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Deep Reinforcement Learning for Ad Personalization

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The work contained in this thesis is my own work unless otherwise stated.

Signed: Martin Batěk

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Abstract

ABSTRACT GOES HERE

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1 Introduction

The global digital advertising market is worth approximately \$602 billion today. Due to the increasing rate of online participation since the COVID-19 pandemic, this number has been rapidly increasing and is expected to reach \$871 billion by the end of 2027 (eMarketer, 2023). Many of the major Ad platforms such as Google, Facebook and Amazon operate on a cost-per-user-engagement pricing model, which usually means that advertisers get charged for every time a user clicks on an advertisement. This means that these platforms are incentivized to make sure that the content shown to each user is as relevant as possible in order to maximize the number of clicks in the long term. Attaining accurate Click-Through Rate (CTR) prediction is a necessary first step for Ad personalization, which is why study of CTR prediction methods have been an extremely active part of Machine Learning research over the past through years.

Initially, shallow prediction methods such as Logistic Regression, Factorization Machines (Rendle, 2010) and Field-Aware Factorization Machines (Juan et al., 2016) have been used for CTR prediction. However, these methods have often been shown to be unable to capture the higher order feature interactions in the sparse multi-value categorical Ad Marketplace datasets (Zhang et al., 2021). Since then, Deep Learning methods have been shown to show superior predictive ability on these datasets. The focus of my research project is therefore to explore the merits of different Deep Learning architectures for click-through rate prediction.

A number of Deep Learning models have been proposed for CTR prediction, some of which will be explored in this report. Each of these models outperform their shallow counterparts in terms of predictive ability. In a static environment, these models are able to serve the CTR prediction function of Ad personalization, but in a dynamic environment, the model must be able to adapt to the changing user preferences. This is where Reinforcement Learning comes in. Reinforcement Learning is a type of Machine Learning that is used to make a sequence of decisions in an environment in order to maximize some notion of cumulative reward. In the context of Ad personalization, the environment is composed of the user, the Ad platform and the advertisements, whereas the reward is the users' engagement with the advertisements and with the Ad platform.

In this report, I aim to construct a Deep Reinforcement Learning model for Ad personalization that is able to adapt to the changing user preferences and advertisement characteristics available on the platform. In chapter 2, I begin by providing a background to the problem of Click-Through Rate prediction in the context of Ad personalization, and explore the unique challenges posed by the typically sparse multi-value categorical datasets that are common in the Ad marketplace. I then proceed to review the literature on Deep Learning models for CTR prediction, highlighting the different techniques that each framework uses to capture the key feature interactions in the data. I also review

the literature on Deep Reinforcement Learning and its applications across different domains. In chapter 3, I evaluate the performance of different Deep Learning models for CTR prediction on three well-known benchmark datasets, Criteo (Tien et al., 2014), KDD12 (Aden, 2012) and Avazu (Wang and Cukierski, 2014). In chapter 4, I construct a Deep Reinforcement Learning model for Ad personalization and evaluate its performance on the same benchmark datasets. Finally, in chapter 5, I discuss the results of the experiments and provide some concluding remarks.

2 Background

2.1 Deep CTR Prediction

In their respective surveys on the use of Deep Learning methods for CTR prediction, Gu (2021) and Zhang et al. (2021) outline the problem of CTR prediction as one that essentially boils down to a binary (click/no-click) classification problem utilizing user/ad-view event level online session records. The goal of CTR prediction is to predict the probability of a user clicking on an advertisement given the information available about the user, advertisement and the context in which the advertisement is shown. Suppose that $\mathbf{x} \in \mathbb{R}^n$ is a vector of features that describes the user, ad and platform for a given instance, and $y \in \{0, 1\}$ is the binary label indicating whether the user clicked on the ad or not. The goal of CTR prediction is to learn a function $f : \mathbb{R}^n \rightarrow (0, 1)$ such that:

$$f(\mathbf{x}) = \mathbb{P}(y = 1|\mathbf{x}) = \mathbb{P}(\text{click}|\mathbf{x})$$

In other words, for a given set of features \mathbf{x} , the model should output the probability that the user will click on the ad.

