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A Hybrid Jiang Conrath Product Recommendation System for E-commerce in The Case of Data Sparsity

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Abstract. Collaborative Filtering (CF) is commonly used in e-commerce recommendation systems, but it has limitations in cold-start conditions and data sparsity. This study implements the Hybrid Jiang-Conrath method to address these issues. This approach combines the semantic similarity of WordNet-based Jiang-Conrath Similarity (JCN) with the behavioral similarity of CF. JCN evaluates how conceptually similar the definitions of product categories were. Both approaches were combined using contribution values. The best contribution value across four datasets was α = 0.1 (10% CF, 90% JCN). The Hybrid model outperformed CF in the Industrial & Scientific dataset (MAE 0.64096, RMSE 0.88609). In contrast, the User-Based model achieved the lowest errors in Grocery & Gourmet (MAE 0.94661, RMSE 1.42904) and Video Games (MAE 0.04194, RMSE 0.04194). The Musical Instrument dataset showed comparable results between Item-Based (MAE 0.63247) and User-Based (RMSE = 1.05750) methods. Overall, the Hybrid model demonstrated better stability across diverse data sets. Compared to regular CF that offers only 31 products, hybrid Jiang-Conrath can generate more predictions for 65 product recommendations.

1 Introduction

The adoption of e-commerce experienced a sharp increase, especially during the COVID-19 pandemic, which forced many activities to shift online. According to reports released during the pandemic, there was a 26% increase in sales, along with a 51% rise in new consumers who began using e-commerce services. This growth not only demonstrates the great potential of e-commerce but also creates intense competition among service providers to retain and attract users.[26]. Implementing recommendation systems is one of the main tactics used by e-commerce industry participants to improve customer experience. By

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making product recommendations based on user preferences, these systems hope to boost user pleasure, engagement, and platform loyalty. Amazon E-commerce, said Bradley T from Amazon Statistics [27], serves approximately 310 million users with over 600 million products. Amazon has user reviews collected in the MacAuley Lab dataset [12] that span across 33 distinct product categories. This massive data scale highlights the importance of accurate recommendation algorithms, as even small improvements in prediction accuracy can significantly influence user interactions and purchasing. One of the most commonly used methods in recommendation systems is CF **[1].** CF works by leveraging past user interactions, such as reviews, ratings, or purchase history. CF is divided into two main approaches: User-Based CF, which recommends items based on similar preferences between users, and Item-Based CF, which recommends items based on relationships between items that are frequently bought or rated together by many users[2]. However, CF has some significant limitations, particularly in conditions of cold-start and data sparsity **[7]**. Cold-start occurs when the system lacks sufficient data about new users or new items, making it difficult to generate accurate recommendations. Data sparsity, on the other hand, refers to situations where only a small portion of data is available for modeling relationships between users or between items[4]. This is particularly critical for small or medium-sized business owners seeking to build new e-commerce platforms, as their user base is still limited and user interactions are minimal[3]. To overcome these limitations, a hybrid approach is employed, which combines CF with a semantic similarity measurement method based on WordNet, specifically using JCN. This method not only takes user interactions into account but also understands the semantic meaning of the items to be recommended. The combination of these two methods forms the Hybrid Jiang-Conrath approach, which is expected to provide more accurate recommendations even under cold-start conditions. Jiang-Conrath Similarity itself is one of the methods used in semantic similarity, based on the taxonomic structure of WordNet. JCN measures the similarity between two concepts based on their semantic distance within WordNet and the related information content. Previous studies have shown that the Hybrid Jiang-Conrath approach performs better than pure CF, particularly in situations with limited data**.** Evaluations carried out with scenarios where users and recommended items were limited to no more than 50 showed that this method achieved lower MAE scores compared to traditional Collaborative Filtering. Using four datasets from Amazon Review '23—Video Games, Industrial & Scientific, Music Instruments, and Grocery & Gourmet Food—this study innovates by testing the methodology. Each dataset has a total review and the number of products, which consists of 5074160 reviews and 287209 products, while musical instruments only had 1512530 total reviews and 50300 total products, both producing the lowest numbers. Industry & Scientific continues after musical instruments with 66500 total products and 1758333 total reviews. Video games place before the highest total product and review, which is Grocery & Gourment with 84893 total product and 2,565,349 reviews (HuggingFace,2023). Every dataset is different; a single product may fall under more than one category. These categories can be integrated with item-based collaborative filtering and utilized in the Jiang-Conrath Similarity computation. In order to quantify the degree to which the recommendation results from the Jiang-Conrath combo differ from the Item-Based CF results, this study also introduces a new assessment metric called Root Mean Square Error (RMSE).

