ISSN: 2182-2069 / E-ISSN: 2182-2077

Next Basket Recommendation Paradigm Multi-Layer Stacked Sequence to Sequence Bidirectional GRU Model with Multiplicative Attention

Sourav Sinha[1], Dr. Revathi Sathiya Narayanan[2*], and Dr. Indrajit Mukherjee[3]

[1]Research Scholar, Department of Computer Science & Engineering, B.S. Abdur Rahman Crescent Institute of Science and Technology, Vandalur, Chennai, India. sourav_cse_phd_17@crescent.education, https://orcid.org/0000-0002-3327-8215

[2*]Professor, Department of Computer Science & Engineering, B.S. Abdur Rahman Crescent Institute of Science and Technology, Vandalur, Chennai, India. srevathi@crescent.education, https://orcid.org/0000-0001-9584-5089

[3]Associate Professor, Department of Computer Science & Engineering, Birla Institute of Technology Mesra, Ranchi, India. imukherjee@bitmesra.ac.in, https://orcid.org/0000-0001-8839-9981

Received: July 24, 2024; Revised: September 4, 2024; Accepted: October 3, 2024; Published: November 30, 2024

Abstract

The Recommendation System is one of the latest application tools developed through Deep Learning research activities under the Machine Learning technical domain. The application might have recognized an idea for establishing a user-item relationship on consumables with guidance from the user's historical purchasing transaction data to achieve future demand predictions. Researchers had been able to bring out memory-based concepts at the beginning supplemented with model-based tools for further refinements with time. Incidentally, the significance of RS was well accepted by business entities, hence personalized services had been initiated to reduce user agony to search out the desired item. In recent years marked improvement was observed with the development of hybrid RS ornamented with the addition of Transformers in the model. The success of the introduction of Next Basket Recommendation relied on the capacity to analyze the user sequential change pattern in purchasing behavior.

Keywords: Next Basket Recommendation, Deep Learning, Transformers, Sequence to Sequence.

1 Introduction

The e-commerce business on consumables items and electronics products had grown faster to an explosive outcome level due to rapid technological advancement in Services and Mobile devices. The study and assessment of feedback on product reviews in social media or any other communication forum has become difficult to perform under the present regime of information overload. Hence the requirement for authentication on product approval for fresh users could be achieved only by personalized recommendation services complementary to the Recommendation system domain. The concept of the Recommendation System gained popularity among users mostly due to its capability in

Journal of Internet Services and Information Security (JISIS), volume: 14, number: 4 (November), pp. 542-553.
DOI: *10.58346/JISIS.2024.I4.034*

*Corresponding author: Professor, Department of Computer Science & Engineering, B.S. Abdur Rahman Crescent Institute of Science and Technology, Vandalur, Chennai, India.

the analytical assessment of review helpfulness and active participation in delivering efficient purchase decisions with the provision of personalized items or services in the shortest timespan. Reputed Business Houses preferred to initiate personalized services of RS to the users to reduce the searching time cost ultimately improving corporate sales growth positivity.

The prime aspect of the design of RS as an application tool lies in its capacity to tackle the information overload problems when users are inundated with a huge volume of information but struggling to make choices among the options available. Hence the RS architecture is designed in such a pattern that during model training it is used to have the capacity to acknowledge the casual feedback mentioned by users during purchase (Pawlicka et al., 2021). RS is demonstrated as a technical domain dedicated to predicting the rating and preference of a user with guidance in the appropriate choice of item strategically. In business, the more valued practice is the accuracy in the prediction of user preferences to improve customer satisfaction and loyalty. Hence enhancing the predictive accuracy of user preference to an optimum level is a major challenging research area to be addressed through innovative algorithms. The basic function of RS is to introduce a program to reciprocate recommendations to the user with the items of his or her choice after prediction based on data on the item and the user's behavioral trend analysis. The recommended items might be either consumable products or services while users are individuals and business entities.

Collaborative filtering was the RS, developed initially when the relationship concept between a single user versus a single item in the system had been emphasized. But in real-time applications, the user's multi-behavioral intent might get exposed with the desire to have more complementary interests with the item. The situation appeared to be complicated while interacting with items in an e-commerce scenario like putting tags on favorites, carting, buying, etc. are being interpreted more as the user's multi-behavioral attitude. However, the multi-behavioral intent likely indicated the level of multi-interests of the user. This memory-based CF model mainly depends on historical user-item interaction data to provide personalized recommendations on items or services to the users. It needs to be mentioned that the multi-behavioral intent of the user might get noticed in the sequential manner of interaction. The study on users' dynamic sequential interactive attitude on items with multi-behavioral outbursts might help fine-tune the RS algorithms. Figure 1 represents the various types of recommendation system paradigms that currently exist and are broadly classified.

