

# Enhancing online learning: sentiment analysis and collaborative filtering from Twitter social network for personalized recommendations

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## ABSTRACT

Online learning presents a major challenge for learners, namely the diversification of courses and information overload. In response to this issue, recommender systems are widely used. Nowadays, social networks have become a global platform where individuals share a multitude of information. For instance, Twitter is a social network where users exchange messages and interact with various communities. These interactions on social networks have created a new dimension in the field of online learning. In this article, we propose a novel approach that combines sentiment analysis of learners' reviews on social networks with collaborative filtering methods to provide more personalized and relevant course recommendations. To achieve this, we explored different models to analyze the sentiments of tweets related to online courses. Additionally, we used collaborative filtering based on k-nearest neighbors (KNN). Our results demonstrate that integrating sentiment analysis provides more relevant recommendations. This has also been shown based on the calculation of root mean square error (RMSE) compared to a traditional approach. In this study, we demonstrated that by leveraging this information from social networks like Twitter, online learning platforms can enhance the effectiveness of their course recommendations, tailoring them to each individual learner's needs.

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## 1. INTRODUCTION

Social media plays a crucial role in our daily lives, allowing users to share their opinions, experiences, and emotions on various topics, including online courses [1]. In the field of e-learning, these data streams from multiple social media platforms provide a wealth of valuable information on how learners perceive and interact with different courses and subjects of study. The study conducted in [2] demonstrates the benefits of sentiment analysis adapted to e-learning platforms. This approach enables the collection of relevant learner feedback and a better understanding of their opinions, emotions, and preferences regarding the proposed educational content. Recommender systems have seen rapid expansion over the decades, being widely used in various domains such as entertainment, travel, music, and also in online learning platforms. For example, Spotify utilizes recommender systems to suggest music based on users' favorite music genres and listening habits. Similarly, travel platforms like Booking.com or TripAdvisor use recommender systems

to suggest hotels, restaurants, and tourist activities based on user preferences and reviews [3]. In the realm of e-learning, platforms like Coursera or Udemy also leverage recommender systems to suggest courses based on learners' interests and skills, considering user ratings and comments to provide the best-matched courses for their learning goals. Sentiment analysis can be particularly relevant in the recommendation system, as demonstrated in [4]. On the other hand, tacit knowledge, originating primarily from experience and often challenging to share, suggests an approach that combines sentiment analysis with a hybrid model of recommender systems [5]. This approach enhances the relevance and personalization of suggestions for food and movie reviews on Amazon.

Despite the advantages of collaborative filtering in recommender systems, it presents significant limitations. One of the main limitations is "data sparsity". In many systems, there is a large number of users and courses, but each user has only rated a small subset of these courses. This low data density makes establishing similarity relationships between users and courses challenging, leading to unreliable and potentially biased recommendations. Another limitation of collaborative filtering is the "gray-sheep" problem. Some users may have unique tastes and preferences that do not closely match those of other users. These "gray-sheep" users may be overlooked by traditional collaborative filtering, as their profiles do not align well with other users, resulting in recommendations that do not cater to their specific interests. To address these issues and enhance the reliability of recommendations in e-learning recommender systems, we propose an innovative approach that combines sentiment analysis of user reviews and feedback from social media platforms with collaborative filtering methods. By integrating sentiment analysis, our approach can leverage the wealth of data from social media to supplement the often-sparse ratings in collaborative filtering systems. Using natural language processing and machine learning techniques, we can extract and analyze the sentiments expressed by users toward the courses, providing valuable insights into learner satisfaction, interest, and preferences regarding the recommended content. By incorporating this information into the recommendation process, our approach delivers more relevant and personalized recommendations to users, considering not only their explicit ratings but also their implicit sentiments and emotions. This facilitates a more engaging, satisfying, and tailored online learning experience for each learner's individual needs. By efficiently harnessing data streams from social media and overcoming the limitations of collaborative filtering, our approach opens new avenues to enhance the overall quality of e-learning recommender systems.

In summary and to guide our research, we pose the following research questions:

- How can user sentiment analysis on social media enrich the quality of recommendations in collaborative filtering systems for online learning?
- To what extent can the integration of tacit knowledge through a hybrid approach improve the personalization of recommendations and address the challenges of "data sparsity" and the "gray-sheep" problem?

