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Integrating contextual information into multi-class classification to improve the context-aware recommendation.

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Abstract

Researchers and practitioners in various fields, including e-commerce customization, information retrieval, ubiquitous and mobile computing, data mining, marketing, and management, have realized the value of contextual information. Context-aware recommender systems assist users in finding their chosen material in a reasonable amount of time by utilizing information that describes the scenario in which the items will be consumed. For better personalized user recommendation, recommender systems leverage the contextual information in their process of recommendation called context-aware recommendation. Classification is used for context-prediction which represents the prediction of future context based on recorded previous context. The context prediction algorithm's goal is to recognize typical behavior patterns that have been seen in the past and then offer the most likely continuation of a presently observed collection of context components based on this knowledge. In this article we study the correlation between the multi-class classification and the context-aware recommendation.With this correlation we conclude that the linkage between contextual information and classification enhance and improve the recommendation results.

Keywords: Multi-class classification, Context-aware recommendation system CARS, Semi-supervised learning, Unlabelled data.

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1. Introduction

Recommender systems (RS) have effectively addressed the problem of information overload by giving tailored and targeted suggestions to end users. There are different types of recommendation systems.The content-based filtering uses the opinions of users similar to the active user. The collaborative filtering uses only the preferences of the current user to make recommendations [30],[31]. Hybrid filtering groups together the both previous methods to offer suggestions to users [29]. A recommender system is knowledge-based when it provides recommendations based on particular queries made by the user rather than a user's rating history. Context-based approaches make suggestions to users depending on the user's, item's, or interaction's circumstance. The goal of demographic-based recommender systems is to categorize users based on characteristics and generate suggestions based on demographic classes. The growth of online content gives people more alternatives to select from, resulting in information overload. The customized suggestions take into consideration the user's choices to provide recommendations based on his or her interests and are likely to be favored by the user. The recommended things can be products such as books, music, videos, movies, electronic goods, or resources such as learning resources, papers, news, or people such as friends, peers, or activities such as download, watch, and connect. Products on Amazon, individuals on LinkedIn, music and movies on Netflix, and friends on Facebook are all instances of websites that provide suggestions [1].

Context-based (aware) recommendation is becoming more popular since the user may have rated the products based on context and also requires the recommendation based on the present context [7]. The context might be the current circumstance, the time of day, or the place [22]. The context, in conjunction with additional data such as user and/or item characteristics, can be used to improve the relevance and accuracy of recommendations [2]. The context of a user, an object, or an activity may be collected and preserved when digital technologies such as mobile, social networking, and e-commerce are used in daily life.

We concentrate our research work around the use of context-based filtering to investigate the relationship between multi-class classification and context aware recommendation, as well as how the incorporation of contextual information into the classification may enhance recommendation outcomes. We organize this paper as follows: Sect. 2 contains the background and motivation of our work that depicts two parts: the multi-class classification using unlabeled data and the context-aware recommender system. We describe the state-of-the art in Sect. 3. Then in Sect. 4, we will elaborate our proposed approach. At the end of the work, we conclude all the work in Sect. 5.

2. Background And Motivation

2.1. Part 1: Multi-class classification algorithms with unlabelled data

Classification tasks bank intensely on labeled data or tagged information to achieve an efficient classifier. However, because of the technical support from specialist's also the very long time consumption of a manual process for data labeling, it seems troublesome to get enough labeled data to create an efficient classifier. The amount of labelled data is rare, whereas unlabelled data is straightforward. Because of the extreme data space dimension, unlabeled observations are usually possible in large quantities, whereas labelled samples are uncommonly small. Semi-supervised classification (SSC) is a learning paradigm focused on increasing classifier performance by utilizing unlabeled data for this purpose. Semi-supervised learning (SSL) techniques are considered as an appropriate approach when the amount of labeled data is small and insufficient to build a good classifier and when the number of unlabeled data is high.

A. Semi-supervised approach:

In the absence of labeled data and the adequacy of unlabeled data in the training phase, semi-supervised learning is often the best and most efficient solution. The purpose of proposing a semi-supervised system of learning is to improve the outcomes of learning and resolve the different issues based on data types. For semi-supervised learning, several algorithms have recently been developed such as Self-labeled methods, Semi-supervised boosting methods, Margin-based methods, and Graph-based methods..

- Self-labeled methods:

Self-labeled methods can be divided in two sub-categories: Self-training and Co-training.

