Google's Multitask Ranking System - An Overview

Gautam Putcha (gputcha2)

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In this review, I will be covering an overview of Google's very powerful multitask ranking system. This is an extremely powerful system that takes several factors/parameters into account when providing the user with a recommendation on an "Up-Next" video. Some of these include user clicks, time spent on a video, liking a video, the user's context, etc. In a paper by the authors of this system, they clearly articulate the need for a multi-objective learning system. It is very important that the system focuses on multiple user behaviors to make a prediction because oftentimes a single action from the user does not imply utility. The authors provide an example of the user clicking on a video but not necessarily liking it. Two of the biggest challenges encountered with this system were multiple competing ranking objectives and implicit selection biases in user feedback. I will go into more detail on both of these later on.

To provide some background, most of the recommendation systems we see today are comprised of a two-component system:

1. **Candidate Generation** : This is the component in which a few hundred candidates are retrieved from a very large corpus based on several different criteria. The focus of this multi-rank system is not on the candidate generation. The system proposed in the paper uses a few different algorithms for candidate generation. Some of the ones used in the proposed system were based on matching topics and matching videos based on how often the video has been watched with the query video (the video the user is currently watching). Based on these and many other criteria, a set of candidates are pooled together and are ready to be ranked.
2. **Ranking**: This is the component that generates a ranked list from all of the candidates of the previous step. This step tries to maximize the utility of the video

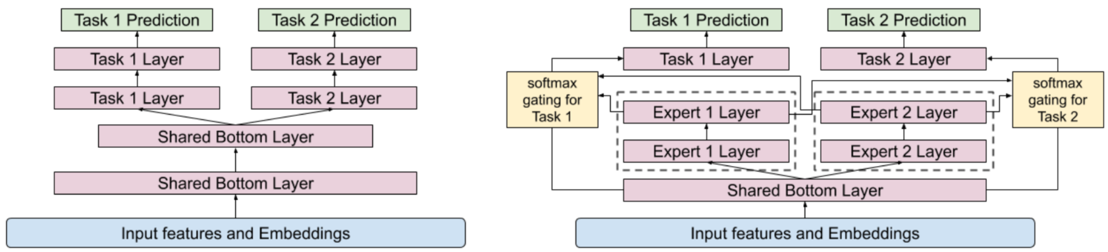
at the top of the list for the user (the video that is “up-next”). A neural network architecture is used for this component.

The paper from the researchers of this topic focused on the ranking part of the system and tried to address the two main issues that came with this while developing it.

- **Multiple Competing Ranking Objectives**: It can be difficult to predict user behaviors using training data. As mentioned earlier, one action from a user does not necessarily imply utility. A user may click on a video but not like it. Therefore, the ranking system needs to take multiple user behaviors into consideration and combine the scores to form a final utility score. Some of the ranking objectives used are classified into 2 categories:
    - Engagement Objectives - Behaviors such as clicks or time spent watching.
    - Satisfaction Objectives - Behaviors such as clicking like or leaving a rating.
- **Selection Bias in the Feedback**: Since the proposed system uses user logs as training data, the user behaviors captured are based on the current production system. This could cause selection bias. An example to demonstrate this is a user may click on a video because he/she sees it on the screen labeled “up-next” and it appears to be at the top of the list on the screen. This does not necessarily mean that this video was the most useful video to the user. Because of the placement of the video in the current production environment, the training data is skewed towards the decisions of the current recommendation system. The new ranking system should ideally remove such a selection/position bias.

Let us now review how these challenges were overcome using the proposed system.

- To address the challenge of multiple competing ranking objectives, it adopts and extends a model architecture called the Multi-Gate Mixture-of-Experts or MMoE. It is designed to model conflicts between tasks. The existing system uses something called a “shared bottom layer”. The idea is to replace a shared bottom layer with a MMoE layer to help learn modularized information from the input. A multimodal feature space can be modeled much better using this layer. The MoE system in general essentially works by having "experts" shared across multiple tasks. This system proposes adding experts on top of a shared hidden layer. This is shown in the figure below.

