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# A Recommender System for YouTube Video based on deep neural network

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***Abstract***— YouTube is video sharing sites where a user can create own profile, upload videos and watch the multiple videos. The YouTube uses the recommender system. With the help of recommendation system we boost the popularity of videos. The recommendation is based on the relation between the number of views and the average number of views on particular videos. The recommendation also considers the likes and comment section. When the viewers view the same type of video then YouTube recommends the same type of video. The YouTube recommendation is based on machine learning technique. In machine learning we used the concept of the deep learning method. With the help of deep learning we solve the sophisticated problem. In this paper we see the working of deep neural network to recommend the video based on viewers.

***Keywords***— Boost, Sophisticated, Deep Learning.

## I. INTRODUCTION

A recommender system is a system which recommends the item or anything using the different types of method. A recommender system is a subclass filtering system for information. Now days the recommender system used in every area like music, movie, article, research, book, social tags etc.

Deep learning is a type of machine learning.
The YouTube is very large website for sharing the all types of videos. The user can upload the own videos. The YouTube also connected with multiple social sites and other web sites. The YouTube is very famous because we used the recommender system. The recommender system can be implemented using deep neural network. The deep neural network is able to track the human brain activity. The activity means pattern recognition and the input of the user. The deep neural network deal with unstructured data. The recommendation is based on three major perspective scale, freshness and noise.

**1. Scale**
The candidate generation model is using the small number of candidate video from the overall population and the ranking model scores the candidate. The highest score video represents as a recommendation video.

**2. Freshness**
The freshness is related with new video uploaded on YouTube. The a new video is also important for the recommendation. The user also wants and prefers the fresh content on YouTube.

**3. Noise**
The noisy data aren't giving proper result or analysis.

**Candidate generation:** YouTube collection wins down to hundreds of user-relevant videos. Then, for better performance, we use the hierarchical softmax classification.
**Ranking:** The primary role of ranking is to specialize the candidate predication for the particular user interface. In the ranking three things are important feature representation, modeling expected watch time and experiments with hidden layers.
In This paper, we explain the methodology of recommendation for deep learning. The methodology is above explained in short form.

 

