Review on Google's multitask ranking system

Introduction

The paper *Recommending What Video to Watch Next: A Multitask Ranking System* by Zhao et al (2019) proposes a multi-objective ranking system for recommending high utility videos to watch next on the video sharing platform YouTube. Many challenges exist in such systems such as the necessity to efficiently optimize for multiple, potentially conflicting objectives such as user engagement and user satisfaction. Another main challenge includes the inherent presence of selection bias from largely implicit user feedback data. To address these concerns, Zhao et al. extend the Wide and Deep framework commonly used to represent memorization and generalization in recommender systems. A Multi-gate Mixture-of-Experts is used for the deep component and can learn to rank based on multiple, unrelated objectives without incurring excessive computational cost. A shallow tower is used for the wide component to learn and apply the implicit selection bias to the final predicted rank. This framework has been shown to outperform standard multi-objective systems that use a shared-bottom approach via live experiments conducted on the world's largest video sharing platform, YouTube. In this review, the system architecture is discussed with potential methods to further improve its computational efficiency while increasing performance of multi-objective optimization with bias mitigation.

Body

Google's multirank system aims to solve the problem of recommending the next video for a user to watch and enjoy. Specifically, this system focuses on video ranking on YouTube, after the candidate generation phase that has selected the most promising videos to recommend. This problem is complex and challenging for multiple reasons. First, YouTube is one of the largest video platforms, with 1.9B monthly active users, creating hundreds of billions of user logs every day from user interaction with recommended results (Zhao et al., 2019). The large-scale property and complexity of these types of real-world recommendation systems means that the user behavior and video popularities can change significantly every day. This can also cause sparseness of input data due to the large corpus of videos available to choose from and are not yet watched. An efficient learning to rank framework would be required that balances effective learning and computational cost. Additionally, video recommendation is unique in that the training data includes multiple modalities that can influence user engagement (text from video titles, thumbnails, descriptions, visual and audio from video thumbnail and video, views, recency, user context and profile). Second, most recommendation systems are optimized for singular metrics i.e. views or engagement time. However, there are often different and potentially conflicting metrics that should be optimized for simultaneously. In this case, YouTube may want to recommend videos that would not only be viewed and have high engagement time but also be liked, rated highly or shared with friends. Third, there exist multiple biases in recommendation systems such as position bias, presentation bias, and trust bias (Yue 2010, Joachims 2005, O'Brien 2006). Of these, position bias is a main challenge especially when using data based on implicit feedback i.e. user clicks. Multiple studies have proven that users are more inclined to click on top ranked recommendations, simply because they are displayed at the top, regardless of their relevance or utility (Joachims 2005). Therefore, the models trained on this system with an absence of explicit relevance feedback will be biased, causing a feedback loop effect (Sinha et al., 2016).

To mitigate these challenges, the multi-rank system adapts the Wide and Deep framework commonly employed in recommender systems (Cheng et al, 2016). This framework is inspired by how humans learn, and jointly trains wide linear models and deep neural networks representing memorization and generalization respectively. The linear wide component requires well-defined features for the model to learn feature contribution, whereas the deep component needs models like neural networks to generalize information without as much feature engineering. Joining both components combines their respective benefits while decreasing the risk of overgeneralization, which is common with neural networks alone. Zhao et al. (2019) extend this framework by using a shallow tower as the wide component to learn feature contribution to position bias, and a Multi-gate Mixture-of-Experts (MMoE) as the deep component to learn user utility optimized on multiple ranking objectives.

The Multi-gate Mixture-of-Experts (MMoE) supports multi-task learning by leveraging the standard Mixture-of-Experts structure and having experts shared across all tasks with separate gating networks for each task. In contrast, other architectures used for multi-task learning have a shared-bottom model with separate towers for each task. Such a model means hard parameters are shared, which can introduce inductive biases and decrease predictive performance when tasks have low correlation (Ma et al., 2019). Similarly, other multi-task models use regularization and transfer learning, which are sensitive to data distributions and relations among tasks and sometimes result in lower performance than single-task models (Ma et al., 2018). By having a shared network of experts with gating structures above a shared hidden layer, this allows for flexible soft-parameter sharing, and learning of modularized information from the input layer. This structure enables capturing task differences with fewer required parameters and lower computation cost over layering shared networks directly above input layers.

