

Approaching the Ad Placement Problem with Online Linear Classification

The winning solution to the NIPS'17 Ad Placement Challenge

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ABSTRACT

The task of computational advertising is to select the most suitable advertisement candidate from a set of possible options. The candidate is selected in such a way that the user is most likely to positively react to it: click and perform certain actions afterwards.

Choosing the best option is done by a “policy” – an algorithm which learns from historical data and then is used for future actions. This way the policy should deliver better targeted content with higher chances of interactions.

Constructing the policy is a difficult problem and many researches and practitioners from both the industry and the academia are concerned with it. To advance the collaboration in this area, the organizers of NIPS'17 Workshop on Causal Inference and Machine Learning challenged the community to develop the best policy algorithm. The challenge is based on the data generously provided by Criteo from the logs of their production system.

In this report we describe the winning approach to the challenge: our team was able to achieve the IPS of 55.6 and secured the first position. Our solution is made available on GitHub¹.

1. INTRODUCTION

In computational advertisement the goal is to select the best possible advertisement for the user. Consider the following scenario: a user opens a website with advertisement slots (“impressions”). Our system has many possible options (“a candidate set”) for filling these slots. To do it, a “policy” is leaned from the past interactions of users with the system. Such policy is then used to select the best candidate from the candidate set for the future visits to the website.

This problem is quite important for the online marketing community and many researches are concerned with it. Even a slight improvement in the CTR (“Click-Through Rate”) will lead to revenue increase and better user experience.

As a part of NIPS'17 Workshop on Causal Inference and Machine Learning, the organizers prepared the Ad Placement task. In the task they challenged the Data Science community to develop a policy based on historical data. Criteo has generously donated a large dataset with interactions from their production system [2]. Based on this data, the participants could approach this task and build policies to optimize the CTR. The challenge was hosted at the [crowdai.org](https://www.crowdai.org) platform². The solutions of the participants were evaluated using IPS – Inverse Propensity Score (see [2] for more details about evaluation).

In this paper we present our approach to the challenge. Our team used the Follow-The-Regularized-Lead-Proximal (FTRL-Proximal)

algorithm [3] for solving the task. We show that for such large scale sparse classification task FTRL-Proximal is very competitive and was able to produce a high-scoring policy. Our solution was able to achieve the IPS of 55.6, putting us at the first position of the competition leaderboard.

2. DATASET DESCRIPTION

The dataset provided for the competition has two parts: training and testing. The training file is used for learning the policy, which is then executed against the testing part and the results are sent back to the platform for evaluation.

The training dataset contains approximately 10.5 mln candidates set (3Gb compressed), with 12.3 candidates in each set on average. Additionally, we know which candidate was selected by the system, the propensity score of the selected candidate and whether the user clicked at it or not. The CTR in the training data is around 5%.

The test set contains 7 mln groups (1.4Gb compressed) and neither propensity information nor clicks is provided.

A typical candidate set looks like the following (the lines are truncated):

```
17193693 |l 0.999 |p 11.324800021|f 0:300 ...
17193693 |f 0:300 1:250 2:1 10:1 11:1 12:1 ...
17193693 |f 0:300 1:250 2:1 12:1 14:1 21:1 ...
17193693 |f 0:300 1:250 2:1 12:1 14:1 21:1 ...
17193693 |f 0:300 1:250 2:1 12:1 14:1 21:1 ...
17193693 |f 0:300 1:250 2:1 12:1 14:1 21:1 ...
```

Here for the group with `id=17193693` the first candidate is selected by the system. It has the propensity score 11.32 and was not clicked (the label is 0.999). The clicked candidates have the label 0.001. Each candidate is characterized by a set of features, stored in the `feature:value` form. More information about the dataset can be found in the dataset companion paper by D.Lefortier et al [2].

In the next section we will describe our solution in more details.

3. APPROACH

In this section we present our approach to the challenge. First, we describe the hardware and software used for the solution, then we show the validation scheme used in our experiments, and finally we talk about the features, the model we built on these features as well as the post-processing scheme we used for modifying the model's output.

