A Novel Hybrid Machine Learning Framework to Recommend E-Commerce Products

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Chethan Marigowda
StudentID:x21145377

School of Computing
National College of Ireland

Supervisor: Dr. Paul Stynes

National College of Ireland
Project Submission Sheet School of Computing

Student Name:	Chethan Marigowda
Student ID:	x21145377
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A Novel Hybrid Machine Learning Framework to Recommend E-Commerce Products

Chethan Marigowda x21145377

Abstract. E- commerce is the activity of electronically purchasing or selling products in an online platform. Ecommerce recommender systems provide suggestions of products based on the consumer sentiment and ratings. There is often a mismatch between consumer rating and their sentiment. Identifying the accuracy of the mismatch is a challenge in machine learning. This research proposes a Novel Hybrid Machine Learning Framework to Recommend E-Commerce Products based on consumer sentiment and product descriptions. This proposed frame work combines a text embeddings model, sentiment analysis model and a rating engine. The text embeddings model is implemented using gensim doc2vec for consumer reviews and product descriptions. Further it uses neural networks for capturing the consumer product interactions for collaborative filtering. The sentiment analysis model is implemented by inputting distributed text embeddings into neural networks that are trained to capture content feature of products and sentiment of consumer evaluations. The rating engine is implemented by aggregating several embeddings as attention weights for consumers and products, then outputting the prediction score for the consumer–product interaction. This research makes use of the real-world Amazon product category semi structured baby and digital music semi structured datasets, each of which contains information on consumer reviews and product metadata. Mean absolute error (MAE) and the root mean-square error (RMSE) are considered to evaluate the recommendation performance, thereby measuring the accuracy of prediction ratings. Experimental results on Amazon distinct product dataset with promising accuracy metric MAE and RMSE values by 0.5909 and 0.8080 respectively demonstrates that proposed framework performs better on rating prediction in enhancing consumers experience to find their preferences over the E-commerce products.

Keywords – Hybrid recommendation, Consumer review, Product description, Text embeddings, Machine learning, Neural networks, Collaborative filtering.

1. Introduction

Electronic commerce is the widespread application of digital technologies to support online commercial operations like sales and transactions [1]. Worldwide e-commerce sales were close to US$ 5.3 trillion in 2021, and they are expected to expand by nearly 57% in the next years, to about US$ 8.0 trillion by 2026. [2]. Most effective e-commerce marketing strategies revolve around using recommendation systems (RS) to personalise the shopping experience for each consumer [3]. The Personalized Recommendation System primarily uses the following key perspectives to recommend consumers desirable products based on their prior behaviour as well as interpersonal interactions in digital platforms: (i) Influence from other consumers, which can be defined as the impact of a person in whom you have faith. (ii) The interest circle pattern, which reveals who else has the same interests as you, and (iii) The consumer own preferences, which has an impact on the kinds of products one could be interested [4].

In the modern day, reviews and ratings have become an increasingly important part of the decision-making process for consumers [5]. Consumers often offer a number rating in the range of 1 to 5 in order to show their satisfaction with a product. When compared to these consumer ratings, consumer reviews typically incorporate the opinion on the interaction of the product, which actually represent the consumer's true interest preference. However, internet reviews are typically presented as unstructured textual opinions which requires extensive analysis for knowing the sentiment aspects. Identifying the mismatch that consumers appreciate and specific areas that could be improved for recommendation is quite challenging as it requires deeper analysis of reviews. Moreover, RS gather information on the preferences of consumers for a variety of products (like baby items, digital music and so on) in order to forecast the preference each consumer would have for a given product. Thus, recommender systems attempt to tackle a rating prediction difficulty [20]. The majority of researchers utilize hybrid recommendation approaches, which involve combining two or more recommendation models using technologies such as data mining, natural language processing, neural networks, and deep learning to take advantage of the benefits that are complementary to one another and to provide a more robust unified framework. [6]. Table 1 provides a summary of the typical hybridization methods [7].

Table. 1. Hybridization Methods [6]

Hybridization Method	Description
Weighted	In order to arrive at the ultimate recommendation, a linear combination of predictions obtained from several recommendation methods is generated
Mixed	Without doing any computations to aggregate the outcomes, the recommendations that arise from using the various strategies are provided as a integrated list.
Switching	The system is able to switch between several recommendation methods by utilizing a switching criterion.
Cascade	Method with many stages that integrates and ranks the recommendations produced by various other methods.
Feature Combination	The outcomes of the collaborative method are incorporated as an additional feature into the construction of the content-based system that is built on top of the enhanced feature set.
Meta-level	In the stage that follows, the model that was developed from one recommendation approach is used as an input for the next recommendation
Feature Augmentation	Another approach with several stages in which the rating or classification from the first stage is used as an extra feature in the succeeding phases.

