**Interactive movie recommendation system using TV Tropes**

Girish U Rao: [guru3@gatech.edu](mailto:guru3@gatech.edu) Ramesh: rravi37@gatech.edu

Kunal: [ksingh98@gatech.edu](mailto:ksingh98@gatech.edu) Ritu:rparathody3@gatech.edu

Satya: [vkamisetti3@gatech.edu](mailto:vkamisetti3@gatech.edu) Narendra: [dgadidasu3@gatech.edu](mailto:dgadidasu3@gatech.edu)

**Abstract**

The existing recommendation systems fall short of providing precise recommendation based on story lines. So, we propose a novel recommendation system that integrates three different entities: TV tropes, recommendation algorithms and interactive UI. Data is collected by scraping the website, which is fed into recommendation algorithm for apt recommendations and then these recommendations are presented to user through interactive interface.

1. **Introduction**

A [trope](https://tvtropes.org/pmwiki/pmwiki.php/Main/Tropes) can be defined as a storytelling device or convention, a storyteller can assume the audience will recognize. By looking at the tropes associated with a movie, one can get an understanding of its plot. The same can be used for movie recommendation.

Existing recommendation systems for movies currently operate by utilizing the user’s watch history and ratings which has issues such as cold-start. We aim to utilize the trope data to help solve the cold-start problem along with providing an interactive interface for recommendation. Our target users would be those who wish to explore their movie recommendations based on tropes in an interactive fashion.

1. **Literature Survey**
   1. **Recommendation Algorithms**

Collaborative filtering based on user preference has the problem of cold-start and sparsity, which is partially over come in paper [1], by using genre correlation matrix based on the user’s selection. There is also cold-start problem associated with an item(node).However, paper[2] calculates semantic similarity between items on the same level in a tree and provides more accurate recommendation with this data. Collaborative filtering via matrix factorization uses un-interpreted latent factors to make recommendations [3]. This paper [3], deals with generating a new recommendation model based on these interpretable latent factors such as tropes. In addition to matrix factorization methods, TagiCoFi[8] aims to combine user submitted tags so as to capture content based features into the model.

Sentiment analysis [4] using the positive or negative sentiment of the reviews posted online to suggest recommendations based on current movie being reviewed and doesn’t reflect user interest. Parsing the movie plot summaries to get the character information in [5] can be applied to get the story tropes proposed here. Surveying the user ratings to find user’s interest for each of the movie and use this to cluster users to get the nearest neighbor to recommend a movie was discussed in [6]. For live and catch up TV applications, using the implicit and explicit feedback available to learn the ranking of the shows to improve the ranking system was proposed in [7]. An approach used in [12] is a modified K-means based clustering algorithm on users to find the most similar user to the target user to provide recommendations.

* 1. **TV Tropes**

TV tropes are wiki that helps the viewers to identify and document the similar tropes in the media and literature. The paper [9], explains the bipartite graphs of the tropes that were implemented using network analysis techniques to study the propagation of the tropes. The paper [10] provides the descriptive analysis of the dataset that makes the future recommendation system smarter with the help of tropes by films and films by tropes approach. This paper gave help in suggesting the movies by popularity by giving good ontology. The paper [11], uses skip forward that makes use of the TV tropes in proving the content based recommendation using annotation recommenders. The paper fell short in including the overlapping annotations.

* 1. **Visualization**

Most of the existing recommendation engines present results as sorted lists. As a result, user can’t understand the structure of the recommendations. To tackle this, a graph like representation is suggested in [13]. [14] Talks about an application called SmallWorlds that also suggests graph based interface for recommendations based on facebook. Paper [15] also presents graph based interface which is much more interactive and user driven and enhances sense-making by providing users the options to populate similar members, grouping them, fixing them and filtering further results based on groups. Based on [13], [14] and [15] the graph like representation was chosen for the project, Also, [16] suggests that, in addition to distance based structure, various levels of hierarchy of the clusters could provide some insight and proposes a method for the same. Also [17], suggests content based user profiling and then representing them visually using a cartoon giving the user, an overview of his own profile [18] combines the usual recommendation technique using social data across various platforms and marries that with a novel interactive interface which lets user to define weights of various inputs to recommendation engine, giving him better understanding of the output [19] proposes usage of interactive visualizations to involve user in the process of recommendation by visualizing the results through various suitable methods specific to various attributes of the recommendations.

PeerChooser [20], proposes an interface where connected users are positioned at a distance from our target user based on their similarity with them. Additionally the interface has genre nodes. They allow the user to move the genre nodes around, causing the connected users to rearrange thus affecting the recommendation results based on it.

1. **Work in progress**

**Recommendation Algorithm**

* 1. **Data Collection**
* First approach was to retrieve TVTropes data via DBTropes in RDF format. Following drawbacks with RDF format were identified:
* The linked data contained information about different sources and was tough to filter only movie data
* The original RDF would have forced us to conform to the ontology defined for a semantic web domain which made it complex.

Web scraping was suitable approach. Initial plan was to search for movie in the tvtropes [website](https://tvtropes.org/) and then scrape data from the results. However, the result didn’t have a set pattern to isolate tropes. Hence, a second approach was taken, that would scrape a list of movies and its hyperlink in the website. Then, navigate to the website for each movie in the master list and traverse through the content listing tropes. Python along with BeautifulSoup python library to parse the html was used. Each movie’s tropes are then captured in csv file which will serve as data for the algorithms. Further planning is to retrieve movie name details like genre and rating via movieDB [website](https://www.themoviedb.org/?language=en-US).

