LITERATURE SURVEY

\*\*Please fill the serial number according to the Excel Sheet\*\*

# Fab: content-based, collaborative recommendation

The content-based approach to recommendation has its roots in the information retrieval (IR) community, and employs many of the same techniques.Both content-based and collaborative systems can provide such a service, but individually they both face shortcomings. Fab is an implementation of a hybrid content-based, collaborative Web-page recommendation system that eliminates many of the handicaps of the pure versions of either approach.

[Pros in Bullet Points]

* The design of the adapting population of collection agents takes advantage of these overlaps to dynamically converge on topics of interest, both automatically identifying communities of interest and providing the possibility of significant resource savings when increasing the numbers of users and documents.

[Cons in Bullet Points]

* No dynamic users data is taken into consideration.

[Future Scope]

* study the effects of massively scaling up the number of users.

# Combining Content and Collaboration in Text Filtering,

[Paper Summary]

It includes a technique for combining collaborative input and document content for text ltering. This technique uses latent semantic indexing to create a collaborative view of a collection of user proles. The proles themselves are term vectors constructed from documents deemed relevant to the user's information need.

[Pros in Bullet Points]

* it acts as an useful tool for text filering.
* It gives best performance when the right documents are used to generate the best \rose-colored SVD".

[Cons in Bullet Points

* This technique doesn't work for larger datasets with less probability of collection.
* An implicit assumption is often made that interests, user ratings, document similarity, and topical relevance are somehow related.

[Future Scope]

To work on yet any standard test collections for collaborative filtering whose objects contain a significant amount of text. To work on real world data using this algorithm.

# A Framework for Collaborative, Content-based and Demographic Filtering,

[Paper Summary]

[Pros in Bullet Points]

[Cons in Bullet Points]

[Future Scope]

# Combining Collaborative Filtering with Personal Agents for Better Recommendations,

[Paper Summary]

Information filtering (IF) focuses on the analysis of item content and the development of a personal user interest profile. Collaborative filtering (CF) focuses on identification of other users with similar tastes and the use of their opinions to recommend items. In this paper we can identify that a CF framework can be used to combine personal IF agents and the opinions of a community of users to produce better recommendations than either agents or users can produce alone.

[Pros in Bullet Points]

* it becomes less important to invent a brilliant agent, instead we can simply invent a collection of useful ones.

[Cons in Bullet Points]

* It cannot efficiently handle “users” who rate all items and re-rate them frequently as they "learn."

[Future Scope]

* To develop a combined community where large numbers of users and agents co-exist.
* To work on further combinations of users and agents in recommender systems.

# A Collaborative Filtering based Recommender System for Suggesting New Trends in Any Domain of Research

[Paper Summary]

A Collaborative Filtering based Recommender System for Suggesting New Trends in Any Domain of Research.User modeling is the method of gathering information regarding users by analyzing the user’s items or ratings . User models are used by various applications including search engines and recommender systems.

[Pros in Bullet Points]

* The data collected from other researchers browsing history are used in this case which avoids analysis of content issues.
* The similarity measures between the user and research paper profile is precise by making use of the cosine similarity technique.

[Cons in Bullet Points]

* The actual dataset does not have the real ratings of the researcher.

[Future Scope]

Working with a large dataset with dynamic values.

# A Hybrid Approach using Collaborative filtering and Content based Filtering for Recommender System

[Paper Summary]

This paper describes a movie recommendation system that uses a combination of content-based filtering and collaborative filtering techniques to recommend movies to users. The system mines movie databases to collect information such as popularity and attractiveness, which are used to make recommendations. The authors propose a hybrid approach that combines the results of these two techniques in order to provide more precise recommendations. They mention that their system also allows for recommendations to be made to new users, as well as existing users. The authors conclude that, based on informal evaluations with a small set of users, the system has received a positive response, but that further testing and evaluation is needed with a larger dataset. They also suggest that the system could be extended to other domains, such as recommending songs, videos, and e-commerce products.

[Pros in Bullet Points]

1. The proposed movie recommendation system uses a hybrid approach, which combines both content-based and collaborative filtering, to provide more accurate recommendations to users.
2. The system takes into account various attributes such as popularity and attractiveness, which are important factors in movie recommendation.
3. The system can recommend movies to both new and existing users.
4. The system can also recommend products to specific customers based on the genre of movies they prefer.
5. The system uses techniques like clustering, similarity, and classification to get better recommendations and increase precision and accuracy.
6. The system can be extended to other domains such as recommending songs, videos, venues, news, books, tourism and e-commerce sites, etc.

[Cons in Bullet Points]

1. The performance of the system is difficult to evaluate as there is no right or wrong recommendation, it is just a matter of opinions.
2. The authors mention that the system was only informally evaluated with a small set of users, so more meaningful results would require a larger data set.
3. The authors mention that they would like to incorporate different machine learning and clustering algorithms in the future, suggesting that the current implementation may not be optimal.
4. It is not clear from the paper how the system handles new movies that have been released recently and how well it works with movies that have not been popular recently

[Future Scope]

1. Combining the recommendation system with other technologies such as natural language processing and computer vision to provide a more immersive and interactive experience for the users.
2. Conducting more extensive evaluations on a larger dataset to measure the performance of the system and make further improvements.
3. Exploring ways to integrate the recommendation system into other platforms such as mobile devices and smart TVs to make it more accessible to users.
4. Developing methods to incorporate feedback from users to improve the accuracy of the recommendations over time.
5. Investigate the impact of transparency and explainability on the acceptance of the recommendation system by the users.

# Multi-Domain Neural Network Recommender

The research paper proposes a novel multi-branch network for multi-domain recommendation to alleviate the data sparsity problem by utilizing information from other domains. The network is designed to discover sharing-pattern features, which are general preferences of users, and domain-specific features. The model is different from existing methods, which use the same features as sharing factors among domains, instead the model uses the same transformation as sharing pattern. The paper also presents a non-linear procedure with probability to form the final user latent factor. The proposed method is tested on real-world dataset and it outperforms the baseline methods. Results also show that the sparser domains have more room for improvement as they have more absorption from other domains.

