IMPERIAL

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Deep Reinforcement Learning for Ad Personalization

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1 May 2023

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

Signed: Martin Batěk   Date: 17 July 2024

Abstract

ABSTRACT GOES HERE

Acknowledgements

ANY ACKNOWLEDGEMENTS GO HERE

Contents

1 Introduction

The global digital advertising market is worth approximately $602 billion today. Due to the increasing rate of 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 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 advertisment. This means that these platforms are incentivized to make sure that the content shown to each user is as relevent 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 reasearch 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 advertisments, whereas the reward is the users' engagement with the advertisments 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 changeing user preferences and advertisment 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

Background chapter.

2.1 Problem Statement

Section content goes here.

2.2 Literatiure Review

2.2.1 Deep CTR Prediction

2.2.2 Deep Reinforcement Learning

3 Deep CTR model Evaluation

3.1 Model Selection Methodology

3.2 Model Summaries

3.2.1 Shallow Models

Logistic Regression

Factorization Machines

3.2.2 Deep Models

Factirization Supported Neural Networks

Product Based Neural Networks

Wide & Deep Learning

DeepFM

Feature Generation by Convolutional Neural Network

Automatic Feature Interaction Learning

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.

Bibliography

Yi Wang Aden. Kdd cup 2012, track 2, 2012. URL https://kaggle.com/competitions/kddcup2012-track2.

eMarketer. Digital advertising spending worldwide from 2021 to 2027 (in billion u.s. dollars). Technical report, Statista Inc., 2023. URL https://www-statista-com.iclibezp1.cc.ic.ac.uk/statistics/237974/online-advertising-spe

Yuchin Juan, Yong Zhuang, Wei-Sheng Chin, and Chih-Jen Lin. Field-aware factorization machines for ctr prediction. In *10th ACM Conference on Recommender Systems*, RecSys '16, page 43–50, New York, NY, USA, 2016. Association for Computing Machinery. ISBN 9781450340359. doi: 10.1145/2959100.2959134. URL https://doi.org/10.1145/2959100.2959134.

Steffen Rendle. Factorization machines. In *2010 IEEE International Conference on Data Mining*, pages 995–1000, 2010. ISBN 1550-4786. doi: 10.1109/ICDM.2010.127. ID: 1.

Jean-Baptiste Tien, joycenv, and Olivier Chapelle. Display advertising challenge, 2014. URL https://kaggle.com/competitions/criteo-display-ad-challenge.

Steve Wang and Will Cukierski. Click-through rate prediction, 2014. URL https://kaggle.com/competitions/avazu-ctr-prediction.

Weinan Zhang, Jiarui Qin, Wei Guo, Ruiming Tang, and Xiuqiang He. Deep learning for click-through rate estimation, 21 Apr 2021. URL https://arxiv.org/abs/2104.10584.