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Effects of Binary Similarity Metrics on Energy Consumption During Recommendation by Using Collaborative Filtering Approach

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ABSTRACT

The rapid growth of online shopping and web-based services has increased the importance of recommender systems in supporting users' decision-making processes. Among recommendation techniques, collaborative filtering is widely used to predict an active user's preference for a target item or to generate a top-N list of items based on the preferences of users with similar tastes. Since similarity measurement is a core component of collaborative filtering, the choice of similarity metric can significantly influence recommendation accuracy, computational efficiency, and, indirectly, energy consumption. In this context, this study examines the effects of eleven similarity metrics on the performance of a collaborative filtering-based recommender system. A naïve Bayes algorithm was employed for prediction, while the F-measure was used to evaluate recommendation accuracy. In addition, the computational time required by each similarity metric was analyzed to assess efficiency. The empirical results indicate that the Yule similarity metric achieved the highest overall performance, whereas Dice, Hamann, and Kulczynski demonstrated the weakest performance. These findings suggest that the selection of an appropriate similarity metric can enhance recommender system accuracy, reduce computational time, and contribute to lower energy consumption and environmental impact.

Keywords: energy consumption, similarity metric, recommendation, collaborative filtering

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1. INTRODUCTION

Nowadays, the popularity of online shopping has increased. It started especially during the COVID-19. Diaz-Gutierrez et al. (2024) investigated the effects of COVID-19 on online shopping, and they found out that it is significantly increased. The effects of COVID were investigated also by Krunal et al. (2024) in India, by Shaw et al. (2022) in Canada, Germany and United States, by Wang et al. (2021) in China and by Colaço & Silva (2021) in Portugal. In general, they all concluded that COVID effected to increase online shopping. While online shopping became more popular, recommendation of the product or service or information also became popular. One of the recommendation approaches is Collaborative Filtering (CF). CF is an approach for recommendation by using the previous user's tastes (Isinkaye et al., 2022). Goldberg et al. (1992) described the meaning of Collaborative Filtering (CF) as "people collaborate to help one another perform filtering by recording their reactions to documents they read". Thus, the quality and performance of a recommendation is related to similarity between users (Wenbin et al., 2021). Implicitly or explicitly collection of the data also effects the recommendation quality (Rouhia et al., 2021).

When an active user votes for items in dataset and ask to the system to predict a vote for a target item, the system that uses CF suggests a prediction value according to previous users' preferences in dataset. To evaluate previous users' preferences similarity metric should be used. Generating recommendation could be done after forming the neighbourhoods. Data, in other words votes from users, should be collected directly by asking to vote for items or indirectly like, purchasing, reading, listening, watching, spending time on item, etc. Directly collected data could be discrete or continues numeric value, on the other hand indirectly data could be binary values, like/dislike. The Serendipity-2018 (Kotkov et al., 2018) that is used in this study, is a dataset which is formed by collecting data explicitly with the half and integer discrete values between 0.5 and 5. GroupLens Research Team at the University of Minnesota collected data from 49151 users to vote 104661 movies.

A similarity metric affects the results of the prediction accuracy as well as the performance. Related to performance energy consumption is affected. Bayesian algorithm is implemented by using clustering method. With this method an item's prediction can be estimated or a list of items can be recommended as *top-N*. The importance of the prediction is accuracy and performance. Performance can be checked in two parts: offline and online. Offline performance can be ignored as the clusters are created for the first time. Then, for the target item neighbourhood should be calculated for and efficiency depends on this online time.

Lowering energy consumption is affected by the density of the dataset, the number of neighbourhoods, used similarity metric, and used algorithm. Online performance became important for the environment and sustainability as it lowers the energy consumption.

This paper investigates the effects of similarity metrics for the accuracy and performance on a sparse dataset called Serendipity-2018. In this paper, after Literature Survey that indicates contributions of other scientific research, Model Specification and Data section covers binary similarity metrics, Serendipity-2018 dataset, pre-processing of dataset, evaluation criteria, k-modes clustering and Naïve Bayes classification. In the next section results are discussed and the paper concluded with the limitations and future works.