Our main contributions include:

- An evaluation of different models and approaches for selecting the sentiment analysis model.
- An assessment of the impact of user sentiment analysis from social media on enhancing recommendations in collaborative filtering systems for online learning.
- The introduction of an innovative approach that combines sentiment analysis with a hybrid model to integrate tacit knowledge into recommendation systems.

The rest of this article is organized as follows. Section 2 presents the theoretical background and a literature review in the field of sentiment analysis and recommender systems. Section 3 describes the methodology used to combine the two components. Section 4 presents the results and discussion, and section 5 offers the main conclusions and perspectives.

## 2. METHOD

Our research focuses on the intersection of two fields: recommendation systems and sentiment analysis. The proposed architecture consists of several components, as shown in Figure 1. This approach aims to leverage synergies between recommendation systems and sentiment analysis, providing more personalized and effective recommendations based on an understanding of learners' preferences.

Sentiment analysis; the system analyzes tweets related to a specific course to determine the overall sentiments of users towards it. We begin by preprocessing the tweets to remove special characters and links, then employ TextBlob to assign a sentiment polarity to each tweet. Simultaneously, we train the support vector classification (SVC) model on a set of tweets annotated with sentiment labels (positive, negative, and neutral). Sentiment analysis helps to understand how users perceive the article and whether it evokes positive or negative interest among them.

Collaborative filtering; this commonly used approach in recommendation systems is based on the principle that if users share similar preferences for certain items, they are likely to appreciate similar items

[6]. In our proposed methodology, the system pre-processes user ratings for different courses and builds a model to identify similarity relationships between users and courses. Utilizing this information, the system predicts ratings that each user might give to items they have not yet rated.

Combination of both components; once the system obtains collaborative filtering predictions for a given article and sentiment analysis scores from tweets related to it, it combines these two pieces of information to establish a final recommendation. The predicted rating from collaborative filtering represents the user’s preferences based on ratings from other users with similar tastes. On the other hand, the sentiment analysis score of the tweets indicates how twitter users, in general, perceive the course.

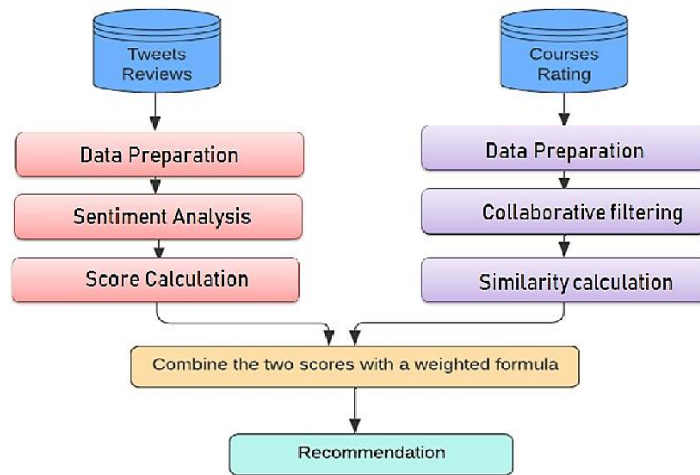


Figure 1. The proposed architecture

**2.1. Sentiment analysis**

This section provides a detailed explanation of the different stages of the methodology and the various approaches used in each stage for the first component Sentiment analysis. Figure 2 illustrates the sequential workflow of the methodology, highlighting the methods, algorithms, and data status in each phase. In essence, this comprehensive exploration enhances the understanding of the sentiment analysis process and its methodological intricacies.

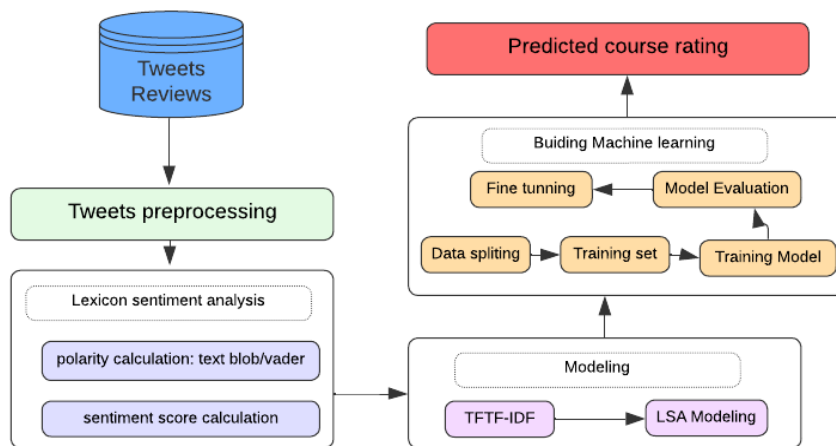


Figure 2. Sentiment analysis process

**2.1.1. Preprocessing**

The process starts with meticulous data preprocessing from the Twitter social network. To ensure data reliability, we apply filters to select relevant and representative tweets within our study context. Once

