Google Youtube Multi-View Deep Learning System

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ABSTRACT
Now a days online services are mostly based on automatic personalization to recommend content to user, based on user search history. One of the widely used online service which use perosnalization concept is Youtube video recommendation system.Youtube also placing advertise based on user serach history.On Youtube,people are uploading 500 hours of video every minute and there are approximately 2 billion of users. What makes Youtube to recommend relevant content to users in this huge dataset? At the startup, Youtube was ranking content based on clicks but that doesn't sound good idea as user can click and close a video.Then to overome this issue Youtube introduced watch time concept where users watch time added more values to recommendation.With increasing number of users and modern technology Youtube introduced Deep Neural Network and machine learning concept to recommend videos to user. So to support miilions of items and biilions of users multi view Deep Neural Network is very helpful.

INTRODUCTION
Recommendation system use collaborative filtering, content based filtering or combine both to recommend data to user.Content based filtering use item features liked by user and recommend similiar kind of items to user.Collaborative filtering recommend items to user based on user similarity or item similarity. Collaborative filtering has problem of cold start if enough user and item feature data is not available.To overcome this probelm system started building user and item features space based on rich features from user serach history by assuming that users online search represents user preference and background.

Deep structured sematic models maps users and items in shared semantic space and recommend items that have maximum similarity.For example, if user search for cricket world cup, then recommend cricket news , cricket games to user.Single Deep neural network is restricted to single domain where as Multi view domain learn features of items from different domain.Multi-View DNN learn more from domain which don't share common feature space.In multi view instead mapping user and features to specific domain, single mapping is done for user features in latent space such that it optimised with features of items from all domains. In this way multi view approach helps to share data across the domain and recoomend more useful data to user which resolve problem of data sparsity. We will look into following concept in more detail
1.Multi-View Neural Network
2.System overview for Youtube system
3.Feedback for recommendation system
4.Feature Engineering
5.Normalizing feature

Multi-View Deep Neural Network

Multi view neural network combines user features and items from different domain with same set of users.System is trying to create latent space where user features and jointly optimise item features from diffrent domain.Optimisation of features is required as all the online services scaling continuously and it's not possible to create separate domain to maintain data.Also Multi view DNN optimise multiple domain simultenously so it will save processing time and space also. For example, user watching videos related to specific game can get news, online games recommendation.Here system is trying to maximize similiarity between user and item feature view.Objective of multi view domain is to transform user feature into space that matches all diffrents item user liked in different space.This kind of data sharing allows domain that don't have enough information to learn good mapping from other domain.All this work based on assumption that user has same taste in other domain as well.

K-Means Algorithm:

K-means clustering technique used to creating number of cluster and sum of distance between each point and it's nearest cluster is minimized.Algorithm is used to group simillar features to same cluster.

System Overview

Overall structure of youtube recommendation is illustarted in following figure.

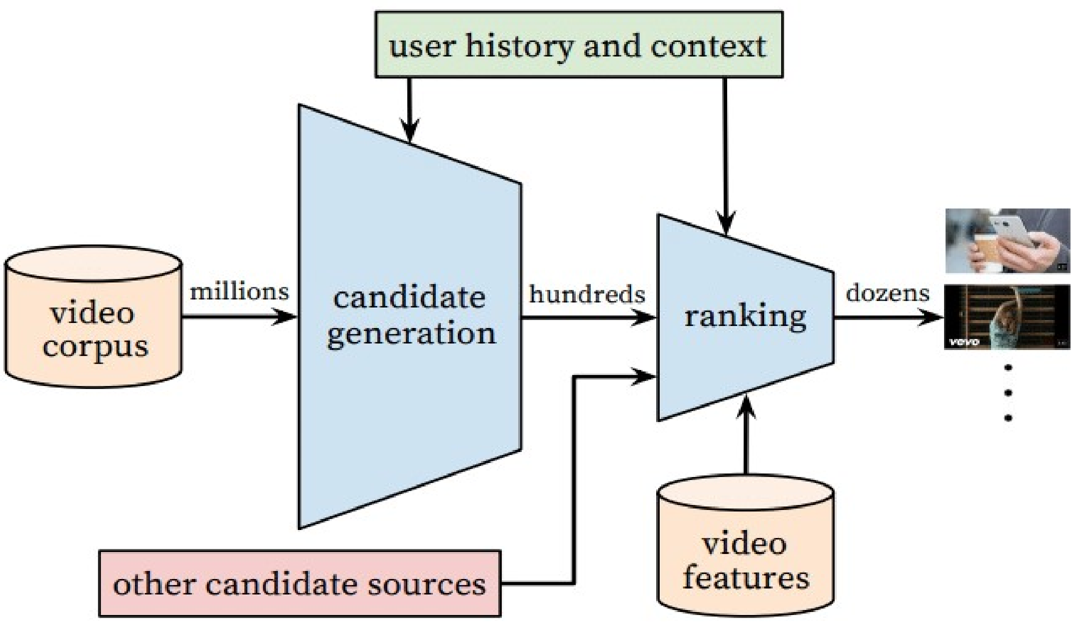


Figure 2: Recommendation system architecture demonstrating the "funnel" where candidate videos are retrieved and ranked before presenting only a few to the user.

(Source: Deep Neural Networks for YouTube Recommendations, 2016)

Recommendation system architecture apply two layer of neural network to provide fine tuning of recommendation to user.following is two neural network for recommendation system:
1.Candidate Generation
2. Ranking.

Candidate generation neural netwrok is helpful in retriving hundreds of videos from large video corpus.Candidate generation uses collaborative filtering to create small subset of data from large corpus.In this step, algorithm uses users history and other parametrs like video id ,demographic information etc.In this stage,precision has higher weight as comapre to recall so that we can pull all relevant videos for user.