The aim of this research is to investigate to what extent a hybrid machine learning framework can accurately recommend e-commerce products. The major contribution of this research is a novel Hybrid Machine Learning Framework (HMLF) is to improving rating prediction in enhancing consumers experience to find their preferences over the E-commerce products. The framework combines text embeddings model, sentiment analysis model and a rating engine. Subsequent process aims at developing hybrid machine learning framework for sentiment analysis model by building consumer sentiment model and product content model to form a neural collaborative filtering. Rating engine is implemented by several embeddings as attention weights for consumer and products with their interactions by regression layer.

This paper discusses hybrid models used for E-Commerce Products recommendation in section 2 related work. The research methodology is discussed in section 3. Section 4 discusses the design components for the hybrid machine learning framework. The implementation of this research is discussed in section 5. Section 6 presents and discusses the evaluation results. Section 7 concludes the research and discusses future work.

2. Related Work

Over the course of the past few years, Recommender Systems (RS) have become an essential component of our day-to-day lives as a direct result of the sharp increase in the number of consumers using e-commerce websites such as Amazon, Alibaba, eBay, and so on [9]. A personalized recommendation system employs a variety of filtering techniques, including knowledge-based filtering (KBF), Content-Based filtering (CBF), collaborative filtering (CF) and Hybrid filtering (HF) as any combination of two or more aforementioned filtering methods [10]. KBF focuses to recommend products to consumers based on specialized domain knowledge on how various product attributes that satisfy the specifications and preferences. CBF is build based on the presumption that consumer would assign comparable ratings to things that have similar attributes.CF is one of the most common approaches utilized in recommendation systems in the ecommerce industry [11]. This method operates under the presumption that those who have previously agreed would continue to agree in the future. This technique generates recommendation results using the explicit user rating profiles and observed to be prone to cold start scalability, and sparsity issues [12].

An essential part of collaborative filtering algorithms is the use of matrix factorization to describe explicit numerical ratings concerning the connection between consumer and product [13]. Numerous studies have been carried out to develop RS employing a variety of machine learning frameworks such as Bayesian methods, clustering, linear regression, ANNs, and probabilistic models [6]. Recent years have witnessed an increase in the usage of deep learning techniques in the development of RS. This is mostly due to the constraints of matrix factorization in terms of fully utilizing the interaction between the product and the consumer [12]. In specifically, the inner product in matrix factorization is replaced with a learned arbitrary function using the neural collaborative filtering architecture [13]. However, due to the fact that it is unable to leverage the products content characteristic, this strategy is not effective in solving the cold start problem that occurs in recommendation systems [14]. Conversely, it is found to be large discrepancy between consumer ratings and their true interest preference on evaluating data on consumer - product ratings on major ecommerce provider like Amazon real data set [19]. According to the study of relevant research, text-based interactive can give more comprehensive consumer input for recommendation models and has demonstrated to be superior to standard non-text interactive RS [15-17]. Tewari et al. [18] indicates that a word2vec-cnn model achieves the best accuracy to predict the sentiment of restaurant reviews that allows to improve the customer experience of a restaurant. This demonstrates the potential path to mine the unstructured textual opinion of consumers to analyse the sentiment of aspects of ecommerce reviews. In addition to this, most recent studies of text-based interactive recommendation rely only on consumer reviews, and there are only a small number of hybrid recommendation models that take into account both consumer reviews and product description text.

To summarize, in order to address the shortcomings of an identical recommendation model, the hybrid recommendation technique, which combines two or more recommendation methods to take use of their complementing advantages, has emerged as a current trend. This research proposes to build on the work of Zhang, Y et al. [19] to combine text embeddings model, sentiment analysis model and a rating engine to enhance better rating prediction in encouraging consumers to find their preferences over the E-commerce products. In this research the real-world amazon product category baby and digital music semi structured datasets, each containing consumer reviews and product metadata information are employed.

3. Methodology

The research methodology consists of five major steps namely data acquisition, data pre-processing, data transformation, data modelling, and evaluation and results as shown in Fig. 2.

