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Multi-domain aspect-oriented sentiment analysis for movie recommendations using feature extraction

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ABSTRACT

Sentiment analysis is a well-recognized research field that has acknowledged significant attention in recent years. Researchers have made extensive efforts in employing various methodologies to explore these domains. Sentiment classification plays a fundamental role in natural language processing (NLP). However, studies have shown that sentiment classification models heavily depend on the specific domain. In the context of movie industry, where the demand for reliable movie reviews is high and not all movies are of exceptional quality and worthy of viewers time. Therefore, people depend on movie reviews before watching a movie. This explores the use of data from various domains to improve classification performance within each domain, addressing the difficulty of multi-domain sentiment classification in natural language processing. Therefore, it is crucial to effectively utilize shared sentiment knowledge across different domains for real-world applications. To solve these issues, a multi-domain aspect-oriented sentiment analysis for movie recommendation using feature extraction techniques. The main contribution of this work is to eliminate the time for users to go through a lengthy list of movies to make their decision. The novelty of this work is analysis of different movie genres, TV shows genres with accurate results. The presented approach's performance is validated by evaluating various metrics, including precision, recall, mean square error (MSE) and F1-score.

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1. INTRODUCTION

Data can be classified into two categories namely structured data and unstructured data. Unstructured data does not have predefined data types and constitutes a significant portion of the data generated in today's world. Social media platforms serve as one of the primary sources of unstructured data. These platforms allow individuals to express their emotions, such as anger, happiness, or sadness, and serve as effective communication channels where people can share their experiences. However, due to the large volumes of data available from these platforms, text mining and sentiment analysis have gained huge importance due to data availability [1].

In recent times, emerged the incredible exploration of sentiment analysis, the main reason is the extensive global presence of web as well as increasing prevalence of social networking platforms such as Facebook, Instagram, and Twitter. These platforms provide large public spaces where individuals engage in conversations, share their thoughts and emotions through various forms of digital content [2]. In the recent times, the technology has great impact on people's lives. Review comments are available on the internet for any service or product that exists in everyday life. The users produces sources with ability to rate, give comments and provide feedback about the services they have experienced [3]. Sentiment analysis involves utilization of text analysis (TA), natural language processing (NLP), computational linguistics, biometrics processing to detect, extract, measure as well as learn subjective information and affective states.

The proliferation of user-generated data in the form of blogs, forums, and tweets has experienced immense growth. As the usage of these platforms has increased, people have begun expressing their opinions on a wide range of topics, spanning from personal to public and from general to specific matters. Social media serves as a powerful platform for understanding individual sentiments [4]. Analysing user posts on social media can inform decision-making in various domains, including business, elections, product reviews, and government [5]. Sentiments refer to the emotions or opinions expressed within texts or images, and they significantly influence decision-making processes.

Commonly referred to as viewpoint examination and opinion mining, sentiment analysis has been largely researched in domains like e-commerce websites and social networks. This has attracted the attention of organizations and associations to understand and analyse public opinions regarding the products and services they offer [6]. Sentiment analysis involves the identification and categorization of opinions and attitudes expressed in texts toward a specific topic or product. The assessments can encompass positive, negative, or neutral sentiments, and the analysis can be conducted at document, sentence, or word level. An increasing number of individuals express their emotions through textual information on social networks at any time and from any location.

Manual identification of sentiment-based comments can be both inaccurate and time-consuming. Automating the sentiment analysis process using machine learning models can provide software professionals with quick insights into the sentiments and opinions of other developers regarding software products, libraries, development, and maintenance tasks at a glance. The main objective is to automatically analyse extensive review datasets and classify them into sentiment polarities: positive, negative, or neutral [7].

Sentiment analysis is an interesting and important research area in NLP. Data-driven techniques like machine learning and machine learning offer direct and effective solutions for solving emotion classification problem [8]. Therefore, the classification implementation is not accurate if processing inputs that include multiple tasks. Concluding the best sentiment analysis model for multitasking situations remains controversial in field [9].