the dataset is compiled, we proceed with several preprocessing steps to clean the tweets and prepare them for analysis. This includes removing special characters, normalizing the text, correcting spelling errors, and eliminating links and HTML tags [7]. These steps aim to ensure data quality and make the tweet text more suitable for subsequent analysis.

### 2.1.2. Polarity

To assess the polarity of sentiments expressed in the tweets, we explore various approaches. We utilize TextBlob, a widely-used natural language processing library [8], and SentiWordNet, a lexicon based database annotated with sentiment scores [9]; these approaches enable us to assign a polarity value (positive, negative, or neutral) to each tweet based on associated words and contexts. In addition, we also employ valence aware dictionary for sentiment reasoning (VADER), a rule-based model that considers word valence and linguistic rules to evaluate sentiments [10].

### 2.1.3. Feature engineering

The transformation of tweets into numerical vectors through term frequency-inverse document frequency (TF-IDF) involves measuring the frequency of specific words in each tweet [11] while considering their relative importance within the entire corpus of tweets. Consequently, keywords frequently mentioned in positive tweets will receive higher TF-IDF scores, whereas less relevant words will be assigned lower weights. This approach allows for quantifying the presence of words and assigning them weights based on their relevance within the overall context of tweets.

### 2.1.4. Model sentiment analysis

Once the TF-IDF matrix is obtained, we use it as input to machine learning algorithms to perform sentiment analysis. In Our case we use it for several models such as naive Bayes; SVC and random Forest. Once the model is trained, we use it to predict the sentiment of new text data by converting the text data into a TF-IDF weighted vector using the same vocabulary set and TF-IDF calculation as before, and then applying the trained model to obtain the predicted sentiment label. Fine tuning hyperparameters: Furthermore, to enhance the performance of the machine learning models, we perform meticulous fine-tuning of hyperparameters. This involves experimenting with different parameter combinations to find optimal values that maximize accuracy and overall model performance [12].

## 2.2. Recommendation system

As seen in Figure 3, there are three types of collaborative filtering models. In our architecture, we implement collaborative filtering using the k-nearest neighbors (KNN) algorithm combined with the Pearson correlation coefficient to calculate user similarity. Our main goal is to predict course ratings that users have not yet evaluated on an online learning platform. Once the data was preprocessed, we used the KNN algorithm to identify the k most similar users to each given user in terms of ratings given to common courses [13]. Using Pearson correlation, we measured the similarity between ratings given by users by normalizing them with their respective means [14].