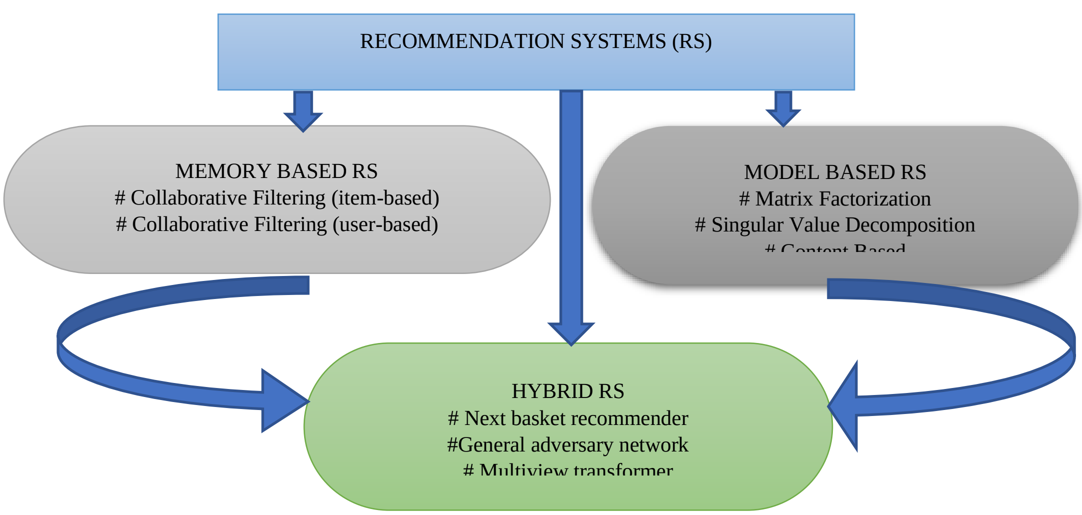

Figure 1: Schematic Diagram to Represent Various Types of Recommendation System Paradigm

Alternatively, the model-based CF might be developed with the advantage of data being processed offline rather than instant computation. Hence constraints faced in real-time applications on complicated user-item interactions can be smoothened with accurate training methods. The model is built on algorithms that reduce the user-item matrix into smaller and simpler ingredients. The model-based CF algorithms are designed to take care of product-specific features in prediction. Hence the algorithm of Matrix factorization (Yadav et al., 2023) and Cluster-based algorithm are basic design components of this kind of RS in model-based CF recommender. The filtering RS namely the Content-based recommendation system usually deals with text-based items, such as documents, news items, or the web.

The latest concept in RS was introduced as Next Basket Recommendation after performing a sincere check and analysis of the user's purchase behavior on his multiple visits to the retail outlet to buy a set of items. The analysis of user sequential behavioral patterns with purchase records might lead to predicting his preferred items to be purchased in future visits to the outlet. The Next Basket Recommendation helped to resolve two aspects of establishing a study sequential change pattern in purchase behavior and its periodicity.

1.1. Challenges in the Recommendation System

In resolving the issues about the Recommendation System model some recurrent challenges are faced during analysis (Chirravuri & Immidi, 2022). Those trouble-making factual observations are mentioned below (Roy & Dutta, 2022).

Challenges	Observed Issue
Cold Start	Recommendation System's inability to infer new items on lack of ratings
Sparsity	During analyzing huge data expected values are missing
Synonymy	Variation in item features of the same nomenclature
Scalability	Recommendation System needs a large volume of training data
Grey Sheep	Isolated lone item feedback is unmatched

1.2. Objective of the Present Study

The latest trend of research studies on Recommendation Systems has been emphasized through a hybrid technique where design architecture is made to follow the algorithms combining CF and Transformer technology simultaneously. The main purpose of this research study is to achieve the following objectives:

1. The paper proposes a novel architecture for predicting the user behavior pattern based on hidden features obtained from the customer and product interactions based on past transaction history.
2. Autoencoder model architecture is integrated for dimension reduction of the textual sparse features obtained from the item-based embedding based on customer and item interactions.
3. Transformer Blocks with multi-head multiplicative attention are used to obtain the customer item sequential interactions based on customer-item past transactions history.
4. Customer Item Sequential interaction is being fed into the multilayer stacked bi-directional GRU layer which further strengthens the sequence-to-sequence learning of the deep neural network and improves the consumer next item buying prediction.

2 Literature Survey

In the last decade, many research works have been carried out to accommodate techniques of various approaches in combination so that aligned prediction processes could improve the recommendation performance. At the onset fusion idea with probabilistic accordance theory was applied in relating UBCF (user-based CF) and IBCF (item-based CF) data sets to achieve initial success.

