Tech Review: Multitask Ranking Systems for Videos

Andre Roberts
andrer2@illinois.edu

1. INTRODUCTION

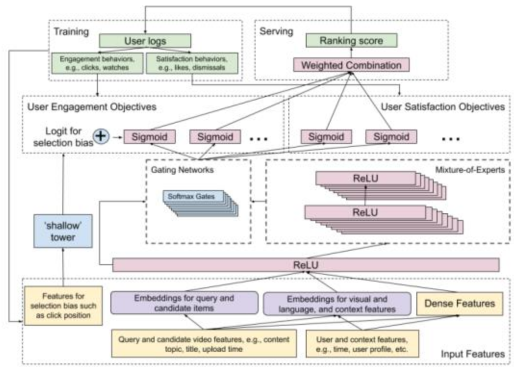
In this tech review we take a look at large scale ranking systems for video platforms like Youtube.

There are many new challenges when it comes to real-world large-scale video recommendations. The first part consists of conflicting objectives. For example, we may want to recommend videos that have a lot of shares, likes, high subscriber count, etc. This second part of the problem is about implicit bias. There might be cases where a user picks a video randomly because they're bored, not because they want to see that content, or perhaps they only wanted to look for one particular interest in that topic, and they may wish not to be recommended anymore of it.

Trying to effectively eliminate or reduce such biases are a difficult task, but there are many working examples, from Youtube itself to researchers proposing new ways to create recommendation systems.

2. Proposed Ranking System

This structure shown below is an extension of Wide & Deep model architecture, a class of networks that use the output of two parts working in parallel, the wide model and the deep model [1].



This new architecture adopts Multigate Mixture of Experts (MMoE) for multitask learning, which explicitly learns to model task relationships from data [2]. This proposed ranking system from the case study has been proven as a great way to utilize MMoE and Wide & Deep Model for video recommendation systems, as we will go over the specifics of what makes this work.

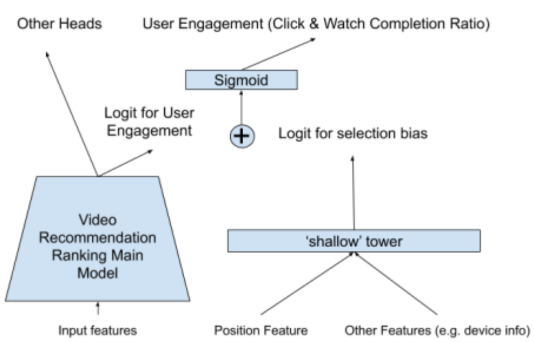
3. Objectives and Bias Handling

The idea of this new model is that there are two separate objectives this system needs to satisfy, engagement and satisfaction objectives. The engagement objectives are about how active a user or users is/are with the particular video, like user clicks and length of user retention. The satisfaction objectives are more focused on a user expressing support and approval for the video, or even the content creator. This can include likes, subscribers to the content creator, praiseful comments, etc.

MMoE is used to automatically learn multiple types of user behaviors by learning parameters to share between the conflicting objectives. The Mixture-of-Experts decomposes the predictive modeling tasks into sub-tasks, training an expert model on each. This develops a gating model that learns which expert to trust based on the input to be predicted, and combines the predictions.

4. Shallow Tower

To finalize the model, it needs to reduce selection bias from the biased training data. This is where the shallow tower concept is added to the main model.



This shallow tower, as the case study explains, "takes input related to the selection bias, e.g., ranking order decided by the current system, and outputs a scalar serving as a bias term to the final prediction of the main model" [3]. This combination of the shallow tower along with the main model helps this system learn the selection bias in an efficient manner, avoiding the issue of selection bias and it avoids resorting to other methods like random experimentation to get the right similarity score.

5. CONCLUSION

Overall, the idea of Multitasking Ranking Systems for Video is mainly based on using a model that can handle neural network learning in parallel, while also including a way to model task relationships from data, and avoid selection bias from the main model, to create a system that can reliably recommend videos based on the user's engagement and satisfaction with the video itself.

6. REFERENCES

[1] Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, et al. 2016. Wide & deep learning for recommender systems. In Proceedings of the 1st workshop on deep learning for recommender systems. ACM, 7–10 Heng-Tze Cheng, Levent Koc, Jeremiah

[2] Jiaqi Ma, Zhe Zhao, Xinyang Yi, Jilin Chen, Lichan Hong, and Ed H Chi. 2018. Modeling task relationships in multi-task learning with multi-gate mixture-of experts. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 1930–1939

[3] Zhe Zhao, Lichan Hong, Li Wei, Jilin Chen, Aniruddh Nath, Shawn Andrews, Aditee Kumthekar, Maheswaran Sathiamoorthy, Xinyang Yi, and Ed Chi. 2019. Recommending what video to watch next: a multitask ranking system. In Proceedings of the 13th ACM Conference on Recommender Systems (RecSys '19). Association for Computing Machinery, New York, NY, USA, 43–51

[4] Xuanhui Wang, Michael Bendersky, Donald Metzler, and Marc Najork. 2016. Learning to rank with selection bias in personal search. In Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information

Retrieval. ACM, 115–124