2. LITERATURE REVIEW

Decision support systems with the Artificial Intelligence (AI) technologies improve the quality of the recommendation and Felfernig et al., (2021) focused how to achieve better result for the sustainability development goals those are listed. AI methods may affect positively or negatively efficiency of energy production (van Wynsberghe, 2021). Merinov (2023) mentioned that in tourism, environment effected by the tourist such as increment of noise level, traffic jam and lowering the social distance. So, recommender systems improve tourism development (Merinov, 2023). Barnerjee

(2023) also focused on tourism industry and Tourism Recommender System (TRS) that focuses the sustainable recommendation. On the other hand, Banik et al. (2023) also explored the effect of TRS and integration of sustainable recommendation with TRS. Addition to them, Khan et al., (2021) surveyed different articles to be able to focus e-tourism.

User's decisions effects the environment that force to improve sustainable recommendation as it effects the social responsibilities (Zhou et al., 2023). Spillo et al. (2023) compared 18 recommendation algorithms in their research,. They compared performance of algorithms in terms of energy consumption. Sustainability challenges can be assessed by integrating Large Language Models into recommender systems (Lin et al., 2024).

The uprising of the environmental problem brings the improvement of energy-saving technologies. Sayed et al. (2022) aimed the full integration of energy efficiency framework into Home-Assistant platform by using energy-saving recommendations. Context-aware recommendation system for energy efficiency effects either economic savings or ecological positive impacts. This approach shows how recommendation effectively encourages energy saving behavior (Sardianos et al., 2020). Senyurek & Kevric (2024) compared the eleven similarity metrics effects on a dense dataset to investigate the performance of the recommendation system. This efficiency, effects the energy consumption. Also, with the comparison of the three similarity metrics on a sparse dataset, performance was investigated by (Senyurek and Kevric, 2022).

3. MODEL SPECIFICATION AND DATA

3.1 Model Specification

In this study, we implemented eleven similarity metrics on a sparse dataset that is called Serendipity-2018 (Kotkov et al., 2018) to investigate the online efficiency of recommender system. As an algorithm k-modes approach is used by implementing naïve bayes. K-modes algorithm finds the most k similar users that is called neighborhood. To choose neighbors we compared the effects of eleven binary similarity metrics. These metrics are as follows: Anderberg (A), Dice (D), Gower2 (G), Hamann (H), Jaccard (J), Kulczynski (K), Ochiai (O), Pearson (P), Simple Matching (SM), Sokal and Sneath (SS), and Yule (Y). Choi et al. (2010) implemented 76 similarity metrics, Rácz et al. (2018) compared 44 similarity metrics, Gupta and Chandra (2020) implemented and compared 13 similarity metrics.

The binary similarity metrics can be used to find out how similar two vectors are. The symbol A represents if the values of two vectors are 1, B represents if the value of first vector is 1 and the value of second vector is 0, C represents if the value of first vector is 0 and the value of second vector is 1, D represents if the values of two vectors are 0. The formula of eleven metrics that are implemented in this study are shown in the following table.

Table 1. *Binary similarity metrics*

Metric	Formula
Anderberg	$\frac{\frac{A}{A+B}+\frac{A}{A+C}+\frac{D}{C+D}+\frac{D}{B+D}}{4}$
Dice	$\frac{A}{(2xA)+B+C}$
Gower2	$\frac{AxD}{\sqrt{(A+B)x(A+C)x(D+B)x(D+C)}}$
Hamann	$\frac{(A+D)-(B+C)}{A+B+C+D}$
Jaccard	$\frac{A}{A+B+C}$
Kulczynski	$\frac{\frac{A}{A+B}+\frac{A}{A+C}}{2}$

Ochiai	$\frac{A}{\sqrt{(A+B)x(A+C)}}$
Pearson	$\frac{AxD - BxC}{\sqrt{(A+B)x(A+C)x(D+B)x(D+C)}}$
Simple Matching	$\frac{((AxD)-(BxC))+1}{A+B+C+D+2}$
Sokal and Sneath	$\frac{2x(A+D)}{2x(A+D)+(B+C)}$
Yule	$\frac{(AxD)-(BxC)}{(AxD)+(BxC)}$

3.2. Data

The sparse dataset, serendipity-2018, was used in this study. It was created by Kotkov et al. (2018) from the MovieLens dataset (http://movielens.org). To make it denser and to be useful for the experiments we processed as follows:

i. The top 3000 users who gave the greatest number of votes for the items were selected.

ii. 2000 of them were separated for train data, and 1000 of them were separated for test data.

iii. Out of all items, 4444 were selected as being voted for most by users.

iv. The votes were transferred to 1 (like) if the vote exceeds 3 and 0 (dislike) otherwise.