The IERT model was introduced when the next basket recommender tool was designed to possess context-aware item representations (Yang et al., 2019) in the system. The system was trained initially with model parameters based on past purchase transaction data and predicted during the online recommendation process. This was followed with the recent multi-view transformer model with novelty in the integration of different information sources of utility matrix and textual sources. In the Generative Adversary Network method, the behavioral parameter in the model was made to match with the sequences followed by real users during purchase, hence maximizing the reward function (Chen et al., 2019). The GAN framework is designed in combination of two trained models namely generative and discriminative models (Goodfellow et al., 2014). Following Table 1 is the tabulation related to extensive research performed in the field of product recommendation systems based on consumer reviews:

Table 1: Comparative Study of Various Research on E-commerce-based Recommendation Systems

Author	Year	Dataset	Recommendation Purpose	Methodology	Evaluation Metrics
Badriyah et al.,	2020	• Review Comments Dataset	• E-Commerce Product Recommendation System	• Proposes Multi-Mode Hybrid Filtering • Hybrid Based Filtering Approach uses Collaborative Filtering and Content-based Filtering	• Precision • Recall • Fallout • Miss-rate • F1-Score
Li et al.,	2021	• Amazon Book • Dataset	• E-Commerce Recommendation Service	• Proposes RHRM Framework • CNN-BiLSTM Hybrid Model Architecture	• Accuracy • Precision • Recall • F1-Score • MAE • RMSE
Ho et al.,	2023	• Movie-Lens • Amazon Toys and Games • Amazon Video and Games • Amazon Electronics	• Recommender systems integrating information service using text data sources and utility matrix	• Multiview Transformer Model for Recommendation • Feature Extraction and Conversion Algorithm	• MAE • RMSE • Precision
Tandel & Rana,	2023	• Movie-Lens Dataset	• Serendipitous • Recommendation	• Nearest Neighbor for the target user • Calculate Bhattacharyya Coefficient • Novelty Score as a performance evaluation metric • Recommended Top N Items	• Novelty Score
Fang,	2021	• Amazon Dataset • IMDb Dataset	• Matrix Factorization • Binary Recommendation • Multi-Class Recommendation	• Transformer-based pre-training deep learning Models using Transfer Learning Novel Approach - User Vector Embedding	• MSAE • Accuracy
Li et al.,	2023	• Yelp • Ifashion • LastFM	• Product Recommendation	• Generative self-supervised learning with graph transformer architecture • SSL-based augmentation with effective rationalization	• Recall@20 • NDCG@20
Rajput et al.,	2023	• Amazon Reviews - Sports and Outdoors • Amazon Reviews - Toys and Games • Amazon Reviews - Beauty	• Generative Based Recommendation	• Transformer Index for Generative Recommendation • Semantic ID-based generation process for corpus	• Recall@5 • NDCG@5 • Recall@10 • NDCG@10
Zhao et al.,	2024	• Task-Specific Recommendation Dataset	• Large Language Models • Recommendation	Discusses about various LLM paradigms: • Prompting • Prompt based Tuning • Instruction based Tuning	• ROUGE • Perplexity • Bleu Score
Wang et al.,	2023	• Micro-Video Dataset	• Generative Recommendation	Generative Recommender Components: • Instructor • Artificial Intelligence Generator	• Cosine@10 • Cosine@5

3 Research Methodology

In the recent past, there has been extensive research on various recommendation system approaches. In this research, a novel model namely the Next Basket Recommendation Paradigm Uses Multi-Layer Stacked Sequence to Sequence Bidirectional GRU (NBRMSBG) for next basket prediction for buyer-based personalized recommendations. This primary objective is to predict the consumer's next item recommendation based on the user's past transaction history and user-item interactions. Below Figure 2 is the architecture diagram for our proposed NBRMSBG model.

