Adapted Tree Boosting for Transfer Learning

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***Abstract*—Secure online transaction is an essential task for e-commerce platforms. Alipay, one of the world's leading cashless payment platform, provides the payment service to both merchants and individual customers. The fraud detection models are built to protect the customers, but stronger demands are raised by the new scenes, which are lacking in training data and labels. The proposed model makes a difference by utilizing the data under similar old scenes and the data under a new scene is treated as the target domain to be promoted. Inspired by this real case in Alipay, we view the problem as a transfer learning problem and design a set of revise strategies to transfer the source domain models to the target domain under the framework of gradient boosting tree models. This work provides an option for the cold-start and data-sharing problems.**

***Index Terms*—fraud detection, transfer learning, fine tuning, gradient boosting tree**

I. Introduction

Two cousins prepared masks and weapons to rob some money. However, they broke into 3 convenience stores before getting caught, only to got 1700 yuan. They are despairing that the money cannot even afford their travelling expenses and tools. This is a real criminal case in Hangzhou,China, a cashless city. The mobile payment spreads all over the city where can pay for almost everything without a wallet.

The robberies nowadays take place more online and harm the public interest. Alipay[1], one of the leading payment platforms, provides the users with convenient payment service as well as the security assurance. The data scientists take efforts to build up models and confront the frauds.

With the develop of Alipay, potential challenges arise [1]. In the fraud detection problem, it is intractable to accumulate enough training data for the models. Especially, the positive samples are collected by case reports from the victims, which indicate the invocatable losses have come into being. On one hand, the data scientists need labels to train the fraud detection models, on the other hand, they are eager to protect the users from frauds. Therefore making full use of existing data is crucial. While providing online payment service to the merchants, the risk management mechanism is set up for each individual merchant, but some small merchants even do not have enough samples to train a usable model. The merchants would like to share the anti-fraud expertise across to form a stronger guard. Another practical scenario is how to quickly build up a risk management system for a new marketplace. In face of the cold start problem, it's a natural choice to refer to the data under similar scenes.

Transfer learning is born to solve these problems. It helps to transfer the information from the source domain, with abundant data, to the exhausted target domain. In this way, the source domain data are reused wisely and the data required to build up a practical model on the target domain is reduced.

Nevertheless, there are implicit restrictions in previous cases. Due to data privacy protection regulations, e.g. General Data Protection Regulation(GDPR)[2], cross-boarder data-sharing is under increasingly strict supervision. The merchants are also unwilling to leak any customer infomation to their competitors. So the model-based transfer learning is the only solution, instead of feature-based and instance-based ones. What's more, the model-based methods also work well when the storage capacity and transmission throughout on the target domain are limited.

Most of the model-based transfer learning algorithms are based on the neural network, which are good at dealing with the image, audio and natural language data. However, the fraud detection features are well-defined and the feature number is relatively small. Neural network is not the optimal choice here, in that the parameters are hard to tune and the model is hard to interpretate. Gradient Boosting Desition Tree(GBDT) is an ensemble model with appealing characteristics, e.g. the ability to handle nonlinearity and not requiring the tedious feature pre-processing. It is a popular option for the machine learning tasks and the following variants optimize the original algorithm in both performance and speed. Many excellent

[1]https://global.alipay.com/

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[2]https://eugdpr.org/

implementations, such as XGBoost[3] and LightGBM[4], are released and widely adopted.

In this paper, we focus on the above mentioned real-world fraud dection problem and propose an adapted tree boosting workflow for transfer learning. We implement the algorithm on top of XGBoost and get a competitive result in the experiment. The rest of the paper is organized as follows. Section II provides a brief review of related work on transfer learning. After that, section III formalizes the basic transfer learning settings as the preliminary. And the key insights and necessary computation details of GBDT and XGBoost are also introduced. In section IV, we first analyze the data and describe the main framework. Then intuitions and related operations to revise a source tree model are explained in detail. Section V contains our experiments and discussions, followed by the conclusion in section VI.

II. Related Work

Transfer learning approaches are designed to transfer the helpful information from the source task to a similar target task and the information is exploited to promote the performance on the target task. Four classic paradigms are proposed based on what to transfer [2]. Instance-based methods reuse the souce domain data by instance weighting and importance sampling [3]–[6]. These methods work well when the data distributions in the source domain and the target domain are sufficiently approximate. Feature-based methods transform the features from both domains to a proper feature space to reach the goal [7]–[12]. They try to find a feature representation that minimizes the difference between the domains. