Solving Fashion Recommendation - The Farfetch Challenge

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Abstract. Recommendation engines are integral to the modern e-commerce experience, both for the seller and the end user. Accurate recommendations lead to higher revenue and better user experience. In this paper, we are presenting our solution to ECML PKDD Farfetch Fashion Recommendation Challenge [7]. The goal of this challenge is to maximize the chances of a click when the users are presented with set of fashion items. We have approached this problem as a binary classification problem. Our winning solution utilizes Catboost as the classifier and Bayesian Optimization for hyper parameter tuning. Our baseline model achieved MRR of 0.5153 on the validation set. Bayesian optimization of hyper parameters improved the MRR to 0.5240 on the validation set. Our final submission on the test set achieved a MRR of 0.5257.

Keywords: {Fashion Recommendation · Catboost · Hyper parameter tuning · Classification}

1 Introduction

In these times of ubiquitous internet access and ever shortening attention span it is imperative to capture your users’ attention before they hop to a different website or an app or worse, to your competitors’ website. The friction-less nature of web mandates the content to align to your users’ liking. Whether it be a blog, social media platform, e-commerce store, search engine or any other form of information aggregator, usage of a recommendation systems is imperative.

Industries like Social Media and Digital Advertisement see extensive use of such systems to reduce cost and increase their Click Through Rate(CTR). This competition too is structured along similar lines of predicting clicks, and recommending only those products to the users that have a high probability of being clicked.

Our goal in this competition was to use a technique that can work with modest resources of a personal laptop as opposed to a distributed cluster in the cloud or a dedicated deep learning workstation. We traded resources with time. Our final model took approximately 35 hours to train including hyper parameter tuning.
optimization. In this paper, we will be discussing the problem statement, our approach to modelling, and results of our approach.

We have divided this paper into 5 sections. Section 2 describes the problem statement and the provided datasets in detail. Section 3 deals with data preparation, modelling, training, and tuning. We discuss the results in section 4.

2 Dataset and Problem Statement

Before we dive into the dataset, we would like to explain the terminology used in the competition. An impression is an unordered set of six products that were shown to a user. If the user clicks on any of the recommended products, it is called a click. The dataset contains information about these impressions along with contextual information. Following are the features provided in the impressions dataset:

- query_id: Unique ID of impression
- user_id: Unique ID of the user this impression was shown to
- session_id: A user can have many sessions. This column contains the session id corresponding to a particular impression
- product_id: Identifier or product shown
- page_type: Type of page where the recommendation was shown
- previous_page_type: Immediately previous page that the user visited
- device_category: Type of device
- device_platform: Platform running on the device
- user_tier: User’s level in Farfetch’s reward program
- user_country: User’s country
- context_type: Comma separated list of types of contexts
- context_value: Corresponding identifiers of contexts from context_type field
- product_price: Normalized price of the product
- week: Normalized Week number of impression
- week_day: Day of week when the impression was shown
- is_click: This is the target variable. Contains 1 if the user clicked on the product, 0 otherwise.

The impression dataset contains rows corresponding to each product recommendation shown. The attribute dataset contains information about individual products. Following are the product attributes available in this dataset:

- product_id: Identifier of product, used to do an inner join with impressions dataset
- gender: Product’s target gender
- main_colour: Principal colour of the product
- second_colour: The second most predominant colour of the product
- season: Fashion season of the product
- collection: Fashion collection identifier
- category_id_l1: Top level product category
- `category_id_l2`: Second level of product category
- `category_id_l3`: Third level of product category
- `brand_id`: Product brand ID
- `season_year`: Year of the fashion season
- `start_online_date`: Number of days the product has been online with respect to a predefined reference date
- `attribute_values`: Comma separated list of miscellaneous product attributes
- `material_values`: Comma separated list of product’s material composition

The dataset contained 3,507,990 anonymized events captured over a duration of 2 months by Farfetch’s internal recommender system. The `context_value` field contained 189,571 unique values. Similarly, the `session_id` field contained 317,426 unique values. The cardinality of other features was lower. The `page_type` column had 5 unique values whereas `previous_page_type` field had 23 unique values.