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2 Methods

Five subsections below describe the methods used in this study, along with metric evaluation, including MAE and RMSE.

2.1 Collaborative Filtering

The fundamental idea behind Collaborative Filtering (CF) is that two users are likely to have comparable preferences for other items if they have similar preferences for some of the same things. Likewise, if a particular item is favored by a group of users, then similar items are likely to be preferred by other users with similar profiles or behaviors **[6]**. There are two primary ways to CF: item-based and user-based. The system makes product recommendations in a user-based approach depending on how similar users' interests are **[8]**. On the other hand, the item-based method uses users' past data to suggest things that show comparable engagement patterns.

2.2 Item-Based Collaborative Filtering

Collaborative Filtering is the general type of recommendation method, while Item-Based Collaborative Filtering(CF) is one of the specific types of Collaborative Filtering. This method is one of the approaches within Collaborative Filtering that focuses on the relationships between items. Item-Based CF is considered more stable than user-based methods because item characteristics tend to remain consistent over time, whereas user preferences may change **[9]**. In its implementation, this method analyzes item rating patterns across various users and calculates the similarity between items to build a **similarity matrix [8]**. One of the commonly used techniques in item-based Collaborative Filtering is **Cosine Similarity**, which measures the angle between two vectors in the same dimensional space **[2]**. In this context, each item is represented as a vector of ratings given by users. The smaller the angle between the vectors (the higher the cosine value), the more similar the two items are. The **Cosine Similarity equation** can be expressed as follows:

$$sim(A,B) = \frac{\sum_{A\in U} r_{A,i} \cdot r_{A,j}}{\sqrt{\sum_{A\in U} r^2_{A,i}} \cdot \sqrt{\sum_{A\in U} r^2_{A,j}}} \quad (1)$$

sim(A, B) describes the similarity level between item A and item B, rA,ij explains the user rating for item A until item i. Meanwhile, U and J represented the set of all users who rated item i. After the similarity between items is obtained, the next step is to calculate the predicted rating for an item that has not yet been rated by the user. This prediction is made using a weighted sum approach, based on the user's ratings of other similar items **[4]**.

$$\hat{r}_{A,j} = \frac{\sum_{i\in I} sim(i,j) \cdot r_{A,i}}{\sum_{i\in I} |sim(i,j)|} \quad (2)$$

whereas $\hat{r}_{A,j}$ explain User A's rating prediction to item j, i represented the list of items that have been rated by A, $sim(i, j)$ means the similarity value between item i and j

2.3 Wordnet

WordNet has been widely used in the fields of Natural Language Processing (NLP) and semantic-based recommendation systems due to its ability to understand and connect word meanings conceptually **[3]**. In the context of recommendation systems, WordNet enables the system to assess the similarity between items not only based on numerical data but also on the semantic meaning of product descriptions or categories. WordNet organizes words into groups of meanings called synsets (synonym sets), which are collections of words that share similar meanings. In addition, WordNet maps semantic relationships between synsets, such as hyponymy (more specific meaning), hypernymy (more general meaning), meronymy (part of), and holonymy (whole of).