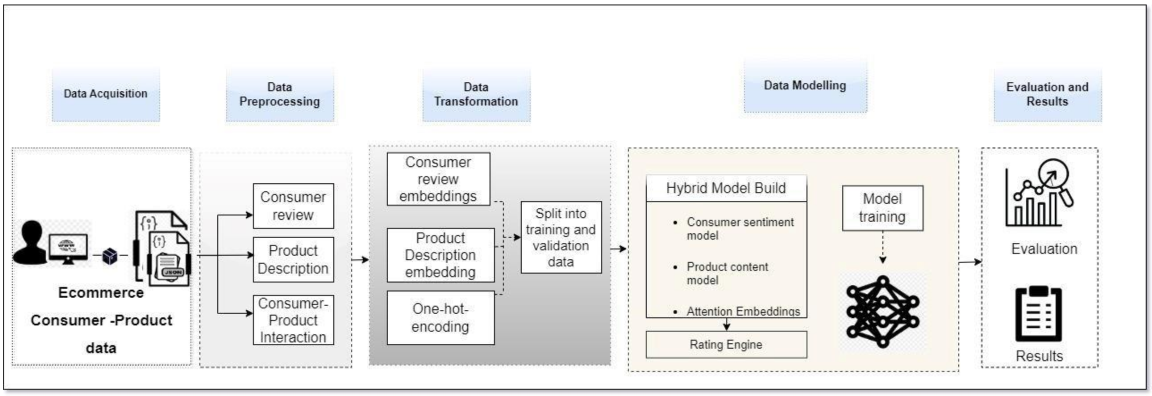

Fig. 2. Research Methodology

The first step, *Data Acquisition*, involves loading compressed semi structured dataset of a selected product from web server. There is a high probability that there are numerous comments posted on Amazon given that it is one of the most well-known online retailers. In the current research, Amazon product category data is leveraged, which is a collection of information that was assembled by academics and made accessible to us. The dataset collected from web server after decompression contains 915445 consumer reviews and metadata of various baby products up to 71316 in semi structured json format for Data set 1[22]. Data set 2[23] contains 836005 consumer reviews and metadata of various digital music products up to 279898 in semi structured json format.

During the second step, *Data Pre-processing*, the reviews are extracted, cleaned by removing punctuations and converted to lowercase. Before feeding test data to a machine learning model, text pre-processing is essential to clean up the test data, which contains a range of noise, including emotions, punctuation, and test in various capitalizations. Further consumer review from the review json file and product review from the metadata json file is converted to respective text files for further data transformation into vector numbers so that machine learning model can process efficiently. The minor contribution of this research includes conversion of the semi structured json data to readable text datasets based on the availability of reviews of consumers and metadata of products followed by pre-processing of the data using Gensim doc2vec pretrained model.

The third step, *Data Transformation*, maps each word in the review text to a word embedding. Each word is mapped to one real-valued vector in a predefined vector space. Genism word2vec [21] pretrained word embeddings are used where dimensionality vector size of paragraph embedding is set to 100. Then, this research build one-hot encodings [13] for consumer review identifiers and product identifiers. These one-hot encoded unique review identifiers and product identifiers are utilized to construct sparse matrices. To minimize sparsity, data are filtered based on the criterion that each ecommerce dataset customer has at least optimum interaction ratings with the products.

The fourth step, *Data Modelling*, uses the two different dense Neural network configurations proposed by [19] which generate customer-sentient model and product content model respectively. This phase involves configuring dense neural network model, training the model, and optimization.

A hybrid model build is used for the training model, which integrates consumer product ratings interactions from one hot encoding, review content, and product description embeddings. The ratings are modelled for collaborative filtering, and the product descriptions and consumer reviews are trained to text embeddings for supplementary modelling. The configuration of the neural network is composed of two dense layers: one for the ratings and sentiments of consumers, and the other for the descriptions of products. The sentiment expressed in the paragraph embeddings of consumers reviews is captured by the consumer sentiment model, while the sentiment expressed in product descriptions is captured by the product dense network model. In the beginning, the input embedding vectors are reshaped and flattened so that they may be processed by a dense layer that uses relu activation. After being processed by a softmax layer and then multiplied by the initial embedding vector, the resulting output is what this research refer to as the latent attention vector. After going through one more intense layer with relu activation, this attention vector that was previously latent is now the ultimate latent vector. The attention vector is created by combining the consumer embedding, the product embedding, the consumer latent, and the product latent. In order to arrive at the final predictions in the rating engine, this attention vector is multiplied with the original latent vectors, and then it is forwarded via a dense vector and a dropout layer with a ratio of 0.5. A 80-20 split is applied to the dataset before it is used for training. The training data comprises 25,685 samples and test data has 6,424 samples for baby dataset 1. Similarly applied to other illustration for digital music amazon dataset 2 ,it comprises of 60728 train data samples and test data has 15181 samples. The training is carried out for a total of ten epochs, with a batch size of 256 each time. Mean absolute error is the loss function which is optimized by adam optimizer with early stopping implemented and it is determined by the validation loss measure.

