Tech Review

Solutions of Video Recommendation Challenges

Video ranking is a prominent thing today given how much online video businesses have grown in the past decade. As online video medium businesses surge, they need to adapt to make the user experience as easy and appealing as possible, and businesses want to do that through recommendation systems in order to keep the user engaged and make it easy for them to navigate through to find the content that they enjoy. However, making video recommendation systems effective has challenges. These challenges can include the presence of multiple competing ranking objectives, as well as implicit selection biases in user feedback [cite], along with other factors to consider such as efficiency and scale; and researchers are looking at how to best address these challenges.

There can be multiple competing ranking objectives to consider when ranking videos for billions of users. The objectives may include such things as recommending videos for a user to watch based on watch time, videos that are rarely highly, or recommending videos to share with other related users based on those factors or click rate. To solve for this, the use of an efficient multitask neural network architecture for the ranking system [pg1], which It extends the Wide & Deep model architecture by adopting Multi-gate Mixture-of-Experts for multitask Learning [pg 1] would be a satisfactory option, particularly proven by the results of one group that indicated promising improvement results in evaluation of their ranking model. Their experiment was set up with a,b,c. The result was x,y,z. As a result, this method of ranking objectives worked really well and help address this challenge.

Secondly, the challenge in ranking systems is bias, particularly selection bias. For example, if a system provides the top ten results for a user query, a user may simply choose the top one, thinking the system has chosen the best match, when in reality this is not the case. The ranking system logs the user has clicked on the video and logged that as a binary relevance judgement. This is fed to the system in future similar queries and it enters a erroneous feedback loop for the user. The same group of researchers address this head on by introducing a shallow tower to model and remove this selection bias in their controlled experiments. Their experiment was setup with a,b,c. The result was x,y,z. Thus, they witnessed a significant improvement in managing bias in the ranking system.

Thirdly, other challenges that come into the mix are challenges of efficiency and scale. There are billions of users for a large scale video platform such as netflix and youtube. These systems much serve ranked recommendations to billions of users across a multitude of video content in a moment, which could be a matter of seconds for a good user experience. There is a trade off of quality and efficiency and scale. Companies must perform the balancing act and decide where to move the needle when judging between the two. The group were able to manage efficiency and scaling by using x, y, z in their experiment. They saw good results and tested with Youtube, a large scale platform to get a real idea of performance of such a large system. Their results were a,b,c in using their system configuration and deep learning models. It is known in the community that quality, efficiency, and scale is still an ongoing topic to further research and dive into for future improvements [cite]. So while a,b may be good to solve the efficiency and scaling factors, there may be other solutions available to ensure the proper ranking along with satisfying many users quickly.

In conclusion, video ranking recommendation systems have challenges which need to be addressed for success. There are challenges of multiple objectives that compete with each other when finding candidates, and there are challenges of bias that are introduced in systems during the ranking phase when results are presented to the users. All the while, there are concerns of managing efficiency and scale, something that businesses today must keep in mind to ensure customer retention to achieve revenues. A ranking system that uses the configuration system of a,b,c addresses the multiple objective concerns and challenges, while the configuration of f,g,h addresses the concerns for selection bias, according to the aforementioned experiments run on Youtube, a large scale video recommending platform -- all the while maintaining a level of efficiency and scale. The group addressed this in their conclusion. Therefore, with the provided results we see a way to mitigate the challenges and create a ideal video ranking system that is efficient and scalable; however, there’s room for improvement with further research to ensure efficiency and scalability.

Works cited

Recommending What Video to Watch Next: A Multitask Ranking System.
Zhe Zhao, Lichan Hong, Li Wei, Jilin Chen, Aniruddh Nath, Shawn Andrews, Aditee Kumthekar, Maheswaran Sathiamoorthy, Xinyang Yi, Ed Chi
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Identify the challenges to video ranking and how to address them

- a large scale multi-objective ranking system for recommending what video to watch next on an industrial video sharing platform
- The system faces many real-world challenges, including the presence of multiple competing ranking objectives, as well as implicit selection biases in user feedback.
    - To tackle these challenges, we explored a variety of soft-parameter sharing techniques such as Multi-gate Mixture-of-Experts so as to efciently optimize for multiple ranking objectives.
    - Additionally, we mitigated the selection biases by adopting a Wide & Deep framework.
    - We demonstrated that our proposed techniques can lead to substantial improvements on recommendation quality on one of the world's largest video sharing platforms.
- This paper focuses on the ranking stage
- Designing and developing a real-world large-scale video recommendation system is full of challenges, including:
    - There are often diferent and sometimes conficting objectives which we want to optimize for. For example, we may want to recommend videos that users rate highly and share with their friends, in addition to watching.
    - There is often implicit bias in the system. For example, a user might have clicked and watched a video simply because it was being ranked high, not because it was the one that the user liked the most. Therefore, models trained using data generated from the current system will be biased, causing a feedback loop efect [33]. How to efectively and efciently learn to reduce such biases is an open question.
- To address these challenges, we propose an efcient multitask neural network architecture for the ranking system.
    - It extends the Wide & Deep [9] model architecture
    - In addition, it introduces a shallow tower to model and remove selection bias
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