The following table shows before and after processed dataset in numbers.

Table 2. *Serendipity-2018 dataset*

Description	Before Process	After Process
Users	104,661	3,000
Items	49,151	4,444
Ratings	9,997,850	2,435,079
Range	0-5	0-1
Scale	0.5	
Density	%0.19	%18.27
Type	Discrete	Binary

The dataset is divided into two subsets, randomly without overlapping. Training dataset double number of users to the test dataset

4. METHODOLOGY

In this study, *k*-modes algorithm is used as dataset votes are converted to binary values. The *k*-modes (Hamzah et al., 2017) algorithm can be implemented as follows:

i. k number of cluster centres are selected.

ii. calculate the distances between each data and the centres

iii. assign each data to the closest cluster centres

iv. recalculate the cluster centres by the mean of the data assigned

v. repeat until no reassignment is needed for cluster

To predict one item's vote, one of the most successful (Berrar, 2018) probabilistic approaches, Naïve Bayesian Classifier (NBC) is used. X denotes the variable set as the predictors while C denotes the set of events as the dependent variable

$$X = \{x_1, x_2, x_3, \dots, x_n\} \qquad C = \{c_1, c_2, c_3, \dots, c_n\}$$

The probability of X belongs to C_i and NBC rule is shown below:

$$p(C_i|x_1, x_2, x_3, \dots, x_n) \alpha p(x_1, x_2, x_3, \dots, x_n|C_i)p(C_i)$$

The conditional probabilities of the independent variables are statistically independent. The highest posterior probability is achieved by the following equation (Berrar, 2018):

$$p(C_i|X) \alpha p(C_i) \prod_{k=1}^{n} p(X_k|C_i)$$

After the clusters are separated, the NBC algorithm is used to predict the vote of an active user a to target item t. To choose neighbors, Senyurek and Kevrić (2022) used three binary similarity metrics. In this study, eleven binary similarity metrics were used and to predict item's vote the following algorithm is used:

i. the similarity between active user a and all the other users in train subset

ii. according to similarity values train users are sorted in order

iii. as neighbors the k most similar users are chosen

iv. the NBC algorithm is implemented for active user a and the most similar k users

v. five items' predictions are selected randomly

vi. all steps are repeated for each active user a in the test subset.

The votes for those five items were replaced by null value and after predictions were produced for all test users, estimated date were compared with the original values. Evaluations were done by Classification accuracy and F-Measure. It is also tested that the online efficiency of the model. All these results are affected by the number of users, the number of items, the number of neighbors, prediction algorithm, clustering algorithm, and the similarity metrics. Efficiency is important for sustainability because of the consumption of energy. Longer period for prediction uses more energy. Energy consumption is not directly measured using hardware-level power monitoring tools. Instead, online computational duration is used as a proxy indicator of relative energy usage. Under comparable and constant hardware conditions, differences in execution time may reasonably reflect proportional differences in energy consumption across similarity metrics. Since all experiments were conducted under identical computational settings, execution time serves as a consistent comparative indicator of relative energy efficiency.

4. EMPIRICAL RESULTS AND DISCUSSION

In this study we used eleven similarity metrics to implement on different number of train users, n values (2000, 1000, 500, 250, 126), test users (1000, 500, 250, 125, 63), the number of neighbourhoods, k values (2000, 1000, 500, 250, 125, 100, 50, 25). Besides the accuracy, the online duration for each of them are recorded. On the charts and tables similarity metrics are represented by the letters, such as A for Anderberg, D for Dice, G for Gower2, H for Hamann, J for Jaccard, K for Kulczynski, O for Ochiai, P for Pearson, SM for Simple Matching, SS for Sokal and Sneath, and Y for Yule. The following Figure 1 and Figure 2 show the computational efficiency results of all similarity metrics with the different number of users, and clusters. In Figure 1, values are grouped with the worst results for the lower time values and best results are for the higher time values.

n	126	126	126	126
k	25	50	100	126
Worst results	Y	Y	Y	Y
	P	P	H	H
	H	SS	SS	SM
	SS	H	SM	SS
	SM	SM	P	P
	A	A	A	A
Best results	G	G	K	K
	J	J	G	J
	O	D	J	D
	D	K	O	O
	K	O	D	G