The last *Evaluation and results* step involves quantifying the efficacy of our suggestions by calculating the mean absolute error (MAE) and the root-mean-squared error (RMSE). These statistics allow us to evaluate the degree of accuracy associated with our prediction ratings. MAE () is computed by:

$$MAE = \frac{\sum_{k=0}^{n-1} |Y(k) - y(k)|}{n}$$

In a more similar manner, RMSE () is computed by:

$$RMSE = \sqrt{\frac{\sum_{k=0}^{n-1} (Y(k) - y(k))\ 2}{n}}$$

Where Y(k) and y(k) represent the actual and predicted value respectively

4. Design

The Hybrid machine learning recommendation framework architecture combines a text embeddings model, sentiment analysis model and a rating engine as shown in Fig. 3. The architecture consists of three subunit modules namely: Input unit comprising text embeddings model presented in Section 4.1, Hybrid Recommendation unit comprising sentiment analysis model presented in Section 4.2 and Rating Prediction unit comprising rating engine presented in Section 4.3. Each subunit has its own set of functionalities for developing this research. The components of each subunit are described further with its architecture.

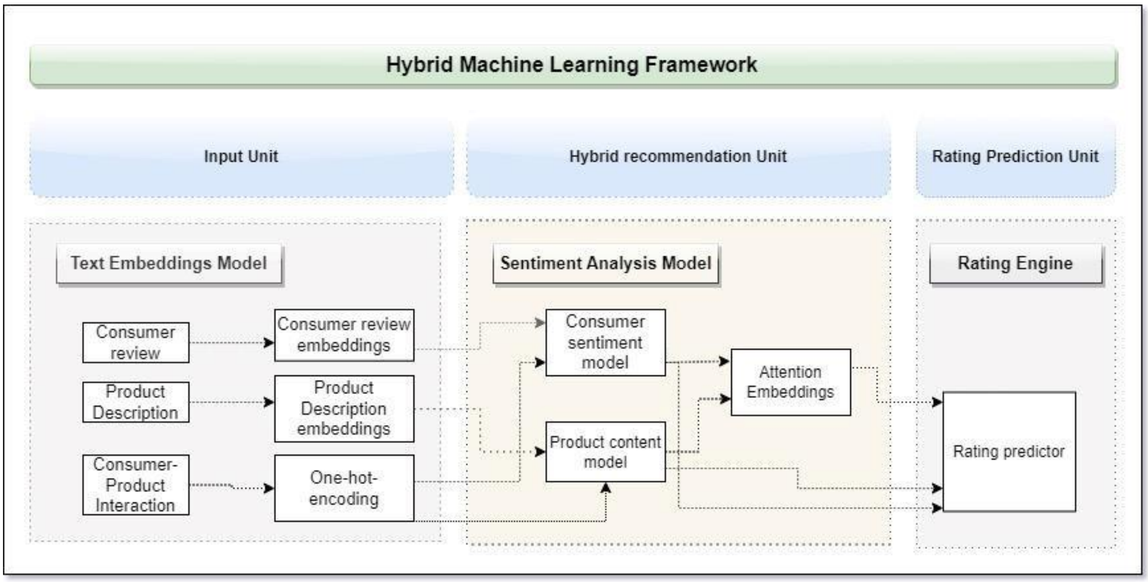

Fig. 3. Hybrid Machine Learning Framework Architecture

4.1 Text Embeddings Model

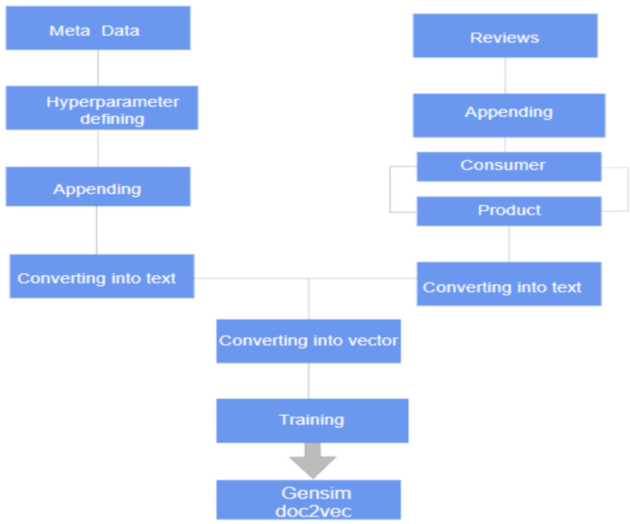

Fig. 4. Input unit module

The text embeddings model feeds and initializes the embedding representations for consumer reviews and product descriptions as illustrated in Fig. 4. The data for each product correlates to two distinct datasets: consumer reviews and meta data. We retrieve consumer identifier, product identifier, the corresponding ratings and textual evaluations from reviews data of each product, and also, we retrieve reviewer identifier and product description from the metadata of each product. The two sets of mappings take place where reviewer id is mapped to products and products to reviewer id. After the two datasets are combined, the gensim doc2vec is used to convert them into paragraph vector form and offer them to training.