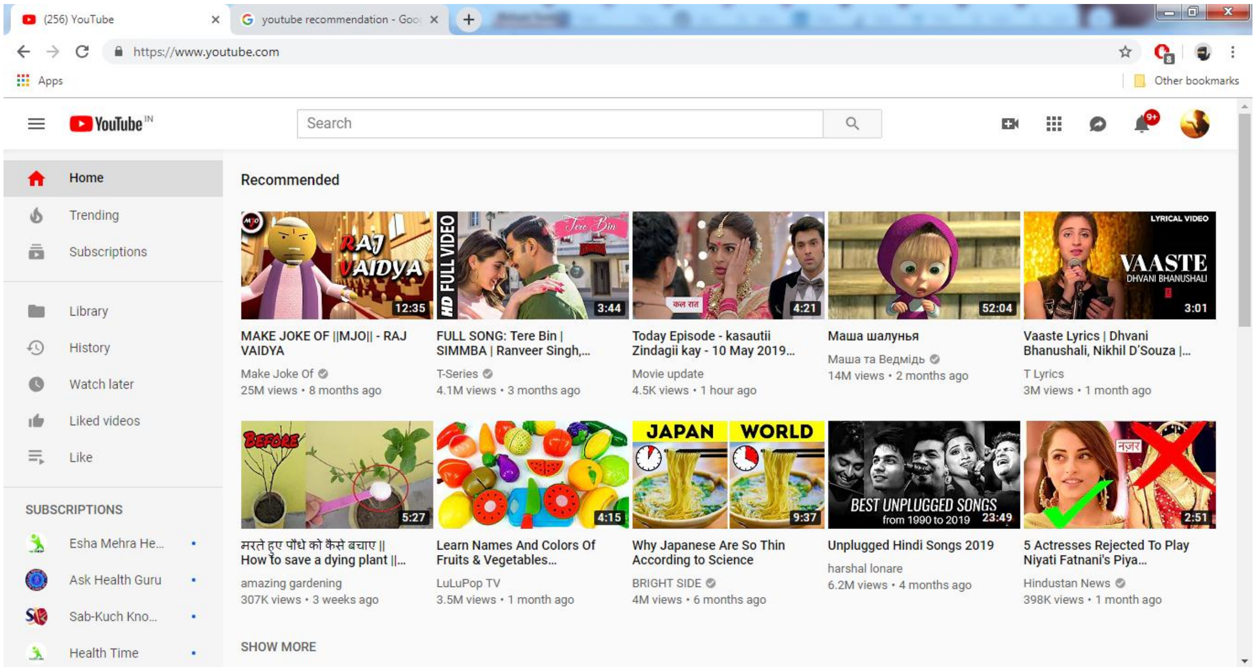


**Fig.1 Recommendation Display on YouTube Desktop Home**

## II. LITERATURE REVIEW

Back in 2005, when YouTube is started, it had a same homepage for all users. This means every user would see the same home page and the creators who would feature there, would get a lot of boost in their viewership. The selection was based on their subscriber count, views, likes, comments and shares, etc. as ads started showing on YouTube videos, the scenario changed. And also increase the number of users. This was a good time to help the users to see what they really wanted to see. And the next level of innovation comes machine learning model. The machine learning model was created to suggest or recommend videos to user.

YouTube is a center of content creation, distribution and learning. Day by day the popularity of YouTube is increasing because of a recommendation system. With the help of recommendation the user can easily get the video and many video is recommended at the same time. Therefore user sees the video long time. The YouTube is trying to increase the watch time of every single video so that the users stay longer on the platform.

For recommendation, we use deep neural network. Deep learning is a part of machine learning methods based on the layers used in artificial neural networks. The recommendation is divided into two parts candidate generation and ranking. Candidate generation uses for videos, users and search features to narrow down the millions of videos to hundreds. We use the deep neural architecture to predict the softmax score for each video to narrow the hundreds. Then we go to the next step or other method ranking model. In ranking model we used more features such as a specific video content features for better recommendation. The goal is to predict the time. The user is how much time spends to watch the video.

## III. METHODOLOGY

**Network Structure:**

 

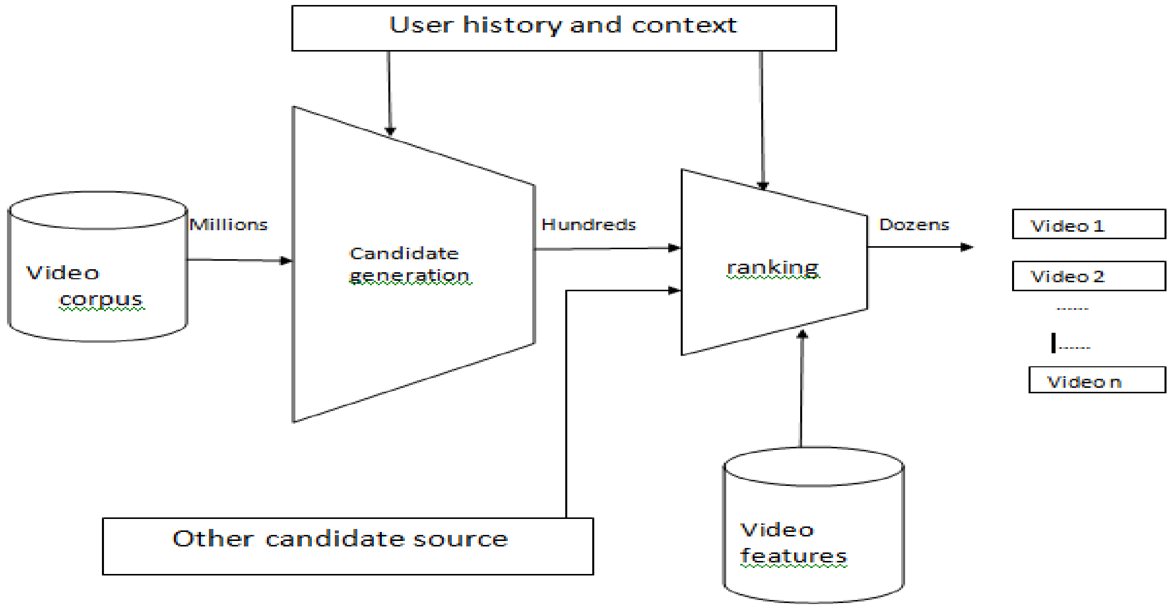


**Fig.2 Recommendation system architecture showing the "funnel" where candidate videos are retrieved and ranked before only a few are presented to the user.**

