Team voyTECH: User Activity Modeling with Boosting Trees

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Abstract. This paper describes our winning solution for the ECML-PKDD ChAT Discovery Challenge 2020. We show that whether or not a Twitch user has subscribed to a channel can be well predicted by modeling user activity with boosting trees. We introduce the connection between target-encodings and boosting trees in the context of high cardinality categoricals and find that modeling user activity is more powerful than direct modeling of content when encoded properly and combined with a suitable optimization approach.

Keywords: competition · boosting · high cardinality categoricals · target-encodings

1 The Competition

The task of the ECML-PKDD ChAT Discovery Challenge 2020 \cite{12} is to predict whether or not a Twitch user has subscribed to a channel (binary classification task) given the list of messages he has posted on the channel and other channels. The dataset consists of 700 million public Twitch comments from English channels published during the month of January 2020 along with metadata. The training data consists of over 29 million and the test dataset of 90,000 channel-user combinations and their comments. In more detail, each input training sample consists of the identifier of the channel, the user-id, and a list of timestamped comments from the user about the specific played game in the channel on the time of comment generation.

1.1 Competition Challenges

The competition presents two peculiarities compared to previous competitions. The first challenge is that only half of the users in the test set have prior history which requires special attention when extracting users and channels features. This challenge draws similarities with the cold start problem in recommendation systems \cite{13}. The second challenge is related to the sampling distribution of the leader-board test set. More precisely, the entire spectrum of user/channel activity levels (low, normal, high) is weighted equally across all groups which is vastly
different to the training set (see Table 1). Namely, for each out of 9 combinations of user activity levels (low, normal, high) and channel activity levels (low, normal, high), 10,000 channel-user samples are sampled uniformly (i.e., one channel-user activity combination group is where the user is of low activity and the channel is of normal activity). Hence, in total 90,000 test samples are generated. In Table 1, we outline statistics of the dataset within the activity groups.

Table 1. Statistics of the training dataset per channel-user activity group. ‘u_low-c_normal’ corresponds to low user and normal channel activity group.

| group             | users | channels | pairs | subscribed | % pairs | % subscribed |
|-------------------|-------|----------|-------|------------|---------|--------------|
| u_low-c_normal    | 141K  | 40K      | 144K  | 5,696      | 0.0049  | 0.0397       |
| u_low-c_low       | 10K   | 7.7K     | 10K   | 611        | 0.0006  | 0.0595       |
| u_normal-c_normal | 480K  | 67K      | 562K  | 35,021     | 0.0190  | 0.0622       |
| u_low-c_high      | 2,153K| 34K      | 2,359K| 181K       | 0.0798  | 0.0768       |
| u_normal-c_low    | 46K   | 23K      | 47K   | 3651       | 0.0016  | 0.0770       |
| u_normal-c_high   | 3,508K| 36K      | 8,740K| 683K       | 0.2958  | 0.0782       |
| u_high-c_high     | 215K  | 36K      | 16,045K| 1,314K     | 0.0819  | 0.0819       |
| u_high-c_low      | 77K   | 31K      | 99K   | 8,498      | 0.0034  | 0.0858       |
| u_high-c_normal   | 663K  | 73K      | 1,531K| 135K       | 0.0518  | 0.0886       |

1.2 User Activity Modeling

Our approach is based on the assumption that modeling user activity is more important than specific content (e.g. message text). User activity is modeled as interactions between the user and key objects of the system he interacts with (e.g. channels and games).

This approach naturally leads to a high dimensional categorical feature/variable representation that has been well studied in the context of recommender systems, click-through-rate predictions and similar industrial applications. It is also closely related to the concept graph-based relational features [1].

Our experimental results (section 3) indicate that the interactions visualized in Figure 1 with features describing the quantity of user activity (e.g. days active, number of frequently used channels) have strong predictive power. Introducing the game as a high level object is especially important for the 50% test set user without history (cold-start). For a cold-start user, the most frequent game-id can effectively proxy the user-id (more details in sec 3.1). Before presenting our solution (section 3.3), we first introduce the concept of target encoding to motivate the combination of high dimensional feature representation and boosting tree models.

1.3 Contributions

The main contributions of this paper are:
2 High Cardinality Categoricals and Boosting Trees

In this section, we discuss in detail the interaction between (high cardinality) categorical features, mean target encodings and boosting trees which is at the core of our winning solution in form the popular CatBoost library.

Several user and channel categorical features are present in the dataset such as which game has been played and activity levels. By computing the interaction features between user and channel categorical features, several categorical with high cardinality are extracted. Due to their sparsity, such high cardinality categorical features pose several challenges in modeling and in general could lead to poor generalization performance. A common class of models to handle such a semi-structured dataset that contains high cardinality categorical features are Gradient Boosting Trees [9] and in particular the CatBoost [5]. The winning solution is based on a single CatBoost model. Model ensembles could further improve our results, but were skipped due to time restrictions.

2.1 Categorical Encodings in Models

The handling of categorical features usually happens during the feature engineering phase, since the modeler has the freedom to arbitrarily transform or extract the input features before those are fed into the model. However, models exist that can handle categorical features under the hood, i.e., the modeler simply specifies the features that should be handled as categoricals without any further pre-processing required. The user of such models is only able to adjust the predefined categorical encoding process with input hyper-parameters. For example, input model hyper-parameters for categorical features include ‘perform one-hot-encoding if cardinality of any categorical is less than a threshold’, ‘perform hash encoding with specified number of hashing dimensions’ to name a few.

Here, we summarize a few recently proposed models that handle categorical features as part of the model definition. Two gradient boosting tree implementations, Microsoft’s LightGBM [11] and Yandex’s CatBoost [5], allow the user to specify which features should be handled as categoricals by the models. The h2o.ai implementation of Random Forests handles categoricals out of the box. Neural networks provide an embedding layer for handling categoricals as an extra layer of a neural network, see Keras embedding layer or the so-called ‘entity embeddings’ [8]. LightGBM splits a categorical feature by partitioning its categories into 2 subsets. If the categorical feature has $k$ levels, there are $2^{(k-1)} - 1$ possible partitions. However, there is an efficient $O(k \log(k))$ time solution for
regression trees [6]. The basic idea is to sort the categories according to the training objective at each split.

CatBoost is a gradient boosting tree implementation that applies a regularized mean target encoding on the top-level tree split as a preprocessing step. Such preprocessing could be considered sub-optimal at least for the case of trees with large depth [4] (see also Section 2.2 for details). Although the CatBoost approach might result in sub-optimal greedy binary splits, CatBoost requires less operations per tree split and offers very efficient and optimized implementation. The efficiency if based on the property that regularized mean target encoding values are computed only once compared to the optimal greedy approach where the mean target encodings have to be maintained or computed on every tree split, see Lemma 1.

In the following section, we provide more background on the fundamentals of CatBoost and, in particular, its connection to mean target encodings since mean target encodings are the core design principle behind CatBoost.

2.2 Target Encodings

In this section, we setup the framework of feature extraction from categoricals that is usually called target encodings from machine learning practitioners.

We denote $m$ samples with $n$ features by a $m \times n$ design matrix $X$ with column coefficients that are either numericals (in $\mathbb{R}$) or categoricals. In other words, the $j$-th column of $X$ is in $\mathbb{R}^m$ or $\mathbb{C}^m$ for a set of elements of categoricals $C_j$. Moreover, we denote by $X_j$ the $j$-th column of $X$ and by $[n]$ the set $\{1, 2, \ldots, n\}$. In addition, we denote by $y$ the $m$-dimensional target vector. The mean value of $y$, also referred to as mean target value, is denoted by $\mu$. The tuple $(X, y)$ contains all relevant information for a prediction task and we call such a tuple design matrix pair or for simplicity, design matrix.

We focus on the typical binary classification task, i.e., assuming an input target vector $y \in \{0, 1\}^m$. The analysis can be extended directly to the regression task. Now we are ready to define target encodings.

**Definition 1 (Target Encodings).** Given $(X, y)$ and an integer $j \in [n]$ so that the $j$-th column of $X$ is categorical, it follows that target encoding is a function $f(x_j, y) : C_j \rightarrow \mathbb{R}$.

From now on, we write $f$ instead of $f(x_j, y)$ for notation convenience. It is important to note that we allow $f$ to depend on the input dataset. Moreover, we say that $f$ is defined (or fitted) on $(X, y)$ to explicitly specify the input data used on the definition of $f$.

A very common example of target encoding is the mean target encoding. That is, assume that the $j$-th column of $X$ is a categorical containing values/levels in...
\( \mathcal{C}_j = \{L_1, L_2, \ldots, L_k\} \). The mean target encoding \( \mu_j \) of the \( j \)-th column is defined as follows: \( \mu_j \) support on \( \mathcal{C}_j \) and for any \( L \in \mathcal{C}_j \),

\[
\mu_j(L) = \frac{1}{N} \sum_{i=1}^{m} y_i \mathbb{1}_{x_{i,j} = L}
\]

where \( N \) equals to the number of occurrences of \( L \) in the \( j \)-th column of \( X \) and \( \mathbb{1}_{\text{pred}} \) is the indicator function, i.e., equals to 1 if \( \text{pred} \) is true, otherwise equals to zero. In words, mean target encodings are roughly defined as the mean target value of any level of the categorical (group).

In general, any property of the target values distribution of the group can be also extracted. For example, ML practitioners frequent use the minimum, maximum, standard deviation, kurtosis, percentiles of the target values in addition to the mean value. The main idea is to extract as much statistical information of the target distribution of the group as possible.

**Regularization of Target Encodings.** By definition, target encodings introduce target leakage and could lead to poor generalization performance, hence, target encoding regularization must always be used [10]. In this section, we outline several regularization methods of target encodings.

Extra caution on regularization should be given in the present of high cardinality categoricals, i.e., categoricals with a large number of distinct levels as present in this competition. In fact, it is relatively easy to construct an example where the naive application of target encodings leads to severe overfitting. In order to exemplify this behavior, a minimal example is constructed by the authors of the ‘vtreat’ package [17]. CatBoost provides an implementation that tackles these issues under the hood, but it is important for the modeler to better understand the general approaches that we outline next.

**Smoothing / Empirical Bayes / Shrinkage of Mean Target Encoding.** In the presence of high-cardinality categoricals, it is quite often the case that individual categorical levels appear only in a small number of samples. In such scenario, the estimates of the mean target encoding don’t generalize well due to the small number of samples used to calculate the statistics. Here, smoothing or shrinkage can be applied which have a similar effect as empirical Bayesian (EB) approaches [7]. Indeed, Empirical Bayesian conditional probabilities of a categorical can be understood as mean target encodings [14].

In our notation, the EB regularized version of the mean target encoding is defined as

\[
\mu_j^{\text{EB}}(L) := \lambda(N)\mu_j(L) + (1 - \lambda(N))\mu
\]

where \( N \) equals to the number of occurrences of \( L \) in the \( j \)-th column of \( X \) and \( \lambda(n) \) is a monotonically increasing function on \( n \) bounded between 0 and 1. A common choice of practitioners for \( \lambda \) is \( \lambda(n) = \frac{1}{1 + \exp\left(-\frac{(n-\ell)/\sigma}{\sigma}\right)} \) which is a s-shaped function with a value of 0.5 for \( n = \ell \) and \( \sigma \) representing the steepness [14, Equation 4]. Thus, Equation 2 is a smoothed version of the mean target encoding.
Bootstrapping / rolling mean. Bootstrapping is another approach to regularized target encodings. A specific instance of bootstrapping and target encodings is implemented in CatBoost [5].

CatBoost uses a bootstrapping rolling mean approach to reduce overfitting while utilizing the whole training dataset for estimating the target encodings. In a nutshell, CatBoost performs a random permutation on the rows of \( X \) and for the \( i \)-th row of \( X \) (with respect to the random permutation) the mean target encoding is computed using only the rows up to the \((i-1)\)-row. Namely, CatBoost averages several independent random permutations and, moreover, adds a shrinkage prior to the global mean.