The MMoE allows for flexibility in choosing the experts to share across tasks however, this flexibility is somewhat limited and is computationally expensive. Since there is only one layer of expert networks, there are limited combinations of sharing structures. A model can have more flexibility by connecting internal layers of single-task models however, this approach comes with great computational cost (Misra et al., 2016). A good balance in the flexibility-cost tradeoff has been shown in the Sub-Network Routing (SNR) framework that modularizes the shared layers into multiple parallel subnetworks where the connectivity is controlled by learnable latent variables (Ma et al., 2019). These latent variables can be learned simultaneously with the model parameters, and the model has been shown to outperform the MMoE framework.

To address position bias inherent in implicit feedback from user activity, the MMoE deep component is complemented with a wide component focused on learning features contributing to position bias. A shallow tower is trained with features related to position bias e.g. position in ranking order and other features e.g. device information since different biases are present with different device layouts. The output serves as a bias term and is added to the final logit of the main MMoE ranking model. This wide component is learned concurrently with the deep component; hence the bias term is learned directly and efficiently from the same data used for the learning to rank function, without requiring extra computational cost of separate experiments that may not share the same data distribution (Wang et al., 2016). Learning position bias and applying it as a normalizer usually requires additional random data (Swaminathan et al., 2015). Other methods to address position bias involve including position as an input feature during model training (Zhao et al., 2019; Chapelle et al., 1997); however, this may cause the MMoE to overly focus on learning the contribution of these features to rank position since they are strongly correlated with user implicit feedback, and under focus on other features that have relatively weaker but still significant relation to user engagement metrics. The shallow tower could be additionally extended to consider features related to other biases such as presentation bias and trust bias (Yue 2010, O'Brien 2006), instead of using these features within the learning to rank function, in order to prevent over-emphasizing their feature importance in ranking. It may also benefit to automatically detect biases within the data and learn to reduce them (Zhao et al., 2019).

Conclusion

The Multi-gate Mixture-of-Experts model in conjunction with the shallow tower has been shown to outperform in engagement and satisfaction metrics over standard multi-objective ranking functions that use shared bottom layers with task-specific high-level towers. More recent studies have introduced a more flexible and computationally efficient system called Sub-network Routing, which has multiple parallel shared networks. The MMoE system proposed by Zhao et al. (2019) is clearly one of many influential works on the application of Mixture of Experts in recommender systems for multi-objective ranking. Future work on extending such a system pertains to increasing its efficiency and latency while balancing increased predictive performance.

References

Olivier Chapelle and Ya Zhang. 2009. A dynamic bayesian network click model for web search ranking. In Proceedings of the 18th international conference on World wide web. ACM, 1–10.

Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, 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.

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.

Jiaqi Ma, Zhe Zhao, Jilin Chen, Ang Li, Lichan Hong, and Ed Chi. 2019. SNR: Sub-Network Routing for Flexible Parameter Sharing in Multi-task Learning. AAAI (2019).

T. Joachims, L. Granka, B. Pan, H. Hembrooke, and G. Gay. Accurately interpreting clickthrough data as implicit feedback. In 28th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), pages 154–161, 2005.

Misra, I.; Shrivastava, A.; Gupta, A.; and Hebert, M. 2016. Cross-stitch networks for multi-task learning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 3994–4003.

M. O'Brien and M. T. Keane. Modeling result–list searching in the world wide web: The role of relevance topologies and trust bias. In 28th Annual Conference of the Cognitive Science Society (CogSci), pages 1–881, 2006.

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

Adith Swaminathan and Thorsten Joachims. 2015. Batch learning from logged bandit feedback through counterfactual risk minimization. Journal of Machine Learning Research 16, 1 (2015), 1731–1755.

Xuanhui Wang, Michael Bendersky, Donald Metzler, and Marc Najork. 2016. Learning to rank with selection bias in personal search. In Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval. ACM, 115–124.

Y. Yue, R. Patel, and H. Roehrig. Beyond position bias: Examining result attractiveness as a source of presentation bias in clickthrough data. In 19th International Conference on World Wide Web (WWW), pages 1011–1018, 2010.

Z. Zhao, L. Hong, L. Wei, J. Chen, A. Nath, S. Andrews, A. Kumthekar, M. Sathiamoorthy, X. Yi, and E. Chi, "Recommending what video to watch next: A multitask ranking system," in Proceedings of the 13th ACM Conference on Recommender Systems, RecSys '19, (New York, NY, USA), pp. 43–51, ACM, 2019.