3.1 Environment

¹<https://github.com/wsdm-cup-2017/conkerberry>

²<https://www.crowdai.org/challenges/nips-17-workshop-criteo-ad-placement-challenge>

The experiments were performed on a Linux Ubuntu 14.04 server with 32GB RAM and 8 Cores.

We used Python 3.5.2 and the PyData stack for our development:

- `numpy` 1.13.3 for numerical operations [5];
- `scipy` 0.19.1 for storing sparse data matrices [1].

We used Anaconda – a distribution of Python with many scientific libraries pre-installed³, including both the aforementioned libraries.

For online learning we used our own implementation of the FTRL-Proximal algorithm⁴ which is available online and can freely be used by anyone.

3.2 Modeling

Validation

We split the training data into four parts by the id of the candidate set. For training we used the parts 0, 1 and 2, and the 3rd part was used for validation. The selected training part contained 10.6 mln candidate sets and remaining 3.5 mln was left for the validation part.

We did not hold out any extra data as a test set: for this purpose we used the provided test set and verified our score using the leaderboard of the competition.

Data Preparation and Features

The organizers have already extracted features from their production logs and represented each candidate by a 74000-dimensional sparse vector. Most of the features were already one-hot-encoded, but not all of them: many features have other values apart from 0's and 1's.

To further process the data we tried the following approaches:

- disregard the value of each feature and always treat it as binary,
- perform the hashing trick for feature + value to ensure it is one-hot-encoded [6].

Online Learning Model

Once the dataset was converted to a sparse matrix, we trained a supervised model. Each click was treated as a positive observation, no click – as a negative one.

To perform the learning we chose the FTRL-Proximal algorithm [3]: it has proved to be competitive in the computational advertisement settings and has showed great performance for other sparse problems. For this challenge we used `libftrl-python` – our own implementation which is highly efficient in multicore environment and performs Hogwild!-style updates [4], thus resulting in very fast training time.

We had two options for data processing: with hashing and without. Our validation did not show any significant difference between these two approaches and thus we preferred the simpler one: treating everything as features with binary values.

However, we noticed that our model sometimes exhibits high variance, which then leads to a suboptimal policy. To overcome this issue we stabilized the model by training it multiple times and then taking the average prediction.

³<https://www.continuum.io/downloads>

⁴<https://github.com/alexeygrigorev/libftrl-python>

Team name	IPS	std
ololo	55.6	4.1
geffy	54.6	1.9
Group	54.3	1.6
atsky	54.1	3.0
mortiarty	48.6	1.2

Table 1: Top 5 participants of the challenge.

Post-Processing

Processing the output of the model was very important in our solution: it allowed to account for the behavior of the competition metric which favored clicks predicted with high certainty.

The IPS metric was computed in the following way:

- model scores are recorded,
- the softmax function over all scores in the candidate set is computed,
- the resulting score of the selected item is multiplied by its propensity,
- only sets with a clicked item are considered, the ones with no clicks are ignored.

Thus it is very important to make sure that the best candidate receives most of the probability. This way it contributes higher score to the overall metric.

To do it we used a two step post-processing procedure:

- apply the sigmoid function to each score, scale it by coefficient C ,
- add M to the maximal value of the set.

The second step alone is not enough: when our model is not correct and selects a wrong candidate, this candidate gets most of the probability and does not give any contribution to the global score. However, the first step makes the re-arrangement of probabilities smoother and not drastic in cases of almost-tie candidates.

The values of C and M were selected using our validation set.

4. EVALUATION RESULTS

Our final model is an average of 10 FTRL-Proximal models trained with the following parameters:

- $\alpha = 0.1, \beta = 1$,
- $L_1 = 75, L_2 = 25$,
- $C = 850100, M = 15$.

This combination lead to the IPS of 55.6, which resulted in the first position (see table 1: our team is in bold⁵).

5. CONCLUSION

In this paper we showed that FTRL-Proximal, an online linear classification algorithm, is still very competitive for large scale sparse problems like the Ad Placement Challenge and it outperformed many other approaches. We also showed that post-processing was an important step in achieving good IPS.

⁵<https://www.crowdai.org/challenges/>

[nips-17-workshop-criteo-ad-placement-challenge/leaderboards](https://www.crowdai.org/challenges/nips-17-workshop-criteo-ad-placement-challenge/leaderboards)

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