2.4 Semantic Jiang Conrath

The Jiang-Conrath semantic method combines corpus statistics (word frequency in text) and lexical taxonomy structures such as WordNet to enhance the accuracy of measuring similarity between words **[3]**. The main advantage of the Jiang-Conrath semantic approach is its ability to measure semantic similarity, allowing for deeper relevance in recommendations and making it useful for addressing cold-start problems for new items with complete attribute information. The smaller the distance value, the more semantically similar the two words are. Equation 3 shown how to calculate the value

$$sim_{JC}\left(c_1, c_2\right) = 1/(IC\left(c_1\right) + IC\left(c_2\right) - 2 \times IC\ (LCS)) \tag{3}$$

IC means Information Content of the word, and LCS describes the most specific word or concept that serves as the lowest common subsumer (shared ancestor) of both words in the taxonomic hierarchy. For example, there are two words: *computer* and *laptop*. The purpose of the Jiang–Conrath semantic similarity measure is to find how closely related these two words are based on their shared ancestor in the WordNet hierarchy. To do this, both *computer* and *laptop* are analyzed in WordNet to identify their Lowest Common Subsumer (LCS), the most specific common ancestor. Then, the Information Content (IC) values of each word and their LCS are obtained to calculate their semantic similarity.

2.5 Hybrid Jiang Conrath

Hybrid Jiang-Conrath is a hybrid technique that combines semantic similarity based on the Jiang-Conrath methodology with Collaborative Filtering (CF) **[3]**. The cold-start and data sparsity issues that are frequently present in conventional recommendation systems are intended to be addressed by this technique. By integrating the findings of CF and semantic similarity, the similarity between products is determined as follows.

$$HybridSim(i,j) = \propto \times sim_{CF}(i,j) + (1 - \propto)\times sim_{JCN}(i,j) \tag{4}$$

$\propto$ = Weight parameter to determine the contribution of each method, $sim_{CF}(i,j)$ = Similarity from the Collaborative Filtering method, and $simJCi,$= Similarity from the Jiang-Conrath Semantic method. Based on Fahrurrozi's research[3], the value $\propto$ is 0.7, which means 70% to Collaborative Filtering and 30% to Jiang-Conrath. Since the value of $\propto$ is not absolute to 0.7, the researcher can tune it to any value to see the contribution between Collaborative Filtering and Jiang-Conrath.

2.6 MAE & RMSE

The Mean Absolute Error (MAE) measures the average absolute difference between predicted values and actual values. The smaller the MAE value, the better the recommendation results will be **[8]** The formula for MAE is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |P_i - A_i| \tag{5}$$

While P i-th predicted value, A =i-th Actual value, N means the Total Number of data points. However, RMSE, which stands for Root Mean Square Error, displays the error ratio similarly to MAE but returns positive values when MAE yields a negative number **[5]** as shown in Equation 6, which has the same parameter as Equation 5.

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$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (P_i - A_i)^2} \tag{6}$$

The smaller the RMSE value, the better the accuracy of the recommendation system**.**

3 Results and Discussion

This section discusses the raw dataset for the input system until the result of the recommendation system, as described below

3.1 Raw Dataset

Four datasets from Amazon Reviews '23 that were made available by the McAuley Lab are used in this study. Product listings and user reviews from the Amazon platform that have been updated through 2023 make up the McAuley Lab's Amazon Reviews '23 dataset. This dataset was chosen because it includes a variety of data, including crucial details like user IDs linked to reviews of various products, product IDs that users have bought, user rating scores, and the timestamp of each review at the time the user gave it a rating. The raw data will be split into systems using a 70:30 train–test data split across four categories of

Amazon datasets, namely Video Game, Industrial & Scientific, Musical Instruments, and Grocery & Gourmet Food. Each dataset includes product metadata and review data. From each dataset, 50 users were selected based on the criterion that each had submitted at least five reviews for products among the top 250 products.

3.2 System's Design

The steps from data extract to the evaluation outcomes are explained in the system design. The flowchart of the recommendation system depicted in Figure 1 is provided.

