DEVELOPING A RECOMMENDATION BENCHMARK FOR MLPerf TRAINING AND INFERENCE

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1 INTRODUCTION

Deep learning-based recommendation models are used pervasively and broadly, for example, to recommend movies, products, or other information most relevant to users, in order to enhance the user experience. Among various application domains which have received significant industry and academia research attention, such as image classification, object detection, language and speech translation, the performance of deep learning-based recommendation models is less well explored, even though recommendation tasks unarguably represent significant AI inference cycles at large-scale datacenter fleets (Jouppi et al., 2017; Wu et al., 2019a; Gupta et al., 2019).

To advance the state of understanding and enable machine learning system development and optimization for the e-commerce domain, we aim to define an industry-relevant recommendation benchmark for the MLPerf Training and Inference suites. We will refine the recommendation benchmark specification annually to stay up to date to the current academic and industrial landscape. The benchmark will reflect standard practice to help customers choose among hardware solutions today, while also being forward looking enough to drive development of hardware for the future.

The goal of this white paper is twofold:

- We present the desirable modeling strategies for personalized recommendation systems. We lay out desirable characteristics of recommendation model architectures and data sets.
- We then summarize the discussions and advice from the MLPerf Recommendation Advisory Board.

Desirable characteristics for ideal recommendation benchmark models should represent a diverse set of use cases, covering a long tail. For example, most recommendation tasks with large candidate sets have both a candidate generation model and a ranking model working together. The candidate generation model tends to be latency-sensitive with a dot-product or softmax on top, while a ranking model tends to have a lot of interactions being considered. The end-to-end model should ideally produce predictions for both click-through rate and conversion rate. To enable a representative coverage of the recommendation task diversity and different scales of recommendation tasks (that are often dependent on the scale of the available data), we want to consider recommendation benchmarks of different scales.

Many enhancement techniques have been explored to improve recommendation prediction quality. For example, variations of RNNs (e.g. attention layers, Transformer/LSTM styles) are under active investigation albeit in the infancy stage for at-scale industrial practice. It is not clear yet how to best exploit the temporal sequence in DNN-based recommendation models. In addition, dense-matrix multiplication with very sparse vectors is an interesting case as well. This could be thought of as embeddings where input vectors are not just indices but also carry numerical value, to, say, be multiplied with the corresponding embedding row. We should keep an eye on the development of the aforementioned enhancement techniques and refine the recommendation model architecture when it is proven to improve inference quality for practical use cases.

Datasets are essential for the success of personalized recommendation tasks. Desirable characteristics for an ideal recommendation benchmark data set should represent the degree of sparsity observed in production use cases. For example, data sets used for Ads click-through-rate (CTR) prediction are typically very sparse. When looking at the data sets considered by MLPerf, the MovieLens data set (Belletti et al., 2019) represents dense interaction whereas the Criteo Kaggle data set (Cri) is more sparse. Thus, Criteo Kaggle data set is more representative to real production use cases than the MovieLens data set. Furthermore, the MovieLens dataset is not the best choice to showcase DNN techniques for recommenders. This is because the MovieLens type of data includes just user and item IDs but no other features. For such a data set, in practice, a more classical than deep learning technique would suffice.
Another important property of recommendation data sets is the availability of both user and item features as well as user/item interactions, such as ratings and clicks. Furthermore, the data sets should follow a Power Law. The number of dense and sparse features for industrial use cases are often 100s to 1000 with a 50:50 split\(^1\). The number of categories (corresponding to the number of rows in an embedding table) can go up to 100M entries. Its important to note that there are also cases with smaller requirements for the aforementioned diversity.

The data sets being considered by MLPerf currently (i.e., MovieLens synthetic and Criteo Kaggle) are both small (limited number of rows and features), with the largest only about 1TB. Industrial use cases from, for example, Google or Facebook, can span data sets up to 10x-100x larger. Without larger data sets, it is difficult to match real practice seen in internet-service companies (such as the use of side-information in the recommendations task), and probably is not reaching the power-law resolution issues at the core of the recommendation problem for problems with a large vocabulary. For example, the memory capacity offered in state-of-the-art ML training systems (16-256GB DRAM) is insufficient to accommodate for many vocabulary, not to mention dense/sparse features. Future work on data set expansion or creation specifically for the recommendation use cases should be considered for the success of at-scale recommendation benchmarks.