2.2 Deep Reinforcement Learning

3 Deep CTR model Evaluation

3.1 Model Selection Methodology

As explained above, I will explore a number of deep learning models. I selected five popular models on the basis of the following criteria

- Competitive prediction accuracy in the KDD12, Criteo and Avazu datasets as published on Papers with Code.
- Ideally, I was looking for a representative set of models for each model type as discussed in (Zhang et. al. 2021). Therefore I was looking for models that employed Product Interaction Operators, Attention Operators and Factorization Machines as a basis.
- The code for the model has to be accessible and intuitive to use.

On the basis of the above criteria, I have chosen the following models to explore:

- Factorization Supported Neural Networks
- Product Based Neural Networks
- Wide and Deep
- DeepFM
- Automatic Feature Interaction (AutoInt)

In the section below, I briefly introduce each of the models, and evaluate against the benchmark datasets loaded and preprocessed above.

3.2 Model Summaries

3.2.1 Shallow Models

Logistic Regression

Factorization Machines

Factorization Machines were first introduced in (Rendle, 2010) as a model class that “combines the advantages of Support Vector Machines (SVM) with factorization models”. The model is able to capture the second order feature interactions in the data, which is a key advantage over Logistic Regression. The model is defined as follows:

$$\hat{y}(\mathbf{x}) = w_0 + \sum_{i=1}^n w_i x_i + \sum_{i=1}^n \sum_{j=i+1}^n \langle \mathbf{v}_i, \mathbf{v}_j \rangle x_i x_j \quad (3.1)$$

where w_0 is the bias term, w_i are the weights for the i -th feature, \mathbf{v}_i are the latent vectors for the i -th feature. Rendle (2010) shows that the learned biases and weights of the FM model can be computed in linear time, “and can be learned efficiently by gradient descent methods”, such as Stochastic Gradient Descent (SGD).

3.2.2 Deep Models

Factorization Supported Neural Networks

The first Deep Learning model that we will consider is the Factorization Supported Neural Network (FNN) model proposed by Zhang et al. (2016). The model works by first training a Factorization Machine model on the sparse-encoded categorical input features. It then uses the latent vectors learned by the FM model (see \mathbf{v}_i in equation 3.1) as inputs to a Neural Network, as shown in Figure 3.1. In doing so, the FNN model is effectively using the FM latent factors to initialize the embedding layer of the Neural Network. The DNN is then able to learn the higher order feature interactions in the data, which the FM model is unable to capture.

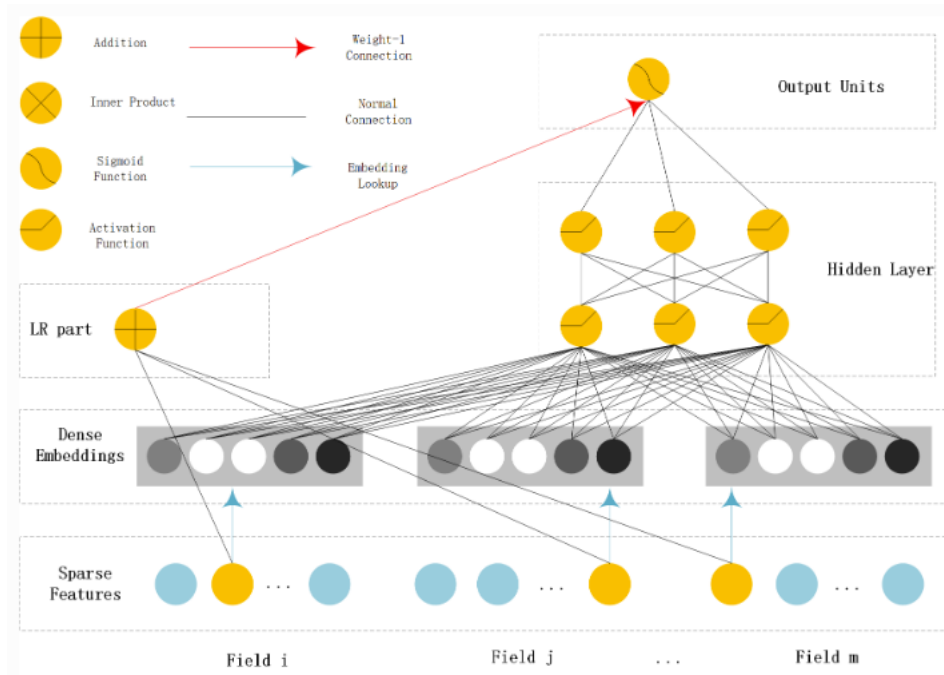


Figure 3.1: Factorization Supported Neural Network as proposed by Zhang et al. (2016).
Image taken from Shen (2017)

