Tech Review: Google's multitask ranking system
Recommending What Video to Watch Next: A Multitask Ranking System

Zhuoya Chen(zhuoyac2)

1.Introduction

Nowadays people watch lots of videos on industrial video sharing platforms like YouTube. There's an increasing need for a better ranking system for recommending what video to watch next. Researchers at Google introduce a larger scale multi-objective ranking system. The ranking system is facing many challenges including presence of multiple competing ranking objectives and implicit selection biases in user feedback as well as multimodal feature space and scalability. The researchers for this paper construct some models including Multi-gate Mixture-of-Experts to improve video recommendation systems and conduct experiments in Youtube to verify its effectiveness.

2.Related Work

Industrial Recommendation Systems

We need large quantities of training data to develop a successful ranking system. Most industrial recommendation systems rely on user logs. Explicit feedback from users has a higher cost, thus can hardly scale up. Therefore, implicit feedback is more commonly used in the ranking system. Candidate generation steps: 1) co-occurrence of items to generate candidates. 2) adopt a collaborative filtering based method. 3)apply random walk on graph 4) learn content representation 5) describe a hybrid approach using a mixture of features. Main challenge is scalability. Critical issue in the industrial ranking system is misalignment between user implicit feedback and true user utility on recommended items.

Multi-objective Learning for Recommendation Systems

User behaviors like clicking, rating and commenting might not necessarily reflect what users truly want. For example, I might click on a trending video but I end up not liking it. And I can only rate things that I have clicked or engaged. The ranking system needs to learn multiple types of user behaviors effectively to compute a more accurate ranking score. The researchers discovered that the existing works are not good enough for either stage. Also lots of ranking systems are designed for certain types of features like text and vision. It's challenging to extend those features with multiple modalities. Researchers think that multitask learning tasks like natural language processing and computer vision help them have a better design for ranking systems

Understanding and Modeling Biases in Training Data

Users clicking may create selection bias. Models trained on biased data will cause a feedback loop effect. Position bias exists in click data and it affects rank models to estimate relevance between query and documents.
How to remove position bias:

1) Inject position as an input feature in model training. Remove the bias through ablation at serving.
2) Learn a bias term from position and apply it as a normalizer

User behaviors and item popularities change a lot in the real world and we need to adapt training data efficiently.

3.Problem

There are lots of challenges when developing a large scale video recommendation system:

- There are different and conflicting objectives. We might want to recommend videos that are trending or nice for sharing, not only fun to watch.
- There is implicit bias in the system. Users might watch a video that is very popular but not necessarily favorable. This definitely affects training models and causes more bias.
- Multimodal feature space. Multiple modalities include video content, thumbnail, titles, audio, user demographics, and etc. Learning representation from multimodal feature space is hard because it's difficult to bridge the semantic gap from low-level content features and learn from sparse distribution of items for collaborative filtering.
- Scalability. Real world recommendation system has to provide real-time, up-to-date recommendations to billions of users.

Candidate Generation

The researchers construct a sequence model using two techniques: generating personalized candidate given user history and generating context-aware high recall relevant candidates.[3]

Ranking

The researchers' ranking system generates a ranked list from hundreds of candidates. Applying machine learning techniques using neural network architecture has improved learning association of features and utilities.

4.Model Architecture

Overview

- Efficient multi task neural network architecture for the ranking system, which extends the Wide & Deep model architecture by adopting Multi-gate Mixture-of-Experts for multitask learning.

- Shallow tower to model and remove selection bias.
- Apply the architecture to video recommendation as a case study: given what user is watching currently, recommend the next video to watch.

Ranking Objectives

Sort multiple objectives to two categories:

1) Engagement objectives(clicks, comments)
2) Satisfaction objectives(likes, ratings)

Use MMoEs to learn parameters and share across potentially conflicting objectives.
We formulate the prediction of these behaviors into two types of tasks: binary classification task for behaviors such as clicks, and regression task for behaviors related to time spent.[1] We train a multitask ranking model for the tasks and compute a combined score using weighted combination functions.

Modeling and Multi-gate Mixture-of-Experts

The researchers of this paper decide to add experts on top of a shared hidden layer like shown in Figure 2b. Their implementation is the same as multilayer perceptrons with ReLU]activations.[2]

Modeling and Removing Position and Selection Biases

Users are inclined to click top of the list videos regardless of utility or preference, which could cause position bias.Architecture factorizes the labels to two parts: the unbiased user utility learned from the main model, the estimated propensity score learned from the shallow tower. We can learn the selection bias without resorting to random experiments to get the propensity score.