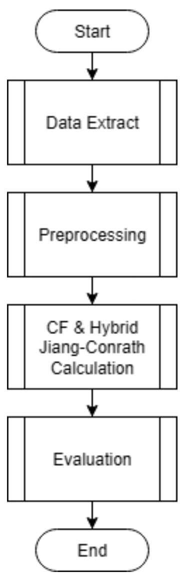

Fig. 1 System's Flowchart

In the initial stage of data extraction, the dataset provides a collection of e-commerce product reviews. This dataset comprises two main components: the product metadata of items being sold, and the review history from users. The preprocessing step inside the system is crucial because data extracted from raw data is treated before being utilized in the CF and Hybrid Jiang–Conrath calculation method. Raw data as data extract is processed first in the preprocessing stage before being used in the CF and Hybrid Jiang–Conrath calculation method. Data preprocessing is carried out through tokenizing and stemming. Tokenizing is the process of splitting words, and stemming is the process of converting words to their most basic form.. CF produced a weighted sum rating prediction after calculating the dataset's matrix value and transferring it to a cosine similarity form. Jiang Conrath determined semantic similarity before merging it with CF in order to compare approaches with CF without Jiang-Conrath. Both CF and CF with Jiang Conrath generated rating predictions that will be verified by two validations; nevertheless, the evaluation metrics of MAE and RMSE will be used. Table 1 shows the product data field as preprocessing results after picking the top 250 products

Table 1 Product Data Field After Pick Top 250 Product

title	average_rating	rating_number	parent_asin	categories
$25 PlayStation Store ...	4,7	261278	B0BL65X86R	['Video Games', 'Online Game Services', 'PlayStation Network', 'Store Currency Cards']
$40 Xbox Gift Card	4,6	171822	B07KRWJCQ W	['Video Games', 'Online Game Services', 'Xbox Live', 'Store Currency Cards']
Roblox Digital Gift Code....	4,5	139255	B07V8YSBFG	['Video Games', 'Digital for the Holidays', 'Digital Video Games']

From 250 sampled products, all categories associated with each product were extracted to perform semantic similarity using the Jiang–Conrath method. Each product has one or more categories. Therefore, these categories undergo preprocessing, including tokenization and stop-word removal. After preprocessing, each token is validated individually. If a token exists in the WordNet lexicon, it is selected as the primary category. If none of the tokens are found in WordNet, the last token is chosen. The chosen category is stored in "clean_category For the review data, we extracted data for 50 users who had rated at least five products from the previously selected top 250 products. That data was split in a 70:30 ratio, with 70% used as training data and 30% as test data. The data splitting was done manually in Excel: the records were sorted by timestamp and then labeled as train or test according to the predefined ratio. Table 2 describes an example of the filtered review data.

Table 2 *Filtered Review Data Field*

user_id	parent_asin	ratin g	trai n
AG34TKNGBARLNDSAMTOYYKYPVVTQ	B000N5Z2L 4	5	train
AGE4MJI4ACCVR2HUDBPA27GVIZFA	B000N5Z2L 4	5	train
AFDL3ZQE4ARYEEBBH2KAPMP4NSHQ	B012DFI02 O	4	test

AFEWTCFBKIFBOZZOERV46OWB7DTA	B07L3D7C2 1	5	test

In the training dataset, a user-item matrix was constructed for the top 250 products and the 50 previously selected users. This matrix was used to compute the cosine similarity. Table 3 represented an example of the user–item matrix.

Table 3 User-Item Matrix

User/Ite m	ProductID 1	ProductID 2	ProductID 3
UserID1	5	0	3
UserID2	0	0	3
UserID3	4	0	5

When calculating Cosine Similarity, using User-Based CF means computing similarity between users (user-to-user), while in Item-Based CF, the computation is performed between items (item-to-item). Table 4 explained an example matrix for Item-Based.

Table 4 Cosine Similarity Item-Based Result

Item/Item	ProductID1	ProductID2	ProductID3
ProductID1	1	0,236112534	0,267261
ProductID2	0,236112534	1	0,441726104
ProductID3	0,267261242	0,441726104	1

After obtaining the cosine similarity, the Jiang–Conrath similarity was computed. This calculation applies only to Item-Based Collaborative Filtering. First, the categories for two products were extracted; then the WordNet synsets for these category words were retrieved. If synsets were found, the semantic distance between them was calculated. This distance was then transformed to yield a similarity score. That similarity score was then used to compute the Combined Similarity. The Weighted Sum approach was then used to predict ratings for the test dataset based on the previously calculated similarity matrices (Cosine Similarity & Combined Similarity). A combination of previously determined similarity weights among items yields the projected value. The predicted ratings are shown in Table 5

