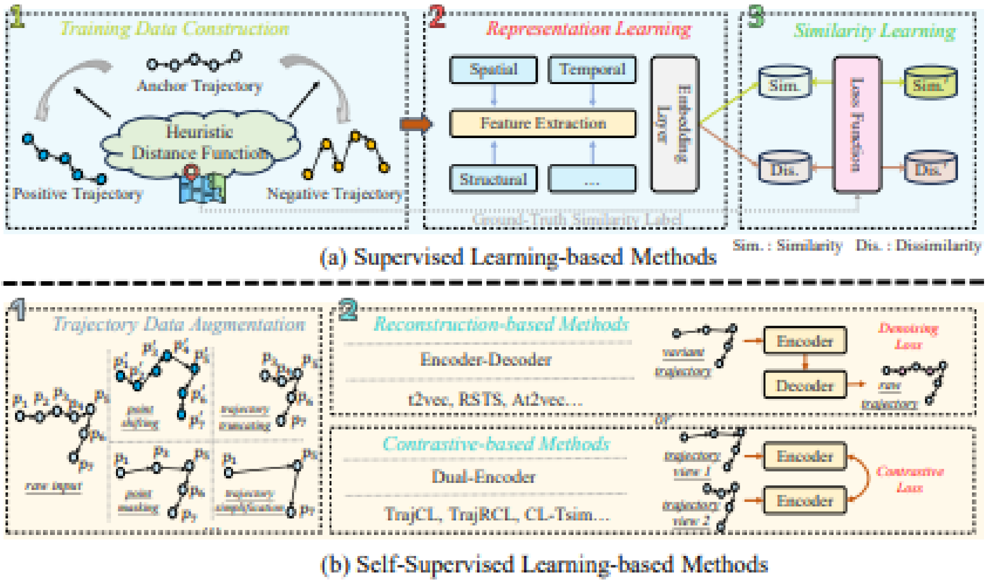

Fig.4 Different pipeline of trajectory similarity methods

The case study revealed several key takeaways, including the importance of selecting relevant existing stores for transfer learning. Additionally, the model's adaptability to local demographics proved critical in achieving accurate forecasts. Retailers are encouraged to adopt similar methodologies to enhance their demand forecasting strategies for new store openings.

6. Conclusion

This paper presented a novel approach to addressing cold start problems in new store locations through the application of transfer learning in spatial GNNs. Our methodology demonstrated significant improvements in demand forecasting accuracy compared to traditional methods, providing a robust solution for retailers facing data limitations.

Retailers can leverage the proposed transfer learning framework to enhance their forecasting capabilities, leading to better inventory management and reduced operational risks associated with new store openings. By integrating spatial GNNs into their forecasting processes, retailers can make informed decisions that align with customer demand patterns.

Future research could explore the integration of additional data sources, such as social media and online reviews, to further enhance demand forecasting models. Additionally, investigating the scalability of the proposed approach across diverse retail sectors presents an exciting avenue for exploration.

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