Many movies are available on all familiar over-the-top (OTT) platforms. These platforms release several new movies daily. Recommendation systems help guide users to choose from overloaded content. Most of investigation on these recommender systems is based on existing movies. It requires model that recommends upcoming movies so that viewers can individually decide that recent movies to watch in the future [10].

Movie recommendation systems help us to looking for the preferred movies and also to reduce the time to find the user favourable movies of information on internet is also increasing rapidly. As output, consumers find it hard to choose exact data they need, and learners find it hard to suggest to users exactly what they need. This is where recommendation systems come into play, directing content based on consumer preferences [11]. In modern world, where technology is at forefront of each industry, information and data are in abundance. Therefore, a recommendation system using sentiment analysis helps to process this huge amount of information and quickly filter out needed data related to user selection [12].

A movie recommendation system predicts or suggests movies that a user may like based on the user's earlier viewing list and history. The movie recommendation system efficiently assists users in discovering movies that match their preferences, whether derived from their own experiences or from the other users. Hence, sentiment analysis is implemented to reviews/comments to also contribute to movie ratings and lead to better recommendations [13]. Multi-domain sentiment analysis approaches focus on developing models to transfer information between different domains. Although these approaches enable the transfer of domain-specific knowledge to other domains, limitation is the need to construct new transfer models for each additional domain analysis [14].

Methodologies for the extraction of textual data primarily concentrate on extracting, scanning, or evaluating the current solid evidence. The information has an analytical dimension, but contextual aspects are reflected in certain other textual material. These aspects form the heart of the sentiment analysis, primarily thoughts, feelings, judgments, behaviours, and emotions [15]. Sentiment analysis can be conducted at different phases like the sentence level, word level, or document level. Adequate volumes of specialized data are necessary for sentiment analysis to be effective. However, the most challenging aspect of the sentiment analysis training process is not the availability of a large amount of data [16].

Over the years, various approaches and systems are presented to predict the movie reviews, however they are not accurate and most of the research works were not focused on multi-domain analysis of different genres of Television (TV) shows and movies. To solve these issues, this work presents a multi-domain aspect-oriented sentiment analysis approach for recommending movies. Utilizing feature extraction techniques which will improve the accuracy as well analyze different movie genres and TV shows in real time with better results.

The rest of the work is organized as follows: the section 2 describes the literature survey where different research works related to sentiment analysis, movie recommendation systems. The section 3 presents multi-domain aspect-oriented sentiment analysis approach for recommending movies, utilizing feature extraction techniques. The section 5 analyzes the result analysis. Finally, the conclusion is discussed in section 5.

2. LITERATURE SURVEY

A method is integrated with sentiment analysis as recommendation systems. A new approach is described which uses aspect sentiment analysis and external knowledge to predict the ratings and to generate content, personalized-rich recommendations. Fine tuned bidirectional encoder representations from transformers (BERT) is used for the sentiment analysis and transformer performance is extended for the generation of recommendations through the attention of BERT. The results showed that this method has better performance than baseline models [17].

Tourist recommendation system didn't treat well for current trend and sentiment analysis from knowledge of microblogging. Tourist's sentiments on attractions determine the attitude of tourist’s over attractions and recommends the attraction with appropriate sentiments. The reason of using tourist tweets is to understand present trend, public opinions, and user’s reaction to that particular place. An experiment performed using a public database yielded better results. The performance of presented approach is need to improved in future [18].

The framework primarily focuses on generating a database using two different sources: pre-existing data and data extracted from Twitter, specifically movie ratings. natural language processing, sentiment analysis concepts are utilized in Python to extract data from Twitter. Once the complete dataset is generated, it is passed to BERT model to identify key features for binary classification of ratings as either good or bad. This recommendation system offers improved options to customers based on their interests, using historical data. This model could be improved in future work to further guide the model modification, which may bring better analysis performance [19].