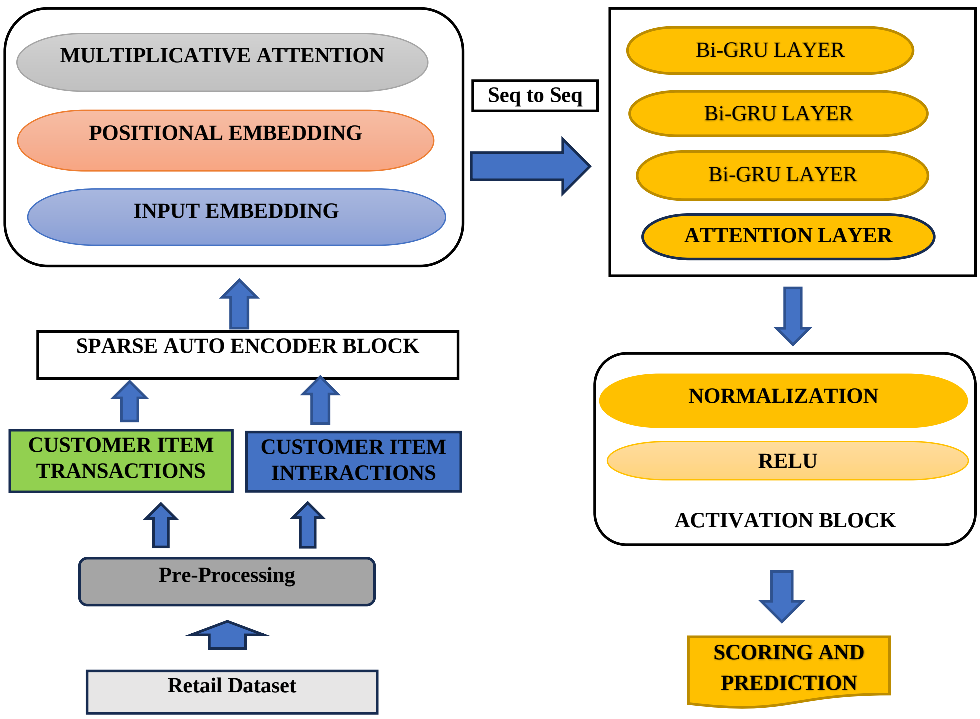

Figure 2: Architecture Diagram for Proposed Next Basket Recommendation Paradigm using Multi-Layered Stacked Bi-Directional GRU with Multiplicative Attention Mechanism

3.1. Dataset

For the current scope of research, we referred to UCI machine learning repository-based online retail datasets namely (UCI Online Retail I) which was donated on 05-Nov-2015, and (UCI Online Retail II) which was donated on 20-Nov-2019. These datasets contain transactional information related to UK-based online retail stores. The characteristics of the dataset used are Sequential, Multivariate, and time-series which are suitable for supervised learning tasks like classification, regression, and unsupervised learning tasks like clustering. The dataset consists of two primary identifiers namely Invoice number and Stock code and the remaining six features namely product name, customer identifier, quantity, invoice date, unit price, and country respectively.

3.2. Simulation Environment

The simulation was performed on UCI machine learning repository-based online retail datasets. The simulation was performed using the Google Collab cloud platform using the Python programming language with the help of a T4-GPU configuration with 16 GB GPU memory, 12 GB RAM, and 120

GB Hard disk memory. We conducted the simulation by using two computing units namely an HP 15s du3564 laptop with 16 GB RAM configuration and a Zebronics NBC 3S laptop with 8 GB RAM configuration as client machines for connecting with the Google Colab cloud platform. We also used Raspberry Pi 3 Model B+ with 1GB RAM configuration and Raspberry Pi 4 Model B with 2 GB RAM configuration as client machines for connecting with the Google Colab cloud platform.

3.3. Proposed Model Framework

In this research, the paper proposes a novel Multi-Layered Stacked bi-directional-based Transformer (NBRMSBG) model with a multiplicative attention mechanism for next Basket prediction for buyers using personalized recommendations.

- **Preprocessing Block –** In this block, the given online retail dataset is being pre-processed into different number of batches based on batch size to be computed in each epoch and then the key features are extracted based on consumer buying behavior and past transaction history to form TF-IDF matrix representations.
- **Sparse Autoencoder Block –** This block consists of 4 layers of sparse variational Auto Encoder model Architecture. The preprocessed data from the preprocessing block is passed to the auto-encoder block where the encoder compresses the preprocessed data into compressed representations and the decoder learns from the compressed representations. Auto Encoder helps in learning and better representation of the learned features by using dimension reduction.
- **Transformer Block –** The compressed representations are passed into the transformer block, where the token input positional embedding is used along with the multi-head transformer with the multiplicative attention mechanism. Input Embedding is used to capture the semantic meaning of the user items interactions and position embedding is used for relative positions of the items in the list of item transactions. In the attention layer, the model learns the significance of the different products concerning the purchase history of the user.
- **Sequence to Sequence Block –** In sequence-to-sequence architecture, the stacked multi-layer bidirectional GRU model with the Attention mechanism is being integrated with the output embedding obtained from the transformer layer. The Normalization Layer normalizes the activations of the neurons which further improves the stability of the overall training process.
- **Activation Block -** At the dense layer, all the layer's output are being concatenated using the batch normalization which is being applied along with rectified linear unit activation function in equation 1.

RELU Activation Function = $\begin{cases} x \text{ when } x > 0 \\ 0 \text{ when} x \leq 0 \end{cases}$ ....(Equation 1)

- **Prediction –** The prediction score is calculated based on the learning representations obtained from the hidden features using the customer-item interactions and performing raking of the transactions based on learned representations found from the transaction date from previous buyers.