❖ Self-training:

Self-training is the first iterative technique for semi-supervised learning, it is among the main models of repetitive strategies for semi-supervised learning. In self-training, with labeled data, a classifier is initially trained. This classifier is then used to assign each of the unlabeled data to a label and apply the most trustworthy unlabeled points together with their anticipated labels to the training set [19]. To overcome these challenges,[17] suggest a neural network approach of deep reinforcement learning to dynamically learn the self-training technique and collect the characteristics of training instances. [25] Propose a novel and simple approach for classifying semi-supervised texts. First, as a form of model ensemble, the approach produces two sets of classifiers and then initializes the word embeddings differently: one using random, the other using pre-trained word embeddings. The suggested method focuses on various predictions for unlabeled data between the two class-sifiers when observing the self-training.

❖ Co-training:

Co-training is an algorithm used by machine learning where a limited volume of data is labelled and a multitude of data is unlabeled. Co-training is a method in semi-supervised learning with two viewpoints.[23] suggest a new Reinforced Co-Training approach to pick unlabeled high-quality samples in order to properly co-train. More precisely, with a small labelled dataset, the suggested technique uses Q-learning to learn a data collection strategy and then utilizes this policy to automatically train co-training classifiers. [24] propose an approach to enable co-training for handling multi-label data, two classification models are generated by dichotomizing the feature space with diversity maximization, and then pairwise ranking predictions on unlabeled data is iteratively communicated for model refinement.

- Semi-supervised boosting methods:

Boosting, with many applications, is known as a supervised learning method. The aim of the boost is to minimize marginal costs. [27] This approach considers semi-supervised learning as a task of clustering and aims to increase the detection rate of clusters using named data as prior information.

- Margin-based methods:

In semi-supervised learning, various experiments have been carried out to improve these approaches. The extensions of a support vector machine (SVM) for semi-supervised learning are typically a collection of margin-based techniques. [26] SVM algorithm supports binary classification. But through the support vector, multi-knowledge based system SMK design proposed it shows four types of classification by using multiple knowledge based system KBS the uses of SVM in multiple knowledge based systems handle large amounts of unstructured data and to support multi-class classification.

- Graph-based methods:

Graph-based methods in semi-supervised learning are based on the theory of strings. These methods describe a graph in which nodes (labeled or unlabeled) are samples, and edges represent sample similarities. [27] suggest a new Adaptive Graph Driven Embedding (AG2E) method for semi-supervised multi-label annotation, which uses minimal labeled data associated with large-scale unlabeled data to promote performance of learning.

2.2. Part 2: Context-aware recommendation using multi-class classification

2.2.1. *The use of multi-class classification in context-aware recommendation*

Classification methods are widely used to construct prediction models in machine learning and data science. In general, the main goal of classification is to effectively classify or forecast target class labels whose contextual feature values in a context-aware model are known but class values are unknown. The concept of context prediction has been investigated in the field of ubiquitous computing. However, there are significant distinctions between the issue of context prediction in the area of recommender systems and that of ubiquitous computing. In ubiquitous computing, context prediction is typically described as the process of anticipating forthcoming context information to facilitate proactive adjustments.

3. Related work

Several CARS methods, such as differential context modeling, context-aware splitting approaches [3], context-aware matrix factorization, and so on, have been created to aid item suggestions in contexts. Contextual information, by that definition, is considerably more flexible and should not be confused with general user information and the item metadata [11]. To enhance music suggestions, [2] employed a time context pre-filtering approach. They compared several techniques for calculating these divisions. [6] performed a context-relevance evaluation to examine the effect of various contextual factors on user ratings in the tourism sector, by asking users to envision a particular contextual scenario and evaluate its significance. [8] investigate a novel approach for collecting and using contextually dependent ratings in recommender systems. They propose the idea of "best context," which refers to the contextual settings that are best suited for recommending a specific item. Enhancing RS using contextual information, defined as information that may be used to characterize the situation and surroundings of the entities participating in such a system [9],[10] has been a hot study subject over the last decade. [12] proposes a novel solution to address these problems with automated information extraction techniques. Based on a fresh dataset obtained using the suggested technique, they also examine different ways for leveraging context. Classification techniques seem to be the most prominent and commonly used methods for predicting contexts [13]. [14] Concentrate on two things: movie mood tags and movie narrative keywords. Their goal is to propose movies to a user depending on their mood, thus they devised an unique mood-specific movie similarity measure and enhanced the recommendation based on this measure by including the second movie similarity measure. [16] apply to tagging, recommendation and ranking which are the motivating applications for extreme multi-label learning. They expand earlier attempts to derive unbiased losses based on the restricted premise that labels disappear evenly at random from the ground truth. [18] propose a context-adaptive matrix factorization method for multi-context recommendation by simultaneously modeling context-specific factors and entity-intrinsic factors in a unified model.

4. Proposed approach and experimental results

4.1. Aim of the study

However, our interest is not to find a general classification procedure, but rather to build an automatic algorithm capable of classifying movies to a specific genre. Our goal is to provide a model that on the one hand and from a business perspective helps users detect the most important genre that dominates a specific movie , on the other hand understand the relationship between the classification and the recommendation and for this, there are several questions already discussed in the previous section.