A novel approach for sentiment analysis with neural attention network is describes. The authors collect online data through the Twitter App, their performance is assessed using a confusion matrix that includes parameters like true positive (TP), true negative (TN), false positive (FP), and false negative (FN). Semi-supervised topic is employed for extracting the aspects of different products and their related sentiment lexicons from the reviews of user, and the reviews are applied to long short-term memory (LSTM) encoder through an interactive neural attention mechanism to obtain better results. This model needs to be explored to deal with both implicit and explicit feedbacks for rating and ranking performance [20].

Sentiment analysis is used for the creation of feature vectors as input nodes. This system performed the noise reduction on the dataset for improving the performance of user ratings classification. Deep belief network (DBN) is employed for providing good recommendations [21].

To enhance accuracy as well as timeliness of mobile movie recommendation methods, it provides movie recommendation analysis depended on hybrid models and sentiment analysis on Spark platform. This approach uses a hybrid recommendation method to build a preliminary list of recommendations. Then use sentiment analysis to optimize list. Finally, a hybrid recommendation method with sentiment analysis is executed on the spark platform. More effective interactions will need to be explored between micro-video sentiment information, content information [22].

A new model that uses social networks and analyzes user preference data expressed in microblogs to evaluate similarities between online movies and TV episodes. To best the knowledge, this is initial attempt to bridge the gap between film and television viewing spheres through social media activity. This task will be simple implemented to online media streaming sites, where microblogging can be mined to provide clients with intelligent program recommendations [23]. A unified visual content matrix factorization is used for the integration of features for movie recommendation systems. Although this technique showed good results only in terms of accuracy, the F1-score still has a lot of room for improvement, particularly for sentiment classes that are infrequently present in dataset [24].

A new project for movie recommendation system by utilizing user opinion and similarity analysis is described. The main purpose of this approach is to identify type of opinion (positive, negative, or neutral) about the movie and suggest a list of top K recommendations to the user. Aspect-based specific ratings are obtained from the ratings, and the recommended ratings for users also vary according to the user's similarity and their rating patterns. Finally, validate the suggested movie recommendation system using various evaluation criteria and showed that our suggested method also outperformed the conventional system [25].

From the literature review, it is observed that, many research works are presented on movie recommendation system but not focused on different genres of TV shows and movies. Earlier approaches were not obtained more than 95% of performance in terms of Precision, F1-score and recall. Here in this work, we will fill this gap and our proposal will achieve more than 95% performance in terms of precision, recall and F1-score.

3. MULTI DOMAIN ASPECT ORIENTED SENTIMENT ANALYSIS FOR MOVIE RECOMMENDATION

The paper introduces a multi-domain aspect-oriented sentiment analysis approach for recommending movies, utilizing feature extraction techniques. The main aim of this system is to provide the accurate movie reviews to the users in real time using sentiment analysis and deep dense model with hueristic weight. This approach analyzes the different TV genres, movie genres which have most number of positive reviews. Figure 1 presents a workflow diagram that illustrates the proposed approach. The study of NLP includes important research in multi-domain sentiment classification. In order to accomplish this objective, data is collected from a wide range of sources, including various websites as well as popular social media platforms. The collected reviews are preprocessed to remove the unnecessary data, noise.

In sentiment analysis, feature extraction plays a vital role by pre-computing features for each modality. These computed parameters are then utilized as inputs for transformer blocks. In context of text sentiment analysis, the goal is to extract emotions-related information from a large volume of documents. To achieve this, an ideal representation method is needed to effectively extract structured data from unstructured text. This method should accurately capture essential information such as text content, theme, domain, and structure, while also reduces dimensionality of feature space and strengthening textual information.