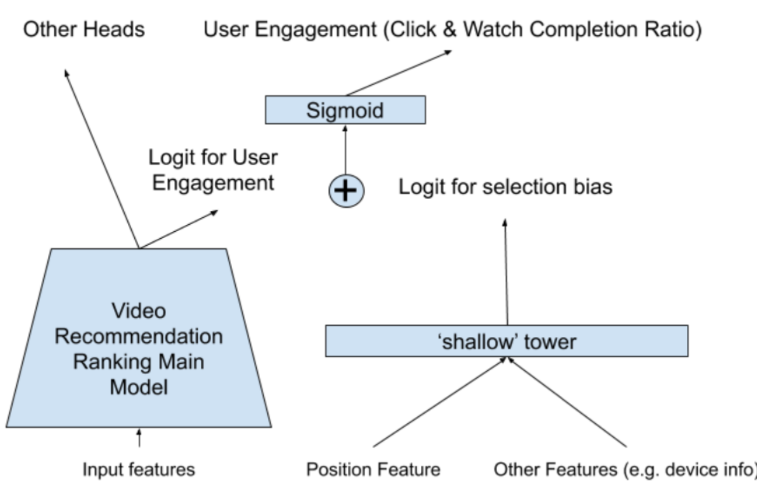


(a) Shared-Bottom Model with shared bottom hidden layers and separate towers for two tasks.

(b) Multi-gate Mixture-of-Expert Model with one shared bottom layer and separate hidden layers for two tasks.

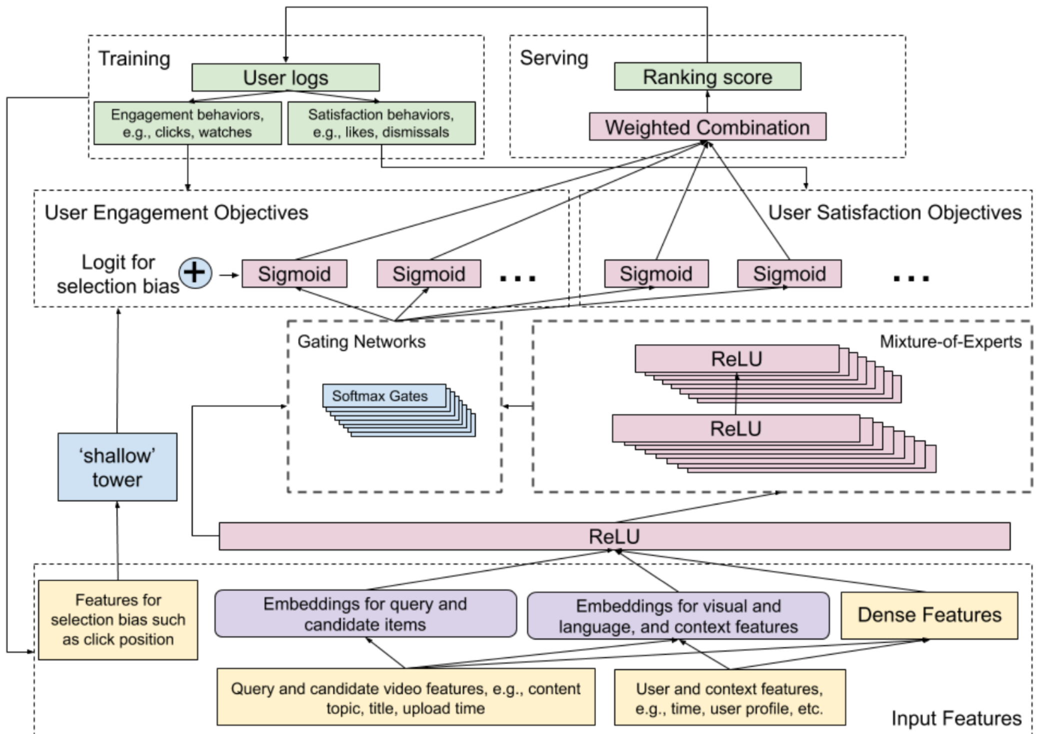
Source: Zhe Zhao, Lichan Hong, Li Wei, Jilin Chen, Aniruddh Nath, Shawn Andrews, Aditee Kumthekar, Maheswaran Sathiamoorthy, Xinyang Yi, Ed Chi. 2019. *Recommending What Video to Watch Next: A Multitask Ranking System.* In Thirteenth ACM Conference on Recommender Systems (RecSys '19), September 16–20, 2019, Copenhagen, Denmark. ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3298689.3346997

