A Lexicon-based Collaborative Filtering Approach for Recommendation Systems

Mara Deac-Petruşel
Faculty of Mathematics and Computer Science, Babeş-Bolyai University, Cluj-Napoca, Romania

Keywords: Recommendation Systems, Collaborative Filtering, K Nearest Neighbours, Vader Lexicon, Text-based Reviews, Sentiment Score.

Abstract: Users purchasing items from e-commerce websites are expressing their satisfaction and sentiment about their acquisition using text-based reviews and numerical ratings. Traditional collaborative filtering techniques are entirely dependent on the users' scalar ratings, which are lacking any semantic explanation of the users' preferences. This approach was designed to explore the text-based item evaluation using a Sentiment Analysis Lexicon. The proposed lexicon-based k nearest neighbors collaborative filtering technique replaces the numerical rating with a computed sentiment rating in the neighborhood determination step. The conducted experiments reveal that the resulting text-based recommendation system produces reliable values in terms of mean absolute error and root mean square error and accurate recommendations for users.

1 INTRODUCTION

E-commerce websites are important sources of data generation. People are buying items based on the reviews of other peers. Users evaluate the purchased items, expressing their satisfaction and opinions through numerical ratings and text-based reviews. Classic recommendation systems produce suggestions for users using the given numerical ratings for items. Scalar ratings are not able to offer a semantic explanation about the users' preferences. Therefore, recommendation systems are facing the challenge of efficiently analyzing information in textual form.

The proposed approach was designed to capture the users' interests from the text-based items' reviews to produce good rating predictions for items and accurate generated recommendations for users. The items' descriptions are passed to a Sentiment Analysis Lexicon, which outputs a sentiment score indicating the polarity of the text (positive, negative, or neutral). Based on the sentiment score, a k-nearest neighbor (kNN) user-based collaborative filtering algorithm was applied. The recommendation system uses solely the sentiment scores (called *sentiment ratings*), instead of the numerical ratings. Results have proven a positive impact of the text-based approach on the performance of the recommendation system.

The original contributions of the papers are:

- Analysing the textual information of an item and applying the Vader Sentiment Analysis Lexicon (Hutto and Gilbert, 2014) to obtain the sentiment rating;
- Integrate the lexicon-based data into the k nearest neighbors user-based collaborative filtering algorithm;

The rest of this paper is organized as follows. Chapter two surveys the state-of-art approaches that integrate the rich information contained in text-based items' descriptions in the recommendation process. The third chapter describes a detailed methodology used to design this approach. The fourth chapter presents the experimental setups conducted and gives an overview of the selected data sets in terms of their features and volume. Also, the evaluation metrics used in the textual recommendation system are briefed and comparisons to other approaches are discussed. In the last chapter, the overall summary of this work is presented, highlighting the main findings, results, and future work plans.

2 RELATED WORK

This section offers an overview of several state-of-the-art approaches where text-based reviews are explored and integrated into the collaborative filtering

Deac-Petruşel, M.
A Lexicon-based Collaborative Filtering Approach for Recommendation Systems.
DOI: 10.5220/0010801200003116
In *Proceedings of the 14th International Conference on Agents and Artificial Intelligence (ICAART 2022) - Volume 3*, pages 203-210
ISBN: 978-989-758-547-0; ISSN: 2184-433X

recommendation process to improve rating prediction.

(Terzi et al., 2014) proposes a text-based user-kNN algorithm that uses text-based reviews instead of numerical ratings to compute the users' similarity. The idea is to determine the similarity between two users by computing the similarity between reviews' words for every item reviewed by both users. The text-based user-kNN is compared with several approaches using numerical ratings in the rating prediction step. For the numerical experiments, two data sets are used: RottenTomatoes and an AudioCD from AmazonProductReviews. Slightly better results are obtained for root mean square error (RMSE) between the actual and the predicted ratings in the text-based user-kNN approach over the ratings-based ones.