3.4. Model Evaluation

In our proposed model, there are n number of users {u_1, u_2, u_3, u_4 till u_N} and the associated item transactions are {i_1, i_2, i_3, i_4, i_5 till i_T} where total number of transactions and users are T and N respectively. Here we compute the probability that the item will be purchased next time using the SoftMax function as shown using the equation 2 below:

$$p_i = \frac{\exp(i_T R_u L_{ui})}{\sum_{i=1}^{T} exp(i_T R_u L_{ui})} \quad \text{.......(Equation 2)}$$

where i_T = number of item transactions

R_u = Vector representations of the user

L_u = Learned representations of user-item transactions

The proposed NBRMSBG model has been designed to learn from the consumer item transactions and the past transaction history associated with the consumer. The model has been trained to minimize the loss using the objective function and optimize the learning rate. The objective (Loss) function(L) is represented by equation 3 for the proposed NBRMSBG model has been optimized during the learning process.

$$L = \sum_{u=U} \sum_{t=T} \sum_{i=1}^{n} -y_i \log p_i - (1 - y_i) \log(1 - p_i) \quad \text{.......(Equation 3)}$$

where $y_i = \begin{cases} 1 & if\ item\ is\ purchased\ next\ time \\ 0 & if\ item\ is\ not\ purchased \end{cases}$

$p_i =$ the probability that the item will be purchased next time

4 Result & Discussion

The next basket recommendation is a sequential time series-based problem where the online transactions consumed or bought by the user in the past help to generate the product basket sequence that the other user would like to buy next. The performance evaluation using an accuracy score applied on three UCI online retail datasets was plotted as shown in Figure 3. Our proposed model was evaluated using various information retrieval metrics namely accuracy, loss, mean square error (MSE), and normalized discounted cumulative gain (NDCG) as tabulated in Table 2 and Table 3.

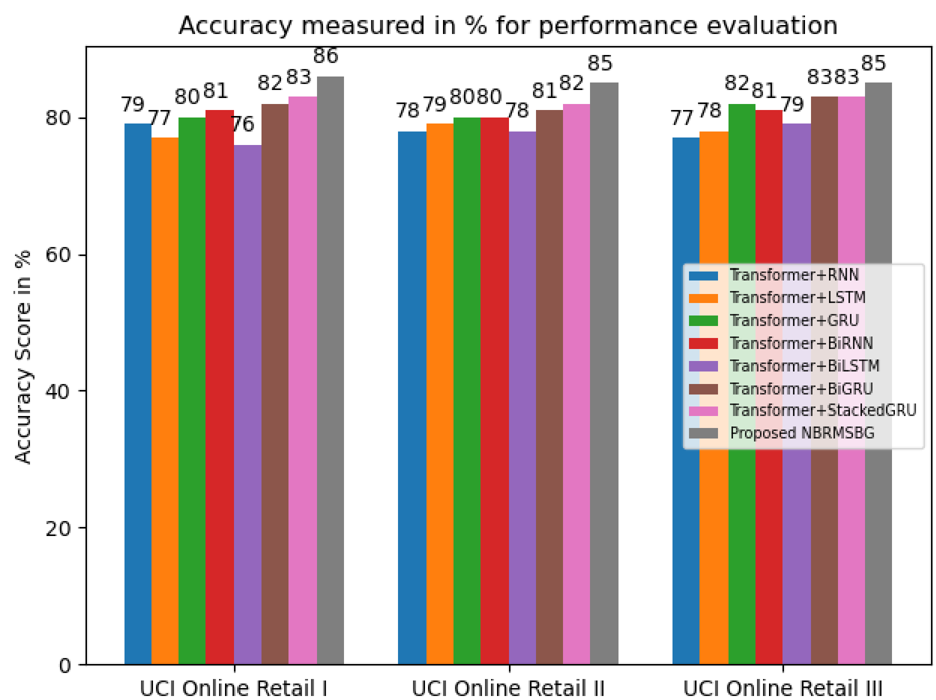

Figure 3: Plot of Accuracy Score on Various UCI Datasets for our Proposed NBRMSBG Model

Table 2: Accuracy and Loss Computed by Our Proposed Next Basket Recommendation System