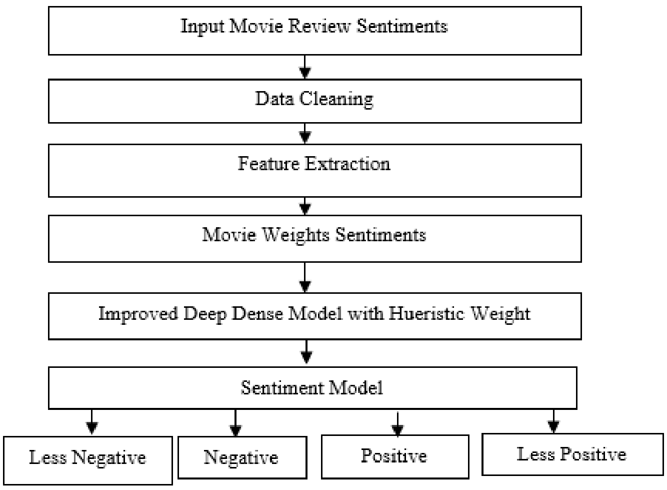

Figure 1. Block diagram of multi-domain aspect oriented sentimental analysis appraoch

Sentiment analysis of a movie review aims to determine the positive/negative sentiment expressed in review, which can ultimately contribute to the overall rating of the movie. Within a neural network, weight is the parameter responsible for modifying input data within hidden layers of network. The network comprises nodes, or neurons, with each node possessing inputs, weights, and a bias value. Heuristic weights are assigned to each variable, and these weights increase when the corresponding variable is involved in a dead-end during search. The variable with the highest weight is selected for instantiation. A simple hybrid recommender is implemented using the content based and collaborative filter based engines. The input and outputs of hybrid recommendor are as follows: input: user ID and the title of a movie. Output: similar movies sorted on the basis of expected ratings by that particular user.

Content-based recommenders make use of user-provided data, either explicitly or implictly. This data is utilized to generate a user profile, which is then used to recommend items for users. In context of a content-based recommendation system for movies, attributes like genre, director, description, and actors are utilized to provide suggestions. The underlying concept is that if a user enjoyed a particular movie or show, they are likely to appreciate movies or shows to it. Two content-based recommenders are implemented based on different factors: i) movie taglines as well as overviews, and ii) movie crew, cast, genre as well as keywords. Due to limited computing power available, a subset of all available movies is used. The overall transfer function of the collaborative filter presented as in (1) describes the criteria with weights formulation on each type of feature response for movie recommender. Let W be the weight prediction feature and Two inputs of count values from the dataset movie features are considered with vote count voting average. Let 'S' be the value for weight chosen randomly for rating of the particular movie to be 3 or greater than 3. 'K' is the value for rating less than 2. 'M' is the value for greater than 4. The overall rating value is given by:

$$R\_i = (Sum(P\ (x_i).X_i) + (Sum(P\ (y_i).Y\_i)/(x\_i^{*}y\_i))) \quad (1)$$

the effect of feature transfer function on the type of weights calculated via two datasets chosen and estimated its accuracy. For dataset meta dataset, this design provides an IGCF (model with its linear prediction. The linear formulation for the recommender is given by:

$$R(i) = \frac{\sum_{i=1}^{N} P(x_i)*X_i + \sum_{j=1}^{N} P(y_j)*Y_j}{x_i*y_i} \quad (2)$$

$$O(i) = \frac{\alpha}{R(i)} + \frac{\beta}{R(j)} \quad (3)$$

the (3) is very similar to the design of TF function in (4) hence approximated with linear feature from (2).

$$TF = \beta * \frac{\sum_{i=1}^{N} x_i^8 * w_i}{\sum_{i=1}^{N} W_i^8 * \sum_{i=1}^{N} y_i} + \alpha * \frac{\sum_{i=k}^{N} x_i^{16} * w_{i-k}}{\sum_{i=1}^{N} W_i^{16} * \sum_{i=k}^{N} y_{i-k}} \quad (4)$$

Here β, α are the parameters for the similarity percentages, which could vary from (0, 1). Depending upon the above equation parametric, with the filter weights of W_i^{n1}, W_i^{n2} is estimated with different rating assigned for each similarity movie index.