Product Based Neural Networks

The Product Based Neural Network (PNN) model proposed by Qu et al. (2016) is another Deep Learning model that was developed around the same time as the FNN model. The key innovation of the PNN model is the use of a pair-wisely connected Product Layer after a field-wise connected embedding layer for the categorical features, as shown in Figure 3.2. The Product Layer is able to directly model inter-field feature interaction by means of either an inner product or outer product operation, and then further distill higher feature interactions by passing the output of the Product Layer through fully connected MLP layers.

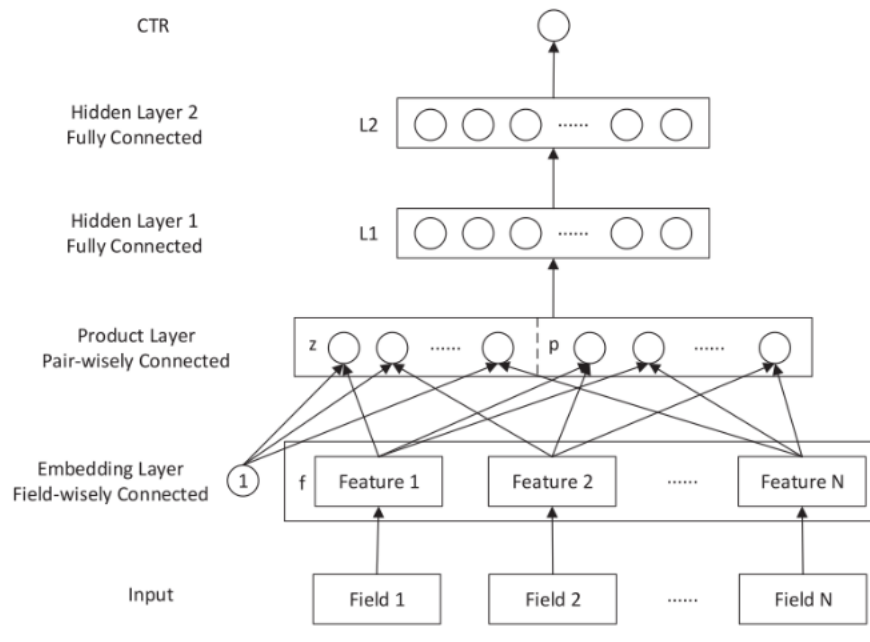


Figure 3.2: Product Based Neural Network as proposed by Qu et al. (2016). Image taken from Shen (2017)

Wide & Deep Learning

The Wide & Deep Learning (WDL) model proposed by Cheng et al. (2016) introduces the concept of dual-tower model architecture (Zhang et al., 2021). While both the FNN and the PNN models generally tend to be constructed as a single fully connected DNN model, the Wide & Deep model consists of a wide component, consisting of a three layer Deep Neural Network that takes the concatenated embedding vectors of the categorical features as input, and a deep component, consisting of a cross product transformation of selected sparse categorical features. The logits from the wide and deep components are added together to produce the final prediction. The architecture of the WDL model

is shown in Figure 3.3.

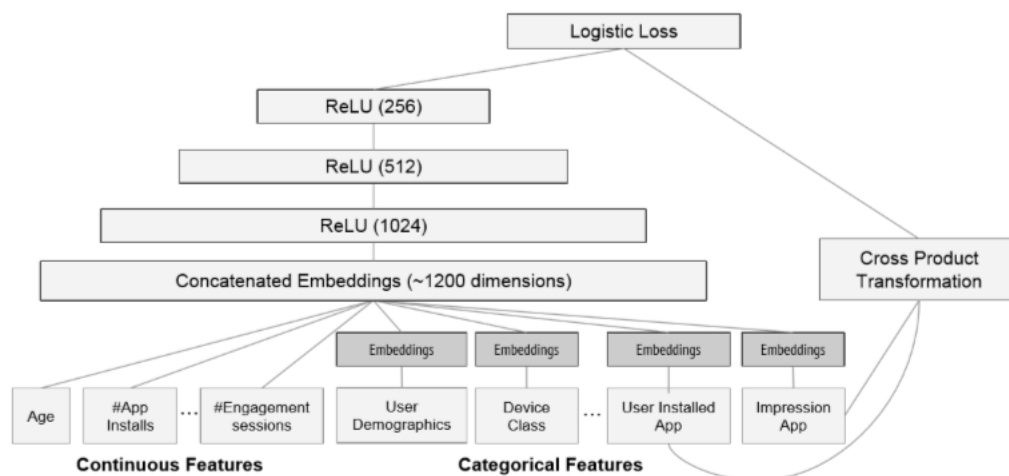


Figure 3.3: Wide & Deep Learning model as proposed by Cheng et al. (2016)