- To address the challenge of implicit bias, the authors propose an architecture similar to the "Wide & Deep" architecture. Essentially, a component called a "shallow tower" is trained with features contributing to selection bias, and it is fed into the main model to mitigate or offset the selection bias that may be occurring in the main model. Here is a figure to show what is being done to address this challenge.



Source: 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.* In Thirteenth ACM Conference on Recommender Systems (RecSys '19), September 16–20, 2019, Copenhagen, Denmark. ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3298689.3346997

After adding all of the changes to the new proposed system, it looks as follows:



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Once the system was developed, it was tested against some baseline systems to observe the effects of the new system. The platform used was Youtube and experiments were conducted online (live) as well as offline. It was clearly found that the proposed system improved both the engagement as well as the satisfaction scores. Engagement score is a metric to measure how much time was spent on recommended videos and satisfaction score captured the user survey responses with ratings. Here is their findings after testing against the baseline model:

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%

Table 1: YouTube live experiment results for MMoE.

Source: 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.* In Thirteenth ACM Conference on Recommender Systems (RecSys '19), September 16–20, 2019, Copenhagen, Denmark. ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3298689.3346997

An analysis of the selection bias was also conducted. This was done using an analysis of click-through rates (CTR). It was found that there was indeed a significant selection bias and using the shallow tower approach, the system was able to learn the bias by position in the ranked list as shown.

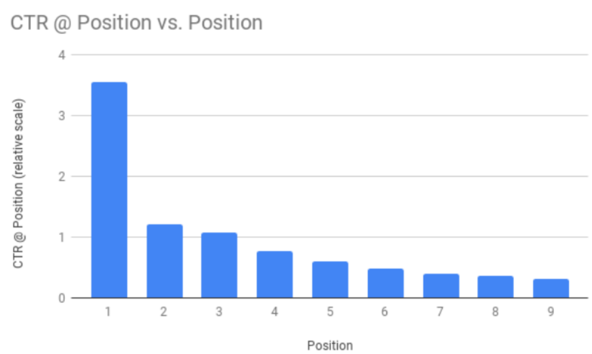
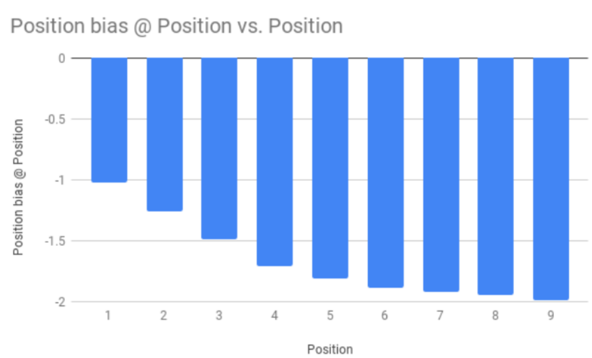


Figure 6: CTR for position 1 to 9.



Source: 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.* In Thirteenth ACM Conference on Recommender Systems (RecSys '19), September 16–20, 2019, Copenhagen, Denmark. ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3298689.3346997

Overall, through the experimentation, it was shown that the new proposed model had a significant improvement over the existing system. Some future applications/directions were also outlined by the authors of this new proposed system. Some of these included exploring a new model architecture for multi-objective ranking, exploring architectures that can automatically identify potential biases and reduce them, and even different compression techniques for ranking. The system architecture proposed clearly showed positive results and a significant improvement in metrics such as engagement and satisfaction metrics. It is indeed very interesting to understand the variety of processes under the hood of something we see everyday, the video “up-next” on Youtube!

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.* In Thirteenth ACM Conference on Recommender Systems (RecSys '19), September 16–20, 2019, Copenhagen, Denmark. ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3298689.3346997
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