Self Attentive Product Recommender – a Hybrid Approach with Machine Learning and Neural Network

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Abstract— People are choosing products from online ratings and comments. Experience from Amazon , Flipkart and other leading online shopping portals in India, the buyer 's product choice is mostly based on the other buyer's review. We have found an interesting case study of Netflix video recommendation based on so many criteria. Product recommendation is one of the demanding area of recent time where efficiency of prediction of which product a buyer can choose over other hundreds of product is a challenging task. Artificial intelligence has helped researchers in developing algorithm that has self aware method for machine with machine-learning, deep-learning and natural language processing. In this research, we are introducing a hybrid approach of recommendation for products. There are many ways to find out the people who have similar choice and combining their choices can lead us to suggestions for other products. Collaborative filtering algorithms are use for Recommender systems widely. They have been successful in solving many issues of the system recommendation. User behaviour analysis, sentiment score, product reviews, popularity score can be a decisive factor along with neural network with classification method can lead to more efficient results. Self attentive product recommendation is one such technique which focuses on automated form for recommendation which is independent of a dataset and its data type. We have examined other approaches for combining multiple algorithms for predicting user ratings and discuss some results from the analysis of various strategies.

Index Terms— Collaborative filtering, content based filtering, neural network, Recommender, negative sampling

I. INTRODUCTION

Recommender System(RS) are widely used in various fields like e-commerce websites , news services, social media or online music & many other fields. Such this automated systems can reduce search time & transaction cost in an online shopping environment. It is very useful in other activities like improve decision making process & easy to purchasing items on e-commerce sites, analyzing & predicting web usage, provide indigent quality of recommendation etc. Machine-learning (ML) was traced as cognitive science yet was named and actualized in mid-1990s.AI are widely used in product recommendations. As, it was easy to integrate with existing models of recommendations & also helps in order to increase sales & revenue significantly. Famous companies like the walt disney company is using recommendations with AI to help their users to well-served & easily understandable, eMAG company serves more then 1B unique recommendations to their users per month & increase their revenue with widely usage of AI in Rs & other Social communication sites like Google, Netflix, LinkedIn, Twitter owe a lot of success with use of RS. Netflix has increased 80% of its revenue with AI.As e-commerce business analysts require to know and understand the user's behaviour to navigate them through the websites, as well as trying to identifying the interest of users to provide them best recommendations.

Various types of recommendations models are available which are based on input data such as:

1. Content Based Filtering Recommendations

This type of recommendations provides results with high recommendations which are transparent & this technique is easier for implementation or it changes which compare to other recommendations like collaborative, neural-session aware recommendations. As, content Filtering technique includes tokenization function and cleaning functions both.So, it is based on keywords, which are analyzed & this techniques are used to find out to link data. They are used in a variety of different domains ranging from news articles, recommending web pages, restaurants, television programs, various items for sale[3].

2. Collaborative Based Filtering Recommendations

This recommendations rely on the total preference and rating of all users instead of a single user's preference and rating. Person who wants to see movie with friends for example, so he might ask for recommendations of movies from friends to watch. Recommendations of some friends who have similar interests are trusted more than recommendations from other persons. This information is used in the decision on which movie to see. So, Collaborative recommendation relies on the ratings of similar users to take further decisions. Therefore, similar users have to be found in order to generate recommendations in this type of recommendations.

3. .Neural-Session Aware Recommendations

Neural session-aware recommendation is compare with session-based, sequential top-N recommendation. so problem with them are representative of matrix factorization approaches-does not perform well for sequential-recommendation. E.g. matrix factorization, neighborhood-based algorithms are designed to model user general preferences & consider user-item interactions as independent events. [6].

4. Hybrid Recommendations

It is used to combine two or more filtering method together. AS, example it is combination of collaborative filtering & content filtering. So, those techniques are:

Separately implementing content-based and collaborative algorithms and combining the prediction result.

a. Adding some content-based characteristics to the collaborative algorithm.
b. Adding some collaborative algorithm characteristics to the content-based algorithm.
c. Incorporating both algorithms and building a general framework.

II. LITERATURE REVIEW

Target: Applying & learning of SBPR to different dataset in order to achieve Recommendations[1].

Approach: Style-aware Bayesian personalized Rankings with deep-learning techniques like CNN as collaborative learning to explore the correlation between user and item. So, it can utilized style information in predicting a user's preferences and also used to improve the performance in recommender systems.

Way of process: Style-features are first calculate as in order to predict the recommendation score by SBPR after that it will incorporates style-features extracted by convolutional neural network. As, collaborative used to predict the recommendations with input & embedding layer, prediction layer & objective function.

Parameters: style featuring recommendation model, visual recommendation, CNN, Style-aware Bayesian personalized Rankings, Collaborative filtering approach.

Better Result: As SBPR(Style-Aware Bayesian Personalized Ranking) will compare to BPR-matrix factorization model, visual BPR model, BPR adopts deep learning techniques-deepstyle model in which SBPR have highest & accurate result. So, it is better than other current model.