The content analysis and sentiment analysis neural networks of a product both acquire their input from the pre-trained consumer reviews and product descriptions that are included inside the input module. Throughout the whole of the research project, paragraph vectors are put to use to create embeddings for consumer ratings and product descriptions. After this, the paragraph vectors are trained to become distributed vector representations. Additionally, one-hot encoding is utilized in the input module in order to perform user and item input initialization. Research considers identities of consumer and products as an input feature, and then turn those identities into binarized sparse vectors using a one hot encoding for the ratings of consumer-product interactions. The ratings are modelled for collaborative filtering

4.2 Sentiment Analysis Model

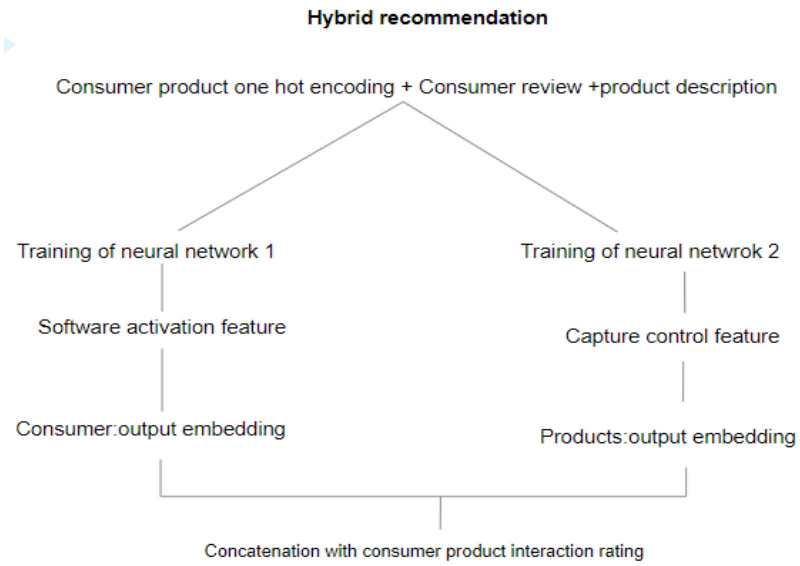

Fig. 5. Hybrid Recommendation unit module

Sentiment Analysis model is intended to unify the one-hot encoding of consumer and products, as well as the text embedding of consumer reviews and products descriptions as depicted in Fig.5 resulting in hybrid approach. Using data collected from consumer reviews and product descriptions, this research involves in training two neural networks to identify and extract consumer emotion and product content. Evaluations from consumers Using a SoftMax-activated layer, Dense network examines the sentiment of an entire propagation based on the embeddings of individual paragraphs from consumer reviews. For this reason, neural network layer product content dense is used to recover product content from paragraph embeddings. After that, a dense layer combines the output embeddings of the consumer sentiment dense network with the product content dense network to produce attention embeddings.

4.3 Rating Engine

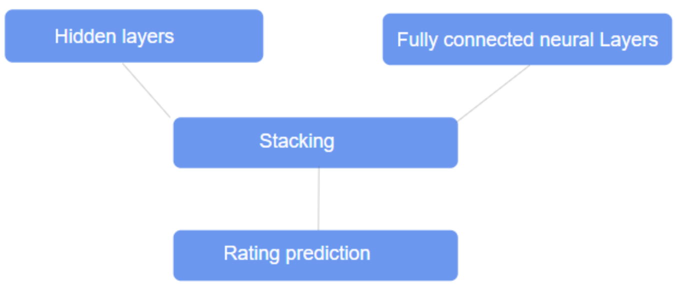

Fig. 6. Rating Prediction unit module

The rating prediction subsection uses a neural network to combine several embeddings into a single, consistent representation as depicted in Fig. 6. From this model, we get the rating prediction score for the consumer-product combination under consideration. To further enhance the effectiveness of the recommendation, we may also stack more nonlinear layers, since adding more hidden layers might lead to adding a high degree of non-linearity when optimizing model parameters. Dropout is also used to randomly ignore the selected neurons during training which are dropped out randomly so that it reduces the overfitting of neural networks.

5. Implementation

Analysis was based on data collected from products that are offered on Amazon. The collection includes consumer ratings as well as information on the products themselves. In total, there are over nearly 14 million reviews in the dataset, which ranges from May 1996 to July 2014. Out of different product kinds, due to space limitation particular categories like baby, digital music product data sets are considered for implementation. This research is able to reduce the sparsity of the dataset by applying a filter to the data based on the criterion that every consumer's interaction rating with the products on Amazon must be total at least 20. Python is used as the programming language for the keras-based algorithm in google collaboratory notebook . This research test 20% of each dataset and train 80%. This study uses a grid search to choose the optimal text embedding representation and start with paragraph embeddings trained on consumer reviews and product descriptions.