Dataset	Model	Accuracy	Val Accuracy	Loss	Val Loss
Online Retail I	Transformer + RNN	0.7931	0.7996	0.4122	0.4217
	Transformer + LSTM	0.7732	0.6950	0.4127	0.6255
	Transformer + GRU	0.8045	0.8012	0.4089	0.4203
	Transformer + Bi-RNN	0.8126	0.7921	0.4142	0.4307
	Transformer + Bi-LSTM	0.7688	0.4270	0.4015	0.7489
	Transformer + Bi-GRU	0.8212	0.7894	0.3768	0.3712
	Transformer + Stacked RNN	0.8012	0.7781	0.4166	0.4231
	Transformer + Stacked LSTM	0.8246	0.7939	0.3700	0.3890
	Transformer + Stacked GRU	0.8332	0.7868	0.3732	0.6465
	Proposed Model	**0.8602**	**0.8038**	**0.3668**	**0.4058**
Online Retail II	Transformer + RNN	0.7857	0.7986	0.4160	0.4245
	Transformer + LSTM	0.7926	0.7796	0.4136	0.4579
	Transformer + GRU	0.8020	0.7989	0.4145	0.4210
	Transformer + Bi-RNN	0.8015	0.7984	0.4158	0.4233
	Transformer + Bi-LSTM	0.7891	0.7548	0.3817	0.3261
	Transformer + Bi-GRU	0.8108	0.7938	0.3782	0.3821
	Transformer + Stacked RNN	0.8011	0.7972	0.4161	0.4270
	Transformer + Stacked LSTM	0.8227	0.8010	0.3739	0.3777
	Transformer + Stacked GRU	0.8240	0.7967	0.3701	0.4034
	Proposed Model	**0.8511**	**0.8199**	**0.3568**	**0.3793**

Table 3: MSE and NDCG Computed by our Proposed Next Basket Recommender System

Dataset	Model	MSE	Val MSE	NDCG	Val NDCG
Online Retail I	Transformer + RNN	0.1341	0.1370	0.8071	0.7735
	Transformer + LSTM	0.1342	0.2078	0.8073	0.7585
	Transformer + GRU	0.1330	0.1364	0.8049	0.7677
	Transformer + Bi-RNN	0.1348	0.1405	0.8097	0.7683
	Transformer + Bi-LSTM	0.1305	0.3755	0.8188	0.7606
	Transformer + Bi-GRU	0.1221	0.1232	0.8150	0.7664
	Transformer + Stacked RNN	0.1356	0.1375	0.8155	0.7865
	Transformer + Stacked LSTM	0.1200	0.1262	0.8199	0.7739
	Transformer + Stacked GRU	0.1209	0.3138	0.8102	0.7661
	Proposed Model	**0.1185**	**0.1278**	**0.8262**	**0.7745**
Online Retail II	Transformer + RNN	0.1354	0.1377	0.8539	0.7537
	Transformer + LSTM	0.1346	0.1482	0.8590	0.7542
	Transformer + GRU	0.1349	0.1367	0.8579	0.7662
	Transformer + Bi-RNN	0.1353	0.1374	0.8596	0.7629
	Transformer + Bi-LSTM	0.1237	0.3209	0.8371	0.7622
	Transformer + Bi-GRU	0.1236	0.1233	0.8497	0.7612
	Transformer + Stacked RNN	0.1354	0.1384	0.8501	0.7611
	Transformer + Stacked LSTM	0.1222	0.1229	0.8293	0.7607
	Transformer + Stacked GRU	0.1211	0.3150	0.7934	0.7467
	Proposed Model	**0.1156**	**0.1223**	**0.8603**	**0.7712**

The proposed Recommendation system successfully predicted the desired items with the help of autoencoder transformer-based architecture with multi-layer stacked Bi-GRU to address challenges like data sparsity, synonymy, scalability, and improving personalized recommendations to new buyers. NBRMSBG model evaluates the user's sequential behavioral patterns with purchase records which helps to predict the preferred items to be purchased in future visits by prospective buyers. The latest trend in research related to Next Basket Recommendation helps to resolve two aspects related to the sequential change in a user’s buying pattern and its periodicity.

The simulation was performed on UCI machine learning repository-based online retail datasets. The performance evaluations have been carried out by using IR measures namely accuracy and loss as shown in Table 2 and Table 3 respectively. The simulation results of the NBRMSBG model on the UCI online dataset Retail I and UCI online dataset Retail II are shown in table-4 and table-5 respectively. As shown in below Table 4 and Table 5, the top 5 product recommendations have been predicted by our NBRMSBG model applied to UCI online dataset retail I and UCI online dataset retail II respectively.

Table 4: Next Basket Prediction by Our Proposed System on UCI Online Dataset Retail I

Customer ID	**Invoice Date**	**Stock Code**	**Product Name**	**Prediction Score**	**Ranking**
12398	25-10-2011 10:27	22492	MINI PAINT SET VINTAGE	0.9965	1
	25-10-2011 10:27	23310	BUBBLEGUM RING ASSORTED	0.9856	2
	25-10-2011 10:27	21212	PACK OF 72 RETROSPOT CAKE CASES	0.9767	3
	25-10-2011 10:27	21975	PACK OF 60 DINOSAUR CAKE CASES	0.9729	4
	25-10-2011 10:27	23307	SET OF 60 PANTRY DESIGN CAKE CASES	0.9698	5
15819	21-10-2011 14:50	23308	SET OF 60 VINTAGE LEAF CAKE CASES	0.9996	1
	21-10-2011 14:50	23203	JUMBO BAG DOILEY PATTERNS	0.9928	2
	21-10-2011 14:50	23199	JUMBO BAG APPLES	0.9853	3
	21-10-2011 14:50	23201	JUMBO BAG ALPHABET	0.9815	4
	21-10-2011 14:50	23200	JUMBO BAG PEARS	0.9791	5
17976	24-11-2011 14:22	22423	REGENCY CAKESTAND 3 TIER	0.9895	1
	24-11-2011 14:22	85123A	WHITE HANGING HEART T-LIGHT HOLDER	0.9721	2
	24-11-2011 14:22	23203	JUMBO BAG DOILEY PATTERNS	0.9692	3
	24-11-2011 14:22	22720	SET OF 3 CAKE TINS PANTRY DESIGN	0.9635	4
	24-11-2011 14:22	20725	LUNCH BAG RED RETROSPOT	0.9534	5

