Paper: Recommending What Video to Watch Next: A Multitask Ranking System
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Introduction:

In this paper, researchers from Google propose a large-scale multi-objective ranking system by extending Multi-gate Mixture-of-Experts model [1], which efficiently optimizes for multiple ranking objectives, and apply it to solve the problem of recommending what video to watch next. Researchers face many real time challenges, including the presence of multiple competing ranking objectives, such as engagement objectives and satisfaction objectives, and implicit selection biases in user feedback, such as user liking a video on YouTube and leaving a rating on the recommendation. To address the first challenge, they choose to use MMoE to automatically learn parameters to share across potentially conflicting objectives. To model and reduce the selection bias from biased training data, they propose to add a shallow tower to the main model, which can be seen as an extension of Wide & Deep model [2]. To evaluate this proposed ranking system, they design and conduct offline and live experiment to verify the effectiveness on a real-world large-scale video recommendation system.

Body:

Problem descriptions

- Multimodal feature space
    - In a context-aware personalized recommendation system, they need to learn user utility of candidate videos with feature space generated from multiple modalities, e.g., video content, thumbnail, audio, title and description, user demographics.
    - How to bridge the semantic gap from low-level content features for content filtering.
    - How to learn from sparse distribution of items for collaborative filtering.
- Implicit feedback
    - The interactions between users and the current system create selection biases in the feedback. For example, a user may have clicked an item because it was selected by the current system, even though it was not the most useful one of the entire corpus. Therefore, new models trained on data generated from the current system will be biased towards the current system, causing a feedback loop effect.
- Scalability
    - Existing works on behavior aware and multi-objective recommendation either can only be applied at candidate generation stage or are not suitable for large-scale online ranking.

- many existing multi-objective ranking systems are designed for specific types of features and applications, such as text and vision. It would be challenging to extend these systems to support feature spaces from multiple modalities.

Approach

In the paper, researchers model ranking problem as a combination of classification problems and regression problems with multiple objectives, they transform recommending problem into predicting multiple user behaviors, which is given a query, candidate, and context, the ranking model predicts the probabilities of user taking actions such as clicks, watches, likes, and dismissals.

- For ranking objectives, they use user behaviors as training labels and design ranking system to support multiple objectives. Each objective is to predict one type of user behavior related to user utility, including engagement objectives and satisfaction objectives. Once multiple ranking objectives and their problem types are decided, we train a multitask ranking model for these prediction tasks. For each candidate, we take the input of these multiple predictions, and output a combined score using a combination function in the form of weighted multiplication. The weights are manually tuned to achieve best performance on both user engagements and user satisfactions.
- Modeling task relations and conflicts with Multi-gate Mixture-of-Expert (MMoE). MMoE is a soft parameter sharing model structure designed to model task conflicts and relations. It adapts the Mixture-of-Experts (MoE) structure to multitask learning by having the experts shared across all tasks, while also having a gating network trained for each task. The MMoE layer is designed to capture the task differences without requiring significantly more model parameters compared to the shared-bottom model. The key idea is to substitute the shared ReLu layer with the MoE layer and add a separate gating network for each task.
- Modeling and removing position and selection biases. They use Wide & Deep model architecture to remove position and selection biases. First, they factorize the model prediction into two components: a user-utility component from the main tower, and a bias component from the shallow tower. Then they train a shallow tower with features contributing to selection bias, such as position feature for position bias, then add it to the final logit of the main model.

Evaluation

They conduct experiments of this proposed ranking system on one of the largest video sharing platforms, YouTube. They apply both offline and online experiments to evaluate the performance of the recommendation system.

- To evaluate the performance of adopting MMoE for multitask ranking, they compare with baseline methods and conduct live experiments on YouTube.
- They evaluate how they model and reduce one type of selection biases, i.e., position bias, with their proposed light-weight model architecture.

Conclusion:

This paper describes a few challenges on recommending what to watch next, which are multiple competing ranking objectives and implicit selection biases in user feedback. They don't simply consider objectives like "click" and "watches", they put all related objectives into consideration, such as "durations", "shares" and "preferences". At the same time, they want to avoid falling into a trap of selection bias. To tackle these challenges, they choose to use multitask neural network. They first etends the Wide & Deep model architecture by adopting Multi-gate Mixture-of-Experts (MMoE) for multitask learning. And then they introduce a lightweight and effective method to model and remove the selection biases, especially position bias. Furthermore, via live experiments on one of the world's largest video sharing platforms, YouTube, it shows that their proposed techniques have led to substantial improvements on both engagement and satisfaction metrics.
What impresses me are that they formulate the problem of recommendation as returning a few high-utility items given a query, a context, and a list of items, and they come up with their solution inspired by multitask learning techniques, while at that time many multitask learning techniques proposed for representation learning are not practical for constructing ranking systems.

Reference:

[1] Ayan Sinha, David F Gleich, and Karthik Ramani. 2016. Deconvolving feedback loops in recommender systems. In Advances in Neural Information Processing Systems. 3243–3251.

[2] Heng-TzeCheng, LeventKoc, JeremiahHarmsen, TalShaked, TusharChandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, et al. 2016. Wide & deep learning for recommender systems. In Proceedings of the 1st workshop on deep learning for recommender systems. ACM, 7–10.