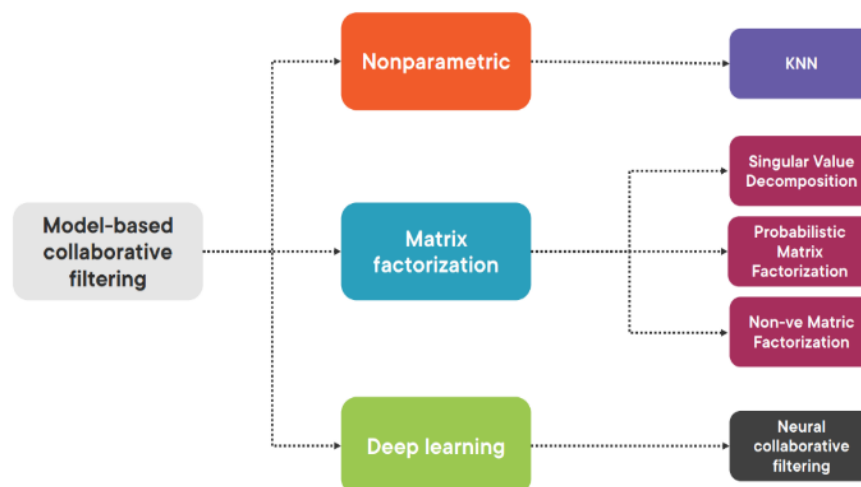


Figure 3. Models-based collaborative filtering

Collaborative filtering can be affected by several issues of “sparsity” meaning the lack of ratings for certain courses [15]. This makes it challenging to find similar users and can impact the accuracy of predictions. Another problem is that collaborative filtering can be biased towards popular courses or those highly rated by a large number of users. This may lead to predominant recommendations for these popular courses, neglecting lesser-known ones. Additionally, new courses pose a challenge as collaborative filtering may struggle to make accurate recommendations due to insufficient ratings. To address these issues, we will integrate sentiment analysis into the recommendation system component. By incorporating sentiment analysis, we can leverage rich data from social media to overcome the common lack of ratings in collaborative filtering systems.

### 2.3. Recommendation system combined with sentiment analysis

The proposed recommendation method is a collaborative filtering approach based on Pearson’s correlation, incorporating sentiment analysis. In our approach, we employ a recommendation algorithm that combines Pearson similarity and sentiment score through a weighted formula to derive an overall similarity score between users. It takes the courses rated by the given user and calculates the Pearson similarity with other users. Then, it combines the Pearson similarity scores and sentiment scores to predict the rating for the specific course. The adjustable weight allows controlling the relative importance of each score. Finally, the system returns the predicted rating for the course, facilitating the recommendation. The following steps are followed:

- Collection of courses rated by user  $ua$ .
- Calculation of Pearson similarity between user  $ua$  and all other users based on the shared course ratings and reviews. The  $k$  most similar users to  $ua$  are selected. For this, we use the (1).

$$sim\ ua, ub = \frac{\sum_{i \in I_{ua} \cap I_{ub}} (r_{ua,i} - r^{ua})(r_{ub,i} - r^{ub})}{\sqrt{\sum_{i \in I_{ua} \cap I_{ub}} (r_{ua,i} - r^{ua})^2 \sum_{i \in I_{ua} \cap I_{ub}} (r_{ub,i} - r^{ub})^2}} \quad (1)$$

where  $sim\ ua, ub$  is the Pearson similarity users  $ua$  and  $ub$ ;  $r_{ua,i}$  is the rating given by  $ua$  for course  $i$ ;  $r_{ub,i}$  is the rating given by  $ub$  for a course  $i$ ;  $r^{ua}$  is the average rating given by  $ua$  for self-rated; and  $r^{ub}$  is the average rating given by  $ub$  for self-rated.

This formula measures the linear correlation between the ratings given by the two users by normalizing with the users’ rating averages. The similarity ranges from -1 (perfect negative correlation) to 1 (perfect positive correlation). We then combine the Pearson similarity scores and sentiment scores to obtain an overall similarity score between users. We select the  $k$  most similar users and use their ratings to predict the rating for the specific course. For this, we use (2). This formula combines the Pearson similarity scores and sentiment scores using a weighted formula, where  $w$  is a weight that controls the relative importance of each score. This allows us to adjust the contribution of each score based on its importance. The resulting overall score represents the overall similarity between two users, considering both their rating similarity and sentiment similarity, which improves the quality of the rating prediction.

$$similarity\_score = (w \times prs\ scr) + ((1 - w) \times smt\ scr) \quad (2)$$

where  $w$  is a weight between 0 and 1 that controls the relative importance of the Pearson similarity scores and sentiment scores. A  $w$  of 1 means that only the Pearson similarity is used, while a  $w$  of 0 means that only the sentiment similarity is used;  $prs\ scr$  is the Pearson similarity score between two users; and  $smt\ scr$  is the sentiment similarity score between two users.

## 3. RESEARCH METHODS

### 3.1. Sentiment analysis

Ezaldeen *et al.* [16] introduce the valence aware dictionary and sentiment reasoner (VADER) model, a rule-based sentiment analysis approach for social media texts using a pre-annotated word dictionary and linguistic rules. While effective, VADER has limitations in detecting figurative expressions and cultural variations. Feature engineering techniques like TF/IDF and logistic regression, as demonstrated by Saaqib *et al.* [17], enhance sentiment prediction in Amazon product reviews, though potential biases may arise. Lou *et al.* [18] employ Convolutional Neural Networks for sentiment analysis in movie reviews, finding the “bag-of-words” model superior in classification. Samih *et al.* [19] propose the “Improved words vector for sentiment analysis,” outperforming doc2vec and TF-IDF in sentiment classification using XGBoost.

