AutoRec: An Automated Recommender System

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Realistic recommender systems are often required to adapt to ever-changing data and tasks or to explore different models systematically. To address the need, we present AutoRec, an open-source automated machine learning (AutoML) platform extended from the TensorFlow ecosystem and, to our knowledge, the first framework to leverage AutoML for model search and hyperparameter tuning in deep recommendation models. AutoRec also supports a highly flexible pipeline that accommodates both sparse and dense inputs, rating prediction and click-through rate (CTR) prediction tasks, and an array of recommendation models. Lastly, AutoRec provides a simple, user-friendly API. Experiments conducted on the benchmark datasets reveal AutoRec is reliable and can identify models which resemble the best model without prior knowledge.

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1 INTRODUCTION

Most recommender systems are highly specialized to handle specific data and tasks. For example, NCF [8] takes user-item implicit feedback data as inputs for the rating prediction task; and DeepFM [6] leverages both numerical and categorical data for the CTR prediction task. However, high degree of specialization comes at the expense of model adaptability and tuning complexity. As recommendation tasks evolve over time and additional types of data are collected, the originally apt model can either become obsolete or require tremendous tuning efforts. So far, several pipelines for recommender systems, e.g., OpenRec [16] and SMORe [4], tried to address the adaptability issue via providing modular base blocks that can be selected according to the context of recommendation. Nevertheless, both determining the blocks to use and tuning the model parameters are not straightforward when facing new data and changing tasks.

In order to bridge the gap, we present AutoRec, which aims to provide an end-to-end solution to automate model selection and hyperparameter tuning. While many AutoML libraries, such as Auto-Sklearn [5] and TPOT [12] have shown promising results in general-purpose machine learning tasks (e.g., regression and hyperparameter tuning) and

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1 AutoRec GitHub: https://github.com/datamllab/AutoRecSys
2 AutoRec Video: https://www.youtube.com/watch?v=z0HkKGVAQkE
As shown in Figure 1, a recommender is composed of 3 kinds of specialized Blocks: mapper, interactor, and optimizer. A mapper is responsible for converting data features into low-dimensional latent factors (embeddings) so different entities can be compared numerically. The numerical/dense features (e.g., time, rating, listening count) are naturally comparable and thus directly mapped as embeddings. For categorical/sparse features (e.g., device, item category, and user and item identifiers), the preprocessor must fit and transform the features before the mapper can be applied. Figure 2 line 3 to 14 shows the declaration of multiple mappers.

Interactor. This base block simulates different ways of interactions between entities. Currently, the 7 pre-structured interactions are as follows: MLPInteraction, ConcatenateInteraction, FMInteraction, CrossNetInteraction, SelfAttentionInteraction, ElementwiseInteraction, and RandomSelectInteraction and each of them have different tunable hyperparameters. In contrast, the eighth interactor, HyperInteraction, is unstructured and supports both hyperparameter tuning and model search. Figure 2 line 15 to 16 shows how multiple mappers are chained into an interactor.

our fruitful efforts with AutoKeras [9] extended AutoML to multi-modal data and multi-task training (e.g., text and image classification), few models incorporate AutoML for recommendation tasks. And for the few which do, their approaches are often too narrow for general recommendation models. For example, AutoInt [14] and AutoCTR [13] focus on searching interactions for only CTR prediction task. Hence, one major novelty of AutoRec is its modular, searchable pipeline architecture tailored for recommendation models.

2 AUTOREC ARCHITECTURE OVERVIEW

2.1 Recommender Construction

As shown in Figure 1, a recommender is composed of 3 kinds of specialized Blocks: mapper, interactor, and optimizer, and the Graph is responsible for putting them together to form a recommendation model’s search space. The HyperModel is the basis for Block. And the Tuner is the basis for Searcher’s tuning algorithms.

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Fig. 1. AutoRec architecture and the TensorFlow ecosystem. Notice red (blue) indicates package (file).

