410 Tech Review on recommendation systems

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Introduction:

Recommendation systems play an important role in the IT industry and are vastly applicate in many areas to filter information and help people make better decisions. One of the most famous applications of recommendation systems is video recommendation. Many online video platforms are known for their advanced recommendation systems, including YouTube and Netflix. However, as the online video database grew exponentially, it is progressively hard to design a recommendation system that satisfied users' needs. The call for a stout, larger-scale recommendation system is urgent.

Recommendation systems can be categized into two parts: rating prediction and ranking tasks. Rating prediction is the dominant approach in the recommendation systems research area. However, as the rating prediction approach introduced unresolved disadvantages, including failing to prioritize the head of recommending list, more focus is given to the ranking tasks.

Google proposed a large-scale multitask ranking system to address some of the major challenges of recommendation systems for video.[1] In this paper, we would give an overview of Google's approach to the major challenges, as well as a discussion on the potential challenges in different video platforms and future improvements for the multitask ranking system.

Overview and Discussion

1. Google's approach to the major challenges

The purpose of a video recommendation system is to use the video data users are currently viewing and user profiles to recommend the next video for the user to watch. However, two major challenges are being introduced in this task: conflicting objectives and selection bias.

Confliction interests refer to the optimization of different objective functions such as engagement objective, including time spend and clicks, and satisfaction objective, including rating and shares. Google's multitask ranking model introduced a Multi-gate Mixture-of-Experts(MMoE) architecture in the Wide & Deep model to resolve the conflicts of multiple objectives. The Wide & Deep model combines a wide mode linear model with a deep neural network to generate a prediction for engagement and satisfaction objectives. Different features such as the content, date, clicks, user profile, etc. are fed into the model as input. The MMoE contains multiple experts to predict different objectives. A SoftMax function is used as a gate function for each objective. By effectively sharing weights over different objectives, MMoE can reduce the influence of conflict objectives.

Selection bias refers to the implicit bias introduced by the bias data. for example, the position of the video could contribute greatly to users' decision of whether to click the video. Users might decide to click on the top few recommended videos even when some lower-rank recommendations might yield a higher satisfaction. Dr. Zhao proposes a “shallow tower” model to approach the challenge. A shallow tower is a linear model that is trained with features like the position of the video that the user decided to click and watch the video. The output of the model is combined with the features of the engagement objective learning in MMoE to remove biases.

The result of the paper suggested the implementation of MMoE and shallow tower in their Multitask Ranking systems substantially increase the performance of the recommendation system in both engagement and satisfaction aspects.

2. Different Challenges brought by the different natures of video platforms

Different online video platforms have different types of videos, which will lead to variation in the priority or principle while designing the recommendation systems.

Google's multitask ranking system is designed based on one of the biggest online video platforms, YouTube. Unlike some other online video platforms, such as Netflix or TikTok, which is either consist of almost pure long video or a short video, YouTube contains videos in various lengths, from a few minuses, even seconds, to a few hours. The variation in video lengths gives a very noisy dataset. The nature of YouTube raises one big challenge: how to measure the user time spend on the shorter video against the longer video. It is more likely for the user to finish a short video than a long one even when the longer video might be more satisfying than the short video. Google's multitasks ranking system failed to mention their attempts to this problem.

The rank order of the recommended video also has a different significance depending on the layout of the online video platform. The layouts of video platforms such as Netflix and YouTube allow algorithms to recommend several videos at once to the users, while the layout of video platforms such as TikTok only allows the algorithm to suggest exactly one video to watch next. In the latter case, the first rank video becomes significantly more important than the former. However, very few research articles try to address this problem.

Conclusion and Future Outlook:

In this paper, we conducted a summary of the two major challenges recommendation systems facing and the approaches of Google’s multitasked systems taken. We also discussed how the different natural, such as video length and website layout, contribute to different priorities or principles of the recommendation systems. We introduced a potential fault in Google’s design when addressing the conflict bias introduced because of the different nature of the online video platform, as well as how the layout of TikTok might lead to a need for algorithms that are more focused on the first rank video.

For future research in recommendation systems, the nature of different video platforms can be systematically compared and analyzed to give researchers a better idea of how to design a recommendation system satisfying the requirements of different video platforms.

References

[1] Zhao, Z., Hong, L., Wei, L., Chen, J., Nath, A., Andrews, S., Kumthekar, A., Sathiamoorthy, M., Yi, X., & Chi, E.H. (2019). Recommending what video to watch next: a multitask ranking system. *Proceedings of the 13th ACM Conference on Recommender Systems*.