(Poirier et al., 2010) determines sentiment scores from text-based reviews using a Naïve Bayes model. As a first step, the text-based reviews are analyzed and text mining techniques are applied in order to build the user-item-rating matrix. Reviews are classified into two sentiment classes: positive and negative using the KHIOPS tool (Boullé, 2007). Then, the item-based collaborating filtering algorithm is applied to generate the recommendations. Experiments are conducted using Flixter, Netflix, and IMDB data sets. RMSE is used as an evaluation measure.

(Ma et al., 2017) designed an original user-preference-based collaborative filtering (UPCF) approach to exploit free-text online reviews to retrieve users' preferences. Firstly, aspect-level opinions mining techniques were applied to transform the free-text reviews into structured aspect opinions. Next, the user preferences were determined on one hand from the aspect importance and, on the other hand, from the aspect need. The aspect importance means that opinions on important aspects are more influential to the overall ratings than other aspects, and uses the similarity between the opinions on one aspect and the overall ratings. The aspect need is calculated as the difference between the opinions of a user on an aspect and those of other users, which indicates the differentiated needing level on this aspect with respect to the user. Based on this, a user-based collaborative filtering approach is designed so that the users' aspect preferences are integrated to calculate the similarities between users.

(Musto et al., 2017) implemented a user and item-based collaborative filtering approach that includes aspect opinion data. For both user and item-based use cases, aspect-based user/item distances are calculated using the sentiment ratings extracted from the reviews' aspects. The similarity between users/items is determined based on the inverse of the users/items distances and ratings' predictions are computed using the collaborative filtering algorithm.

3 SYSTEM ARCHITECTURE

As exemplified in Chapter 2, the text-based items' descriptions reveal more valuable information compared to the plain numerical ratings for the recommendation process. The focus of the proposed approach is to make use solely of the textual information when building the recommendation system, regardless of the numerical ratings. The textual input is exploited using a lexicon-based technique to determine the polarity score of a review. The resulted scores are the sentiment ratings taken into consideration for the user-based kNN collaborative filtering algorithm. After the data collection phase, the text-based items' reviews serve as input for a sentiment lexicon that determines a sentiment rating for an item. The data set enhanced with the computed sentiment rating is further passed to a recommendation system.

3.1 Data Pre-processing

The proposed recommendation system handles textual information, therefore, a data cleansing process was applied to the input data sets before being used by the sentiment lexicon. The following techniques have been applied:

- Removal of punctuation and stop words;
- Lower-casing;
- Removal of URLs;
- Stemming

3.2 Sentiment Lexicon

The proposed approach uses, for the sentiment analysis task, a sentiment lexicon, which was selected based on the complex and thorough comparison presented in (Hutto and Gilbert, 2014). The *Vader Sentiment Lexicon* was compared to several ones from literature (Linguistic Inquiry Word Count, General Inquirer, Affective Norms for English Words, SentiWordNet, SenticNet, Word-Sense Disambiguation) and produced,in most cases, the best results.

Vader (*Valence Aware Dictionary and Sentiment Reasoner*) lexicon (Hutto and Gilbert, 2014) is a rule-based sentiment analysis tool based on a dictionary that maps words to positive, neutral, or negative sentiment scores. The sum of all these scores defines a compound score which is normalized between -1 and

1. A value closer to -1 indicates a negative sentiment for the item's review, while a value closer to 1 a positive one. The sentiment score of a review is determined as follows:

$$score(review) = \sum_{i=1}^{n} score(word_i), \quad (1)$$

where

- n is the number of words of a review.
- $score(word_i)$ is the sentiment score of the i^{th} word, based on the Vader lexicon.

3.3 Recommendation Process

The data set containing in addition the reviews with sentiment scores represents the input data for the recommendation system. The *kNN collaborative filtering algorithm* is then applied as recommendation technique, as follows (Petrusel and Limboi, 2019):

- The most similar k users (called *neighbors*) for a target user are determined based on the calculated users' similarity. Several similarity measures from literature can be used at this step.
- For not yet reviewed items of the target user, the rating prediction is computed and *top-n* recommendations are generated.