Target: To give specific product recommendation and ratings by understandings user reviews about product features by using sentiment analysis & natural language processing Algorithms.[2]

Approach: Use of opinion mining technique and natural language processing technique to read input & applying sentiment analysis to reviews about product features. It also compares the adjectives which are obtained in sentences to seed list of positive and negative words which are defined earlier and returns the polarity of sentences.

Way of process: Firstly taken user reviews about features of product as input to integrate all features to calculate polarity of review sentences & classified in similar groups in order to calculate score to mention good or bad features of the product.

Parameters: Consumers Reviews, product ratings, Sentiment Analysis, Polarity of each Feature, Natural language Processing Algorithms, Feature identification, alchemy API, opinion mining.

Better Result: As using of sentiment analysis on product reviews as if we tested 120 dataset then we have get 108 correctly rated & recommended which is 88.33% in proposed system. So, Results obtained from this system are testing and verifying manually.

Target: To recommend products like books, transportation, job placements, music files, people with help of one of the filtering method which is called Content-filtering method.[3]

Approach: Categorize students based on their credentials. So, it discovers best solutions for generating recommendations for various fields.

Way of process: Take categorized keywords for searching as preprocessing to extract it for filtering. After in filtering we applied tokenization and cleaning functions to clustering in similar groups to identifying the user for which we have to provide recommendation.

Parameters: Recommendation system(RS), Content-Based Filtering technique, Explicit System or Machine Learning or Placement System, Pre-processing, filtering, classification, Identification of User. Better Result: In comparison with other filtering techniques like collaborative filtering & hybrid filtering, in this approach it provides results of recommendations, which are transparent & this technique is easier to implement or change.

Target: To provide Based Personalized Knowledge Recommendation Approach as CED Approach which is known as Correlation-Experience-Demand Recommendation[4]

Approach: knowledge is comprehensively evaluated to combine the values of DoC and DoD and the personalized knowledge recommendation service is achieved. eld demonstrate that the proposed CED approach outperformed that three baselines on three ranking evaluation metrics as 3 algorithms such as NB, CIG, and Item-CF algorithms.

Way of process: Firstly Knowledge recommendation process is completed with 4 models like Task Assignment ,Objective similarity computation, DOC value computation, DOD value computation & then apply knowledge ontology model which is known as CED approach to know to solve problems like CC what to recommend TT, CC who to recommend TT, CC when to recommend TT, and CC how to recommend TT problems simultaneously.

Parameters: Collaborative filtering technique, degree of assistance technique, degree of correlation, degree of demand, knowledge recommendation , ontology model , Co-relation-Experienced Model, Product data management.

Better Result: As we using three evaluation metrics of NDCG@n, HLU@n, and MAP@ with CED approach. so, CED has overall more stable performance than the other three baselines algorithms as NB, CIG, and Item-CF algorithms which are based on collective intelligence technique.

Target: Effects of RS on sales concentration are moderating by users awareness types to provide recommendations with content-based filtering method.[5]

Approach: contradictory phenomenon of winner-takeall and long-tail could co-exist in the E-commerce market because of various recommendation strategies like content-based filtering adopted in the systems in order to increase the sales concentration.

Way of process: sales of concentration in E-commerce are predicting by these two theories as winner-take-all & long-tail theory & related their results. So, we will compare different types of RS and infer their effects on sales concentration.

Parameters: winner-take-all theory, long-tail theory, content-based recommendation

Better Result: Content-based Filtering recommendation systems can more optimally utilized their advertising and supply chain expenses by more focused on selected their popular products, as sales concentration tends to increase.

Target: Give recommendations in e-commerce websites with Neural-Session-Aware Recommendation[7].

Approach: Using NSAR(novel solution to the session-aware recommendation) as the proposed solution ,which consists of two recipes: GRU RNN model which is using for session modeling & a mechanism which is using for effective integration of user related information into the model in order to achieve personalize session-based recommendations.

Way of process: Using NSAR along with other strategies for user and session integration with different methods such as Embedding, Session-Modeling with GRU RNN model. After that described as the experiments using different data-set, Evolution-Metrix, Baselines models, Optimization & hyper-parameter tunning to present experimental results .

Parameters: Recommendation systems, recurrent neural networks models, session-aware recommendation technique, session-based recommendation technique, sequential top-N recommendation technique.

Better Result: Neural session-aware recommendation is compare with session-based recommendations & sequential top-N recommendations, so problem occur with them is representation of matrix-factorization approach doesn't perform well for sequential-recommendation settings. The method achieve as the lowest Recall and MRR scores among available three datasets. After comparison we saw that NSAR method is the most accurate method which measuring by Recall@K and MRR@K which are classical evaluation metrics in classification algorithms.

III. Proposed System Algorithm

Input : Dataset with user information and product ratings and reviews

Step 1 perform denoising auto-encoder to generate labels (on unlabelled data)

$$\mathbf{y} = s(\mathbf{W}\mathbf{x} + \mathbf{b})$$
$$\mathbf{z} = s(\mathbf{W}'\mathbf{y} + \mathbf{b}')$$
$$L_H(\mathbf{x}, \mathbf{z}) = -\sum_{k=1}^{d} [\mathbf{x}_k \log \mathbf{z}_k + (1 - \mathbf{x}_k) \log(1 - \mathbf{z}_k)]$$

Step 2 perform factorization

Step 3 $K = M \sum U^T$

Step 4 check if numerical values

a. store ratings to a matrix

i. if categorical data

1. store user type selection

Step 5 Perform negative sampling.

