Tech review

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Title of the paper: Recommending What Video to Watch Next: A Multitask Ranking System

Author of the paper: Zhe Zhao, Lichan Hong, Li Wei, Jilin Chen, Aniruddh Nath, Shawn Andrews, Aditee Kumthekar, Maheswaran Sathiamoorthy, Xinyang Yi, Ed Chi

Summary of the paper:

This paper consists of 2 major changes to improve the effectiveness of recommendation system. The first change is it introduced the Multi-gate Mixture-of-Experts(MMoE) structure to learn multiple ranking objects. The second change is to use a shallow tower to learn and reduce selection bias.

Good things about the paper :

For the first change, the article demonstrated the MMoE structure to improve the ranking objects. I really like the idea that we may need to use this type of structure to focus on different aspects of input. The article mentioned that using hard-parameter sharing techniques sometimes harm the learning. To reduce this type of conflicts of multiple objectives, the MMoE model architecture comes into use. Because now we have multi-gates and mixture of different experts within the model, we can reduce the conflict and have a better result overall. It definitely makes sense that separate experts node in model structure will covers different aspects of the input. What surprises me is that the article mentions that in part 5.2.3 that they let the gating networks directly take input from the input layer instead of the shared hidden layer, so that the input features can be directly used to select experts. And they observed no substantial differences compared to the MMoE layer of the shared hidden layer. This means that not only we can save so much resources in model training and serving cost, but also we don’t get a bad result. I think this is the best part.

For the second change, the article introduced this "shallow" tower model structure to learn selection bias. Selection bias is one of the bias that exists in training data. Because training data uses implicit user feedback. And there's a gap between the implicit feedback and true user utility. If we can know the true user utility, we can make the best informed decision for recommendation. However, the true user utility is really hard and maybe impossible to get. So we can only try our best to narrow this gap. And also because people may have higher possibility to click on higher ranked position items, to isolate this position related selection bias out of the system, we need to evaluate how much is the impact for this selection bias itself. The article performs an analysis of click through rates(CTR) for different positions. And the results clearly shows that when position is lower, CTR is lower too. For the higher position, the CTR is higher but also it is a combination effect from both position and true relevancy of the item itself.

Major comments:

What's the p value for the results? How do we know the result showing improvement is truely from the model improvements and not some other random factors? I saw the improvements is around 0.24% compared to -0.07% for input feature and 0.01% for Adversarial loss. Those numbers are all seems very small to me and I don't have a general idea how big of the magnitude of a difference is this. I can see 0.24% is definitely improvements but I want to be sure if that is from a significant result.

Minor comments:

In part 4.3 Modeling Task Relations and Conflicts with Multi-gate Mixture-of-Experts, the second paragraph has a duplicated word "the" in this sentence: "The MMoE layer is designed to capture the the task differences without requiring significantly more model parameters compared to the shared-bottom model.

Recommendations: Yes, I recommend to read this article.