To sum up, CatBoost performes categorical encoding for a level \( L \in C_j \) as follows. For the \( i \)-th row and a fixed permutation of the rows, CatBoost computes

\[
\mu_{j}^{\text{Cat}}(L, i) := \lambda \mu_{j}(L; (X_{1:(i-1), j}, y_{1:(i-1)})) + (1 - \lambda) \mu
\]

where \( \mu \) is the mean target value and \( \lambda \) is a smoothing hyper-parameter.

Optimal Greedy Categorical Tree Splits and Boosting Trees. In this section, we provide a theoretical explanation why mean target encoding works well in practice when combined with tree-based models such as gradient boosting trees. The key ingredients are two classical results on the optimal binary tree split of categoricals features for classification [4] and regression trees [6].

Our explanation here follows [4]. Recall that we denote the levels of a categorical as \( C := \{ L_1, L_2, \ldots, L_k \} \). The standard set of binary splits for \( C \) consists of all splits of the form \( \{ x \in S \? \} \) for a subset \( S \subset C \).

Before stating the main result (Lemma 1), we remind the reader of the notion of impurity during a binary tree split. Roughly speaking, purity measures if the child nodes are on average ‘purer’ than the parent node. Two commonly used measures of impurity in the decision trees literature are the Information Gain and the Gini index, see [16, Proposition 7.1, pp.217] for a formal definition.

The following lemma is a reformulation of [4, Chapter 9, Section 9.4, Proposition 8.16] and the main result of [6]. The result is well known in literature, and it is referenced in several publications, i.e., see [9, Section 9.4.2, p.310] and [16, Proposition 7.1, pp.218].

**Lemma 1 (Optimal Categorical Tree Splits).** Let \( C := \{ L_1, L_2, \ldots, L_k \} \) be the \( j \)-th categorical column of the design matrix \((X, y)\). Moreover, for any \( i \in [k] \), define \( \mu_j(L_i) \) as the mean target encoding (Eqn. 7). Order the levels of the categorical so that \( \mu_j(L_{t_1}) \leq \mu_j(L_{t_2}) \leq \cdots \leq \mu_j(L_{t_k}) \). Then, the optimal split with respect to:

(a) both impurity measures (Information Gain and Gini index) for the classification task

(b) or, variance reduction of mean square error for the regression task

on the \( j \)-th categorical feature (over all possible binary splits) is one of the \( k - 1 \) splits of the form

\[
is x \in \{ L_{t_h}, \ldots, L_{t_k} \}? \quad \text{for any } \ h = 1, \ldots, k - 1.
\]
In other words, the above lemma states that if mean target encoding is applied on a categorical and the encoded values are used as a numeric feature during the next binary tree split, then the optimal binary tree split is returned. Optimality is over all binary tree splits of the categorical (exponential in $k$). For the classification task, the optimality holds in terms of Information Gain and Gini index, whereas for the regression task it holds in terms of mean square error reduction. It is worth mentioning that the original motivation of the Lemma 1 was computational efficiency. Namely, the lemma reduces the cardinality of the search space of the best subset of levels from $2^k - 1$ to $k - 1$ subsets. In contrast, the above lemma is used here to explain the generalization effectiveness of mean target encodings.

Although, Lemma 1 (b) can be easily extended to gradient boosting trees since each boosting tree iteration fits a regression tree on the pseudo-residuals, the technical details are not quite straight-forward [3].

3 Winning Model and Additional Experiments

In this section, we describe the winning solution in more detail and present additional experimental results that better explain the critical aspects of the performance.

3.1 Features Engineering

A basic set of features include number of messages per game (‘game_count’), time of first/last message per channel (‘t_min’, ‘t_max’), days the user was active in a channel (‘days’), median, maximum and total number of characters per message (‘m_total’, ‘m_median’, ‘m_max’), number of channels per user (‘n_channel’), user activity as given in competition (‘u_group’). For channel features, we used channel id, number of users per channel and channel user activity (‘c_group’).