Pros:

1. The proposed Multi-Domain Neural Network (MDNN) addresses the data sparsity problem in recommendation systems by utilizing knowledge from other domains.
2. The MDNN is able to learn complex patterns and extract important information from hidden layers that are closely related to the task.
3. The MDNN uses a novel multi-branch network to discover sharing-pattern features and domain-specific features for multi-domain recommendation.

Cons:

1. It is not mentioned in the paper if there are any limitations to the proposed method.

Future Scope:

1. The paper suggests future work to study new ways of formulating domain-shared information and exploring the relationship between data sparsity and learning capacity.

# Neural Autoregressive Distribution Estimation" by Larochelle and Murray

The paper presents the Neural Autoregressive Distribution Estimation (NADE) models, which are neural network architectures applied to the problem of unsupervised distribution and density estimation. The main advantages of NADE models include:

* Tractability: NADE models are able to compute the marginal probability of the data, p(x), efficiently, given an arbitrary ordering of the dimensions of x.
* Good generalization performance: NADE models have been shown to achieve competitive performance in modeling both binary and real-valued observations.
* Flexibility: NADE models can be used to solve a variety of types of inference problem, such as classification, regression, missing value imputation, and many other predictive tasks.
* Handling high-dimensional data: The paper suggests that deep NADE models can be trained to be agnostic to the ordering of input dimensions used by the autoregressive product rule decomposition.
* Handling images: The paper also shows how to exploit the topological structure of pixels in images using a deep convolutional architecture for NADE.
* The paper also suggests future scope of NADE models. Some possible ways that NADE models could be used in the future include:

Improving performance: Further research could focus on finding ways to improve the performance of NADE models, such as by developing more sophisticated architectures or training algorithms.

* Handling other types of data: NADE models could be adapted to handle other types of data, such as time series data or sequential data.
* Combining with other models: NADE models could be combined with other models, such as RNNs or GANs, to create more powerful distribution estimation models.
* Applying to other tasks: NADE models could be applied to other tasks, such as anomaly detection or generative modeling.
* Investigating the theoretical properties: Further research could focus on investigating the theoretical properties of NADE models, such as understanding how they are able to generalize well despite being trained on limited data.

[Pros in Bullet Points]

Pros:

* Tractable, flexible and competitive alternative to directed and undirected graphical models for unsupervised distribution estimation.
* Can be applied to a wide range of settings, including topic modeling of documents and images, modeling of music sequential data, natural images and attention mechanism in image classifier.
* Can serve as a powerful prior over the latent state of directed graphical model.

[Future Scope]

Based on the conclusion of the paper, some potential future applications for the Neural Autoregressive Distribution Estimation (NADE) model include:

* Topic modeling of documents and images
* Modeling music sequential data
* Integrating an attention mechanism into an image classifier
* Serving as a powerful prior over the latent state of directed graphical models
* Other unsupervised distribution estimation tasks where NADE's flexibility and effectiveness can be leveraged.

# A Survey of Collaborative Filtering Algorithms for Social Recommender Systems

This paper discusses various collaborative filtering algorithms used in social recommender systems. Collaborative filtering is a technique used to make recommendations by identifying patterns in user behavior. The paper describes several algorithms, such as user-based, item-based, and hybrid collaborative filtering, and compares their performance in terms of accuracy and scalability.

Pros:

1. Detailed explanation and comparison of various collaborative filtering algorithms
2. Discussion of the challenges and limitations of using collaborative filtering in social recommender systems
3. Evaluation of the algorithms using real-world datasets

Cons

1. The research is limited to collaborative filtering algorithms and does not discuss other types of recommendation methods

Future Scope

1. Investigating other types of recommendation methods and comparing their performance with collaborative filtering
2. Incorporating more recent data and evaluating the algorithms on larger and more diverse datasets
3. Examining the robustness of the algorithms and their ability to handle missing or noisy data.

# Neural Factorization Machines for Sparse Predictive Analytics∗

[Paper Summary]

The paper proposes a novel model called Neural Factorization Machine (NFM) for prediction under sparse settings. NFM combines the linearity of Factorization Machines (FMs) in modeling second-order feature interactions and the non-linearity of neural networks in modeling higher-order feature interactions. The authors argue that while FMs have been successful in many prediction tasks, their performance can be limited by their linearity and ability to model only pairwise interactions. The NFM is conceptually more expressive than FMs and is able to capture the non-linear and complex underlying structure of real-world data. Empirical results on two regression tasks show that NFM significantly outperforms FMs, with a 7.3% relative improvement. Compared to recent deep learning methods like Wide&Deep and Deep Cross, NFM uses a shallower structure but still achieves better performance, making it easier to train and tune in practice.

[Pros in Bullet Points]

Pros of NFM:

* Consistently achieves the best performance on both datasets with the fewest model parameters besides FM
* Models higher-order and non-linear feature interactions effectively
* Bi-Interaction operation allows neural network to learn more informative feature interactions at a lower level
* Simple yet effective solution for sparse data prediction
* Reduces the demand for deeper structures for quality prediction

Cons of NFM:

* Efficiency of NFM can be improved by resorting to hashing techniques, making it more suitable for large-scale applications
* Further research is needed to study its performance for other information retrieval tasks such as search ranking and targeted advertising
* Limited expressiveness may hinder the performance when modeling real-world data with complex inherent patterns
* Deeper models do not necessarily lead to better results and are less transparent, more difficult to optimize and tune

[Future Scope]

# MIGAN: Mutual-Interaction Graph Attention Network for Collaborative Filtering

Many web platforms now include recommender systems. Network representation learning has been a successful approach for building these efficient recommender systems. However, learning the mutual influence of nodes in the network is challenging. Indeed, it carries collaborative signals accounting for complex user-item interactions on user decisions. For this purpose, in this paper, we develop a Mutual Interaction Graph Attention Network “MIGAN”, a new algorithm based on self-supervised representation learning on a large-scale bipartite graph (BGNN). Experimental investigation with real-world data demonstrates that MIGAN compares favorably with the baselines in terms of prediction accuracy and recommendation efficiency.

Pros:

1. The use of graph neural networks to model the interactions between users and items in the recommendation process
2. Achieved state-of-the-art performance on benchmark datasets
3. Showing the ability of MIGAN to capture the dynamic interactions between users and items

Cons:

1. The results are based on the specific datasets used in the paper, which limits the generalizability of the findings
2. The paper is from 2020, so the research is not up-to-date with the latest advancements in the field.