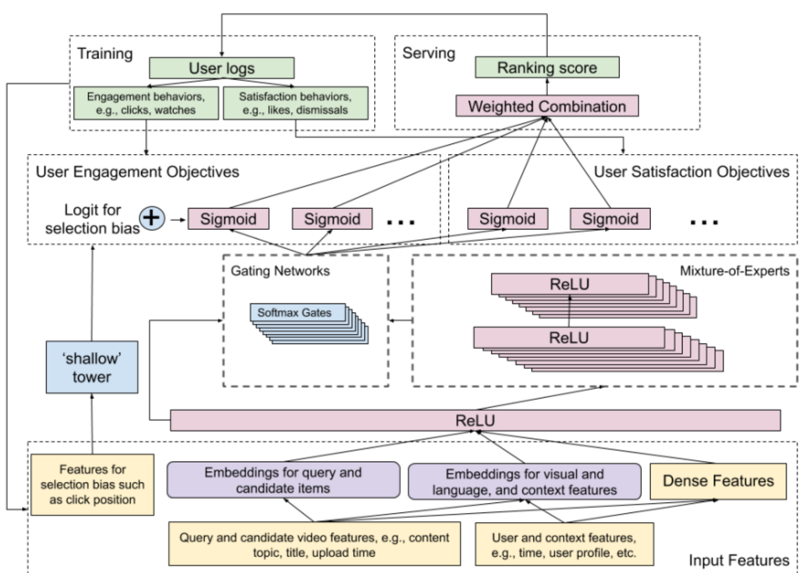
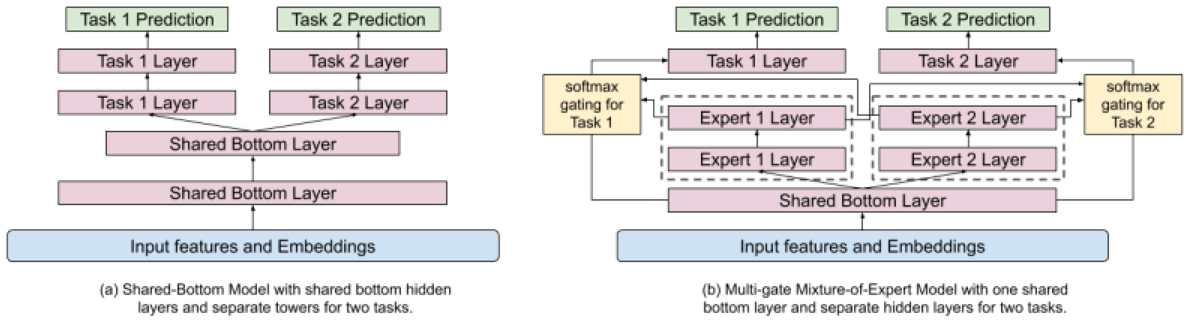


Figure 1: Model architecture of our proposed ranking system. It consumes user logs as training data, builds Multi-gate Mixture-of-Experts layers to predict two categories of user behaviors, i.e., engagement and satisfaction. It corrects ranking selection bias with a side-tower. On top, multiple predictions are combined into a final ranking score.



(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.

Figure 2: Replacing shared-bottom layers with MMoE.

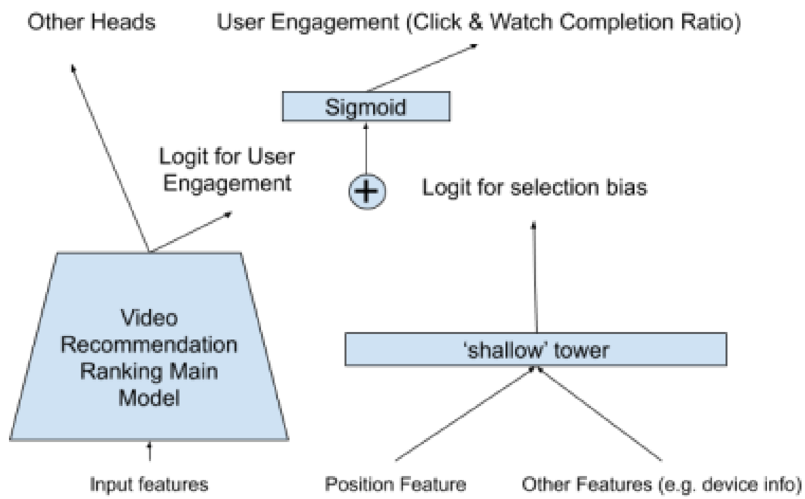


Figure 3: Adding a shallow side tower to learn selection bias (e.g., position bias).

5.Experiments

Design and conduct offline and live experiments to verify the effectiveness of 1) multitask learning 2) removing a common type of a selection bias. Researchers use YouTube to conduct experiments. Researchers use TensorFlow to build the training and serving of the model. Researchers conduct multitask ranking with MMoE using both baseline methods and live experiment results as shown in Table1, which both captures time spent watching videos and rating scores.
Researchers plot accumulation probability in the softmax gating network for each task to have a better understanding of MMoE's influence on multi-objective optimization. It turned out that MMoE's gating networks can effectively modularize input information.
Researchers of this paper also propose a lightweight model for reducing position bias. Conducting an analysis of click through rates verifies position bias exists. They evaluate their model using baseline methods including directly using position features as input as well as

adversarial learning. In the live experiment results, table 2 shows that the method improves engagement metrics significantly.

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.

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

Table 2: YouTube live experiment results for modeling position bias.

6.Conclusion

In this paper, the researchers talked about real world challenges while developing video recommendation systems and they propose a large-scale multi-objective ranking system which includes extending Multi-gate Mixture-of-experts model architecture using soft parameters and proposing an efficient model to reduce selection bias. Via experiments on YouTube, they have shown their techniques have immensely improved engagement and satisfaction metrics. I have learned that different ranking objectives influence ranking scores and we should categorize needs before using complicated large-scale models. Reducing bias is also very important in ranking systems since users might provide feedback that are causing conflicts between usability and preference.

References

[1] Zhao, Z., Hong, L., Wei, L., Chen, J., Nath, A., Andrews, S., ... Chi, E. (2019, September). Recommending what video to watch next: a multitask ranking system. In Proceedings of the 13th ACM Conference on Recommender Systems (pp. 43-51).

[2] Jiaqi Ma, Zhe Zhao, Xinyang Yi, Jilin Chen, Lichan Hong, and Ed H Chi. 2018. Modeling task relationships in multi-task learning with multi-gate mixture-of-experts. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 1930–1939.

[3]Paul Covington, Jay Adams, and Emre Sargin. 2016. Deep neural networks for YouTube Recommendations. In Proceedings of the 10th ACM conference on recommender systems. ACM, 191–198.