Table 5: Next Basket Prediction by our Proposed System on UCI Online Dataset II

Customer ID	Invoice Date	Stock Code	Product Name	Prediction Score	Ranking
13995	24-11-2011 14:22	20725	LUNCH BAG RED RETROSPOT	0.9995	1
	24-11-2011 14:22	23209	LUNCH BAG VINTAGE DOILY	0.9835	2
	24-11-2011 14:22	20727	LUNCH BAG BLACK SKULL.	0.9795	3
	24-11-2011 14:22	23583	LUNCH BAG PAISLEY PARK	0.9724	4
	24-11-2011 14:22	22423	REGENCY CAKESTAND 3 TIER	0.9693	5
16379	21-11-2011 15:27	22554	PLASTERS IN TIN WOODLAND ANIMALS	0.9984	1
	21-11-2011 15:27	22553	PLASTERS IN TIN SKULLS	0.9956	2
	21-11-2011 15:27	20981	12 PENCILS TALL TUBE WOODLAND	0.9874	3
	21-11-2011 15:27	22383	LUNCH BAG SUKI DESIGN	0.9823	4
	21-11-2011 15:27	23199	JUMBO BAG APPLES	0.9794	5
18272	07-12-2011 15:42	22907	PACK OF 20 NAPKINS PANTRY DESIGN	0.9945	1
	07-12-2011 15:42	22423	REGENCY CAKESTAND 3 TIER	0.9878	2
	07-12-2011 15:42	23307	SET OF 60 PANTRY DESIGN CAKE CASES	0.9798	3
	07-12-2011 15:42	22969	HOMEMADE JAM SCENTED CANDLES	0.9756	4
	07-12-2011 15:42	22666	RECIPE BOX PANTRY YELLOW DESIGN	0.9689	5

The chart communicates the outcome results about the top 5 personalized recommendations of the next basket for new buyers. The columns indicate stock code, and invoice details against specific customers while prediction scores and rankings are mentioned against the predicted items. On both occasions, the prediction results were favored as per the user's choice and deserved to be acknowledged for well-performed personalized recommendations.

5 Conclusion

In this study, we propose an innovative approach for the efficient performance of the Next Basket Recommendation model using a sequence-to-sequence BiGRU layer with multiplicative attention by integrating with the Multi-Head Self Attention Transformer Model. Our NBRMSBG model effectively generated the next basket prediction using the user purchase pattern and user-item interaction. It also achieved better performance in terms of higher Accuracy, higher Normalized Discounted cumulative gain (NDCG), and lower Mean Square Error (MSE). Our proposed model addressed the data sparsity problem by using the various attention mechanisms during the learning phase and the synonymy problem was overcome by implementing the L1 and L2 regularization mechanisms.

6 Future Work

The scope of current research work can be extended towards users-based personalization to increase the trustworthiness and it will be interesting to extend the integration of the conversational chatbot services with the personalized recommendation. This will help improve customer engagement and enhance the business opportunities for various e-commerce websites in the long run. It will be interesting to adapt this recommendation system with the search engine algorithms as the search engine algorithm becomes very tedious and time-consuming while assessing the user-item interaction behavior and user past item transactions. Another interesting future work would be to address the cold start recommendation engine problem for new user interaction.

References

[1] Badriyah, T., Ramadhan, Y. G., & Syarif, I. (2020, September). An Efficient Framework of Hybrid Recommendation System based on Multi Mode. In *2020 International Electronics Symposium (IES)* (pp. 351-355). IEEE. https://doi.org/10.1109/IES50839.2020.9231842

[2] Chen, X., Li, S., Li, H., Jiang, S., Qi, Y., & Song, L. (2019, May). Generative adversarial user model for reinforcement learning based recommendation system. In *International Conference on Machine Learning* (pp. 1052-1061). PMLR.