Future Scope:

1. Investigating the robustness of the model and its ability to handle missing or noisy data
2. Incorporating side information (e.g. demographic information) to improve the recommendation performance.
3. Analyzing the interpretability of the model and understanding the factors that influence its predictions.

# Hybrid recommendation system combined content-based filtering and collaborative prediction using artificial neural network

This paper presents a hybrid recommendation system that combines content-based filtering and collaborative filtering using artificial neural networks. Content-based filtering is a technique that makes recommendations based on the characteristics of the items themselves, while collaborative filtering is a technique that makes recommendations based on the behavior of other users. The authors propose a hybrid approach that combines the strengths of both techniques by using an artificial neural network to learn the representations of items and users. The system is evaluated using a dataset of movies and the results are compared with those of traditional content-based and collaborative filtering methods.

Pros of this research include:

1. The use of a hybrid approach that combines the strengths of both content-based and collaborative filtering
2. The use of artificial neural networks to learn the representations of items and users
3. Evaluation of the system using a real-world dataset.

Cons of this research include:

1. The paper is from 2018, so the research is not up-to-date with the latest advancements in the field
2. The results are based on a specific dataset of movies, which limits the generalizability of the findings.

Future scope for this research could include:

1. Investigating the robustness of the system and its ability to handle missing or noisy data.
2. Incorporating more recent methods and models such as graph-based or deep learning based models and comparing the performance.
3. Analyzing the interpretability of the model and understanding the factors that influence its predictions.
4. Investigating the scalability of the system and how it can be adapted to large-scale datasets.

# Deep Learning Architecture for Collaborative Filtering Recommender Systems

[Paper Summary]

This paper presents a deep learning architecture for improving collaborative filtering in recommender systems by incorporating prediction errors (reliabilities) in the deep learning layers. The proposed architecture has three stages, providing three stacked abstraction levels: (a) real prediction errors, (b) predicted errors (reliabilities), and (c) predicted ratings (predictions). Experiments have been run on three representative datasets, resulting in strong prediction and recommendation improvements, particularly for the recall quality measure.

[Pros in Bullet Points]

1. The recommendation quality improves as the dataset size increases.
2. The proposed deep learning architecture can be enhanced by applying hybrid approaches such as demographic, social, context-aware, content-based, etc.
3. The architecture learns the non-linear relationships between accuracy and reliability to select the most reliable predictions and determine the most accurate recommendations.

[Cons in Bullet Points]

1. As the number of items recommended increases, the recall improvement decreases, since the most reliable and accurate items run out.

[Future Scope]

1. Future work is proposed to improve the proposed architecture results by enhancing its reliability extraction stage and adding a wide learning component to the neural architecture.

# A personalized movie recommendation system based on collaborative filtering

[Paper Summary]

The paper presents a recommendation engine that utilizes collaborative filtering techniques to suggest movies to users. The system uses standard user demographics such as gender, age, and occupation, as well as user ratings to identify other users with similar tastes. Recommendations are made based on the best-rated movies of the nearest neighbor and are also made time-sensitive. The results of the experiment on the MovieLens dataset show that the proposed model generates more personalized movie recommendations compared to other models. The paper suggests that future work could include using more demographic information, making the application available on cross-platforms, incorporating input from review sites, and integrating social media profiles to improve the recommendations.

[Pros in Bullet Points]

1.It is based on collaborative filtering, which is a widely used and promising approach for building recommendation systems.

2.The system uses standard user demographics such as gender, age, and occupation, which can provide valuable information for making recommendations.

3.The system utilizes time-sensitive recommendations, which can help keep up with changing user preferences.

4.The system is evaluated using precision, recall, and F-measure, which are commonly used metrics for evaluating recommendation systems.

[Cons in Bullet Points]

1.The system only considers a limited set of user demographics, and more information such as nationality, race, location, mother-tongue, and languages spoken could be used to make recommendations more personalized.

2.The system relies on user ratings to make recommendations, but input from other sources such as consolidated internet databases and authentic review sites could also be used to improve recommendations.

3.The system does not integrate with social media profiles, which could provide valuable information for making more personalized recommendations.

4.The system does not consider location-based data, which could be used to make recommendations more relevant to the user's current location.

[Future Scope]

The future scope of the paper can include incorporating more demographic information such as nationality, race, location, mother-tongue, and languages spoken to make the recommendations more accurate and personalized. The recommendation system can also be made available on cross-platforms to extend its reach and functionality. Additionally, the system can be integrated with social media profiles and location-based apps to improve recommendations based on real-life user interests. Furthermore, the system can factor in data from consolidated internet databases and authentic review sites like IMDb and Rotten Tomatoes to enhance the recommendation process.

# "Neural Collaborative Filtering" by X. He and L. Liao and T. N. Kieu and Y. Zhang (2017),

The paper presents a neural network architecture, named NCF (Neural network-based Collaborative Filtering), for modeling latent features of users and items in recommender systems. The authors propose using a multi-layer perceptron to learn the user-item interaction function and show that the proposed approach significantly improves the performance of state-of-the-art methods on two real-world datasets. The authors also demonstrate that using deeper layers of neural networks offers better recommendation performance. The main contributions of the paper are the development of the NCF framework for collaborative filtering and the use of deep neural networks to model noisy implicit feedback signals in recommender systems.

[Pros in Bullet Points]

Pros:

* The proposed NCF framework uses neural networks to tackle the key problem in recommendation - collaborative filtering - on the basis of implicit feedback
* The neural architecture can learn an arbitrary function from data, making it more versatile than traditional matrix factorization methods
* The use of a multi-layer perceptron allows for the incorporation of non-linearities, resulting in improved recommendation performance
* Extensive experiments on real-world datasets show significant improvements over state-of-the-art methods
* Using deeper layers of neural networks offers better recommendation performance

Cons:

* The method is mainly focused on implicit feedback, and may not be as effective for modeling explicit feedback
* The approach is still relatively new and may not have been as extensively tested or refined as traditional matrix factorization method

[Future Scope]

* Further research on improving the accuracy and robustness of the proposed model
* Extension of the model to handle more complex and realistic scenarios
* Incorporation of additional sensor modalities, such as LiDAR or RGB-D cameras
* Use of the model in real-world applications, such as autonomous vehicles or robotics
* Combination of the model with reinforcement learning techniques for decision making and control
* Investigation of the model's performance in large-scale and diverse environments
* Study of the model's ability to handle dynamic objects and changing conditions
* Comparison of the model's performance with other state-of-the-art methods for semantic segmentation.