It's possible to train the algorithm in the same manner as one would train other keras-based deep learning networks. This research incorporates regression layer on top of the recommendation model, and then utilize that layer's output as loss function. This allows to achieve objective of rating prediction.

6. Results and Discussion

The aim of the research is to evaluate the proposed novel Hybrid Machine Learning Framework (HMLF) to improve rating prediction in enhancing consumers experience to find their preferences over the Ecommerce products which combines text embeddings model, sentiment analysis model and a rating engine.

The series of experimental studies were carried out to determine effectiveness of proposed model. Section 6.1 presents the state of art outcome; Section 6.2 presents state of Art replication with changed product category data set outcome; Section 4 presents sentiment analysis studies outcome and Section 5 presents cold start analysis studies outcome.

6.1 State of Art:

The aim of this experiment is to evaluate the accuracy of State of Art rating prediction in enhancing consumers experience to find their preferences over the Amazon Baby product category dataset 1 [22].

In this novel research, the custom neural network model proposed by [19] was modified to use vector size of paragraph embedding that was set to 100, a dropout layer with a varied ratios as shown in Table. 2.The training is carried out for 10 epochs with a batch size of 256. This research assess the effectiveness of our proposed model using the release of Amazon Baby dataset 1 [22] which comprise consumer reviews, ratings, products descriptions feature for products purchased on amazon ecommerce website. Mean absolute error is the loss function which is optimized by adam optimizer with early stopping implemented based on validation loss metric.

The table 3 summarizes the results of several studies evaluating the accuracy of various models on same baby dataset. The results of the proposed model are comparable to those of other conventional machine learning models [24] used to evaluate the model's efficacy. Further, In Figure7, this study depicts both the training loss function and the validation loss function with relation to the number of epochs. The best performance is achieved with dropout value of 0.3 and the kernel initialiser as normal distribution, the mse values have not reduced significantly as it takes the square-root of the squares of difference in error. By using normal distribution as initialiser, the values of the kernels is taken from the normal distribution graph which has helped in accurate and faster convergence of the model. In this regard, research studies find the loss function decreases exponentially till epoch equal to 3, and then it forms a linear curve. Results demonstrate that the proposed model achieved an efficient accuracy for the baby dataset.

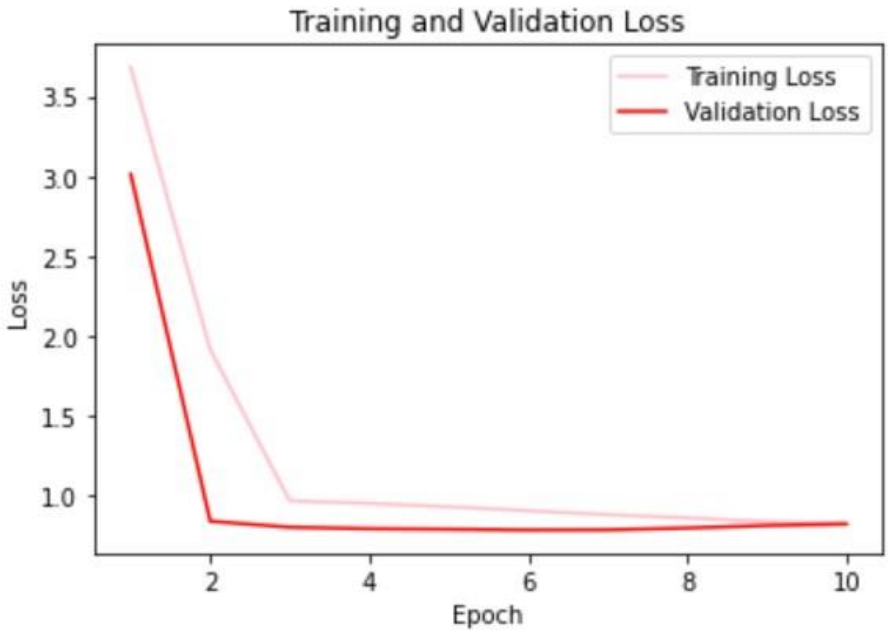

Fig. 7. Training and validation loss

Table. 2. Baby data set MAE and RMSE values.

Hyperparameters	MAE	RMSE
Dropout = 0.5 kernel_initializer = "random uniform"	0.8263	1.0828
Dropout = 0.4 kernel_initializer = "Normal Distribution" (Mean = 0,stddev =	0.8137	1.0816
Dropout = 0.3 kernel_initializer = "Normal Distribution" (Mean = 0,stddev = 0.05)	0.8111	1.0974

Table. 3. Baby data set MAE, RMSE Accuracy metric for other traditional models [19]

Other traditional Models	**MAE**	**RMSE**
ItemKNN approach is an item-based k-nearest neighbour algorithm that identifies related things for each product based on consumer histories.	0.8536	1.1854
SlopeOne approach computes the average rating difference between two products for consumers who rated both	0.8557	1.2012
SVD is well-known matrix factorization approach that divides an m by n matrix X into three matrices that forecast missing scores in the original scoring matrix.	0.8123	1.0704

6.2 Replicating state of Art with different product category data set:

The aim of this experiment is to evaluate the accuracy of replicated State of Art rating prediction in enhancing consumers experience to find their preferences over the Digital Music product category dataset 2 [23].