To determine the unknown rating prediction for an item i and the target user a, the following formula is used (Victor et al., 2011):

$$p_{a,i} = s\bar{co}re_a + \frac{\sum_{u \in R_+} w_{a,u}(score_{u,i} - s\bar{co}re_u)}{\sum_{u \in R_+} w_{a,u}} \quad (2)$$

where:

- $s\bar{co}re_a$ is the mean lexicon-based score rating given by target user a for other items than i.
- $s\bar{co}re_u$ is the mean lexicon-based score given by user u over all items.
- $w_{a,u}$ is the similarity between the two users.
- $score_{u,i}$ is the lexicon-based score determined for item i and user u.
- R_+ is the set of users that rated item i positively.

3.4 Evaluation Process & Confidence Intervals

The recommendation process is evaluated by computing the *Mean Absolute Error (MAE)* and *Root Mean Square Error (RMSE)* (Isinkaye et al., 2015) for a user u, based on the following formulas:

$$MAE(u) = \frac{\sum_{i=1}^{N_r} |p_{u,i} - score_{u,i}|}{N_r} \quad (3)$$

and

$$RMSE(u) = \sqrt{\frac{\sum_{i=1}^{N_r} |p_{u,i} - score_{u,i}|}{N_r}} \quad (4)$$

where $p_{u,i}$ and $score_{u,i}$ are the predicted score, respectively the actual score (determined via lexicon) of user u for item i and N_r is the number of recommended items.

Moreover, 95% confidence intervals are determined to find out the value ranges for the model performance. The confidence interval is a statistic interval for measuring the uncertainty on an estimate. It measures the range of values, from the given data, that includes the true values for estimating good suggestions. A smaller confidence interval means a more precise estimation in comparison with a large one.

4 EXPERIMENTAL SETUP

To highlight the value-added by the proposed *lexicon-based K Nearest Neighbors collaborative filtering* approach in improving the rating prediction accuracy, several numerical experiments were conducted on three data sets containing text-based reviews for items.

For the neighborhood determination in the *kNN*, various popular similarity measures from literature were applied: Pearson Correlation Coefficient (PCC), Cosine (COS), Euclidean (EUC), Constrained Pearson Coefficient (CPC), Spearman Rank Coefficient (SRC), Jaccard Similarity (JAC) (Agarwal and Chauhan, 2017), (Sondur et al., 2016) and PIP (Ahn, 2008). Independent scenarios are designed for different values of k (the neighbourhood size) and n (the number of generated recommendations).

In the evaluation process, the *MAE* and *RMSE* measures are computed to establish the accuracy of the generated recommendations.

4.1 Data Sets

For the numerical experiments, three data sets are used: *Amazon Fashion* (Yan et al., 2019), *Rotten Tomato Critic Reviews* (Firmanto et al., 2018) and *Datafiniti Product Reviews* (Zahid-samza595, 2020).

The *Amazon Fashion* data set contains 100 000 reviews and several features, such as: *review time*, *reviewer name*, *review text*.

The *Rotten Tomato Critic reviews* has 50 000 movies & TV reviews. It is composed of features like *publisher name*, *review type*, *review content* or *review date*.

The *Datafiniti Product Reviews* has 3000 wine, beer and liquor reviews described by the *business name*, *brand*, *category*, *review text*, *review date* or *username*.

4.2 *Amazon Fashion* Data Set Results

In tables **1, 2, 3, 4, 5 and 6** the results obtained for several scenarios are presented. The best values for *MAE* and *RMSE* for the lexicon-based collaborative filtering are achieved using *PIP* similarity measure for the neighborhood size $k = 10$ and number of recommendations $n = 3$.

Moreover, the **95% confidence intervals** were calculated and the best results were obtained for the scenario considering the neighborhood size $k = 10$ and number of recommendations $n = 3$ and are presented in table **7**. Results show that *MAE* was at $x + / - y$ for 95% confidence interval, where x is the lower bound of the interval and y is the upper bound.