# Kernelized Deep Learning for Matrix Factorization Recommendation System Using Explicit and Implicit Information,

[Paper Summary]

The authors explain that recommender systems can help users find items of interest by recommending potential items and maximizing the utility of information utilization. They then give a brief overview of traditional recommendation methods, such as content-based, collaborative filtering, and hybrid recommendation. They focus on matrix factorization as a successful collaborative filtering method and mention that other works have been proposed to improve it by incorporating trust, time, context and other information. They also mention that the matrix factorization method still needs improvement in practical applications, such as dealing with sparse data and the high number of online users and items. They then state that in recent years, deep learning has been used in natural language processing, computer vision, and autonomous driving and it has also been used in recommendation systems. The paper discusses the use of deep learning in recommendation systems and aims to improve the recommendation accuracy.

Some potential advantages of the approach described in the paper could include:

* Improved accuracy: By using deep learning, the paper suggests that it is possible to overcome the limitations of traditional matrix factorization methods and improve the overall accuracy of recommendations.
* Adaptability: The paper suggests that deep learning methods can be used to better adapt to the semantic interpretation of different types of items and users in real recommendation environments, which could make the recommendation system more effective.
* Handling sparsity: The paper also suggests that deep learning methods can be used to effectively handle the data sparsity problem, which is a common challenge in recommendation systems.

Some potential disadvantages of the approach described in the paper could include:

* Complexity: The use of deep learning methods can increase the complexity of the recommendation system, which may make it more difficult to implement and maintain.
* Training data: Deep learning methods typically require large amounts of training data, which may be a challenge to obtain in some applications.
* Lack of interpretability: The internal workings of deep learning models can be difficult to interpret, which may make it difficult to understand why certain recommendations are being made.
* Requirement of computational power: Deep learning methods require a lot of computational resources, which may not be available for some systems.

[Future Scope]

* Expanding the study to include more participants to increase the sample size and make the findings more generalizable.
* Incorporating more advanced machine learning techniques to improve the accuracy of the prediction model.
* Testing the model on different types of datasets and in different contexts to see if it can be applied to other areas of study.
* Exploring the use of the model in a clinical setting to see if it can be used to predict and prevent negative outcomes in patients.

# Collaborative Filtering Recommender Systems

The paper discusses the field of collaborative filtering for recommender systems, which is a method for filtering through large information and product spaces to help users find what they are looking for. The paper covers the history of research in this area, the different algorithms and tools available for evaluating performance, and the challenges of embedding recommender technology in specific domains. It emphasizes the importance of considering the specific tasks, information needs, and item domains when designing and evaluating recommenders, and provides guidance on the best practices for addressing these issues. Overall, the paper aims to provide an introduction to the important issues underlying recommenders and current best practices for addressing these issues.

Pros:

* Collaborative filtering is a powerful method for enabling users to filter through large information and product spaces
* Provides personalized recommendations based on the user's past behavior and similar users' behavior
* Can be used in a variety of domains including e-commerce, music and movie recommendations, and social media
* Has a rich collection of tools for evaluating performance

Cons:

* May not take into account other important factors such as new and trending items
* Can suffer from the "cold start" problem for new users with no past behavior
* Can be biased towards popular items, leading to a lack of diversity in recommendations
* Can be sensitive to changes in users' behavior, leading to a need for constant retraining of the model.

[Future Scope]

# Research on Collaborative Filtering Recommendation Algorithm Based on Mahout and User Model

While working on collaborative learning , system administrators only need to implement the machine learning algorithm based on the user model according to the rules of the training sample instead of doing a lot of repeated calculation.In order to optimize the system and implement a collaborative filtering algorithm on the cloud computing platform, we chose Hadoop platform as the basis for implementation.

[Paper Summary]

[Pros in Bullet Points]

* Not only solves practical problems but also implements more an effective and more personalized recommendation for users

[Cons in Bullet Points]

* . In the construction of the online recommendation field, model-based algorithms has essential reference values to improve the quality and speed of user search information.

[Future Scope]

While working in a network environment with large data working towards improving the running speed and reducing the workload of the server.

# Item-Based Collaborative Filtering Recommendation Algorithms

[Paper Summary]

Item-based techniques first analyze the user-item matrix to identify relationships between different items and then use these relationships to indirectly commute recommendations for users.Different item-based recommendation generation algorithms are used. Different techniques for item-item similarities(item-item correlation vs cosine similarities between item vectors)and different techniques for obtaining recommendations from them(weighted sum vs regression model).

[Pros in Bullet Points]

1. Item-based algorithms provide dramatically better performance than user-based algorithms.
2. The proposed algorithm provides better quality of recommendation than the best available user-based algorithms.

[Cons in Bullet Points]

1. The item-item scheme provides better quality of predictions than the user-user scheme but the improvement is not significantly large.

[Future Scope]

As it is a model-based approach it is possible to retain only a small subset of items which eventually opens the scope for improvement for obtaining better working of the model that retains a large set of items.

# Deep Learning based Recommender System: A Survey and New Perspectives

[Paper Summary]

This article aims to provide a comprehensive review of recent research eorts on deep learning based recommender systems. More concretely, we provide and devise a taxonomy of deep learning based recommendation models, along with providing a comprehensive summary of the state-of-the-art. Finally, we expand on current trends and provide new perspectives pertaining to this new exciting development of the eld.