In e-learning, El Maazouzi *et al.* [20] integrate sentiment analysis into a chatbot using LSTM, achieving 91% accuracy. Another study [21] evaluates online education sentiments during the coronavirus disease of 2019 (COVID-19) pandemic, employing machine learning models like random forest and support vector machines. This provides insights into student concerns and complements earlier social media sentiment analysis. Clarizia *et al.* [22] propose a sentiment analysis approach using improved word representation and BiLSTM networks, outperforming traditional methods but acknowledging limitations. Madathil *et al.* [23] present a hybrid recommendation system in online learning, integrating adaptive profiling and sentiment analysis, though the accuracy

### 3.2. Recommender system

Liu *et al.* [24] provide a comprehensive analysis of course recommendation systems, examining various approaches, techniques, and algorithms, and exploring factors such as user preferences and contextual information that impact system performance. Fayyaz *et al.* [25] focus on personalized recommendation in IoT scenarios, employing collaborative filtering to tailor product or service suggestions based on user preferences and device interactions. Experimental results show the effectiveness of this system, although challenges like managing internet of things (IoT) datasets and adapting to dynamic user preferences persist. In e-learning, Salloum and Rajamanthri [26] emphasize the importance of recommender systems, highlighting their role in enhancing the learning experience by providing personalized content. They stress the tools' effectiveness in optimizing student engagement and academic progress. Khanal *et al.* [27] discuss the significance of technology-enhanced learning (TEL) in higher education, emphasizing the benefits of learning object repositories and open educational resources. They introduce MoodleREC, a hybrid recommendation system, promising improved search and selection of relevant learning objects, along with socially generated insights on their usage in other courses, contributing to the evolution of digital education.

## 4. RESULTS AND DISCUSSION

In this study, we conducted several experiments to assess the effectiveness of two text feature extraction approaches, namely the bag-of-words (BoW) model and term frequency-inverse document frequency (TF-IDF). The objective was to analyze how these techniques influence the representation of texts. Concurrently, we explored the impact of data preprocessing on model performance, examining how different data cleaning and preparation methods can influence the results. Additionally, our study delved into the effectiveness of combining recommender systems with sentiment analysis. We investigated how the integration of these two approaches can enhance the accuracy of recommendations. Furthermore, we examined the use of Pearson similarity as a measure of similarity for the recommender system, evaluating the relevance of recommendations based on this metric.

### 4.1. Dataset

The dataset used in our recommendation algorithm consists of two distinct parts: E-learning course: Tweets review dataset: This open dataset contains reviews and comments left by Twitter users on various E-learning courses. Each record in this dataset includes a unique course identifier, the content of the tweet (review), optionally user information who left the comment, and other relevant metadata. Open-source dataset: On online courses: This second dataset consists of detailed information about online courses from different learning platforms. It gathers diverse data such as course identifiers, course names and descriptions, evaluations, and ratings given by users who have taken these courses, as well as statistics on their popularity and difficulty level. This dataset is comprehensive, covering thousands of online courses from multiple platforms, and includes over 9 million comments left by learners.

### 4.2. Sentiment analysis

#### 4.2.1. Feature engineering

Involves transforming raw data into a format suitable for machine learning algorithms. One common method of feature engineering is data vectorization using term frequency inverse document frequency (TF-IDF). In our study, two approaches were adopted for feature engineering: The first approach involves creating a bag-of-words (BOW) model from e-learning-related tweets [28], representing each document as a vector of word frequencies. Then, the TF-IDF model is constructed using the BOW vectors, assigning weights to words based on their frequency in the document and rarity across the corpus. The second approach directly utilizes the TF-IDF model on the text data without creating a separate BOW model. The comparative analysis of the two approaches has shown that the second approach offers significant advantages in terms of speed of execution and simplified processing. Furthermore, despite the absence of the BOW model, the second approach managed to retain sufficient contextual information in the tweets.

#### 4.2.2. Polarity

In our study, we used three different approaches (TextBlob, SentiWordNet, and VADER) to evaluate the polarity and subjectivity of the texts. Polarity measures the emotional tone of a text, ranging from positive to negative, with neutral in between [29]. Comparing the results of the different approaches, as shown in Figure 4, we observe a similarity between TextBlob and SentiWordNet in terms of polarity, while VADER exhibits a greater variation.