4.3 *Rotten Tomato Critic Reviews* Data Set Results

For the *Rotten Tomato Critic Reviews* data set (Firmanto et al., 2018), the results for all scenarios setups are presented in tables **8, 9, 10, 11, 12 and 13**. Best values were achieved when using the *PIP* similarity measure with neighbourhood size $k = 10$ and number of generated recommendations $n = 3$.

Table **14** reveals the 95% confidence interval computed for the best scenario with neighbourhood size $k = 10$ and number of generated recommendations $n = 3$.

4.4 *Datafiniti Product Reviews* Data Set Results

Tables **15, 16, 17, 18, 19 and 20** showcase the results obtained for all the test scenarios, for the *Datafiniti Product Reviews* data set. Best values were achieved when using the *Spearman Rank Coefficient* in the lexicon-based kNN collaborative filtering approach for the neighbourhood size $k = 5$ and number of generated recommendations $n = 3$.

Table **21** presents the 95% confidence interval for the best scenario when using the neighbourhood size $k = 5$ and number of generated recommendations $n = 3$.

4.5 Comparisons and Discussions

This section offers an overview of the *MAE* values obtained for the best scenarios for each data set. When comparing the results presented in figures **2, 3 and 4**, it can be observed that the best performance in terms of *MAE* was achieved for the *Datafiniti Product Reviews* (Zahid-samza595, 2020) using the *Spearman Rank Coefficient*.

Moreover, the proposed lexicon-based approach is compared to another text-based kNN collaborative filtering approach described in (Terzi et al., 2014), in terms of *Root Mean Square Error* performance measure. Both approaches use text-based reviews instead of numerical ones and the experiments are conducted on the *Rotten Tomato Critic Reviews* data set. Although both approaches make use of textual items' descriptions, there is a difference in the sentiment score definition (substituting the numerical rating). (Terzi et al., 2014) computes the distance between two words based on the shortest distance between them, while in the proposed approach the sentiment score is obtained based on the information derived from the Vader Lexicon (Hutto and Gilbert, 2014).

Results are presented in table **22**. Even though the quantitative results in (Terzi et al., 2014) are better, the presented approach is different from a qualitative point of view, using a lexicon-based collaborative filtering technique. The proposed technique has value especially from the semantic point of view, considering words' polarities (positive, negative, neutral) compared to (Terzi et al., 2014), which is based on the set of common words. Overall, this comparison highlights the fact that the presented approach generates good and trustworthy results and confirms again that text-based reviews indeed offer valuable information for the recommendation process.

5 TABLES & FIGURES

Table 1: Amazon Fashion k=5 and n=3.

Similarity Measure	MAE	RMSE
PCC	0.45	0.67
COS	1.19	1.07
EUC	1.90	1.70
CPC	0.75	0.85
SRC	0.20	0.31
JAC	0.29	0.49
PIP	**0.10**	**0.30**

Table 2: Amazon Fashion k=5 and n=5.

Similarity Measure	MAE	RMSE
PCC	0.41	0.64
COS	1.04	1.002
EUC	1.90	1.70
CPC	0.86	0.91
SRC	0.20	0.30
JAC	0.29	0.49
PIP	**0.10**	**0.31**

Table 3: Amazon Fashion k=5 and n=10.

Similarity Measure	MAE	RMSE
PCC	0.34	0.58
COS	1.03	0.99
EUC	1.80	1.70
CPC	0.72	0.84
SRC	0.20	0.30
JAC	0.29	0.49
PIP	**0.10**	**0.31**

Table 4: Amazon Fashion k=10 and n=3.

Similarity Measure	MAE	RMSE
PCC	0.45	0.67
COS	0.70	0.82
EUC	0.77	0.66
CPC	0.73	0.84
SRC	0.13	0.27
JAC	0.29	0.48
PIP	**0.10**	**0.19**

Table 5: Amazon Fashion k=10 and n=5.

