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In the essay *Recommending What Video to Watch Next: A Multitask Ranking System,* the authors introduce a new neural network architecture that is able to improve the YouTube recommendation system. The research problem authors try to address is that the presence of multiple competing ranking objectives moreover implicit selection bias is included in user feedback in the Youtube. The key finding is that during the process to overcome the research problem, the researchers discover two main challenges: First is Multiple Objective Functions and second is Removal of Implicit Bias. The main contribution of this paper is to focus on updating the recommendation system ranking stage by imposing an efficient multitask neural network architecture.

The Google researchers first brief introduction how the recommendation system works. A recommendation is divided into two stages: candidate generation and a ranking. In this paper, researchers choose to focus on the ranking stage. The Google researchers design a Model architecture for updating the ranking system. Using user logs as training data, it builds Multi-gate Mixture-of-Experts layers to predict two categories of user behaviors - engagement and satisfaction. It reduces ranking selection bias with a side-tower. At the top, multiple predictions are combined into the final ranking score.

First problem researchers meet is how to design complicated multiple objective functions. The paper divides the multiple objective into two groups: 1.Engagement Objective which includes user clicks and the degrees of engagement of users while watching recommendation video. 2.Satisfaction Objective which contains users clicking on likes and rating the recommendation videos in YouTube. The authors formulate the prediction of these two objectives into two types of tasks: binary classification task for behaviors such as clicks, and regression task for behaviors related to time spent. To solve the multiple objective functions, the paper proposes a mixture-of-experts (MMoE)[2]layer along with a Gating Networks. MMoE is a combination of Multi Layer Perceptrons followed by ReLU activations and each of the experts in the MMoE layer will learn a different input feature. During the training process, each of these objectives will look at each of the experts and choose one or more relevant experts for that objective function. An objective can decide whether to share the experts or not with others. The output of the MMoE layer is fed into a Gating Network. Later the output of Gating Networks and shared hidden layers are used into the different objective functions. Therefore it can be used to solve multiple conflicting objectives.

The second challenge researchers meet is how to remove the selection bias in the recommendation system. An ideal data collection to train a recommendation system should be explicit data that indicates whether users like the recommendation video or not. However, those data are hard to collect. Users may click on a video simply because of an accident or ranked high on the front page instead of liking it. Thus the training data generated from the current system will be biased. To remove the bias issue, the authors introduce a shallow tower in the model architecture. The shallow tower is trained to use features that contribute to bias such as recommendation position and to predict whether current instance contains bias.To make the network learn how to remove bias, the selection bias output is also put into the engagement objectives.

The performance of the model is tested at YouTube online. Overall the result is ideal, it is observed that this model is able to improve performance of engagement and satisfaction matrices. However, in my opinion, YouTube is a world-wide video platform. People all over the world and from different cultural backgrounds have access to this platform. I am curious about whether the training data in the essay was collected world-wide or just from specific areas. If the data collection is world-wide, I am wondering whether the bias reduction functionality is able to remove bias that is caused by political propaganda or culture conflicts. In my future research, I will focus on this topic.

To conclude, the Google researchers begin by discovering some real-world challenges in the recommendation system, especially the ranking system. Those challenges include how to solve the ranking of multiple objectives and how to remove recommendation bias. The researchers implement a large-scale multi-objective ranking system. To improve the ranking of multiple objectives, authors a (MMoE) layer along with a Gating Networks model. To reduce the bias in recommendation results, they propose a shallow tower in the model architecture. And the test result shows this model can efficiently improve on both engagement and satisfaction metrics.

References

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