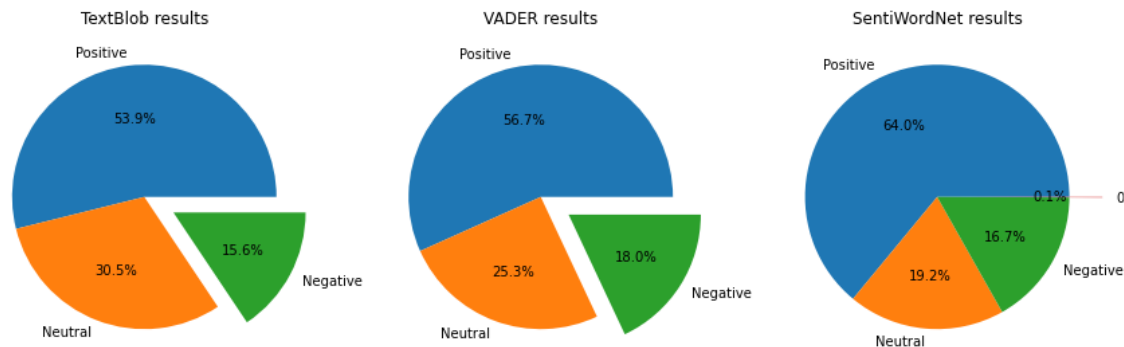


Figure 4. Comparative analysis of polarity: TextBlob, SentiWordNet, and VADER

#### 4.2.1. Building machine learning

In our study, we used three models for sentiment analysis: naive Bayes classifier, SVC, and random forest. The naive Bayes classifier is based on Bayes' theorem [30], SVC is a machine learning model based on support vectors, and random forest is an ensemble model based on decision trees. To evaluate their accuracy, we compared them to the TextBlob, SentiWordNet, and VADER methods. Accuracy measures the precision of predictions compared to the total predictions made [31]. This evaluation allows us to determine which method provides the best performance for sentiment analysis in our study. Naive Bayes: When comparing the naive Bayes models applied to TextBlob, VADER, and SentiWordNet, we found that the naive Bayes model applied to TextBlob achieved the highest accuracy as shown in Table 1. As presented in Table 1, the naive Bayes model, using the TextBlob approach, exhibited high precision in predicting the sentiment of texts. This can be attributed to its probabilistic approach based on Bayes' theorem, which considers the independent features of the texts to determine sentiment Figure 5.

VADER, a lexicon, and rule-based model also yielded satisfactory results, albeit with slightly lower accuracy compared to naive Bayes-TextBlob. SentiWordNet, which assigns sentiment scores to words based on their semantic properties, demonstrated lower precision in comparison to naive Bayes-TextBlob and VADER. However, it remains a useful method for evaluating word polarity and aggregating this information to determine the overall polarity in a text. For the rest of the models, we will use TextBlob.

SVC/random forest: For the next steps, we employ the SVC model, which is an efficient supervised learning algorithm for binary and multiclass classification problems. It can effectively separate different data classes using an optimal hyperplane, even in higher-dimensional spaces through the use of kernels. Additionally, we also explore the utilization of the random forest algorithm, an ensemble learning method that combines multiple decision trees for classification or regression tasks. Each tree is trained on a random subset of the data and a random subset of features, enhancing the model's performance and robustness by reducing overfitting and increasing overall accuracy. We utilize evaluation metrics such as precision, and F1-score to compare the performance of the three models and determine which one provides the most reliable and accurate results for our approach to enhancing e-learning recommendations [32].

In conclusion, when comparing the three models: naive Bayes, SVC, and random Forest, for sentiment analysis as shown Table 2, we found that SVC achieved the highest accuracy. naive Bayes, a probabilistic model, performed well in predicting sentiment but had slightly lower accuracy compared to SVC. It relies on the assumption of independence between features and uses Bayes' theorem for classification. SVC, based on support vectors, demonstrated the best accuracy among the three models. It searches for an optimal hyperplane to separate different sentiment classes. SVC is known for its ability to handle complex datasets and nonlinear relationships. Random forest, an ensemble model combining multiple decision trees, yielded competitive accuracy results but was slightly behind SVC. It utilizes the aggregation of predictions from individual trees to make final predictions. Considering accuracy as the primary metric, SVC emerged as the most effective model for sentiment analysis in our study.