Similarity Measure	MAE	RMSE
PCC	0.42	0.64
COS	0.86	0.90
EUC	1.77	1.66
CPC	0.85	0.90
SRC	0.20	0.32
JAC	0.29	0.49
PIP	**0.10**	**0.29**

Table 6: Amazon Fashion k=10 and n=10.

Similarity Measure	MAE	RMSE
PCC	0.35	0.59
COS	0.83	0.89
EUC	1.77	1.66
CPC	0.72	0.84
SRC	0.20	0.32
JAC	0.29	0.49
PIP	**0.10**	**0.29**

Table 7: Amazon Fashion 95% CI.

Similarity Measure	95% CI
PCC	(0.447,0.453)
COS	(0.697,0.703)
EUC	(0.767,0.773)
CPC	(0.727,0.733)
SRC	(0.128,0.132)
JAC	(0.287,0.293)
PIP	(0.098,0.102))

Table 8: Rotten Tomato Critic Reviews k=5 and n=3.

Similarity Measure	MAE	RMSE
PCC	0.78	0.77
COS	0.57	0.59
EUC	0.66	1.70
CPC	0.80	0.76
SRC	**0.39**	**0.52**
JAC	0.98	0.85
PIP	0.71	0.71

Table 9: Rotten Tomato Critic Reviews k=5 and n=5.

Similarity Measure	MAE	RMSE
PCC	0.85	0.82
COS	0.69	0.69
EUC	1.05	0.88
CPC	0.85	0.79
SRC	**0.46**	**0.58**
JAC	0.78	0.76
PIP	0.47	0.59

6 CONCLUSIONS & FUTURE WORK

Recommendation systems are important tools for defining suggestions for users. Lately, a lot of effort was put into incorporating the text-based reviews in the recommendation process. The scope was to enhance the classical collaborative filtering algorithms and to explore the power of these descriptions. The text-based reviews describe the user's opinions and feelings about items more accurately than a numerical value and, therefore, the text-based techniques can produce accurate items' rating predictions and recommendations. With this in mind, a recommendation system that incorporates the textual information

Table 10: Rotten Tomato Critic Reviews k=5 and n=10.

Similarity Measure	MAE	RMSE
PCC	0.68	0.71
COS	0.64	0.66
EUC	0.70	0.72
CPC	0.84	0.79
SRC	0.54	0.62
JAC	0.49	0.59
PIP	**0.39**	**0.53**

Table 11: Rotten Tomato Critic Reviews k=10 and n=3.

Similarity Measure	MAE	RMSE
PCC	0.72	0.71
COS	0.44	0.55
EUC	0.54	0.61
CPC	0.49	0.58
SRC	0.57	0.65
JAC	0.97	0.83
PIP	**0.20**	**0.32**

Table 12: Rotten Tomato Critic Reviews k=10 and n=5.

Similarity Measure	MAE	RMSE
PCC	0.62	0.67
COS	0.62	0.63
EUC	0.66	0.70
CPC	0.59	0.65
SRC	0.53	0.62
JAC	0.53	0.62
PIP	**0.24**	**0.42**

Table 13: Rotten Tomato Critic Reviews k=10 and n=10.

Similarity Measure	MAE	RMSE
PCC	0.64	0.68
COS	0.64	0.67
EUC	0.61	0.67
CPC	0.81	0.76
SRC	**0.51**	**0.61**
JAC	0.67	0.70
PIP	0.55	0.64

Table 14: Rotten Tomato Critic Reviews 95% CI.

Similarity Measure	95% CI
PCC	(0.717,0.723)
COS	(0.437,0.443)
EUC	(0.537,0.543)
CPC	(0.487,0.493)
SRC	(0.567,0.573)
JAC	(0.969,0.971)
PIP	(0.198,0.202))

Table 15: Datafiniti Product Reviews k=5 and n=3.

Similarity Measure	MAE	RMSE
PCC	0.71	0.74
COS	1.73	1.22
EUC	1.66	1.61
CPC	1.21	1.01
SRC	**0.04**	**0.09**
JAC	0.74	0.82
PIP	0.06	0.17

Table 16: Datafiniti Product Reviews k=5 and n=5.