Fig. 2. Building a searchable recommendation model for the rating prediction task (AutoRec-RP).
Table 1. AutoRec platform performance for the click-through rate prediction task (logloss).

| Model       | Tuner | Random | Greedy | Bayesian | Random | Greedy | Bayesian | Random | Greedy | Bayesian | Random | Greedy | Bayesian |
|-------------|-------|--------|--------|----------|--------|--------|----------|--------|--------|----------|--------|--------|----------|
| DeepFM      | 0.4064| 0.4012 | 0.4025 | 0.4014   | 0.4022 | 0.4042 | 0.3992   | 0.4028 | 0.4035 | 0.4014   | 0.4034 | 0.4039 | 0.3995   |
| DLRM        | 0.4811| 0.4795 | 0.4772 | 0.4759   | 0.4743 | 0.4783 | 0.4713   | 0.4786 | 0.4755 | 0.4718   | 0.4739 | 0.4793 | 0.4742   |
| AutoInt     | 0.4776| 0.4817 | 0.4762 | 0.4755   | 0.4751 | 0.4761 | 0.4713   | 0.4761 | 0.4755 | 0.4718   | 0.4739 | 0.4793 | 0.4742   |
| CrossNet    | 0.4752| 0.4797 | 0.4762 | 0.4755   | 0.4751 | 0.4761 | 0.4713   | 0.4761 | 0.4755 | 0.4718   | 0.4739 | 0.4793 | 0.4742   |
| AutoRec-CTR | 0.4752| 0.4817 | 0.4762 | 0.4755   | 0.4751 | 0.4761 | 0.4713   | 0.4761 | 0.4755 | 0.4718   | 0.4739 | 0.4793 | 0.4742   |

Table 2. AutoRec platform performance for the rating prediction task (MSE loss).

| Model       | Tuner | Random | Greedy | Bayesian |
|-------------|-------|--------|--------|----------|
| Movielens 1M| 0.7550| 0.7502 | 0.7517 | 0.7653   |
| Netflix     | 0.7478| 0.7462 | 0.7447 | 0.7533   |

Optimizer. This base block specifies how to generate predicted values and how to measure the deviation between the predicted value and the ground truth, i.e., rating for the rating prediction task and label for the CTR prediction task. Figure 2 line 17 shows how the interactor is chained into an optimizer.

2.2 Searcher Construction

The automated search stage generates a searcher object, which is composed of 3 types of tuner algorithms: RandomSearch, Greedy, and BayesianOptimization. To interact with the searcher, simply pass the recommender object obtained from the recommender construction stage, as shown in Figure 2 line 20 to line 29.

3 EVALUATION

3.1 Framework Simplicity and Adaptability

The example function calls for the AutoRec is shown in Figure 2. As we can see, the entire process can be done by chaining declaration calls and execution calls. Using this simple interface, we show the searchable version of many mainstream recommendation models, such as DeepFM [6], DLRM [11], AutoInt [14], CrossNet [15], MF [10], NCF [8], and MLP, can all be assembled with a few lines of code.

3.2 Recommendation Performance

We use 500K data from Avazu dataset [2] and Criteo dataset [1] for the CTR prediction task, and we use the complete Movielens 1M dataset [7] and Netflix dataset [3] for the rating prediction task. The train-validation-test ratio is 8:1:1. The training parameters are: epoch=10, dimension=64, early stop=1, and trial=10. Due to its large size, Netflix dataset has batch size set to 512000, while others have batch size set to 1024.

Table 1 and Table 2 show the performance of AutoRec in terms of hyperparameter tuning and model search. Specifically, AutoRec tunes the hyperparameter for all models, with AutoRec-CTR and AutoRec-RP further subject to model search. We remark all models found by AutoRec in both tasks yielded satisfactory results by experience, verifying the platform’s reliability. In Table 1, AutoRec-CTR is able to find the model whose performance is the closest to the best model, CrossNet, testifying AutoRec’s modeling ability without prior knowledge. In Table 2, AutoRec-RP simply identifies the best models with different tuner algorithms, and its other findings are also very promising.

4 CONCLUSION

Realistic recommender systems often need to adapt to ever-changing scenarios or to explore options systematically, and AutoML fits right into the spot. In this demonstration, we present AutoRec, an open-source AutoML platform for
recommendation tasks based on the TensorFlow ecosystem. AutoRec supports both hyperparameter tuning and model search, and our experiments verify it can identify close-to-the-best model without prior knowledge. In the near future, we plan to update AutoRec for larger search space and comprehensive plug-and-play examples. In addition, we look forward to your participation in this open-source project.

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