# Graph Neural Network Models for Retail Basket Recommendation Prediction

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Accurately predicting customer purchases is crucial for personalized retail recommendations. The complexity of product relationships in purchase history challenges basket recommendations. This research introduces advanced methods to better capture these interactions, aiming to enhance prediction accuracy and improve customer satisfaction.

## Data Preparation and transformation

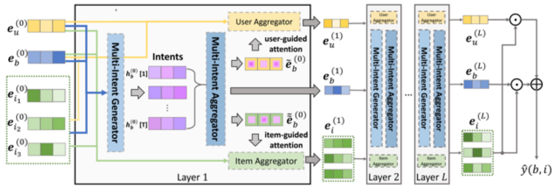
Data preparation and transformation were performed to the datasets for the model. With three distinct datasets, each representing sales data in different formats, specific preparation steps were applied to each:

- Basket for Each Customer: Timestamps were used to group items purchased together into baskets, capturing the relationship between customers and their baskets, which is crucial for the model's predictions.
- Items in Each Basket: Each basket's items were clearly listed to understand co-purchase patterns, ensuring the model can accurately analyze purchasing habits.
- Train and Test Dataset: The data was split into training and testing sets, with an equal number of baskets in each, to meet the model's requirements.

## Model Prediction

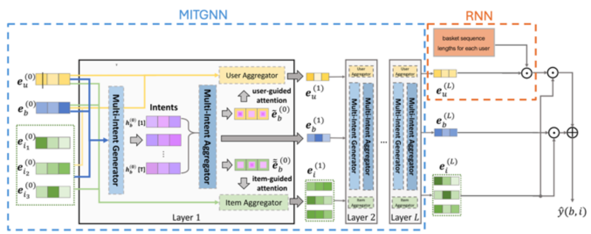
For model predictions, Multi-Intent Translation Graph Neural Network (MITGNN), and Recurrent Graph Neural Network (RGNN) designed to capture and utilize multiple intents in basket recommendations, thereby improving the recommendation accuracy and relevance.

- MITGNN: This model leverages translation mechanisms to generate multiple latent intents and utilizes a graph neural network framework to learn the relationships between users and items within the context of these multiple intents.




One of the datasets represents items by their names, and then BERT embeddings and cosine similarity scores are introduced.

- BERT embeddings and Cosine similarity: This logic involves converting words (item names) into numeric vectors using a BERT tokenizer, which are then processed through the BERT model to obtain embeddings that capture their semantic meaning. Cosine similarity is used to assess the similarity between embeddings, helping to understand basket-to-item and customer-to-item relationships before inputting them into MITGNN.
- RGNN: To incorporate the sequential nature of basket data into the model, the RGNN was applied. RGNN integrates the ability of Recurrent Neural Networks (RNNs) to capture sequential patterns with the structural modeling capabilities of Graph Neural Networks (GNNs). In this context, the MITGNN framework is utilized to model the relationships between entities within the graph. Specifically, a Long Short-Term Memory (LSTM) model was employed to handle the temporal sequences in the data, allowing the model to better understand and predict customer behavior over time.




## Evalustion Metrics

Evaluation was conducted using four key metrics.

- Recall@K: It measures the proportion of relevant items included in the top K recommendations. It's calculated as the number of relevant items in the top K divided by the total number of relevant items.
- Precision@K: It measures how many of the top K recommendations are relevant. It's the ratio of relevant items in the top K to K. This metric is crucial when the accuracy of top recommendations is more important than covering all relevant items.
- Hit Ratio@K (HR@K): It checks if at least one relevant item appears in the top K recommendations. This metric evaluates whether the model successfully recommends at least one relevant item within the top K.
- NDCG@K: It evaluates the ranking quality of the top K recommendations, considering both the position and relevance of items. It's calculated by normalizing DCG (Discounted Cumulative Gain) by IDCG (Ideal DCG). NDCG@K rewards models that rank relevant items higher.

## Model Comparison and Conclusion

k=10

| Dataset | | MITGNN | MITGNN with Cosine Similarity | RGNN |
|---|---|---|---|---|
| Groseries Data | Recall | 0.26247 | 0.26604 | 0.20685 |
| | Precision | 0.07087 | 0.07155 | 0.05544 |
| | Hit | 0.54611 | 0.55597 | 0.45666 |
| | NDCG | 0.17924 | 0.18031 | 0.16662 |

The model comparison focused on K=10 for practical, accurate recommendations. MITGNN with cosine similarity excelled at K=10, emphasizing quality over quantity, with the highest recall, precision, hit ratio, and NDCG.

## Reference

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