Similarity Measure	MAE	RMSE
PCC	0.98	0.82
COS	1.60	1.19
EUC	1.73	1.63
CPC	1.04	1.94
SRC	**0.10**	**0.22**
JAC	0.74	0.82
PIP	0.06	0.16

Table 17: Datafiniti Product Reviews k=5 and n=10.

Similarity Measure	MAE	RMSE
PCC	0.89	0.81
COS	1.63	1.20
EUC	1.73	1.63
CPC	1.05	1.94
SRC	**0.10**	**0.22**
JAC	0.74	0.82
PIP	0.06	0.16

about an item by a user was proposed. In comparison with the majority of approaches presented in 2 that use machine learning algorithms, the proposed one focuses on a lexicon-based kNN collaborative filtering technique. The text-based review is processed by the Vader Lexicon (Hutto and Gilbert, 2014), which computes the sentiment rating. Then, the data set augmented with the sentiment rating is used as input for the kNN collaborative filtering algorithm.

The results obtained in the conducted numerical experiments show that the presented approach can be successfully used to solve recommendation tasks, for data sets containing text-based user reviews. As future work, the approach could be extended to also consider different types of review elements besides words, such as review topics or aspect opinions.

Table 18: Datafiniti Product Reviews k=10 and n=3.

Similarity Measure	MAE	RMSE
PCC	1.02	0.82
COS	1.57	1.76
EUC	1.40	1.52
CPC	0.88	0.87
SRC	**0.08**	**0.21**
JAC	0.58	0.70
PIP	0.09	0.24

Table 19: Datafiniti Product Reviews k=10 and n=5.

Similarity Measure	MAE	RMSE
PCC	1.01	0.82
COS	1.47	1.16
EUC	1.11	1.41
CPC	1.05	0.90
SRC	**0.15**	**0.27**
JAC	0.63	0.76
PIP	0.16	0.33

Table 20: Datafiniti Product Reviews k=10 and n=10.

Similarity Measure	MAE	RMSE
PCC	0.97	0.83
COS	1.69	1.23
EUC	1.12	1.42
CPC	1.05	0.94
SRC	**0.15**	**0.27**
JAC	0.63	0.75
PIP	0.16	0.34

Table 21: Datafiniti Product Reviews 95% CI.

Similarity Measure	95% CI
PCC	(0.694,0.726)
COS	(0.422,0.458)
EUC	(0.522,0.558)
CPC	(0.472,0.508)
SRC	(0.552,0.588)
JAC	(0.964,0.976)
PIP	(0.186,0.214))

Table 22: Lexicon-based CF approach vs. (Terzi et al., 2014) approach.

Approach	RMSE
Lexicon-based CF	0.32
(Terzi et al., 2014)	0.14

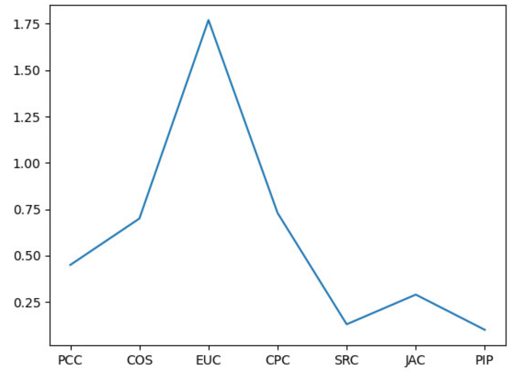

Figure 1: MAE for Amazon Fashion, k=10 and n=3.

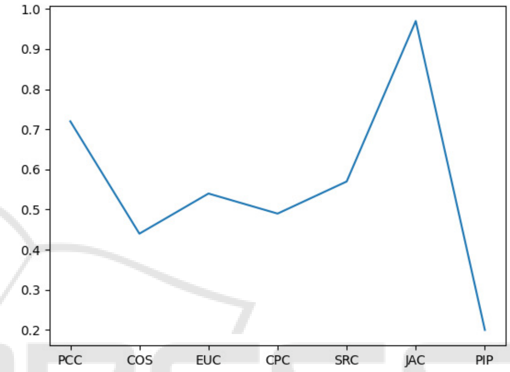

Figure 2: MAE for Rotten Tomato Critic Reviews, k=10 and n=3.