Table 1. TextBlob, VADER, and SentiWordNet comparison

Model	TextBlob	VADER	SentiWordNet
Accuracy	0.83	0.79	0.7
Macro avg	0.79	0.76	0.47
Weighted avg	0.83	0.79	0.71

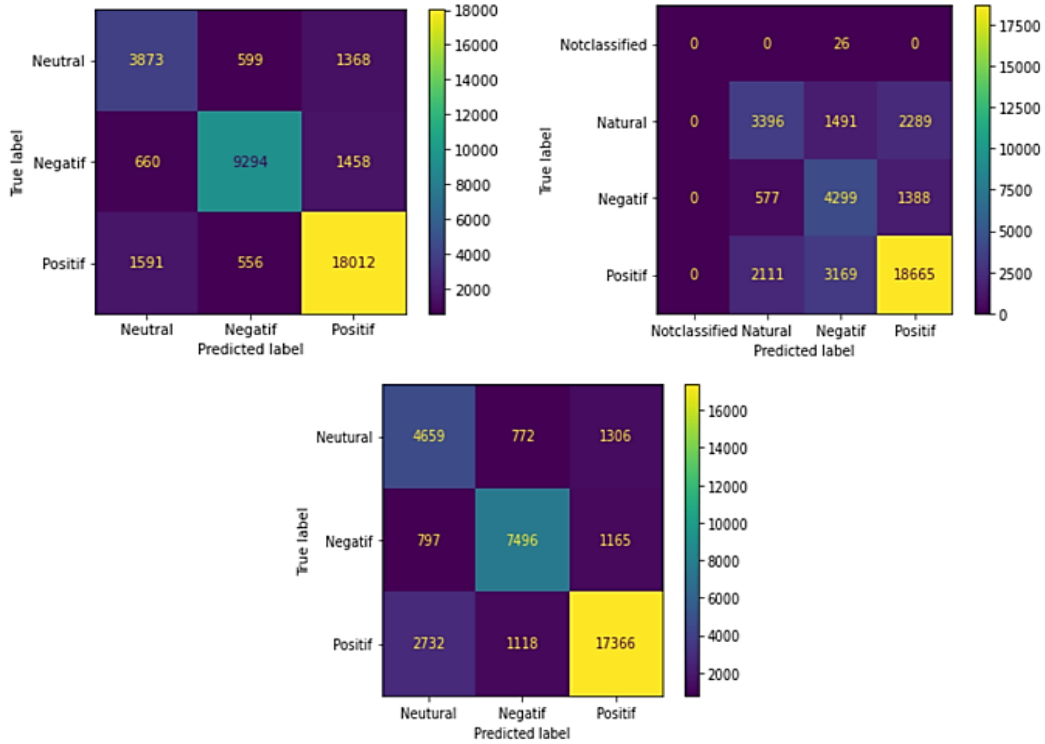


Figure 5. Sentiments label’s comparisons

Table 2. Model’s comparison

Model	Naive Bayes	VADER	Random forest
Accuracy	0.83	0.95	0.95
Macro avg	0.79	0.97	0.91
Weighted avg	0.83	0.97	0.90

4.3. Recommender systems combined with sentiment analysis

4.3.1. Recommendations based on correlations

We use the Pearson correlation coefficient (R) to assess the linear correlation between the evaluations of two courses [33]. Interestingly, the course with the highest average evaluations does not necessarily have a high rating. Consequently, relying solely on the number of evaluations for recommendations can lead to errors. To enhance the system, users with fewer than 40 evaluations and courses with fewer than 100 evaluations are excluded to ensure statistical validity of the results. Table 3 displays courses similar to “HTML5”, “CSS3”, and “JavaScript”. We further computed the overall similarity of the chosen course to each of the similar courses. The similarity distance between two courses determines their degree of similarity.