(a)

n	250	250	250	250	250
k	25	50	100	125	250
Worst results	Y	H	Y	Y	Y
	SS	SS	P	P	H
	H	P	H	SS	SS
	P	Y	SS	SM	SM
	A	SM	SM	H	P
	G	A	A	A	J
Best results	J	G	G	G	K
	K	J	J	J	A
	O	O	D	K	G
	SM	K	K	D	O
	D	D	O	O	D

(b)

n	500	500	500	500	500	500
k	25	50	100	125	250	500
Worst results	SS	P	Y	Y	Y	H
	SM	SS	P	P	H	SM
	Y	SM	H	SS	P	P
	H	H	SS	H	SS	Y
	A	Y	SM	SM	SM	SS
	P	A	A	A	A	J
Best results	G	G	G	G	G	K
	J	J	O	J	J	G
	O	D	J	D	D	D
	D	O	D	K	O	O
	K	K	K	O	K	A

(c)

n	1000	1000	1000	1000	1000	1000	1000
k	25	50	100	125	250	500	1000
Worst results	SS	P	P	P	Y	Y	SS
	SM	SS	Y	Y	SM	H	Y
	H	SM	SS	SS	SS	P	H
	Y	H	A	SM	H	SS	SM
	A	A	SM	A	P	SM	P
	P	Y	H	G	A	G	J
Best results	G	G	G	H	G	A	K
	J	J	J	J	J	D	A
	D	D	D	D	D	J	D
	O	O	O	O	O	K	G
	K	K	K	K	K	O	O

(d)

n	2000	2000	2000	2000	2000	2000	2000	2000
k	25	50	100	125	250	500	1000	2000
Worst results	SS	P	P	P	P	P	SS	SM
	H	SS	H	SS	Y	SM	H	H
	SM	H	SS	H	SS	Y	P	SS
	Y	A	A	SM	H	SS	SM	P
	A	SM	SM	A	SM	H	A	J
	P	Y	G	G	A	A	G	A
Best results	G	G	Y	Y	G	G	J	D
	J	J	J	J	J	J	D	K
	D	D	D	D	D	D	O	O
	K	O	O	O	O	O	K	G
	O	K	K	K	K	K	Y	Y

(e)

Figure 1. *Similarity metrics order depending on the Duration results with varying k values for (a) n=126, (b) n=250, (c) n=500, (d) n=1000, and (e) n=2000 users*

Different k values were compared, and it has been found that the online duration is worsening while k values are increased. All experiments were done with the computer Intel(R) Core(TM) i5-10310U CPU @ 1.70GHz (2.21 GHz) with 16 GB RAM. Energy consumption was estimated using the processor's Thermal Design Power (TDP) of 15 W as specified by Intel (Intel corporation, 2026).