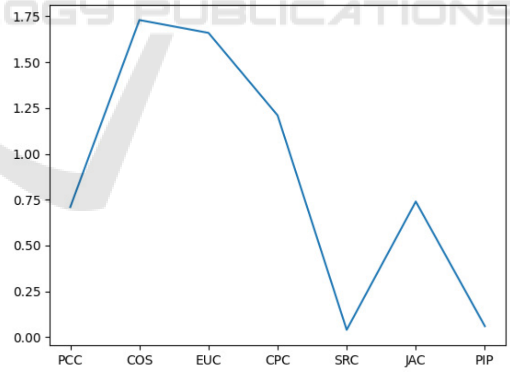

Figure 3: MAE for Datafiniti Product Reviews, k=5 and n=3.

REFERENCES

Agarwal, A. and Chauhan, M. (2017). Similarity measures used in recommender systems: a study. *International Journal of Engineering Technology Science and Research IJETSR, ISSN*, pages 2394–3386.

Ahn, H. J. (2008). A new similarity measure for collaborative filtering to alleviate the new user cold-starting problem. *Information sciences*, 178(1):37–51.

Boullé, M. (2007). Compression-based averaging of selective naive bayes classifiers. *The Journal of Machine Learning Research*, 8:1659–1685.

Firmanto, A., Sarno, R., et al. (2018). Prediction of movie sentiment based on reviews and score on rotten tomatoes using sentiwordnet. In *2018 International Seminar on Application for Technology of Information and Communication*, pages 202–206. IEEE.

Hutto, C. and Gilbert, E. (2014). Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 8.

Isinkaye, F. O., Folajimi, Y., and Ojokoh, B. A. (2015). Recommendation systems: Principles, methods and evaluation. *Egyptian informatics journal*, 16(3):261–273.

Ma, Y., Chen, G., and Wei, Q. (2017). Finding users preferences from large-scale online reviews for personalized recommendation. *Electronic Commerce Research*, 17(1):3–29.

Musto, C., de Gemmis, M., Semeraro, G., and Lops, P. (2017). A multi-criteria recommender system exploiting aspect-based sentiment analysis of users' reviews. In *Proceedings of the eleventh ACM conference on recommender systems*, pages 321–325.

Petrusel, M.-R. and Limboi, S.-G. (2019). A restaurants recommendation system: Improving rating predictions using sentiment analysis. In *2019 21st International Symposium on Symbolic and Numeric Algorithms for Scientific Computing (SYNASC)*, pages 190–197. IEEE.

Poirier, D., Fessant, F., and Tellier, I. (2010). Reducing the cold-start problem in content recommendation through opinion classification. In *2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology*, volume 1, pages 204–207. IEEE.

Sondur, M. S. D., Chigadani, M. A. P., and Nayak, S. (2016). Similarity measures for recommender systems: a comparative study. *Journal for Research*, 2(3).

Terzi, M., Rowe, M., Ferrario, M.-A., and Whittle, J. (2014). Text-based user-knn: Measuring user similarity based on text reviews. In *International Conference on User Modeling, Adaptation, and Personalization*, pages 195–206. Springer.

Victor, P., Cornelis, C., De Cock, M., and Teredesai, A. M. (2011). Trust-and distrust-based recommendations for controversial reviews. *IEEE Intelligent Systems*, (1):48–55.

Yan, C., Chen, Y., and Zhou, L. (2019). Differentiated fashion recommendation using knowledge graph and data augmentation. *Ieee Access*, 7:102239–102248.

Zahid-samza595, S. (2020). Sentiment analysis of hotel reviews-performance evaluation of machine learning algorithms.