Table 3. Online courses: similarity and recommendations for HTML5, CSS 3, and JavaScript

Title	Category/Sub	Similarity
React Shopping Cart (Node, Express, React, MongoDB)	Web Development	0.8319
Master Laravel & Create High-Level Application	Web Development	0.7934
Master .NET and C# Unit Testing	Web Development	0.6898
C# pour les debutants	Web Development	0.6876
Data Analysis on Datasets used in Energy Economics	Data Science	0.4321



### 4.3.2. Collaborative filtering using KNN

In this section, we analyzed our recommendation system using KNN. We randomly selected a user from the dataset, where each user had rated a total of 40 courses. By using the user's preferred courses, we calculated similar courses from a set of new courses, creating a list of recommended courses based on their preferences. Recommendation combined with sentiment analysis with sentiment analysis: we compiled a collection of courses, forming a potential set of new courses to recommend to the randomly selected user. Next, to make the final selection, we calculated the combined score as presented in (2) with a value of 'w' equal to 0.2. The ten courses finally recommended to the user are listed in Table 4. We can observe that all the selected courses receive high similarity scores and predicted ratings among the set of courses.

Table 4. Course recommendations for the selected user: similarity and combined score with sentiment analysis

Title	Category/Sub	Similarity	Predicted rating text	Combine - score
React Shopping Cart (Node, Express, React MongoDB)	Web Development	0.8319	6.8	3.656
Master Laravel & Create High-Level Application	Web Development	0.7934	6.7	3.632
Master .NET and C# Unit Testing	Web Development	0.6898	6.5	2.956
C# pour les debutants	Web Development	0.6876	6.4	2.921
Data Analysis on Datasets used in Energy Economics	Data Science	0.4321	6.3	2.675
Learn C#10 & .Net 6 by coding Beginners in Arabic	Coding languages	0.343	6.2	2.567
ALL PHP Basics	Coding languages	0.234	6.1	2.342
The Complete Linux Privilege Escalation Course 2022	IT &software	0.211	6.7	2.258
DAX Dashboard Design - 10 Easy Steps	IT &software	0.134	6.7	2.189
Microsoft SQL Server Failover Cluster	Database Design	0.103	6.1	2.087

### 4.3.3. RMSE

On the other hand, to verify the effectiveness of the presented methodology, we conducted a comparative evaluation with the traditional collaborative filtering approach. For this purpose, we selected three courses from the dataset, filtering them based on the "Business and Development" category, and analyzed the sentiments of tweets related to these courses on Twitter. Using collaborative filtering, we predicted the ratings for these courses, and then applied our proposed approach to generate new predictions. Finally, we calculated the root mean square error (RMSE) for each approach to compare their performance Table 5. The analysis of the results shows that our approach has a significantly lower RMSE compared to the traditional approach, demonstrating its superior effectiveness in data prediction. This improvement was observed across all algorithms and values of "w". The optimal performance was achieved when w was set to 0.2.

Table 5. RMSE calculation architecture

Title	Without sentiment analysis	With sentiment analysis
How to create online courses	0.689	0.683
27 hrs data structures+Algorithms	0.745	0.741
How to master the law of attraction- Abundance	0.415	0.408

## 5. CONCLUSION

In conclusion, our study proposes an innovative approach that combines sentiment analysis of user reviews and feedback from social media platforms with collaborative filtering methods to enhance e-learning recommender systems. By integrating sentiment analysis, our approach leverages the rich data from social media to supplement the often-sparse ratings in collaborative filtering systems. Using natural language processing and machine learning techniques, we extract and analyze the sentiments expressed by users towards the courses, providing valuable insights into learner satisfaction, interest, and preferences regarding the recommended content. Incorporating this information into the recommendation process allows our approach to deliver more relevant and personalized recommendations to users, considering not only their explicit ratings but also their implicit sentiments and emotions. This facilitates a more engaging, satisfying, and tailored online learning experience for each learner's individual needs. By efficiently harnessing data streams from social media and overcoming the limitations of collaborative filtering, our approach opens new avenues to enhance the overall quality of e-learning recommender systems. For future work within the e-learning domain, we can explore the integration of deep learning models like RNNs or transformers for sentiment analysis and recommendation systems. Additionally, developing hybrid models that combine

collaborative filtering with content-based filtering or knowledge-based approaches can lead to more comprehensive recommendations. Expanding data sources beyond tweets, such as course reviews and user feedback, can provide a more holistic understanding of sentiment. Incorporating contextual information, such as user demographics and course metadata, can further enhance recommendations. Furthermore, evaluating user satisfaction and incorporating feedback loops can continuously improve the recommendation system.




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