The purpose behind the Dual-Tower architecture is to counteract the tendency of the fully connected single tower DNN models to lose the ability to capture low-order feature interactions (Zhang et al., 2021). The Wide component is able to capture the low-order feature interactions, while the Deep component is able to capture the higher order feature interactions.

DeepFM

The DeepFM model proposed by Guo et al. (2017) can be thought of as an improvement of the aforementioned FNN (Zhang et al., 2016) and WDL (Cheng et al., 2016) models. Like the FNN model, the DeepFM model utilises the Factorization Machine model (Rendle, 2010) to learn lower-order feature interactions. However, it also employs a dual-tower architecture like the WDL model, with the Wide component being the FM model and the Deep component being a fully connected DNN model. The DeepFM model is therefore able to avoid the limitations on capturing low-order interactions that are inherent in the FNN model. In addition, due to the application of the FM to all feature embeddings, the DeepFM model eliminates the need to choose which features to feed through the wide component, as is the case in the WDL model. The architecture of the DeepFM model is shown in Figure 3.4.

Automatic Feature Interaction Learning

The Automatic Feature Interaction Learning (AutoInt) model proposed by Song et al. (2019) makes use of a multi-head self attention network to model the important feature interactions in the data. The initial paper separates the model into three parts: an

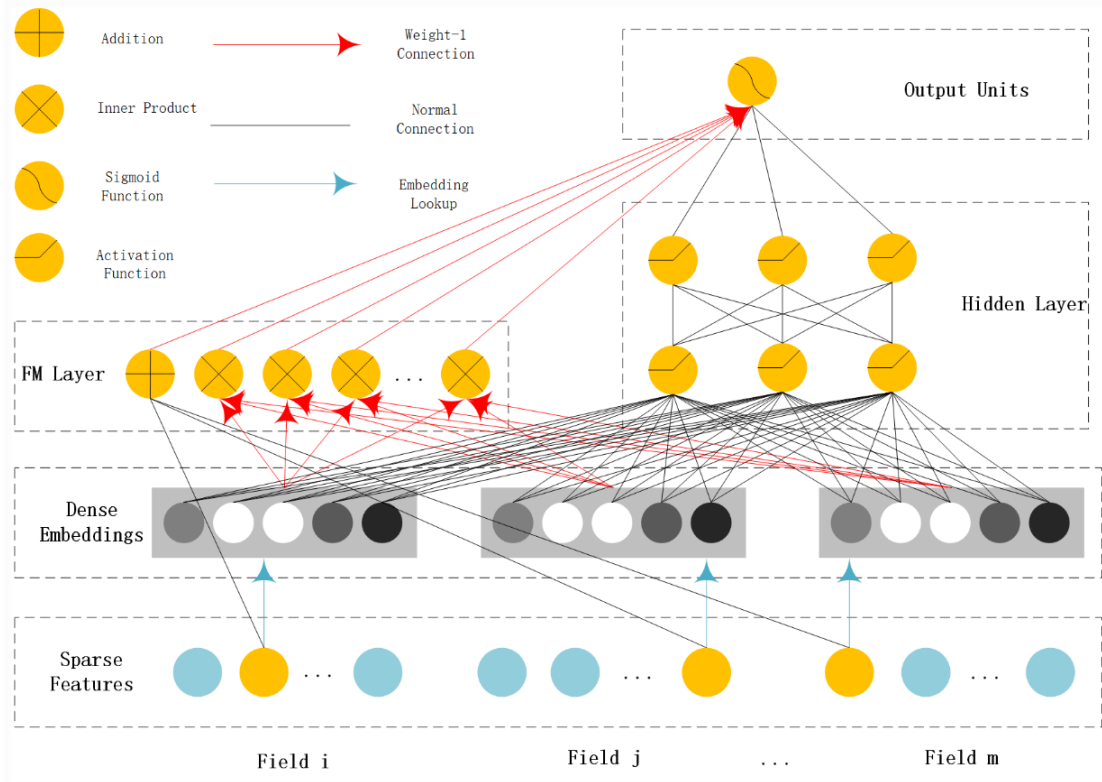


Figure 3.4: DeepFM model as proposed by Guo et al. (2017). Image taken from Shen (2017)