* 1. **Recommendation Algorithm**
* Analysis and evaluation of the clustering algorithms
  + The raw data fed directly into the Clustering based collaborative filtering algorithm for finding the movies with similar tropes. The algorithm was implemented in python using scikit-surprise package. K-Nearest neighbors’ (KNN) model was used to gauge the similarity output. As shown in Table [1], the results were not optimal enough to consider for further experiments. The raw data obtained was not fully sufficient to find the similarity. The data needs pre-processing. The pre-processing involves, including user preferred movies list and weighted tropes.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Evaluating RMSE, MAE of algorithm KNNWithMeans on 5 split(s). | | | | | | | |
|  | Fold1 | Fold2 | Fold3 | Fold4 | Fold5 | Mean | Std |
| MAE(testset) | 8453.176 | 8565.126 | 8258.653 | 8146.744 | 8423.642 | 8369.468 | 148.3982 |
| RMSE(testset) | 13861.58 | 13884.02 | 13527.21 | 13374 | 13699.06 | 13669.18 | 195.628 |

**Table 1: Clustering results**

* Analysis and evaluation of collaborative filtering algorithms.
  + A matrix with all the movies as rows and the tropes as columns, which indicate the presence of that particular trope in the movie was created. Similarity measurement based on this input was good enough to find the common tropes and the nearest neighbor.
* Decision was made to continue with the second approach with following innovations.
  + Using the combination of frequency of a trope and weight of a trope to instead of just plain presence indicator.
  + Use of separate frequency and weightage measurement for the tropes present in the current user interest movies.

The frequency is the number of times a trope occurred in the whole movie database. Future plan is to remove the outliers (too frequent and very rare occurrences). Inverse exponential weightage based on frequency will be used in the matrix. The search vector for similarity is based on the movies present in the user interest. The top tropes in this list along with similar movies (ranked by the total rating obtained from the movieDB API) would be made available to the user via interactive interface. Algorithm would get triggered for user changes and adjusts the recommendations accordingly.

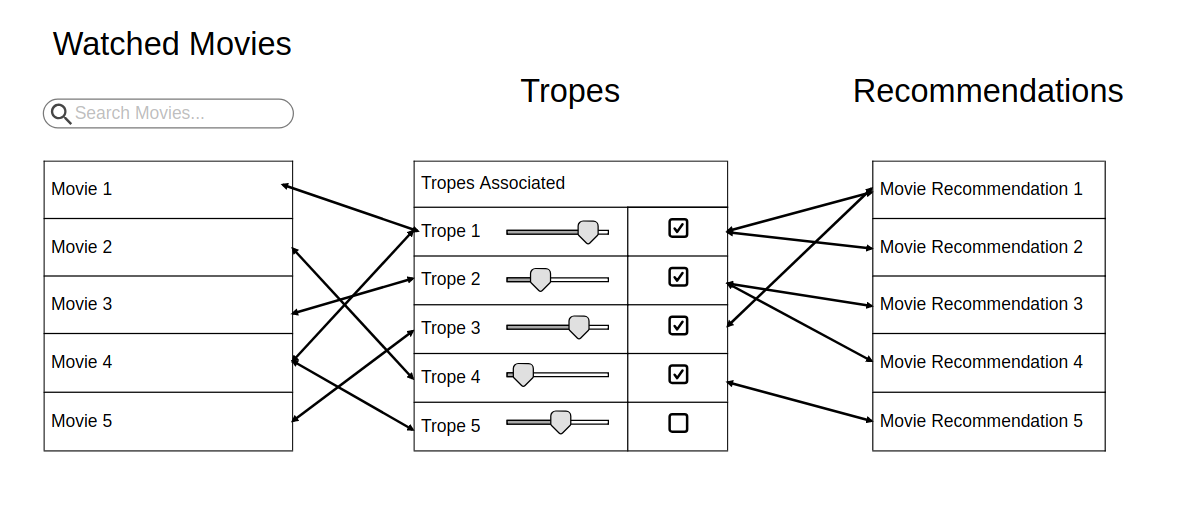
* 1. **Visualization**

Proposed approach was more focused on representing the relationships between the recommend movies and allows user to give feedback by controlling the recommendations itself by deleting items from the list. This approach doesn’t capture as to why the user disliked the particular recommendation and gives little feedback to the algorithm to refine new recommendations.

The new visualization approach is as follows:

* Collect minimum 5 movies as the baseline to understand user's current mood.
* Generate initial set of recommendations.
* Present the recommendations along with the tropes used in generating them
* The tropes are shown as sliders which the user can navigate based on his liking of the recommendations provided.
* As the tropes are calibrated, new recommendations are presented to the user.

It provides explanation ability via the tropes presented and gives user control via the slider for it.



1. **Evaluation**

It was difficult to get any ground truth data to compare results with. So proposal is to create evaluation based on user surveys. Plan is to get top 10 movies list from minimum 50 users. Give the top 5 of this list to the system and also get similar movies from movieDB. Results shall be evaluated against the ground truth and movieDB results using similarity score (cosine distance).

1. **Cost and Development Time**

AWS Instances to

* Train the recommendation system
* Host the user interface.
* Store the datasets.

Proposed solution is targeted to be developed in the duration of the course as per below schedule:

|  |  |
| --- | --- |
| **Item** | **Deadline** |
| Data Collection | Completed |
| Explore and Finalize Algorithm | Completed |
| Implement Algorithm | 13 Nov’18 |
| Develop User Interface | 13 Nov’18 |
| User Surveys | 14 Nov’18 |
| Evaluation based on User Surveys | 16 Nov’18 |
| Enhancements based on Survey | 20 Nov’18 |
| Final Report and Presentation | 23 Nov’18 |

1. **Risks**

* Focusing only on the tvtropes data of a given movie. It might turn out to be insufficient data to make good recommendations for some particular set of users whose interest go in sync with other basic attributes such as genre and rating

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