The test dataset had a reasonable overlap in terms of unique values in these fields. 23.82% of `session_id` values in the training data occurred in the test dataset. Similarly, 23.88% of `context_value` values occurred in the test set. The `user_country`, `page_type`, and `previous_page_type` fields had 88.26%, 80%, and 95.65% unique values from the training set occur in the test dataset.

The target of this modelling is to predict a set of 6 products having the maximum likelihood of being clicked by the user based on the provided impression context. The recommended set of 6 products need to be ordered from most likely to least likely of being clicked. The evaluation metric is Mean Reciprocal Rank which we will discuss in section 3.4.

3 Modelling Approach

3.1 Modelling Overview

As discussed in the previous section, the problem of ranking products based on the preference of the user running a query/impression in a given session is essentially a type of Recommender Systems problem, more specifically, an Implicit Recommender Systems problem [9]. Instead of building a recommender system to rank the products in a query, we started approaching the problem from a binary classification viewpoint because we had the information about labelled interactions of each user with a product in the binary target feature `is_click`. The idea was to rank the products in a query based on the sorted click probabilities from highest to lowest generated by the binary classifier. The feature set that we kept to build the baseline model was all the features that were present in the validation set and test set.

3.2 Data Preprocessing

There were a total of 15 hashed feature vectors ($X$) present in the training set. Out of these 15 feature vectors, 14 feature vectors were categorical in nature and
1 feature vector was a continuous feature. The target feature \textit{is\_click} (Y) was also categorical (binary) in nature.

Since the categorical feature values were all hashed with random signed integers/strings, we started treating them with label-encoding. Suppose a categorical feature vector \( v \) has cardinality of \( m \), then label-encoding will change the \( i^{th} \) feature value \( v_i \) such that

\[
v_i = i, 1 \leq i \leq m; v_i \in v
\]  

(1)

We have applied same mapping for both train and test datasets. For cases where there were other new categories present in a feature vector in validation and test sets, the encoding will label new numbers to those categories.

As an initial step to treat the missing values in the training set we replaced the missing values in categorical features with an arbitrary integer -999 and missing values in continuous features as the mean of that feature.

### 3.3 Choosing a Classifier

As seen in section 2, the training data set was tabular in nature and had more than 3 million rows. The columns \textit{session\_id}, and \textit{context\_value} had extremely high cardinality. Consequently, the capability of handling high cardinality features and large dataset with limited resources motivated our choice of algorithm - Catboost [12]. Catboost is a new boosting framework that often outperforms other boosting implementations in terms of quality of prediction especially in case of tabular heterogeneous data [8,12]. Being a Gradient Boosted Tree method, Catboost also has the added benefit of providing feature importance which helps in interpreting the result.

The classical approach of handling categorical data is one-hot encoding [6,5,10]. But the problem with one-hot encoding is that it creates high-dimensional feature vectors and this exacerbated in case of features with high cardinality. Other methods like target encoding [10] may also lead to target leakage as discussed in [12]. Other classifiers such as XGBoost consumes more memory than Catboost [8]. Another reason to choose Catboost, over other bagging-based classifier such as RandomForest, was its ability to handle categorical feature vectors, which is central to its design. Catboost performs Ordered Target Encoding for categorical columns by performing random permutations of the dataset and then target encoding each example using only the objects that are placed before the current object. This ordered target encoding solves the problem of target leakage and is shown to produce better results as compared to other encoding methods [12]. It can also create new categorical features combining the existing ones and has a method to handle encodings for new categories in the test set that haven’t appeared in the training set using priors [12]. This capability of Catboost allowed us to avoid expensive feature engineering.
3.4 Evaluation Metric

The goal of this competition was to rank the products by their likelihood of being clicked, hence we chose to keep track of the Logloss of the predictions. Mathematically, Logloss for a single training example is defined as:

$$L_{\text{log}}(y, p) = -(y \log(p) + (1 - y) \log(1 - p))$$  (2)

where $p$ is the probability of the class given by the learned model and $y$ is the actual label of the class.

It is important to note that since the final goal is to rank the products, only the relative probabilities matter instead of the actual magnitude of the probabilities and because of this the precision-based metrics are not very important to evaluate the model in this case.