In addition, the following interaction features have been computed as per user and per channel features. The number of days between first and last message (‘t_days’), fraction of days active in month (‘t_active’), total number of messages (‘n_mes’), number of games (‘g_n’), game with most messages per user (‘g_top’), number of messages for game “just chatting” per user (‘g_chat’), and fraction of messages for ‘g_top’ (‘g_top_frac’).

3.2 Best Performing Model

Model definition. The model is based on the CatBoost library version 0.23.1. The loss function is set to be logistic loss or also known as cross-entropy loss. Training of the model is early stopped based on the performance on the validation set using the autostop capabilities of CatBoost with parameter ‘od_type’ set to ”Iter” and od_wait set to 20. The best model is selected when stopped by setting use_best_model=True.
Fig. 2. CatBoost’s feature importance show clear differences between train and our constructed test data that can be attributed to the group activity shift (especially pronounced for the uid features). The top 10 test features have been selected for a simplified model (table 3).

The top performing submission is a single CatBoost model trained with the following hyper-parameters: 'l2_leaf_reg': 64, 'learning_rate': 0.08, 'threshold': 0.167, 'depth': 9, 'random_strength': 0.5, 'max_ctr_complexity': 2. These parameters have been manually selected on our constructed test set.

Table 2. Leaderboard results of the competition. Our submission ranked first with $F_1$ score 0.3433.

| Rank | Teamname        | Test $F_1$ score |
|------|-----------------|-----------------|
| 1    | voyTECH         | 0.3433          |
| 2    | CoolStoryBob    | 0.2647          |
| 3    | ItsBoshyTime    | 0.2593          |
| 4    | StinkyCheese    | 0.1422          |
| 5    | Random Baseline | 0.0741          |

Cross validation Setup. Training and testing data had a vastly different distribution, hence, a careful cross validation setup was crucial for model training and hyper-parameter tuning. It is given from the competition description that half of the users in the test set have no history and user-channel interactions are sampled uniformly from low, normal, and high activity levels. Therefore, our goal is to construct a validation set with similar properties. To do so, the train dataset is sampled with a ‘max_per_group’ parameter per channel-user group. The validation set is constructed as follows: we sample in total 45,000 channel-user pairs (5,000 pairs per activity level pair group), ensuring that these pairs do not appear in the training set. These 45,000 channel-pairs are duplicated in the validation set by modifying the user-id with an unknown identifier not present in the training set.
3.3 Additional Experiments

We find that we can achieve strong performance even with a very small set of features (Figure 2). However, the sub-sampling of the train pairs decreases the model performance (see Figure 3) and the interaction between features (max ctr compl > 2) is important.

Table 3. Model performance with respect to train data size, features, and hyper-parameter (random-strength=0.5, threshold=0.167, l2-leaf-reg=64 and depth=9 are the same for all rows).

| f1 leaderboard | f1 mytest | train data | features | max ctr compl | lr  |
|----------------|-----------|------------|----------|---------------|-----|
| 0.3433         | 0.3522    | 16m        | all      | 2             | 0.15|
| 0.3382         | 0.3505    | 8m         | all      | 2             | 0.08|
| 0.3345         | 0.3490    | 16m        | top-features | 2   | 0.15|
| 0.3329         | 0.3417    | full       | top-features | 1   | 0.08|
| 0.3322         | 0.3421    | 16m        | top-features | 1   | 0.15|

Fig. 3. Activity group specific F1-score. The differences between the full and reduced feature model is most pronounced for the highest (h,h) and lowest (l, l) activity groups.

3.4 Conclusions & Further Work

In this work we introduced the connection between target encodings and boosting trees in the context of high cardinality categoricals and highlighted differences in the two popular boosting tree implementations CatBoost and lightgbm. We plan to conduct further experiments and also compare Boosting Trees to Factorization Machines [15], a model that has been used successfully to model user activity in an earlier Discovery Challenge [2].

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