Overall, the key parameters of a recommendation benchmark (of a medium scale, representing current industrial use cases) are summarized as follows:

- Number of features/embeddings tables: **10-100**
- Number of categories per feature/rows of a table: **10K-10M**
- Dimensionality of the latency/rows: **32-256**
- Is hashing a common practice for embedding table access: **50:50 split**
- Are embedding enhancement concept mature enough: **Maybe**
- If so, what techniques should we consider: **Attention, RNN**
- Is a tower-based model representative: **Yes**
- How deep should MLP layers be: **Less than 10**
- How wide should MLP layers be: **Dataset dependent**

\(^1\)The statistics for the dense and sparse features and the proportion are based on the survey outcome conducted in December 2019 with the MLPerf Advisory Board.

## 2 Challenges and Future Direction

Distributed training is a common practice for recommendation models at companies, e.g., Facebook and Google. Communication patterns between the parameter servers and trainers can influence training time significantly. Without a large enough data set, we will not be able to study at-scale recommendation training. On the other hand, not all recommendation models require distributed training. There is a long tail in the model architecture and parameter sizes, in general. Would MLPerf consider a recommendation benchmark with three different scales (small, medium, and large)? Or having a larger, more computation-intensive version to represent ranking use cases? Model parameters representing large-scale use cases are typically 10 times larger than the aforementioned parameters of a medium-size model, with the number of features between 100 and 1000 and the number of categories per feature between 10M to 100M. To overcome potential overfitting, the implication is that the size of data sets will have to scale proportionally with model capacities, demanding, e.g., 10 to 100 billion rows of examples.

In addition to Deep Learning-based modeling approaches (Naumov et al., 2019; Zhou et al., 2018; 2019; Zhao et al., 2019), matrix factorization techniques (Rendle, 2010; Koren et al., 2009), for example, using the two-tower models for retrieval these days, are used widely. Also, we can consider the use of normalized equations as the solver instead of SGD. Furthermore, techniques, such as factorized regression, factorization machines or linear model with matrix factorization, are fairly common. Pairwise feature crossing is another interesting aspect for personalized recommendation. It is particularly important when there are pairwise interactions between different features – similar to the wide part of the Wide and Deep model architecture (Cheng et al., 2016), pairwise interactions in Factorization Machines, or latent crossing for contextual features. RNNs, attention layers, and Deep and Cross Network (DCNs) add more advanced enhancement with extra complexity for recommendation models going forward (Wang et al., 2017). Finally, despite a potential performance bottleneck, capturing and modeling the long tail on the feature category histogram is important to system performance evaluation for performance recommendation use cases.

Looking ahead, we want to pay attention to other recommendation approaches, such as multi-armed bandit and reinforcement learning. Furthermore, the community would really benefit from a taxonomy of recommendation model breakdown.
3 THE MLPerf Recommendation Benchmark Advisory Board

MLPerf Recommendation Advisory Board (chaired by Carole-Jean Wu) consists of academic researchers and industrial leaders with years of experience in recommendation algorithms, datasets, and metrics for recommendation optimizations:

- Prof. Robin Burke, University of Colorado
- Dr. Ed Chi, Google
- Prof. Joseph Konstan, University of Minnesota
- Prof. Julian McAuley, UCSD
- Dr. Yves Raimond, Netflix
- Dr. Hao Zhang, Facebook

The goal here is to have the board of advisors meet with MLPerf (MLP; Mattson et al., 2019; Reddi et al., 2019) and discuss important characteristics of a recommendation model and a data set. The discussion is then used to help steer the selection of an industry-relevant, representative recommendation benchmark.

The advisory board was formed in October 2019. An initial document was shared with the board of advisors (Wu et al., 2019b) for the kickoff meeting held in November 2019. The key findings and insights from the kickoff meeting and offline conversations are summarized and used to form this white paper. Based on the advice and further discussions with MLPerf, we designed a questionnaire to summarize representative parameters for a personalized recommendation benchmark to cover recommendation models of three different scales. The response is summarized and shared with the advisory board in December 2019. The feedback will be used to form a recommendation benchmark for the upcoming MLPerf v0.7 submission. In addition, it will also be used to construct future recommendation benchmarks going forward. We will specify the parameters most practical for MLPerf to implement a recommendation benchmark. The additional data will help guide the work for future benchmark iterations.

We plan to have a closing discussion where we seek to agree on a final recommendation and meet for an update discussion roughly once a year and revise this document.

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MLPerf. https://mlperf.org/.

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