embedding layer, an interaction layer and an output layer. The embedding layer aims to project each sparse multi-value categorical and dense numerical feature into a lower dimensional space, as per the equation 3.2:

$$\mathbf{e}_i = \frac{1}{q} \mathbf{V}_i \mathbf{x}_i \quad (3.2)$$

where \mathbf{V}_i is the embedding matrix for the i -th field, x_i is a multi-hot vector, and q is the number of non-zero values in x_i . The interaction layer employs the multi-head mechanism to determine which higher order feature interaction are meaningful in the data. This not only improves the efficiency of model training, but it also improves the model's explainability. Lastly, the output layer is a fully connected layer that takes in the concatenated output of the interaction layer, and applies the sigmoid activation function to produce the final prediction. The architecture of the AutoInt model is shown in Figure 3.5.

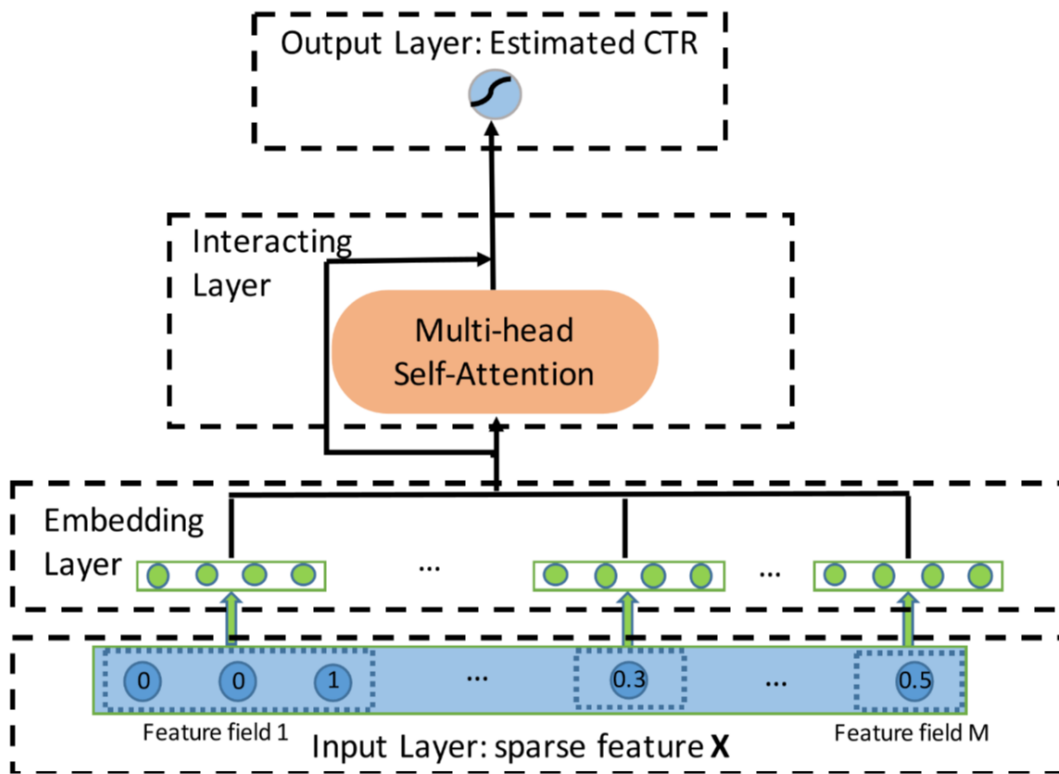


Figure 3.5: AutoInt model as proposed by Song et al. (2019)

3.3 Benchmark Datasets and Exploratory Data Analysis

3.4 Model Evaluation

3.5 Deep CTR Model Results

4 Deep Reinforcement Learning for Ad Personalization

4.1 DeepCTR-RL Framework

4.2 Experiment Setup

4.3 Results

5 Discussion

Discussion goes here.

6 Conclusion

Conclusion goes here.

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