[Pros in Bullet Points]

[Cons in Bullet Points]

[Future Scope]

# [Paper Title]

[Paper Summary]

[Pros in Bullet Points]

[Cons in Bullet Points]

[Future Scope]

# [Paper Title]

[Paper Summary]

[Pros in Bullet Points]

[Cons in Bullet Points]

[Future Scope]

# An entropy-based neighbor selection approach for collaborative filtering

[Paper Summary]

Traditional collaborative filtering algorithms solely utilize entity similarities in order to form neighborhoods. In this paper an entropy-based neighbor selection approach which focuses on measuring uncertainty of entity vectors. Such uncertainty can be interpreted as how a user perceives rating domain to distinguish her tastes or diversification of items’ rating distributions. The proposed method takes similarities into account along with such uncertainty values and it solves the optimization problem of gathering the most similar entities with minimum entropy difference within a neighborhood.

[Pros in Bullet Points]

1. The proposed method can significantly improve traditional k-NN-based collaborative filtering methods without worsening online performance.
2. The proposed approach can also be integrated with other compatible previous methods.

[Cons in Bullet Points]

1. The paper does not mention any potential limitations of the proposed model or any areas where it may not perform as well.

[Future Scope]

1. To employ a multiple knapsack solution to introduce a new clustering method for recommender systems.
2. To include uncertainty information of users- or items in privacy-preserving collaborative filtering schemes.

# A Movie Recommender System: MOVREC

[Paper Summary]

The paper proposed a movie recommendation system named MOVREC. It is based on a collaborative filtering approach that makes use of the information provided by users, analyzes them and then recommends the movies that are best suited to the user at that time. The recommended movie list is sorted according to the ratings given to these movies by previous users and it uses the K-means algorithm for this purpose. MOVREC also helps users to find the movies of their choices based on the movie experience of other users in an efficient and effective manner without wasting much time in useless browsing.

[Pros in Bullet Points]

1. It allows a user to select his choices from a given set of attributes and then recommend a movie list based on the cumulative weight of different attributes and using K-means algorithm.
2. For a small set of users the proposed method gave better performance as it uses an information filtering approach that is used to predict the preference of that user.

[Cons in Bullet Points]

1. As the method was implemented over a small set of users, not sure whether for the large set of users it gives better performance or not.

[Future Scope]

1. To incorporate different machine learning and clustering algorithms and study the comparative results.
2. To implement a web based user interface that has a user database, and has the learning model tailored to each user.

# A Recommendation Model Based on Deep Neural Network

[Paper Summary]

This paper proposes a model combining a collaborative filtering recommendation algorithm with deep learning technology, therein consisting of two parts. First, the model uses a feature representation method based on a quadric polynomial regression(QPR) model, which obtains the latent features more accurately by improving upon the traditional matrix factorization algorithm. Then, these latent features are regarded as the input data of the deep neural network model, which is the second part of the proposed model and is used to predict the rating scores.

[Pros in Bullet Points]

1. Compared with other recommendation algorithms on three public datasets, it is verified that the recommendation performance has been effectively improved by the proposed model.
2. The framework developed is simple and generic, therefore, it is not limited to the method presented in this paper. One can regard the framework as a guideline for developing deep learning methods for recommendation systems.

[Cons in Bullet Points]

1. When the feature dimension is low, the features learned by our model are not sufficiently accurate, and there remains significant room for improvement.
2. If more than 2 hidden layers are used, the performance of the model is almost no longer improved.

[Future Scope]

1. To study and implement convolutional neural network method in recommendation systems and attempt to further improve their performance.
2. To construct some user images by using the user’s rating information, each element of the image corresponds to a certain feature of the user, and then use the convolutional neural network to mine the local features of the user, so as to cluster and recommend.

# Domain-sensitive recommendation with user-item subgroup analysis

[Paper Summary]

This paper proposes Domain-sensitive Recommendation (DsRec) algorithm, to make the rating prediction by exploring the user-item subgroup analysis simultaneously, in which a user-item subgroup is deemed as a domain consisting of a subset of items with similar attributes and a subset of users who have interests in these items. The proposed framework of DsRec includes three components: a matrix factorization model for the observed rating reconstruction, a bi-clustering model for the user-item subgroup analysis, and two regularization terms to connect the above two components into a unified formulation.

[Pros in Bullet Points]

1. The domain information guides the exploration of latent space.
2. The method achieves better performance in terms of prediction accuracy criterion over the state-of-the-art methods.

[Cons in Bullet Points]

1. Clustering users and items into subgroups actually do the work of collecting correlated items and users into different clusters. Thus, a too small number of subgroups cannot clearly partition different user-item interest domains.
2. A way too large number of subgroups make the preferences of the obtained clusters be shared together, and the latent factors of users and items cannot be discriminative enough for effective rating prediction.

[Future Scope]

1. The proposed method is totally based on the user-item rating matrix.The future scope is to explore both user-item interaction information and some external information simultaneously for domain detection.

# Collaborative Filtering and Deep Learning Based Hybrid Recommendation for Cold Start Problem

[Paper Summary]

The traditional CF approach suffers from sparsity and cold start problems. In this paper, they propose a hybrid recommendation model to address the cold start problem, which explores the item content features learned from a deep learning neural network and applies them to the timeSVD++ CF model. Extensive experiments are run on a large Netflix rating dataset for movies. CF, which demonstrates superior recommendation performance models the temporal dynamics of user interests by changing static biases and latent factors into time-dependent ones, which is denoted as timeSVD++. A different modeling scheme on user preferences is presented , where a latent transition matrix is used to summarize the evolving preferences for each user.The proposed hybrid recommendation model with CF and deep learning (shortened as HRCD model). SDAE is an effective deep natural network for reconstructing its input data from a corrupted version. It is used to address the cold start problem of collaborative filtering recommendation models.

[Pros in Bullet Points]

1. The results show that the proposed model performs much better than the simple model using average rating of users for rating prediction of cold start items.
2. HRCD model is effective on rating prediction for both cold start and non-cold start items. HRCD model outperforms four baseline models for rating prediction of non cold start items with a few ratings.

[Cons in Bullet Points]

1. CS(Cold start) item rating has two prediction approaches one is ToA and another is ToU with configuration M(the number of most related items) and L ( size of the test dataset for CS movies) where in the proposed method the ToU approach performance improves largely with M. The ToA approach works well with small M (e.g., using only 20 most related NCS items for rating prediction), but using a large M such as 100 gives the approach a poor performance, which is worse than the SA model.

[Future Scope]

1. To come up with even better neural network algorithms to make the performance better for the better recommended system.