After getting results in state of art for best fit, the experiment is repeated by only changing the dataset set using the release of Amazon digital music dataset 2 [23] which comprise consumer reviews, ratings, products descriptions feature for products purchased on amazon ecommerce website.

Experiment results as shown in table 4 demonstrate that the proposed model achieved an improved accuracy of for the digital music dataset. However, current research could only run on a small set of distinct product dataset because of the constraints of processing capacity and the length of time needed to process the data, but it will be possible to expand the research on much larger datasets of various product categories with the help of GPU.

Table. 4. Digital Music data set MAE and RMSE values.

Changed Dataset	MAE	RMSE
Digital Music	0.5548	0.8080

6.3 Sentiment Analysis:

The aim of this experiment is to determine if the proposed sentiment analysis model is effective in addressing the mismatch between customer ratings and true interest preferences.

The samples of consumer and metadata information of baby data sets are displayed in the figure 9-10 by demonstrating the frequent words distribution, which translates into text embeddings and integrates to a hybrid framework. The examples are taken from the respective data sets. According to Amazon baby product statistics indicated in the Fig 8, 5/5 reviews account for 55% and 4/4 ratings account for 25%. On the other hand, our sentiment analysis mode predicts this rating distribution: 25% of ratings are 5, and 70% are 4. The findings suggest that the mismatch between consumer ratings and genuine interest preferences can be solved by utilizing customer sentiment into the recommendation model.

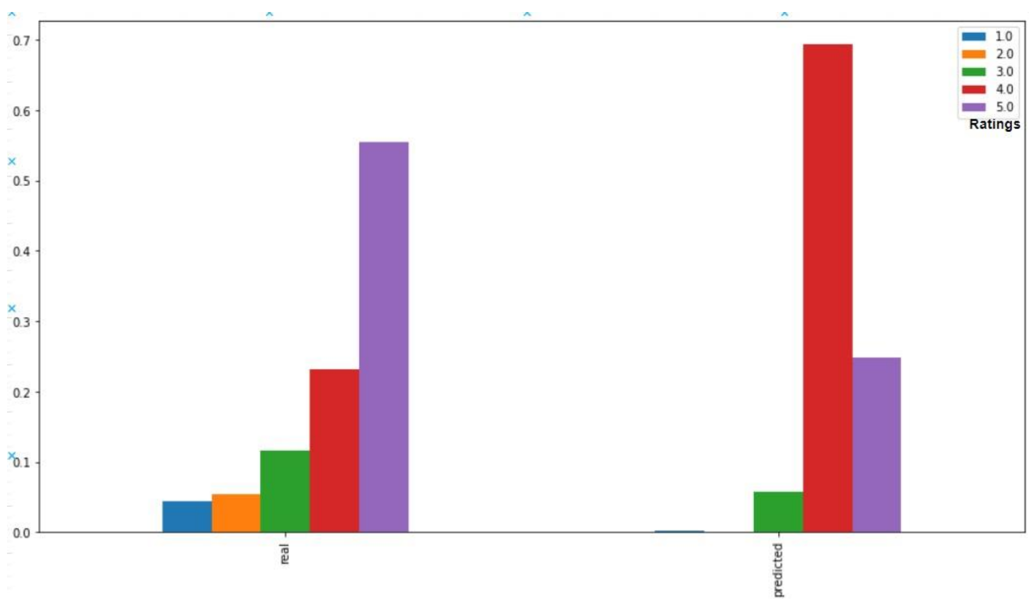

Fig. 8. Baby dataset Histogram plot for real vs predicted ratings.