Once candidate generation system extracted small subset of videos from large corpus, system has to fine tune the data such that only few relevant videos are available to user,this is called ranking.Ranking is most important steps to provide score to videos as per rich user feature set.Recall has more weight in this state to provide high ranked videos to user.

Input:
Embedded video watch, Embedded search token, geographic information of user, User profile information
Output:
Top N video suggestion to user.

Recommendation system use ReLU neural networks as a hidden layers to provide weight on videos so that system can generate top N videos based on inputs.

Recommendation as per watch time

System recommends video based on watch on time of video.

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

Where wt= watch time at t
U – User
C- context
V- video corpus

Task of neural network is to create user embeddings for user u as function of user’s history and context.

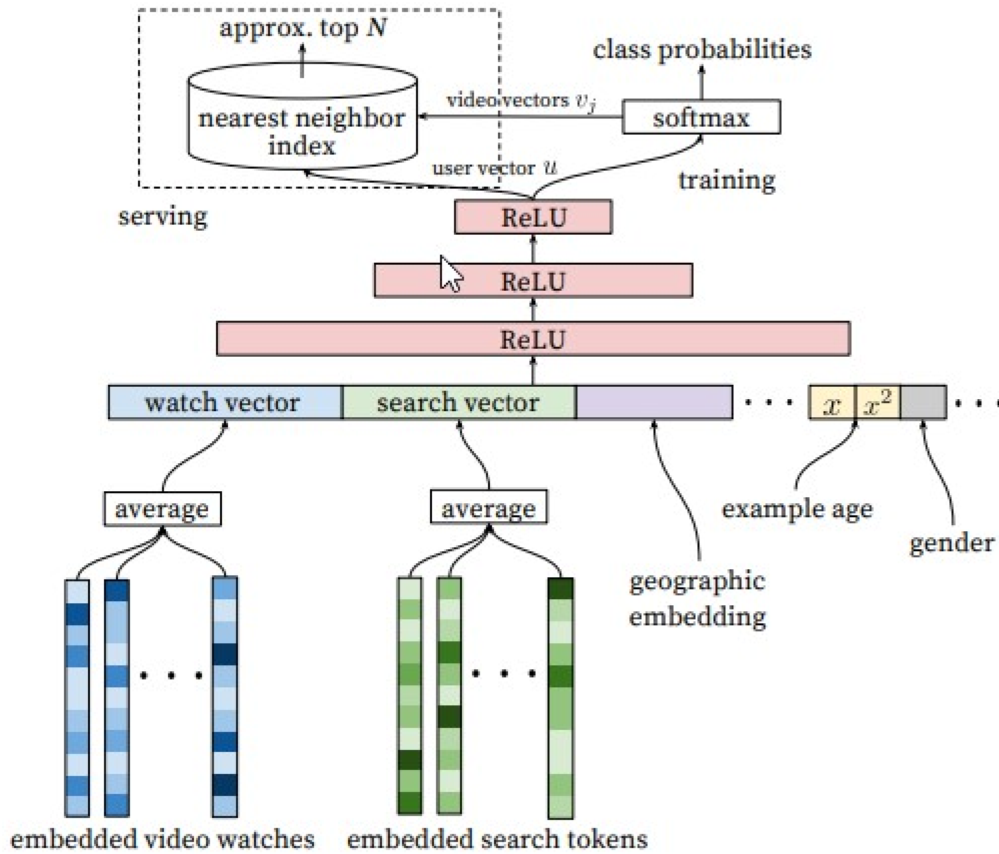
Feedback For Recommendation System

Youtube has explicit and implicit feedback mechanism.
Explicit feedback: user like, dislike videos.
Implicit feedback: system monitors watch time for videos.if user complete video that's positive feedback for video.

If user doesn't watch particular video then youtube has to remodel the data to decrease score for that particular video watch.

Heterogenous Signal

Youtube system started learning from multiple sources like users watch history and user search history.system is suggesting diffrent shopping websites and youtube videos as per users search/watch history.It considers users language and video language also.



Deep candidate generation model architecture with sparse dense features set (Source: Deep Neural Networks for YouTube Recommendations, 2016)

Feature Engineering

Feature enginnering transforms user and video data into features.Recommendation algorithm looks for user interaction with item and other simillar items.For example, it considers user past history for particular channel and last time when user watch particular video related to that channel. Feature engineering is important to filtering objects from huge data set so it is more important to select rich feature set.
User language and video language features are added to network to train model which are considered as categorical features for user.Also normalized last time watch and previous impression are added as input to embedded layer.

Normalizing Features

Day by day, data added to youtube is scaling at huge quantity and hence lead into increasing feature set which creating problem for convergence.It is more important to optimise features with increasing data set.For optimising features, system can pick top k most frequent features with high probability.

CONCLUSIONS

Youtube recommendation system uses collaborative filtering to narrow down large video corpus and recommend top N videos to user.Multi-View NN is useful to resolve cold start problem for domain which doesn't have enough data.Rich feature set is used for build accurate recommendation system.Feature optimisation is challenging as system is scaling up continously with huge amount of data.

REFERENCES

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A Multi-View Deep Learning Approach for Cross Domain User Modeling in Recommendation Systems Ali Elkahky ∗ Department of Computer Science Columbia University New York, NY 10027, USA ame2154@columbia.edu Yang Song, Xiaodong He Microsoft Research One Microsoft Way Redmond, WA 98052, USA {yangsong,xiaohe}@microsoft.com