# Collaborative filtering with temporal dynamics

[Paper Summary]

This paper suggests a more sensitive approach is required, which can make better distinctions between transient effects and long-term patterns as the Classical time-window or instance decay approaches cannot work, as they lose too many signals when discarding data instances. The paper has shown how to model the time changing behavior throughout the lifespan of the data. Such a model allows us to exploit the relevant components of all data instances, while discarding only what is modeled as being irrelevant. Accordingly, they revamp two leading collaborative filtering recommendation approaches. In a factorization model, we modeled the way user and product characteristics change over time, in order to distill longer term trends from noisy patterns. In an item– item neighborhood model, we showed how the more fundamental relations among items can be revealed by learning how influence between two items rated by a user decays over time.

[Pros in Bullet Points]

1. To model the temporal dynamics along the whole time period, allowing us to intelligently separate transient factors from lasting ones.
2. In both factorization and neighborhood models, the inclusion of temporal dynamics proved very useful in improving the quality of predictions, more than various algorithmic enhancements.

[Cons in Bullet Points]

1. Tracking the temporal dynamics of customer preferences to products raises unique challenges. Each user and product potentially goes through a distinct series of changes in their characteristics.
2. We often need to model all those changes within a single model thereby interconnecting users (or, products) to each other to identify communal patterns of behavior.

[Future Scope]

To find even more better models to analyze the temporal dynamic data preferences of the user and get a better recommendation system.

# Generalized probabilistic matrix factorizations for collaborative filtering.

[Paper Summary]

Probabilistic matrix factorization (PMF) methods have shown great promise in collaborative filtering. A model between PMF and BPMF is “parametric PMF” (PPMF). Through extensive experiments on movie recommendation datasets, we illustrate that simpler models directly capturing correlations among latent factors can outperform existing PMF models, side information can benefit prediction accuracy, and accounting for row/column biases leads to improvements in predictive performance.

[Pros in Bullet Points]

1. PPMF generates higher accuracy than PMF and BPMF, as well as the co-clustering based algorithms.
2. The residual models usually have better performance than the corresponding original models.

[Cons in Bullet Points]

1. The side information used was not powerful enough to generate a distinct improvement in accuracy through the ways considered in the proposed work.

[Future Scope]

The future work includes generalizing PMF to work on a series of matrices with different timestamps, and incorporating the side information for multiple entities such as for both users and movies.

# Recommender System Based on Hierarchical Clustering Algorithm Chameleon

[Paper Summary]

The basic necessity of today’s recommender system is accuracy and speed. In this work an efficient technique for recommender systems based on Hierarchical Clustering is proposed. The user or item specific information is grouped into a set of clusters using Chameleon Hierarchical clustering algorithm. Further voting system is used to predict the rating of a particular item. In order to evaluate the performance of the Chameleon based recommender system, it is compared with existing technique based on the K-means clustering algorithm.

[Pros in Bullet Points]

1. The proposed approach for recommender systems using chameleon hierarchical clustering algorithms produces better quality clusters than K-Means and provides an efficient approach for recommender systems.
2. Chameleon clustering algorithm produces lower error thus identifies better quality clusters as compared to K-Means clustering algorithm.

[Cons in Bullet Points]

1. The K-Means has lower running time complexity as compared to chameleon.

[Future Scope]

The scope of reducing the running time of chameleon by using any parallel framework like mapreduce and improve the recommendation system time complexity.

# Content-Based Cross-Domain Recommendations Using Segmented Models

[Paper Summary]

Cross-Domain Recommendation is a new field of study in the area of recommender systems. The goal of this type of recommender systems is to use information from other source domains to provide recommendations in target domains. . In this work, we provide a generic framework for content-based cross-domain recommendations that can be used with various classifiers.They define meta-data features as a set of features to characterize the fields that domains come from and introduce indicator features to segment users into different domains based on values of the meta-data features. We study an implementation of our framework based on logistic regression and perform experiments on a dataset from LinkedIn to perform job recommendations.

[Pros in Bullet Points]

1. This framework is flexible enough to be implemented with various classifiers.
2. The model in this framework can transfer common information among different domains while keeping them distinct.
3. The regularization in the model allows us to pick important features of each of the domains automatically, while keeping it flexible to accept expert knowledge in choosing the features.

[Cons in Bullet Points]

1. The results indicate only slight improvement in recommendation accuracy in the offline setting.

[Future Scope]

1. Implementing the framework based on various classifier algorithms
2. Expansion of experiments of the model using different meta-data features, and experimenting on interaction of various possible domains.
3. Automatic selection of meta-data features.

# Collaborative deep learning for recommender systems

[Paper Summary]

The problem of auxiliary information being very sparse is addressed in this paper by generalizing the recent advances in deep learning from i.i.d. input to non-i.i.d. (CF-based) input and propose a hierarchical Bayesian model called collaborative deep learning (CDL), which jointly performs deep representation learning for the content information and collaborative filtering for the ratings (feedback) matrix.

[Pros in Bullet Points]

1. Experiments on three real-world datasets from different domains show that CDL can significantly advance the state of the art.
2. CDL actually provides a framework that can also admit deep learning models other than SDAE.
3. CDL is sensitive enough to changes of user taste and hence can provide more accurate recommendations.

[Cons in Bullet Points]

1. The paper does not mention any potential limitations of the proposed model or any areas where it may not perform as well.

[Future Scope]

1. Among the possible extensions that could be made to CDL, the bag-of-words representation may be replaced by more powerful alternatives.
2. One promising choice is the convolutional neural network model which, among other things, can explicitly take the context and order of words into account. Further performance boost may be possible when using such deep learning models.

# Hybrid collaborative filtering model for consumer dynamic service recommendation based on mobile cloud information system

[Paper Summary]

Research on web service recommendation systems mainly addresses two problems: prediction and completion of sparse QoS data, and the user's personalized recommendation. This study presents a hybrid collaborative filtering model for consumer service recommendation based on mobile cloud by introducing user preferences. The example verified that the model can effectively reduce the data sparsity and increase the accuracy of the prediction.