### 1. Candidate Generation Model

The **input** is taken from the history of using youtube of the candidate generation model and the small subset of videos is retrie ved from the large corpus.
This candidate is meant to be generally highly accurate to the user. YouTube collection wins down to hundreds of user-relevant videos. The recommender outlines the approach to matrix Factorization.

**Matrix Factorization Methods**: When a user gives a feedback to certain video they saw, this collection of feedback can be **represented** in the form of a matrix. Where each row represents each user, while each column represents different videos. Matrix factorization is the fact that it can incorporate implicit feedback, information that are not directly given, but can be derived by analyzing user behavior. Using this strength we can estimate if a user is going to like a video that he/she never saw. And if that estimated rating is high, we can recommend that video for the user.

1.1 **Recommendation as Classification:** The recommendation is a multiculous prediction where the prediction problem becomes accurately classifying a specific video watch $w_t$ at time t among millions of videos i from User-based corpus V and context C. this is simple softmax where we compare the score for a video I with the sum of the score for all other videos. The inputs for video I and user are embedding. This model is trained using negative sampling.

$$P(w_t = i|U, C) = \frac{e^{v_i u}}{\sum_{j \in V} e^{v_j u}}$$

**Fig.3 the prediction of watch time distribution**

### 2. Ranking

The ranking is the second network of neurons. Used to rank in order the few hundred videos.
Compared to the candidate generation model, this is easy because the candidate generation model provides the small number of videos and there is more information available for each video as well as its user relationship. To score each video, this system uses the logistic regression. Watch time is expected to use the metric here, as the expected click may promote click bait. Our final ranking goal is constantly being tuned based on the results of live A / B testing, but is usually a simple function of the expected time per impression.

 

**Features:** With the help of the features we easily give the ranking to multiple videos. Further Features are broken down **depending** on the weather they only add a single value or multiple values. We also classify the features as they describe properties of the user's item or properties according to the weather.

**2.1 Expected Watch Time:** Our objective is to predict the expected watch time given either positive or negative training examples. We use the weighted logistic regression technique to predict the expected watch time. The model is trained under cross entropy loss with logistical regression. A likelihood E [T] (1+P), where E [T] models the expected print time, and P models the likelihood of clicking the video.

**2.2 Hidden layers :** The impact on per-user loss of a wider and deeper network. Per-user loss was the total amount of watch time that was wrongly predicted, compared to the total watch time on data held.

| Hidden layers | Weighted, per-user loss |
|---|---|
| None | 41.6% |
| 256 ReLU | 36.9% |
| 512 ReLU | 36.7% |
| 1024 ReLU | 35.8% |
| 512 ReLU -> 256 ReLU | 35.2% |
| 1024 ReLU -> 512 ReLU | 34.7% |
| 1024 ReLU -> 512 ReLU -> 256 ReLU | 34.6% |

**Fig.4 Demonstrate the effects on next-day holdout data of wider and deeper networks.**

This allows the model to predict something as a proxy for a better recommendation; instead of predicting a better recommendation itself.

## IV. CONCLUSION

Above paper describes the deep neural network for YouTube recommendation. This recommendation divided into two neural network candidate generation models and ranking model. In the candidate generation, we filter the video and use the two concept matrix factorization and classification. After candidate generation, we give the rank of video depend on features, expected watch time and hidden layers. With the help of this technique we recommend the video to user on YouTube. But the recommendation is done when user view, like or share particular videos. It is the limitation of recommendation for YouTube videos. In Future It is Helpful for the business purpose and also user takes more advantage.

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