[3] Chirravuri, S. N. S. L., & Immidi, K. P. (2022). Major Challenges of Recommender System and Related Solutions. *International Journal of Innovative Research in Computer Science & Technology*, *10*(2), 10-18. https://doi.org/10.55524/

[4] Fang, X. (2021). Making recommendations using transfer learning. *Neural Computing and Applications*, *33*(15), 9663-9676. https://doi.org/10.1007/s00521-021-05730-3

[5] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. *Advances in neural information processing systems*, *27*.

[6] Ho, T. L., Le, A. C., & Vu, D. H. (2023). Multiview Fusion Using Transformer Model for Recommender Systems: Integrating the Utility Matrix and Textual Sources. *Applied Sciences*, *13*(10), 6324. https://doi.org/10.3390/app13106324

[7] Li, C., Xia, L., Ren, X., Ye, Y., Xu, Y., & Huang, C. (2023, July). Graph transformer for recommendation. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval* (pp. 1680-1689). https://doi.org/10.1145/3539618.3591723

[8] Li, Q., Li, X., Lee, B., & Kim, J. (2021). A hybrid CNN-based review helpfulness filtering model for improving e-commerce recommendation Service. *Applied Sciences*, *11*(18), 8613. https://doi.org/10.3390/app11188613

[9] Pawlicka, A., Pawlicki, M., Kozik, R., & Choraś, R. S. (2021). A systematic review of recommender systems and their applications in cybersecurity. *Sensors*, *21*(15), 5248. https://doi.org/10.3390/s21155248

[10] Rajput, S., Mehta, N., Singh, A., Hulikal Keshavan, R., Vu, T., Heldt, L., ... & Sathiamoorthy, M. (2023). Recommender systems with generative retrieval. *Advances in Neural Information Processing Systems*, *36*, 10299-10315.

[11] Roy, D., & Dutta, M. (2022). A systematic review and research perspective on recommender systems. *Journal of Big Data*, *9*(1), 59. https://doi.org/10.1186/s40537-022-00592-5

[12] Tandel, S., & Rana, K. (2023). Novel Serendipitous Recommender System using Relevance Scores for Long Tail Items. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(1), 676–682.

[13] Wang, W., Lin, X., Feng, F., He, X., & Chua, T. S. (2023). Generative recommendation: Towards next-generation recommender paradigm. https://doi.org/10.48550/arXiv.2304.03516

[14] Yadav, K. K., Soni, H. K., Yadav, G., & Sharma, M. (2023). Collaborative Filtering Based Hybrid Recommendation System Using Neural Network and Matrix Factorization Techniques. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(8s), 695–701.

[15] Yang, J., Xu, J., Tong, J., Gao, S., Guo, J., & Wen, J. (2019). Pre-training of context-aware item representation for next basket recommendation. https://doi.org/10.48550/arXiv.1904.12604

[16] Zhao, Z., Fan, W., Li, J., Liu, Y., Mei, X., Wang, Y., Wen, Z., Wang, F., Zhao, X., Tang, J., & Li, Q. (2024). Recommender systems in the era of Large Language Models (LLMS). *IEEE Transactions on Knowledge and Data Engineering, 36*(11), 6889-6907. https://doi.org/10.1109/tkde.2024.3392335

Dataset

[17] UCI online retail dataset I - https://archive.ics.uci.edu/dataset/352/online+retail

[18] UCI online retail dataset II - https://archive.ics.uci.edu/dataset/502/online+retail+ii

Author Biography

Sourav Sinha, received his B.E degree in Information Technology and M.E degree with distinction in Software Engineering from Birla Institute of Technology, Mesra, Ranchi, India in 2009 and 2011 respectively. He is currently pursuing his PhD degree at the B.S. Abdur Rahman Crescent Institute of Science and Technology Chennai, India. His areas of interest are Machine Learning, Artificial Intelligence, Information Retrieval, and Text Mining.

Dr. Revathi Sathiya Narayanan, obtained her B.E.(CSE) in 1994, M.E.(CSE) in 2000 and Ph.D. in 2013. She is currently working as a Professor in the Department of Computer Science and Engineering at B.S. Abdur Rahman Crescent Institute of Science and Technology, Chennai, India. She has published more than 50 peer-reviewed journal and conference papers in the domain of Mobile Ad hoc Networks, the Internet of Things, Network Security, Data mining, etc.

Dr. Indrajit Mukherjee, received an M.Sc., Electronics degree from the University of Ranchi, India in 1995, an MCA degree and Ph.D. (Computer Science) from Birla Institute of Technology, Mesra, Ranchi, India in 2001 and 2013 respectively. Currently, he is an Assistant Professor in the Department of Computer Science & Engineering, Birla Institute of Technology, Mesra, Ranchi, India. His research interests include Web-Based learning, Data Mining, Big Data Handling, Web Service Applications, and Soft Computing. He has more than 20 research papers and 3 Ph.D. awards to his credit. He is a lifetime member of the Indian Society for Technical Education (ISTE), India.