[Pros in Bullet Points]

1. The proposed UCFUP model is able to predict the QoS accurately, with smaller MAE and RMSE values than traditional models
2. The NVs of users and items have been declining over time, indicating that neighbors of users and items start to stabilize
3. The dynamic CF in the proposed model leads to a decrease in variation in similarity value, making the neighbors relatively stable

[Cons in Bullet Points]

1. The research only focuses on the RT and TP databases, and it is unclear how the proposed model would perform on other types of data
2. The proposed model's performance is only evaluated at six sampling moments, so it's not clear how well it would perform over a longer period of time.

[Future Scope]

1. Expanding the data set used to test the model, to see if the improved accuracy holds across a larger and more diverse sample.
2. Exploring other methods to improve the performance of the model, such as incorporating additional information or features.

# A novel deep multi-criteria collaborative filtering model for recommendation system

[Paper Summary]

The text discusses a novel approach to recommender systems that combines multi-criteria predictions with collaborative filtering and deep learning. The proposed model includes two parts: a criteria ratings deep neural network that predicts ratings based on user and item features, and an overall rating deep neural network that uses the criteria ratings to predict the overall rating. The authors claim that experiments on a real-world dataset have shown that this approach outperforms other state-of-the-art methods, suggesting that using deep learning and multi-criteria in recommendation systems is effective.

[Pros in Bullet Points]

1. The proposed model combines multi-criteria predictions with collaborative filtering and deep learning, which the authors claim has led to improved performance compared to other state-of-the-art methods.
2. The model was shown to have a higher MAE, F1, F2, FCP, MAP, and MRR than the other methods tested.
3. The use of multi-criteria ratings in addition to the overall rating is believed to help in understanding why users like certain items, which could lead to more accurate similarity estimates between users.

[Cons in Bullet Points]

1. The article does not mention any potential limitations of the proposed model or any areas where it may not perform as well.

[Future Scope]

1. The authors suggest that future work could include studying different deep learning methods such as Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Autoencoder, as well as using more complex deep networks or other feature representation methods to improve the performance of the model.
2. The proposed model can be applied to other domains and various types of data.
3. The model can be tested on a large-scale dataset to better evaluate its performance.

# A new similarity measure for collaborative filtering based recommender systems

[Paper Summary]

The objective of a recommender system is to provide personalized recommendations using the collaborative filtering technique. The main component of this technique is a similarity measure used to determine the set of users with similar behavior. The paper proposes a new, simple and efficient similarity measure, which is determined through mathematical equations and a nonlinear system, and shows that it is competitive in terms of accuracy compared to other similarity measures in literature.

[Pros in Bullet Points]

1. Proposes a new similarity measure (OS) for recommender systems based on collaborative filtering
2. The similarity measure is developed using advanced mathematical tools (integral equation, system of linear differential equations and nonlinear systems)
3. Experiments using three benchmark datasets (MovieLens100K, MovielLens1M and Yahoo-Music) show that OS is competitive in terms of accuracy and quality of ranking
4. Has the same complexity as classical similarity measures such as COS

[Cons in Bullet Points]

1. No specific cons are mentioned in the given text

[Future Scope]

Investigate to what extent OS could be used as part of a learned similarity measures to enhance the aforementioned metrics.

# A collaborative filtering recommendation algorithm based on embedding representation

[Paper Summary]

The paragraph describes a proposed collaborative filtering algorithm called UI2vec, which embeds both users and items in a potential space and uses item similarity to predict a user's content of interest. The algorithm also includes a variation called VUI2vec, which maps users and items as independent Gaussian distributions and uses variational inference to obtain approximate posterior distributions. The performance of the algorithms was evaluated on three datasets, and the results indicate that they perform well compared to a baseline model. The paragraph also mentions that the impact of super parameters on the model's performance was investigated.

[Pros in Bullet Points]

1. The proposed algorithm, UI2vec, addresses the problem of data sparsity and implicit feedback uncertainty by simultaneously learning embedded representations of users and items.
2. The generative version of UI2vec, VUI2vec, maps user and item embeddings to distributions and uses variational inference to obtain an approximate distribution of the posterior distribution.
3. The experimental results show that the two methods proposed in this paper perform better than the selected baseline models.

[Cons in Bullet Points]

1. UI2vec training obtains the user embedding representation, but no relevant comparative experiments were designed for it, making it difficult to calculate the similarity between users.
2. UI2vec only uses sequences of user interactions and not additional properties of items.
3. VUI2vec can be improved by considering changes in user interests and loss of sequence information.

[Future Scope]

1. Designing relevant experimental indicators and methods for comparing user embeddings.
2. Incorporating additional properties of items into the algorithm to improve recommendation performance.
3. Improving VUI2vec by considering changes in user interests and loss of sequence information.

# A personalized recommendation framework based on MOOC system integrating deep learning and big data

[Paper Summary]

This paper describes a personalized recommendation method for Massive Open Online Courses (MOOCs) using deep learning and big data technology. The method is based on the Bidirectional Encoder Representations from Transformers (BERT) model and includes strategies to improve accuracy, such as acquisition and preprocessing of open data, a recommendation model framework incorporating a self-attention mechanism, and a domain feature difference learning strategy to improve performance. The results of experiments show that the proposed model performs well compared to other methods.

[Pros in Bullet Points]

1. The research proposes a personalized recommendation method for Massive Open Online Courses (MOOCs) that uses deep learning and big data technology.
2. The method is based on the Bidirectional Encoder Representations from Transformers (BERT) model and includes strategies to improve accuracy, such as acquisition and preprocessing of open data, a recommendation model framework incorporating a self-attention mechanism, and a domain feature difference learning strategy to improve performance.
3. The results of experiments show that the proposed model performs well compared to other methods, including User-based Collaborative Filtering (UBCF), Item-based Collaborative Filtering (IBCF), RNN, Long Short Term Memory (LSTM), GRU4Rec, SASRec, and DeepFM.
4. The ablation study demonstrates the effectiveness of the domain feature learning method in improving the personalized course recommendation.

[Cons in Bullet Points]

1. The research lacks theoretical verification.
2. The research lacks large-scale experiment analysis.

[Future Scope]

1. Address the limitations mentioned above by providing theoretical verification and large-scale experiment analysis.
2. Plan to make an application program.
3. Extend the research to other fields like recommending articles, videos, music, etc.
4. Incorporating more user-generated data and feedback to improve the model's accuracy.

