**CS410 - Technology Review**
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**Topic: Recommendation - Google's Multitask Ranking System**

The paper being reviewed describes a large-scale ranking system for video recommendation. The reason this problem is important is due to two major issues: 1) there are often different and conflicting objectives for which a video recommendation system wants to optimize for, and 2) there is often implicit bias from the recommendation system. This bias occurs often because a user may click content simply because it is ranked high and not necessarily because it is relevant. In this class we have often assumed that we can use a user's choices to improve and train our algorithms but sometimes this is incorrect and can bias recommendations generated from such training data as a result. The paper proposes extending wide and deep model architecture by introducing a "shallow tower", which learns in conjunction with the main model thereby enabling learning of selection bias without having to resort to random experiments.

The paper reviews related work in its second part, after proposing an expanded model. Many industrial recommendation systems rely heavily on large amounts of training data and due to the high cost of explicit feedback, rely on implicit feedback such as clicks and engagement instead. Due to the issue of scalability, industrial recommendation systems often are forced to make a trade off between model quality and efficiency by using deep neural network-based point-wide ranking systems. This creates the critical problem of misalignment between user implicit feedback and the true user utility on recommended items.

Sometimes a user will click on an item but end up not liking it and a more sophisticated ranking system needs to be able to learn and estimate such user behaviors. The ranking system can then combine the different estimations for a single utility score for ranking recommendations. Ranking systems that extend collaborative filtering or content based systems are not as effective as those based on deep neural networks, and for that reason this paper describes a DNN based ranking system to support multitask learning. User logs are used as training data and capture user behaviors and responses to recommendations from the current production system. Interactions between the user and the current system can create selection biases in the feedback and thus new models trained on the data will continue to be biased towards the current system - creating the question of how to effectively and efficiently learn to reduce these biases in the system. Position bias has been a main issue and several approaches have been proposed to reduce position bias. One commonly used practice is to inject position as an input feature in model training and then remove the bias later. Some other approaches include learning a bias term from position and apply is as a normalizer, a method we have seen often in this course whether it be to normalize document length, normalizing precision/recall through weighted average precision/recall, or even normalization user utility when assigning non-binary utilities.

In addition to the above challenges, the paper describes two additional issues: 1) multimodal feature space where we need to learn from a variety of types of content (video, thumbnail, audio etc.), and 2) scalability where billions of users must be served in real time.To deal with multimodal feature spaces, features are extracted such as video meta-data and information on the user and time/place/etc, while scalability is addressed by splitting the recommendation system into two stages - candidate generation and ranking.

The model architecture proposed in the paper learns from two types of user feedback. The first in engagement behavior such as clicks and views and the second is satisfaction behaviors such as likes and dislikes. Then the system uses the features of the candidate, query and context as input to learn and predict multiple user behaviors. Then given a query, the system can try to predict the probabilities of a user taking these actions (clicks, views, likes, dislikes, etc), similar to how in the course we try to predict the probability of a document's relevance given a query. The ranking system proposed by the paper is based on Multi-gate Mixture-of-Experts (MMoE), which is designed to model conflicts and relations, but adds experts on top of a shared hidden layer.

The ranking system and baseline is trained sequentially meaning models are trained over data in time-order, which is important because data distributions and user behaviors change dynamically over time. The paper evaluates the success of adopting MMoE for multitask ranking by comparing the results with baseline models and through live experiments on Youtube. The paper shows that both engagement (time spent watching recommended videos) and satisfaction (user-survey responses) metrics are significantly improved by MMoE. In addition, the paper tests click-through-rates (CTRs) to verify that position bias exists in the training data.

The paper does point out some potential issues in the discussion section such as the evaluation challenge, where the system still uses mainly implicit feedback. This is of course a very important issue as we have discussed a number of times in this course the challenge of evaluating a recommendation system and also the challenge of obtaining explicit feedback from users. In addition, overcomplicating the model can reduce scalability and efficiency, which we know from this course where overfitting a model may mean it will be less effective on different data.

Overall, this paper tries to improve the solution to the problem of developing an industrial recommendation system where there are multiple competing ranking objectives and where there are implicit selection biases in user feedback. The paper does a good job explaining the issue and why it exists and tries to extend a recently proposed new architecture - MMoE. The paper recognizes the real-world issues of scalability and efficiency and thus tries to create a light-weight model and is not too clucky and complicated. And finally, the proposed model is tested via live experiments on Youtube with results suggesting substantial improvements in engagement and satisfaction. I think this paper was extremely interesting in its attempt to address the many complexities that real-world applications such as Youtube videos introduce. The problem of biases created by implicit user feedback is clearly a difficult one to tackle as ranking does skew user behavior and conclusions drawn from such behavior may not be accurate due to that bias. I am interested to see how these biases can possibly be eliminated from recommendation systems in the future as that will greatly enhance the ability of recommendation systems to push relevant documents/videos/content to a specific user. Of note, I think privacy is becoming increasingly important and thus it may be more and more difficult to get user specific data which the method in this paper clearly tries to utilize to improve recommendations. Trying to get around this problem by using other data besides search/watch history will become increasingly important, in my view.