CS410 Text Information Systems Technology Review – amohane2

Introduction

This technology review is about the large-scale ranking system for video recommendation. Most recommendation systems use two stage design for recommendation, but this applies a sophisticated model to rank the videos the user would want to watch next. There has also been an attempt to solve the two major challenges like:

(i) Optimizing the videos that are most watched vs most shared.
(ii) Optimizing for most liked vs high ranked [13].

The proposed system uses shallow tower removing selection bias and modeling and then the model is tested on the users and results are noted. To develop the model, the objectives are grouped into two parts like engagement objectives and satisfaction objectives.

Industrial Recommendation Systems

To build machine learning models, there is a requirement of large quantities of data. Some developers use user logs as test and training data, but it is very costly. But there is always a discrepancy between what the user has asked for and what the user is provided with. It is difficult to predict the users' requirements using training data. Different user behaviors do not showcase exact user utility and effectiveness [1]. The training data reflects what the user is engaging with in the current systems and models. There is always a discrepancy in the user's needs. Hence, the new models recently completed training will not be accurately able to predict the user requirements.

Problem Description

To develop clear and effective recommendation systems, there is a need to consider factors like:

(i) The model must consider elements like content of the video, audio, thumbnail, description, title, and other physical factors as well.
(ii) Large scale implementation: The model must not only be able to serve billions of users, but also serve them effectively.

The proposed recommendation has namely two stages, candidate generation and ranking.

Candidate Generation

The recommended system measures all the aspects of the current video and the candidate video in domains like content, length, creator, the next video watched after the current video and user history. The sequencing is hence generated post the measurements. All the recommended videos are then put together, compared and then ranked accordingly.

Ranking

The ranking system in the recommended model works on the basis of the above listed objectives i.e., engagement and satisfaction objectives. Engagement objectives comprise of user behaviors like clicks, watches and click is classified into binary whereas watch time into regression. Similarly, in satisfaction objectives, clicks are classified as binary and engagement like liking the video is considered as regression.

However, there might be conflicts between these two objectives, there is a use of Multi-gate Mixture of Experts which a sharing model for these types of conflicts. When a user is watching a video, they are most likely to click on the video which is ranked the highest, however it might not be the most relevant to the current one, hence the model tries to remove this discrepancy in the ranking system as well.

Experiment, results and discussion

Youtube has been used to train and test the model due to its enormous number of active users, large content of videos, and the number of user logs created everyday and to evaluate the performance, the developers used MMoE comparing with baseline methods and live experiments.

The experimental results showed significant improvements over the current recommendation system.

Many models are designed specifically for accurate recommendation purposes however, they are not able to provide accurate due to variety of factors like [1]:

(i) Feature Spaces: The large variety of physical inputs like video content, thumbnail, duration etc.
(ii) Scalability: Large scale implementation on a huge number of people to provide accurate results.
(iii) Discrepancy in user intention to view a specific video.
(iv) Amount of training data available.
(v) Balance between effectiveness and efficiency.
(vi) Discrepancy in the data available for training purposes.
(vii) Challenges during evaluation.

Conclusion

The various challenges in the present ranking system were present and based on that a recommendation system was created. Different objectives were considered, and various evaluation metrics were also defined. The results showed substantial improvement over the current model.

References

[1] Kumthekar, Aditee Ajit, et al. "Recommending What Video to Watch Next: A Multitask Ranking System." (2019).

[13] Humaira Ehsan, Mohamed A Sharaf, and Panos K Chrysanthis. 2016. Muve: Efcient multi-objective view recommendation for visual data exploration. In 2016 IEEE 32nd International Conference on Data Engineering (ICDE). IEEE, 731– 742.