The general architecture of the transformer encoder involves combining multiple layers of multi self-attention heads, dropout, layer normalization, and two fully-connected layers. In this architecture, layer normalization and dropout layers are applied to contextual word embeddings, which are enhanced with positional information before entering the Transformer. The Transformer utilizes multi-head self-attention layers, as mentioned earlier. Once the Transformer generates attention score matrices, which represent the scores of each word based on different attention patterns, these intermediate features are combined using two fully-connected layers. Subsequently, the movie recommendation is obtained by passing through the pooler, dropout, and the last fully connected layer. The class probabilities are then calculated by using Softmax classifier. The hybrid recommender classifies the movie reviews as positive, negative, less positive and less negative. As a result, the user knows the best movie based on their ratings. The performance of presented system is validated in terms of precision, recall, mean square error (MSE) and F1-score.

4. RESULT ANALYSIS

Multi domain aspect oriented sentiment analysis for movie recommendations using feature extraction is implemented in this section. A hybrid recommender is implemented using content based and collaborative filter based engines. This approach effectively recommends the movie suggestion based on user movie ratings classification. The performance of presented approach is evaluated in terms of validation loss and validation binary accuracy.

MSE (5) is a measure that quantifies the error in statistical models by calculating the average of the squared differences between observed and predicted values.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \widehat{Y}_i)^2 \quad (5)$$

Where 'n' represents number of data points, 'Y_i' shows observed values and '$\widehat{Y}_i$' shows the predicted values. A lower MSE value specifies better performance with a value of 0 representing a perfect model. Learning curves provide valuable insights into assessing performance of machine learning model across different sample sizes of training dataset. Figure 2 illustrates the learning curves of the approach under consideration.

Learning curves provide insights into a model's performance on the training set and the validation set as the number of training samples varies. These curves plot the training and validation scores, represented by MSE values, on the y-axis, while the x-axis represents various sample sizes of training dataset. By examining these curves, we can understand how the model's performance evolves with increasing training data. Learning curves are useful for assessing a model's bias and variance errors. In Figure 2, the x-axis represents the epoch, which refers to a specific date and time used by the computer to measure system time. The y-axis represents the MSE value. Over time, the loss generally decreases, indicating that the model is learning, despite minor fluctuations.

A recommender method is data filtering method that leverages extensive datasets to accurately identify user preferences. The Netflix dataset encompasses diverse attributes, including show_id, type, title, director, cast, country, date_added, release_year, rating, duration, listed_in, and description. The Table 1 shows the performance metrics.

Presented approach has better precison, recall and F1-score values than naïve bayes classfier. Figure 3 shows the comparison of recommendation results between TV shows and movies. In Figure 3, the x-axis represents the type i.e., movie, TV shows and y-axis represents count value. From Figure 3 it is clear that there are more movies than TV shows on Netflix. Figure 4 shows the top geners of movies where different geners such as comedies, international movies (CMI), dramas, international movies, romantic movies (DIMRM), documentation international movies (DocIM), childern and family movies, comedies (ChFMC), childern and family movies (ChFM), dramas, independent movies. International movies (DInMIM), comedy, dramas, international movies (CDIM), stand-up comedy (SuC), documentaries (Doc) and dramas, international movies (DIM) are shown in x-axis while the y-axis represents the ratings. The three highest-ranked movie genres are dramas, followed by international movies and documentaries with standup comedy coming in third place. Figure 5 shows the top 10 genres of TV shows. In Figure 5, y-axis indicates rating and x-axis represents different TV show genres such as TV comedies (TVC), document series (Docs), anmi series, romantic TV shows (ASRTV), international TV shows, romatic TV shows, TV Dramas (ITVRTVD), international TV shows, romatic TV shows, TV comedies (ITVRTVC), reality TV (ReaTV) kid’s TV, TV, comedies (KTVTVC), crime TV shows, TV dramas (CrTVSTVD), international TV shows, TV dramas (ITVTVD), kid’s TV (KTV). The top-3 TV show genres are KTV, ITV shows, TVD followed by crime TV shows.