# Deep reinforcement learning in recommender systems: A survey and new perspectives

[Paper Summary]

this paper is a survey on the recent trends and advancements in deep reinforcement learning (DRL) in recommender systems. The authors provide a comprehensive overview of DRL-based recommender systems, including a taxonomy of current methods, discussion of emerging topics and open issues, and future directions for advancing the field. They also note the limitations of traditional recommendation techniques and how DRL can overcome these limitations by learning from interaction trajectories provided by the environment. The authors also highlighted the differences with existing surveys in the field and the contributions of their survey in providing an up-to-date and comprehensive review of DRL-based recommender systems.

[Pros in Bullet Points]

Pros:

* The paper provides a comprehensive and up-to-date overview of deep reinforcement learning (DRL) in recommender systems, making it a valuable resource for researchers, practitioners, and educators in the field.
* The paper presents a taxonomy of DRL-based recommender systems, which helps to organize and understand the existing literature in the field.
* The paper discusses emerging topics and open issues in DRL-based recommender systems, and provides perspectives on future directions for research.

Cons:

* The paper may be too technical for readers without a background in deep learning and reinforcement learning.
* The paper does not include any experimental results or evaluations of the methods discussed, which may limit its usefulness for practitioners looking to implement DRL-based recommender systems.
* The evaluation of the specific system introduced in the paper is not clear and not well described, so it may be difficult to understand the performance of the system.

[Future Scope]

The research paper on deep reinforcement learning (DRL) in recommender systems is a valuable asset for those working in the field, offering a comprehensive and current overview of the subject. The paper's organization of existing literature via a taxonomy of DRL-based recommender systems allows for a better understanding of the field. Additionally, the paper delves into emerging topics and unresolved issues within DRL-based recommender systems, and offers insight into potential future research directions. Overall, the paper serves as a useful resource for researchers, practitioners, and educators in the field of DRL in recommender systems.

# An intelligent movie recommendation system through group-level sentiment analysis in microblogs

[Paper Summary]

This article proposes a novel model for program recommendation in online media sharing sites, such as YouTube, Youku, and Hulu. The authors aim to address the challenges of limited viewing logs and user friendship networks that traditional recommendation algorithms face by utilizing social networks and mining user preferences expressed in microblogs. The proposed model uses data mining and social computing techniques to evaluate the similarity between online movies and TV episodes, and suggests similar programs to users on other media devices. The authors claim that this is the first effort to bridge the gap between movie and TV watchers with social network activities and to solve the "cold-start" problem in movie and TV recommendation systems. This model can be easily applied to online media streaming sites to provide intelligent program recommendations to users through mining microblogs.

Pros:

* The proposed model utilizes social networks and mines user preferences information expressed in microblogs to evaluate the similarity between online movies and TV episodes.
* The model attempts to bridge the gap between movie and TV watchers domain with social network activities.
* The approach is able to solve the "cold-start" problem in movie and TV recommendation systems.
* The model adopts a series of data mining approaches and social computing models

The model can be easily applied in online media streaming sites to make intelligent recommendations to customers through mining microblogs

Cons:

* The model relies on the availability of social network data, which may not always be accessible or reliable.
* The proposed model is not evaluated on any real-world dataset, limiting its effectiveness and generalizability.
* The paper does not provide any experimental results to evaluate the performance of the proposed model, making it difficult to assess its effectiveness.
* The proposed model may have limitations in terms of scalability and efficiency, especially with large amounts of data.

[Future Scope]

This paper proposes a novel model for program recommendation in online networks, specifically for movie and TV streaming sites. The model utilizes social networks and mines user preferences information expressed in microblogs to evaluate the similarity between online movies and TV episodes. The authors claim that this is the first effort to bridge the gap between the movie and TV watchers domain with social network activities, and that it is the first approach that can solve the "cold-start" problem in movie and TV recommendation systems. The proposed model employs a series of data mining approaches and social computing models and can be easily applied to online media streaming sites to make intelligent recommendations to customers through mining microblogs.

# Movie recommendation and sentiment analysis using machine learning

This paper proposes a novel model for program recommendation in online networks, specifically for movie and TV streaming sites. The model utilizes social networks and mines user preferences information expressed in microblogs to evaluate the similarity between online movies and TV episodes. The authors claim that this is the first effort to bridge the gap between the movie and TV watchers domain with social network activities, and that it is the first approach that can solve the "cold-start" problem in movie and TV recommendation systems. The proposed model employs a series of data mining approaches and social computing models and can be easily applied to online media streaming sites to make intelligent recommendations to customers through mining microblogs.

The pros of this research paper include:

* The use of the Cosine Similarity algorithm for movie recommendation, which has shown to be accurate in recommending related movies based on various factors.
* The use of both the Naive Bayes and Support Vector Machine algorithms for sentiment analysis, which allows for comparison and selection of the best algorithm for classifying reviews.
* The inclusion of prospects for future improvement such as increasing the accuracy of sentiment analysis for handling sarcastic or ironic reviews and expanding the analysis to other languages.

The cons of this research paper include:

* The limitation of the movie recommendation system is if the movie entered by the user is not present in the dataset or if the name is not entered in the same format as in the dataset.
* The limitation of the sentiment analysis to only English reviews and difficulty in correctly classifying sarcastic or ironic reviews.
* The lack of consideration for user preferences in movie recommendations.

The conclusion of the research paper states that there are several prospects for future work in the field of movie recommendation and sentiment analysis. Some of the potential areas of improvement include:

* Increasing the accuracy of sentiment analysis to better classify sarcastic or ironic reviews.
* Conducting sentiment analysis on reviews written in languages other than English.
* Developing a movie recommendation system that takes into account users' preferences such as cast, genre, and year of release.

The research paper also notes that there are some limitations to the current system. One limitation is that if the movie entered by the user is not present in the dataset or if the user does not enter the name of the movie in the same format as it appears in the dataset, then the system will fail to recommend movies. Another limitation is the linguistic barrier in conducting sentiment analysis, as the current system can only analyze reviews written in English. Additionally, the sentimental analysis may also give wrong classification if the reviews are sarcastic or ironic.

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