The final evaluation metric in the competition was Mean Reciprocal Rank (MRR). When considering a set of $n$ queries/impressions, this metric can be expressed as:

$$MRR = \frac{1}{|n|} \sum_{i=1}^{n} \frac{1}{\text{rank}_i}$$  (3)

Where, for the $i^{th}$ impression in the dataset, $\text{rank}_i$ is the rank of the first correct prediction.

3.5 Model Tuning

In order to improve the Logloss, we decided to carry out hyper-parameter tuning of our baseline Catboost model. General methods to do hyper-parameter optimizations include Grid-Search and Random-Search but in this case in-order to tune the hyper-parameters we used Sequential model-based optimization also known as Bayesian Optimization [14]. Bayesian optimization is an efficient method to find global maximiser/minimiser of an unknown objective function $f()$

$$x^* = \argmax_{x} f(x), x \in \chi$$  (4)

Where $\chi$ is some space of interest [13]. Bayesian optimization performs hyper-parameter search in an informed manner i.e. it keeps track of objective score, that is to be minimized or maximised, of the objective function for a set of hyper-parameters in each trial and then selects the next best set of hyperparameters based on the past trials’ results. The time spent in selecting hyperparameters in an informed way is inconsequential compared to the time spent in searching for hyperparameters over a random space like that in Grid-Search or Random Search and thus Bayesian methods can find best hyperparameters in relatively fewer trials. In order to perform this optimization we used the python library Hyperopt [3]. The Catboost parameters we chose to tune were $\text{learning\_rate}$,
which controls the gradient step in minimization methods such as Gradient descent, and the $l2\_leaf\_reg$, which is the coefficient of L2 regularization term of the cost function. The search space for these parameters was configured as follows:

1. `learning_rate`: Search over a uniform distribution between 1e-3 to 5e-1.
2. `l2_leaf_reg`: Quantized log uniform search space $qlognormal$ with $low=0$, $high=2$, and $q=1$

The final values of these hyperparameters after tuning were:

1. `learning_rate`: 0.16610
2. `l2_leaf_reg`: 2

The algorithm that we choose for searching was Tree-structured Parzen Estimator Approach [4].

### 4 Results

We trained the baseline model with stratified K-Fold Cross Validation on the entire training data to make the predictions more robust to high variance for $N$ number of iterations. Every iteration updates $N$ models. We evaluate each model on its own validation dataset on every iteration. This produces $N$ metric values on each iteration $K$.

![Fig. 1. Training and Validation logloss during hyper parameter optimization](image)

Using this model, we predicted the probability of click on the products present in the validation set. We ranked the probabilities from 1 to 6 by grouping over the
query_id column. The baseline model gave an MRR of 0.51526 on the validation-set and a mean training logloss of 0.393526. Mean validation logloss for baseline model stood at 0.309565.

The next stage of training was hyper parameter tuning as discussed in 3.5. We saw a substantial improvement in MRR. Validation set MRR stood at 0.52396 whereas final test set MRR stood at 0.52570 after hyper parameter tuning. We also saw substantial improvement in the training and validation logloss numbers which stood at 0.385014 and 0.297610 respectively. The figure 1 shows the progression of logloss on training and validation set during this phase. The training and validation logloss followed similar trend throughout the training process which indicates that our model did not overfit.

Figure 2 presents the feature importance graph that was obtained after the training. The feature context_value turned out to be the most important feature. This is not surprising and is well known in digital advertising that publisher features which includes URL are very important [11,5]. The session_id feature turned out to be second most important as per figure 2 surpassing the product_id feature which stands for the current product being viewed by the user.

5 Conclusion

There are 3 points that we would like to highlight in the conclusion:

1. Modern Algorithms like catboost perform really well without dedicated feature engineering even in cases of very high cardinality features.
2. Bayesian Hyper Parameter Optimization is an extremely effective way to improve model performance.
3. It is possible to build and train recommendation systems with modest resources. Distributed systems are not always necessary. We would like to emphasise the last point. Data driven recommendations are pervasive. Business not leveraging such a system due to cost concerns are not utilizing data effectively. Cost of building a data driven recommendation system has never been lower and more democratic. Therefore, cost should not be seen as a barrier to start implementing such a system.

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