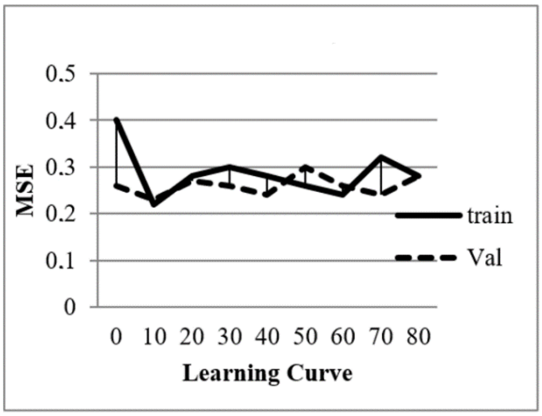

Figure 2. Learning curves

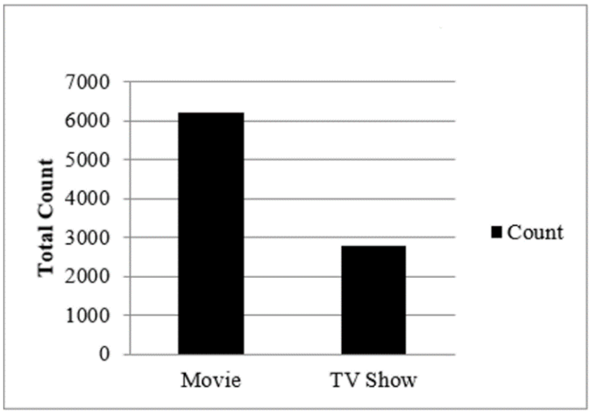

Figure 3. TV Shows versus movies

Table 1. Performance metrics evalaution

Method/parameter	Precision	Recall	F1-score
Multi domain aspect oriented sentiment analysis for movie recommendations using feature extraction	0.94	1.00	0.97
Naïve Bayes classifier	0.82	0.78	0.88

The results illustrate that the multi domain aspect-oriented sentiment analysis for movie recommendations using feature extraction as proposed has achieved high precision, recall and F1-score with 0.94, 1.0, 0.97 respectively. When comparing to state of art approaches, presented approach exhibited better performance in terms of recall, MSE, precision and F1-score. With the exceptional results, this approach will be used as the leading option for a movie recommendation system.

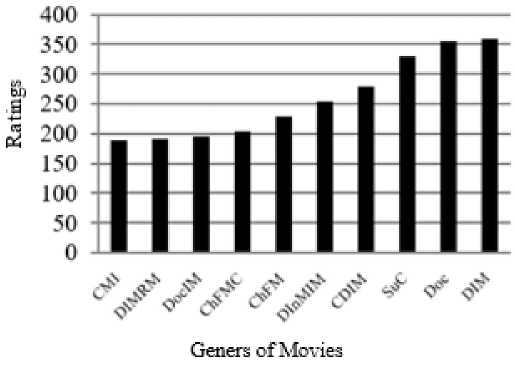

Figure 4. Top genres of movies

Figure 5. Top genres of TV shows

5. CONCLUSION

This work focuses on the implementation of multi domain aspect-oriented sentiment analysis for movie recommendations using feature extraction. Sentiment analysis performs an important part in evaluating the positivity or negativity of movie reviews, thereby contributing to the overall rating of a movie. The initial step involves collecting data from various online sources, such as Twitter, Instagram, Facebook, and other websites containing written movie reviews. Subsequently, data cleaning techniques are applied to enhance the effectiveness of the classifier algorithms and facilitate accurate sentiment analysis. Feature extraction is performed to pre-compute the data for each modality. Hybrid recommender is implemented with content-based recommender and collaborative filtering for providing accurate and effective movie recommendations. This approach classifies the movies as positive, negative, less negative and less positive. Based on these ratings, the user will get the accurate movie suggestions and recommendations. This approach has analyzed the top 10 genres of movies as well as TV shows. The implemented approach's performance is evaluated through various metrics, including precision, recall and F1-score. This approach has achieved better performance than state-of-the-art approaches. In future we will try to get 100% performance in terms of F1-score and precision.

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