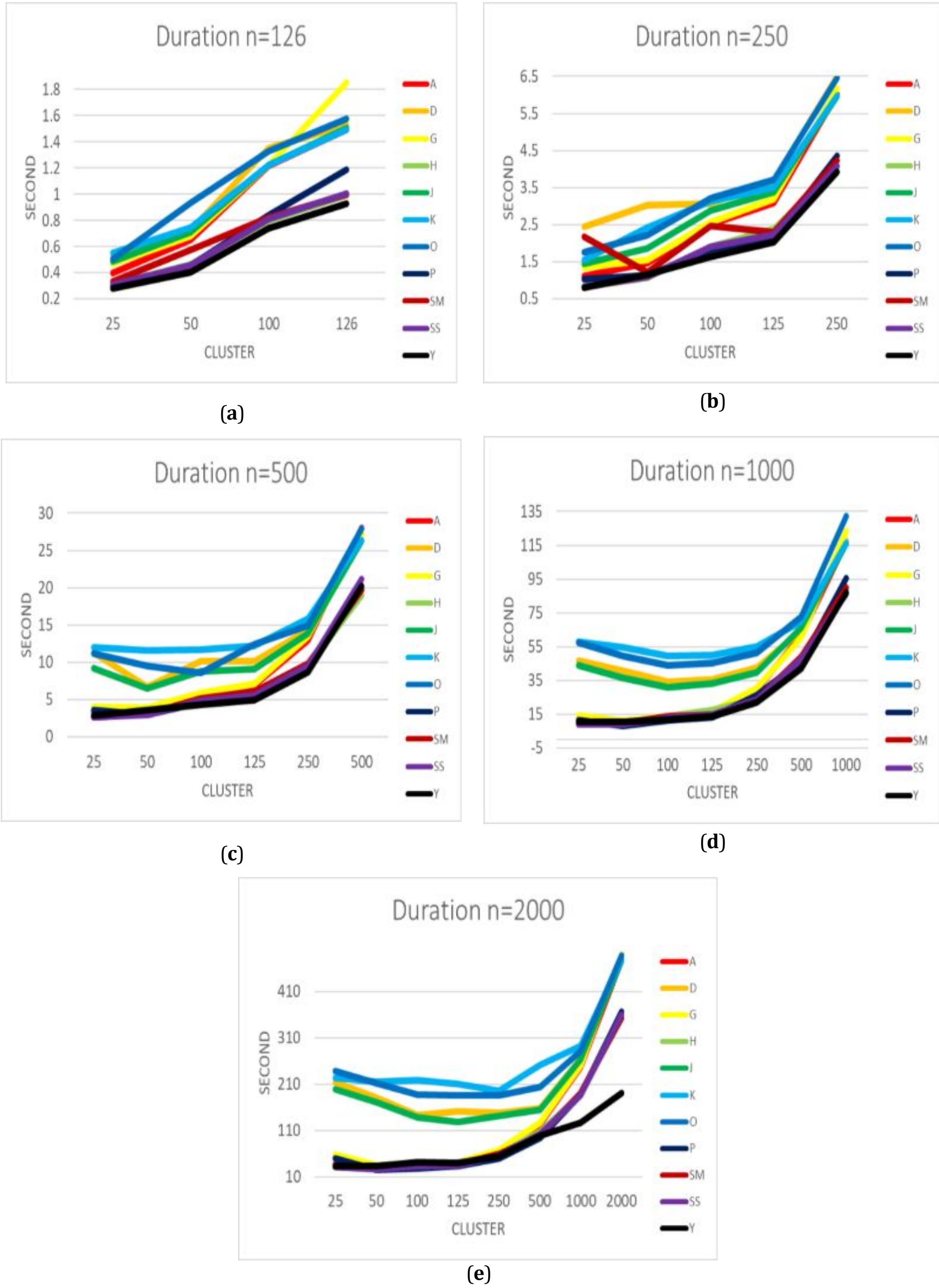

Figure 2. *Online Duration results for different k values and (a) n=126, (b) n=250, (c) n=500, (d) n=1000, and (e) n=2000 users by eleven similarity metrics*

Online duration of the prediction for different number of total users and different k values were compared in Figure 2. For each value should be multiplied by 15W. Borowski (2025) explained the importance of renewable energy sources and mentioned that implementation of renewable energy encourage the technological innovation. That is why, in this study the effects of similarity metrics for recommendation were compared to find out which one effects least energy consumption. While the number of cluster values are increased, the online duration so energy consumption is worsening as seen in Figure 2.

5. CONCLUSION

Train dataset for n users from 2000 to 126, number of clusters for k values from 2000 to 25, test dataset from 1000 to 63 were experimented by eleven similarity metrics. All online performance were recorded, and it was seen that online performance is important to reduce energy consumption.

According to Figure 1, for the online duration tests Y is in the first best group for the number of train users 126, 250 and 500. Except n=250 all train user values SM is also in the first best group. Similar to SM, for all n values except n=500, SS is also in the first best group. In online performance, K, D, O, and G are in the worst performance group for all n values. J is also in the worse group except n=2000. All n values H falls in the best half except the k values 100, and 125 of 1000 train users. While P is a very strong contender, A shows a mixed performance. And the shape of curves is almost similar for online performance in Figure 2 for all n and k values. Thus, for the sparse datasets, P if good choice of similarity metrics for less energy consumption on the other hand K, D, O, and G shouldn't be preferred. Implementation of Pearson (P) similarity metric allows the least energy consumption, so, it is useful to implement especially on sparse datasets for the recommendation.

For the future studies, we are intending to implement same similarity metrics for accuracy and efficiency of a dense dataset. This way the effects of the similarity metrics for energy consumption can be compared on sparse and dense datasets.

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