4.2. Methodology and approach

This section describes the background knowledge used in the proposed methodology. It describes the learning process of the basic phases in our model starting by the classification, moving to the context-prediction and finishing by the context-aware recommendation. We pose a recommendation as extreme multi-class classification where the prediction problem becomes accurately classifying a specific movie among millions of videos from a corpus based on a user context. In this section, we will present the methodology used to create our models. For that, our model can be splitted into three main steps: the input phase, the pre-processing phase, and the output phase.

- Input phase:

We use the movie dataset via the link http://www.cs.cmu.edu/~ark/personas/. The dataset comprises some movies with the attributes: id, name, text, and genre. In this step we try to describe how contextual information is extracted and preprocessed. We removed punctuation, first of all. Next in the text, we translated the capital letter details into the lower cases. In text classification, we have eliminated the stop words that are insignificant in a language and produce noise when used as functions. The next phase is to turn the phrases into their original form. Finally we get our cleaned dataset that we will use on the next step.

- Pre-processing phase:

This step is divided into three concerns:

➔ Classification and Context-prediction as two consecutive steps:

We use the cleaned movie_text as context and we feed it to our first classification model to do the multi-label classification using four algorithms (Logistic Regression, Multinomial NB, Linear SVC, Stochastic Gradient Descent) to predict genre.

➔ Context-aware with multi-class classification method:

Based on the predicted results in the previous step, we propose a voting majority that can help the decision to classify the movie text into one class.

- Evaluation phase:

This phase represents the final step for context-aware recommendation and multi-class classification.

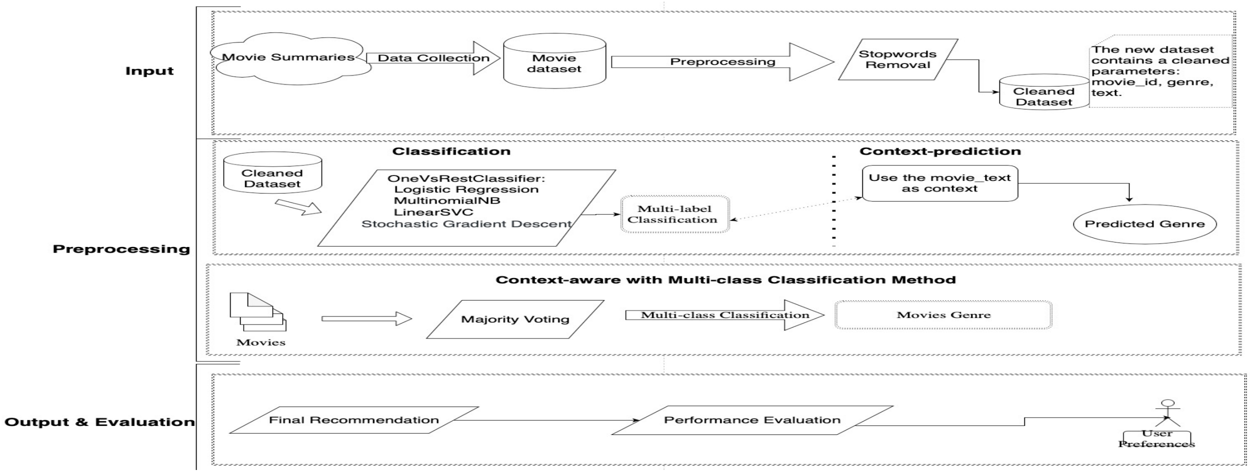

Fig.1. Process of the proposed approach.

5. Results

Table.1: Benchmarking of used approaches.

a) Logistic Regression

Used Approach	Accuracy
Baseline Logistic Regression	62,32%
our proposed approach using logistic regression and oneVsRestClassifier	73,81%

b) Linear SVC

Used Approach	Accuracy
Baseline Linear SVC	63,81%
our proposed approach using Linear SVC and oneVsRestClassifier	69,85%

Table 1 shows a descriptive summary of supervised machine learning approaches results; we choose those that work with one vs rest classifiers because a separate model is trained for each class to predict whether or not an observation belongs to that class (thus making it a binary classification problem). The metric used to evaluate these approaches' performance is accuracy score.

6. Conclusion

In this chapter, we claimed that contextual information mattered in recommender systems and classification techniques, and that it is critical to include contextual information when delivering recommendations. We also discussed how contextual information may be used at various phases of the recommendation process. We also demonstrated that several approaches for multi-class classification utilizing unlabeled data may be combined with contextual knowledge to improve performance recommendation results. Overall, the topic of context-aware recommender systems (CARS) is a very fresh and underexplored area of study, and much more effort is required to thoroughly understand it.

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