Technical Report for CS410

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The technical paper I chose to read is a multitask ranking system for recommending next YouTube video. [1] This paper introduces a multi-objective ranking system to recommend next video to users. The technique can efficiently optimize for multiple ranking objectives and mitigate the implicit selection biases in user feedback. The paper specifically focuses on the ranking stage of the recommendation systems. Currently there are some challenges of the large-scale video recommendation system: sometimes there are different objectives for recommendation, and there can be implicit bias in the systems. Therefore, the paper proposes an efficient architecture for ranking system, which adopts Multi-gate Mixture-of-Experts (MMoE) for multitask learning.

The first step is to group multiple objectives into two categories: engagement objective and satisfaction objectives. The first one means clicking the video and degree of engagement, the second one means user actually likes the video, leaving a comment, etc. MMoE is being used to automatically learn parameters to share across conflicting objectives. The second step is to add a shallow tower to the main model, this is to reduce the selection bias. The shallow towers take input related to the selection bias and output a scalar as a bias term to the final prediction. This proposed technique can be applied to multiple related work, which includes industrial case studies on recommendation systems, multi-objective recommendation systems, and understanding biases in training data. Most current recommendation systems use multiple sources and signals and models to generate candidates; and use learning-to-rank machine learning algorithm for ranking. The major problem of these systems is scalability, so they usually use a combination of infrastructure improvements and efficient machine learning algorithms. The paper identifies the major issue that there is a misalignment between user implicit feedback and true user utility and then introduces a deep neural network-based ranking model to support multiple ranking objectives. In addition, the paper describes a DNN based ranking system and applies an extension of Mixture-of-Experts layer to support multitask learning. Last but not the least, in real-world application, user behaviors are not consistent, there can be implicit bias such as a user clicks an item just because it is on the top of the list. This paper also discusses a more efficient way to reduce such biases of the ranking system.

As mentioned above, there are two main factors to consider when building the ranking system: Multimodal feature and Scalability. To address multimodal feature spaces, the authors extract features including video content signals as representation and use user data as context. To address scalability issue, the authors retrieve hundreds of candidates. For candidate generation, the authors use one algorithm to generate candidate by matching topics, and another algorithm to retrieve videos based on how often the video has been watched together with the query video. For ranking, the system uses a neural network architecture to only keep the most relevant candidates.

In terms of detailed implementation, there are two types of user feedback being used: engagement behaviors and satisfaction behaviors. These behaviors are used as the training labels. For engagement behavior, the authors formulated it as a binary classification task. For satisfaction behaviors, the authors formulated it as regression task. The system takes in multiple predictions and output a combined score. However, there may be conflicts of the multiple objectives, therefore, MMoE is applied. MMoE adapts MoE to multitask learning and can learn modularized information from its input in the system. Additionally, as mentioned previously, the proposed ranking system removes positive bias. The architecture basically factorizes the model prediction into two parts which are user-utility component and a bias component. The shallow tower is trained with features such as position feature, and then it is added to the final logic of the main model.

Experiments are also conducted which includes both offline and live experiments. TensorFlow is being used to build the training and serving of the model. For live experiments, the data of past days are used to train the model so that data distribution and user patterns is dynamic. In terms of offline experiments, both offline and live metrics are used to tune hyper-parameters and then multiple engagement are examined. More specifically, the MMoE model is being compared with the baseline methods, and the same model complexity is being used. For live experiment, both satisfaction metric and engagement metric are being reported. The results show that MMoE significantly improves both metrics.

Implicit feedback is a major challenge in training data, therefore, it is needed to model and reduces biases. An analysis is conducted with click through rates (CTR) for different positions and the results show that position bias exists in the training data. The live experiments results show that the proposed method does reduce the position bias.

In the end, the paper discusses some challenges of existing neural network model architecture for recommendation and ranking. For example, it is challenging to learn from multimodal feature spaces; there are usually multiple ranking objectives; training data can be noisy, etc. There are also future improvements can be made such as exploring new model architecture which balances stability, trainability, and expressiveness; compress the model to reduce serving cost, etc.

To conclude, the paper discusses the current challenges of industrial recommendation system, then it proposed a multi-objective ranking system which addresses some of the challenges. The model efficiently optimizes multiple ranking objectives and reduce the selection bias. Then experiments results are also presented to demonstrate that the model is efficient and effective and truly improves both engagement and satisfaction metrics.

[1] Zhao, Z., Hong, L., Wei, L., Chen, J., Nath, A., Andrews, S., Kumthekar, A., Sathiamoorthy, M., Yi, X. and 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).