Technology Review of *Recommending What Video to Watch Next: A Multitask Ranking System*

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I. Introduction

In today's society where knowledge, information, and entertainment are primarily consumed through videos on dominating streaming platforms such as YouTube, Netflix, Hulu, Prime Video, etc., the need for accurate, quick, and appropriate video recommendations with the least amount of work from the consumer is obvious. Additionally, as society becomes more sophisticated and technology starts to advance, our requirements for recommendation systems become more complex, introducing multiple competing ranking objectives such as videos with the highest views or videos with the most number of comments. This introduces the problem of developing a ranking system that can tackle both multiple competing ranking objectives and the removal of any biases for today's large scale video streaming platforms that have taken ownership of such a huge part of society.

This technology review discusses a large-scale ranking system for video recommendation that hopes to address all the challenges and requirements of today. For the purpose of the review, video recommendation is defined as recommending the next video for a user to consume given the video the user is currently watching. Recommendation systems usually are divided into two main components: candidate generation and ranking. This paper and subsequently, the review, will focus only on the ranking portion.

The challenges that this solution addresses are the following:
- Manage conflicting objectives such as recommending higher rated videos versus videos that have the most views
- Removing any bias in the ranking such as only clicking on video since it is ranked high and not because of actual likeability.
- Scalability
- Being able to parse through various modalities such as content, thumbnail, audio, title, and description

II. System Overview of Proposed Solution

The ranking system described in this paper is trained off of two types of user feedback: engagement and satisfaction. Engagement is defined as clicks and watches of a user, while satisfaction is defined as likes, comments and rejections. The ranking problem is defined as a combination of classification and regression off of several objectives. The ranking model serves to predict the probability of a user clicking, watching, liking, or dismissing a video based off of the query, candidate, and context provided.

The way a user reacts to a certain video becomes the training data for our model. Since users can react to video in various ways, such as liking a video, clicking on a video, commenting on a video, or skipping certain videos, the ranking system needs to support multiple objectives, as discussed.

This solution separates these objectives into two categories: engagement objectives and satisfaction objectives. Engagement objectives are defined as clicks and watches. Predictions are made from engagement objectives in two ways: binary classification tasks for clicks (1 for a click and 0 for lack of click) and regression tasks for watches (how long a user watched a certain video). Satisfaction objectives are defined as ratings or likes on a video. Predictions from satisfaction objectives are made in similar fashion – binary classification tasks for likes (1 for a like on a video and 0 for no like on a video) and regression tasks for ratings (how much a user has rated a certain video). Binary classification tasks are computed through cross entropy loss and regression tasks are computed through squared loss. The multitask ranking model is then trained for these tasks by consuming the input of these predictions and outputting an overall score using weighted multiplication.

The overall concept and key contribution of the proposed solution is the extension of the Wide & Deep model architecture by adopting Multi-gate Mixture-of-Experts for multitask learning. Multitask learning itself is defined as a means for resolving many tasks at once while utilizing input and learnings from each of the tasks themselves.

Prior to the creation of this solutions, ranking systems that had the need for addressing multiple objectives would often use a shared-bottom model architecture. However, when correlation between multiple tasks was low or almost non-existent, this strategy would harm the learning of each of the multiple objectives. This brought upon the advent of the Multi-gate Mixture-of-Experts (MMoE) architecture.

This soft-parameter sharing model was created with the intent of managing task conflicts and relations. MMoE is different from MoE in the sense that experts are shared from all of the tasks, while providing a gating network that is trained for each task. Specifically, the MMoE layer ensures the task differences are highlighted without needing more model parameters than the shared-bottom model.

The solution in this paper proposes adding experts on top of a shared hidden layer in order to learn more sophisticated information from its input. However, this additional layer does incur higher costs and increase model training.

In order to remove selection biases and break the feedback loop, the proposed model architecture is similar to the Wide & Deep architecture. A shallow tower is added that takes in input related the possible bias and outputs a value that represents the amount of bias possibly present in order to add to the main model. This method prevents us from needed to utilize random experiments to get a certain propensity value.

Overall, the contributions of this new system includes:

- Make the ranking problem a multi-objective learning problem and utilize the Multi-gate Mixture-of-Experts architecture
- Remove any bias through Wide & Deep architecture
- Create full end-to-end video recommendation ranking system

III. Experiment Results

In order to ensure that the solution was in fact accomplishing what was intended, the authors of the paper conducted numerous many offline and live experiments on YouTube, one of the largest video sharing platforms today.

The live experiment results on YouTube are seen through the table below. From this table, we can clearly see improvement in both engagement and satisfaction metrics using the MMoE architecture.

Model Architecture	Number of Multiplications	Engagement Metric	Satisfaction Metric
Shared-Bottom	3.7M	/	/
Shared-Bottom	6.1M	+0.1%	+ 1.89%
MMoE (4 experts)	3.7M	+0.20%	+ 1.22%
MMoE (8 Experts)	6.1M	+0.45%	+ 3.07%

The live experiment results on YouTube in relation to bias are seen through the table below. From this table, we can clearly see improvement when using the shallow tower concept compared to the proposed and baseline method of removing position bias.

Method	Engagement Metric
Input Feature	-0.07%
Adversarial Loss	+0.01%
Shallow Tower	+0.24%

IV. Conclusion

This paper proposed a solution for a very relevant society problem of recommending appropriate videos on today's video streaming platforms. The suggested solution incorporated an extension of the Wide & Deep architecture as well as the MMoE architecture. We were able to notice significant improvements using this solution when testing against one of today's largest video streaming platforms, YouTube. Therefore, it is clear these models are very important to continue learning in order to advance society in the future in other capacities.