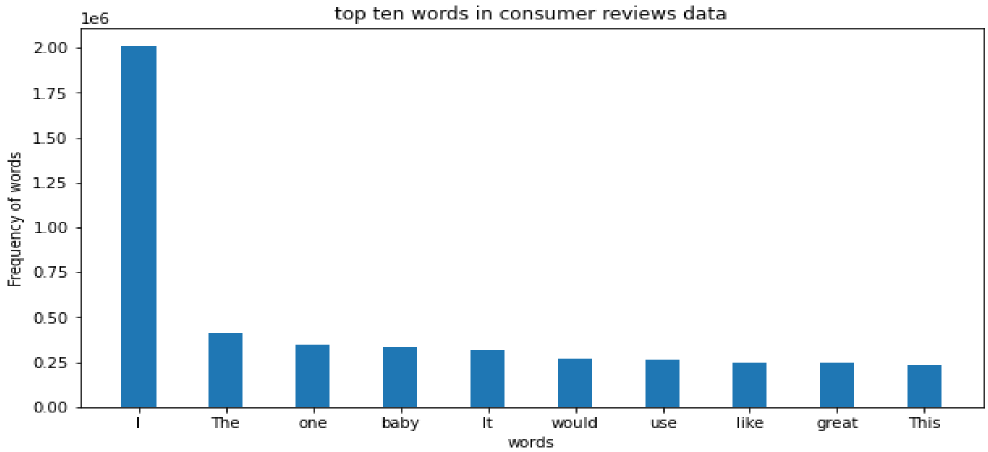

Fig. 9. Baby dataset frequent review words distribution

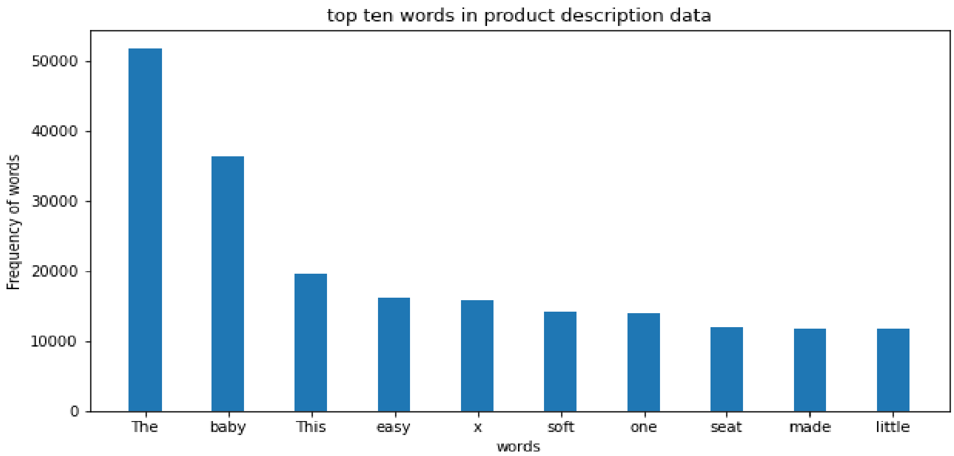

Fig. 10. Baby dataset frequent product words distribution

6.4 Cold Start Analysis*:*

The aim of this experiment is to determine if the proposed framework is effective in addressing the cold start problem. This study is considered since it can affect the accuracy and effectiveness of the recommendations, which can impact the consumer experience and the success of the system.

The cold start problem is a common occurrence in recommendation systems and arises when there is inadequate information available about a consumer or product to make a suggestion. Amazon's digital music dataset [23] is taken into consideration for this analysis. During the stage of data preparation, this experiment categorizes consumers and products into two groups: frequent examples and cold start examples. These groups are determined by the number of times consumers that interact with products. The respective MAE and RMSE accuracy metric cold start lower values as shown in Table. 6. for consumer, product, consumer -product interaction indicate that framework is effective in solving the cold start issue by utilizing product embeddings to acquire the content characteristic for hybrid model.

Table. 6. Digital Music dataset Cold start metric values

Accuracy Metric Value	**Consumer cold start**	**Product cold start**	**Consumer-product cold start**
MAE	0.7330	0.5916	0.7947
RMSE	0.9237	0.8532	0.9728

7. Conclusion and Future Work

The aim of the research is to evaluate what extent a proposed novel hybrid machine learning framework (HMLF) can accurately recommend e-commerce products by enhancing consumers experience to find their preferences over the products.

The proposed framework combines text embeddings model, sentiment analysis model and a rating engine. Results demonstrate that the HMLF framework achieved a promising accuracy metric MSE with values 0.5909 and RMSE with values 0.8080 for a distinct amazon product. The novel framework, was able to identify the rating prediction issue, address sentiment analysis consumer interest deviation and cold start cold start problem by showing smaller MAE and RMSE accuracy metric values by 0.7947 and 0.9728 respectively. Overall, the HMLF framework shows promise for ecommerce industry that would like to improve the customer experience aspects most important to digital personalized recommendation systems.

For future work, this research can be extended by using universal sentence encoder or sentence bert instead of paragraph vectors. Through sentence embedding each sentence's specific embedding can be determined, sentence embedding enables us to comprehend the sentence's meaning. Additionally, it makes possible to group sentences together based on similarities or to forecast the sentiments in the sentence. In addition, future work could include implementing strategies to address class imbalance problems in the data.

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