Recommending What Video to Watch Next: A Multitask Ranking System

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This paper will act as a technical review of the paper that discussed Google's approach of using a multi-task ranking system to improve video recommendations.

1. Introduction

As more people chose to watch videos on online platforms such as Youtube nowadays, providing recommendations on what video to watch next has been a major feature of these video websites to get more exposure, and improving user experience by giving useful suggestions has become one of the companies' major tasks.

The paper first went over the typical design of a recommendation system used for video recommendation, which contains a candidate generation stage and a ranking stage. The paper then presents challenges that the current ranking methods are facing in the ranking stage. One major challenge is that there are multiple objectives that might conflict with each other during the ranking process, such as users may want to see highly-rated popular videos. Another challenge is the user feedback may be implicitly biased, such as users may click on videos just because it's popular instead of finding the content interesting. The paper then proposes an approach to enhance the ranking process through a multitask neural network architecture that adopts MMoE for multitask learning and used shallow tower to reduce the impact of selection bias. The paper also went over a case study process experimenting with the new approach with a large video-sharing platform and proved the approach to be successful through experiment result analysis.

2. Challenges and Model

There are many existing recommendation systems and ranking systems using Neural Network Models, but none of them perform well with video recommendation. There are three main reasons why traditional ranking approaches cannot give the best output on video recommendations. Firstly, a lot of existing models are not scalable and eventually effects the overall qualify and efficiency. Secondly, the process of recommending videos has multiple inputs, which require multi-objective learning for recommendation systems. Lastly, previous ranking models do not efficiently and effectively reduce biases.

To improve the scalability of the recommendation system, the system needs to learn from a large number of users in an efficient way. There are two existing solutions which are pair-wise and point-wise ranking, point-wise ranking model has better real-time performance while the pair-wise has better quality.[1] As video recommendation needs to generate real-time outputs for the user, the model proposed by the authors used deep neural network-based point-wise ranking models to provide a simple and efficient way to scale a large number of candidates.

To deal with multiple objectives during the ranking process, the proposed model divides the objectives into two categories: engagement objectives and satisfaction objectives, and the prediction of the behaviors into binary classification tasks and regression tasks.[1] After the categorization and the prediction, a combination function will be used to combine the outputs and combine a score that will be used in the following steps of the model. The system also adopts the soft-parameter sharing model structure MMoE, the Multi-gate Mixture-of-Expert model, with a gating network trained for each task to reduce the conflicts between different objectives.

Implicit biased user feedback appears in the interaction between the user and the current system, the user may click on items only because it was created by the system. To reduce the effect of the biases, the model proposed utilized shallow tower as a part of the recommending process. The shallow tower will take inputs related to the selection biases, and generate a scalar variance that affects the final result of the model proposed.[1]

3. Experiment

To test the proposed ranking system, the authors conducted experiments on Youtube, a video-sharing platform with 1.9 billion monthly active users. The ranking models are trained using user implicit feedback provided by Youtube, and experiments are conducted both offline and live. The ranking system takes a few hundred candidates from the candidate generation algorithm and both the proposed model and baseline models are trained sequentially to make sure they make adjustments based on the most updated data. The experiment evaluates the performance of the proposed model by comparing its results with baseline methods' results live and statistically on Youtube. The result shows that the proposed model outperforms the baseline model on user engagement and satisfactory metric and shallow tower successfully improves the engagement metric.[1]

4. Conclusion

To sum up, the paper started by describing the typical structure of existing recommendation systems and then presented several problems the current solutions are facing. The challenges are related to a large number of competing ranking objections and sometimes the conflict between these objectives and the implicit selection biases in user feedback. The paper proposed a model using MMoeE and shallow tower and utilize it in the ranking stage to recommend the next videos to the user. The paper also proves the effectiveness of the model by conducting it on a real-life case, although there are possible improvements, the results validate that the system can effectively improve user satisfaction and engagement. In the end, the paper discussed possible future research ideas based on the information discussed in this paper, such as besides MMoE, there is recent work that further improves the stability of the model without hurting prediction performance. Overall, the model proposed worked well in the video recommendation use case and can be improved to achieve better results with more research evidence in the future.

References

[1] Zhe Zhao, Lichan Hong, Li Wei, Jilin Chen, Aniruddh Nath, Shawn Andrews, Aditee Kumthekar, Maheswaran Sathiamoorthy, Xinyang Yi, Ed Chi. 2019. Recommending What Video to Watch Next: A Multitask Ranking System. https://doi.org/10.1145/3298689.3346997