Table 5 Prediction Result from Weighted Sum for Data Test

user_id	parent_asin	Original_rating	predicted_rating
UserID1	B0872ZMXBG	5	4,245678
UserID1	B00347UJQQ	5	4,75
UserID2	B0C8YCH9BJ	5	3,974350918

The purpose of rating prediction is to estimate the user's rating value in scenarios where the user has never previously rated the item. After obtaining predicted ratings for the test dataset, the system can also provide Top-N recommendations for test users. The recommendations consist of products that the user has not rated at all in the original data. The items with the highest predicted ratings will be displayed as the top five products for each user. Table 6 provides an example of predicted products that the user has not previously rated in the original dataset. The system makes product recommendations in a user-based approach, depending on how similar users' interests are.

Table 6 Product Prediction Result for Data Test

user_id	parent_asin	product_name	original_rating	predicted_rating
UserID3	B0872ZMXBG	Oreo original...	5	4,667777
UserID3	B0C956D9Q3	Quaker Chewy...	5	4

3.3 Testing and Results

Both the original ratings and the predicted ratings were needed to evaluate the recommendation system's success. MAE and RMSE were computed using these rating values. Both metrics assess the model's predictive accuracy for ratings, which in turn indicates the caliber of the suggestions generated. The models that were employed were a Jiang–Conrath hybrid, item-based collaborative filtering, and user-based collaborative filtering. The recommendations are better if the MAE and RMSE scores are lower, or closer to zero. Thus, comparing the outcomes of these three models was the aim of this assessment. The first step of evaluation testing was conducted using a single Amazon dataset with different α (alpha) contribution values. Figure 2 shows the MAE and RMSE scores for the various contribution levels.

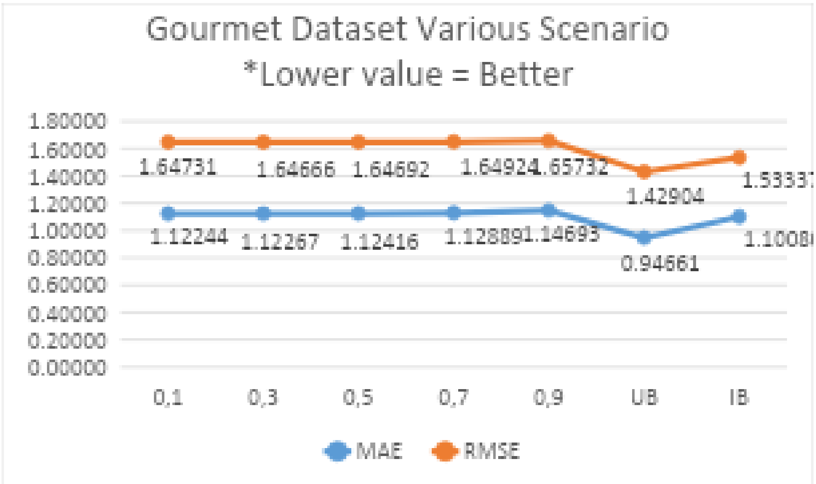

Fig. 2 Testing Various Alpha Scores and Comparing with CF for Grocery & Gourmet Dataset

From the evaluation tests, it was found that the contribution value (alpha) for Jiang–Conrath has a notable impact on recommendation outcomes. Particularly, when alpha = 0.1 (i.e., 10% weight on Collaborative Filtering and 90% weight on Jiang–Conrath semantic similarity), the performance changes significantly. As alpha increases, both MAE and RMSE rise, indicating degraded recommendation quality. Despite this, the hybrid approach still underperforms compared to using only User-Based or only Item-Based CF. The best scores were obtained by the User-Based model, with MAE = 0.94661 and RMSE = 1.42904

Table 7 Evaluation Comparison of MAE & RMSE for Collaborative Filtering (User & Item) and Hybrid Jiang-Conrath