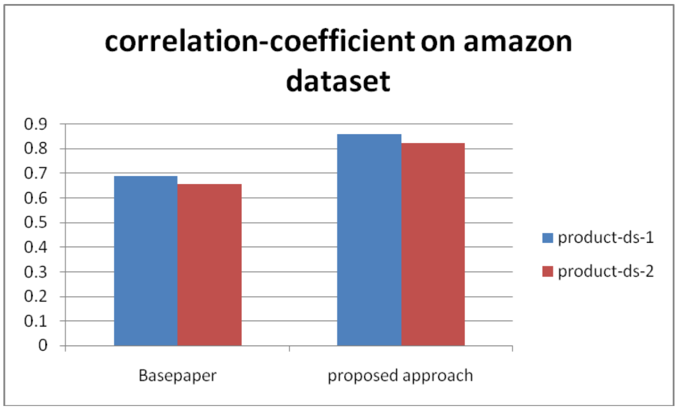
$$\log(\sigma v'_{wo} \;\; T \;\; V_{W_1}) + \sum_{i=1}^{k} E_{wi \sim P_n(w)}[\log \sigma(-v'_{wi} \;\; T \;\; V_{wi})]$$

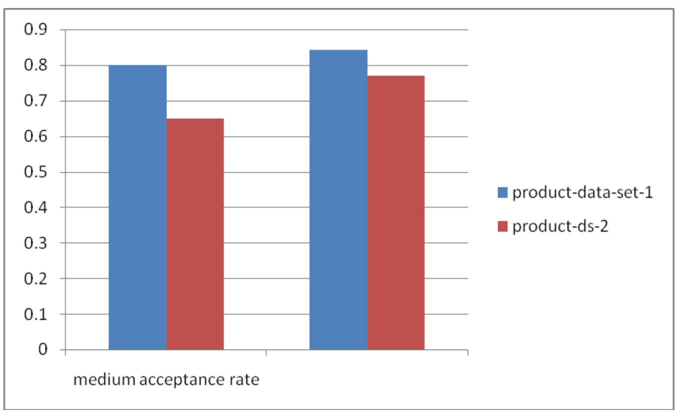
Step 6 Perform classification.

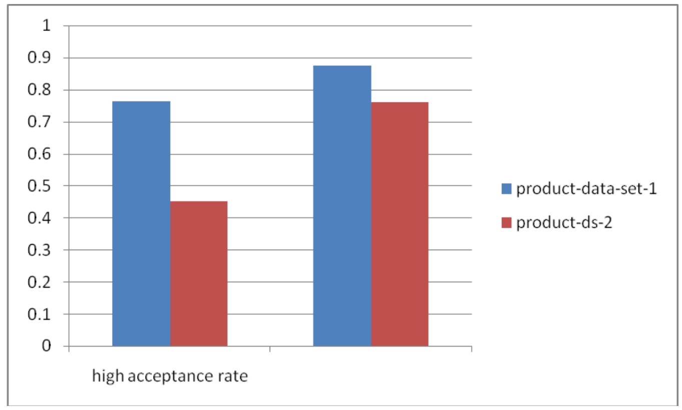
IV. Explanation of Proposed Flow

An alternative to the hierarchical softmax is Noise Contrastive Estimation (NCE), which was introduced by Gutmann and Hyvarinen [4] and applied to language modeling by Mnih and Teh [11]. NCE posits that a good model should be able to differentiate data from noise by means of logistic regression. This is similar to hinge loss used by Collobert and Weston [12] who trained the models by ranking the data above noise. While NCE can be shown to approximately maximize the log probability of the softmax, the Skipgram model is only concerned with learning high-quality vector representations, so we are free to simplify NCE as long as the vector representations retain their quality. We define Negative sampling (NEG) by the objective

V. Results and Analysis







The above results shows that coefficient corelation based various conditions with given customized dataset of amazon products. We have tested the results with no recommendations, high acceptance rate and medium acceptance rate. We also have analysed the results are 57.8% better than the basepaper approach in no recommendation scenario and approx. 30% better in medium acceptance rate.

VI. Conclusion

To make accurate product recommendations you will need a well-built product recommendation system. Knowing whether to use content-based filtering, collaborative filtering, or a hybrid will largely depend on your project, and it will be important to make the right choice, as the quality of your system's recommendations will impact the success of your business and the satisfaction of your customers. Another challenge of product recommendation systems is finding ways of increasing diversity without compromising the precision of the system. While collaborative filtering methods typically use nearest neighbor methods to identify items similar users like, the inverted neighborhood model – *k*-furthest neighbors – seeks to identify less similar neighborhoods for the purpose of creating more diverse recommendations.

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