Amazon	**MAE (Hybrid)**	**MAE (User-Based)**	**MAE (Item Based)**	**RMSE (Hybrid)**	**RMSE (User Based)**	**RMSE (Item Based)**
Grocery & Gourmet	1,12244	0,94661	1,10080	1,64731	1,42904	1,53337
Video Games	0,08804	0,04194	0,10691	0,19413	0,04194	0,21392
Industrial & Scientific	0,64096	1,28333	1,23333	0,88609	1,67962	1,50037
Musical Instrument	0,65951	0,63513	0,63247	1,16365	1,05750	1,07645
Amazon	MAE (Hybrid)	MAE (User-Based)	MAE (Item Based)	RMSE (Hybrid)	RMSE (User Based)	RMSE (Item Based)

The next evaluation was conducted using four different datasets with the same contribution value (α = 0.1). This aims to determine how effective the model was across multiple datasets. Below are the results of the testing on these four datasets in Table 7 and Figure 3.

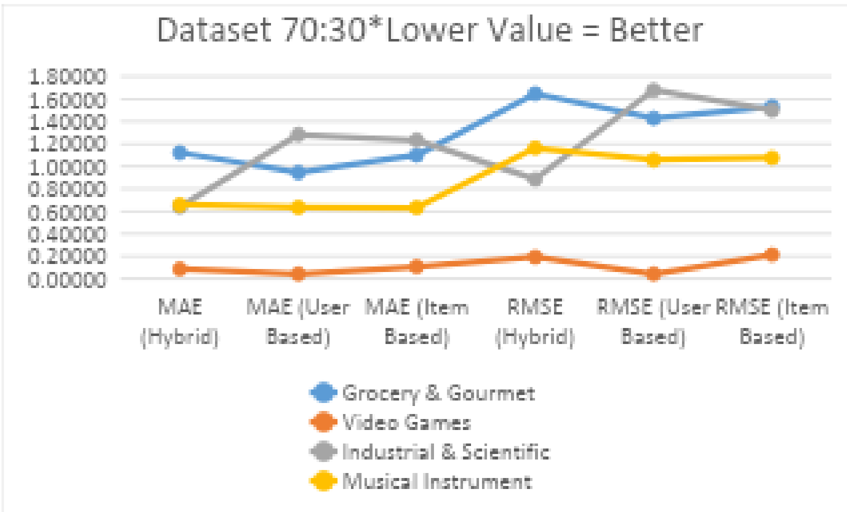

Fig. 3 Comparison of Four Datasets with Alpha Score 0.1

Based on the evaluation, when utilizing User-Based Collaborative Filtering, three of the four datasets demonstrated higher MAE and RMSE scores than both Item-Based and the Jiang-Conrath Hybrid. But for the Industrial & Scientific dataset, the Hybrid model outperformed the User-Based and Item-Based models in terms of MAE and RMSE, improving by 0.59238 in MAE and 0.61428 in RMSE. Although the Jiang–Conrath Hybrid produced worse MAE and RMSE scores compared to pure Collaborative Filtering, it was able to generate a higher number of recommendation predictions. For the ‘Grocery & Gourmet Food’ dataset with 123 test cases, Item-Based CF could only predict ratings for 31 reviews, while the Hybrid Jiang–Conrath model was able to generate predictions for 65 reviews.

4 Conclusion

Based on the conducted experiments, it was concluded that the optimal contribution weight (α) for the Jiang–Conrath component is 0.1, meaning 10% weight assigned to Collaborative Filtering and 90% to the Jiang–Conrath semantic similarity. From four Amazon Review ’23 datasets consisting of Video Games, Industrial & Scientific, Movies & TV, Grocery & Garment Food, the results show that Video Games has better value with 0,08804 for MAE and 0,19413 for RMSE compared to Item-Based. Even that, it is still worse compared to User-Based, with the value 0,04194 for both RMSE and MAE. For a recommendation system, the hybrid Jiang Conrath is able to produce more product recommendations than traditional CF. For example, in the Grocery & Gourmet Food dataset, hybrid Jiang Conrath provides 65 product recommendations while Item-Based CF only provides 31. A previous study from Fahrurrozi [3] showed that the Hybrid Jiang-Conrath approach can improve accuracy compared to using only Collaborative Filtering. The results of this study show better MAE values across three scenarios, namely with five users and 5 data points, 11 users and 15 data points, and 15 users and 18 data points. This research, however, only calculates MAE and has a small amount of data.

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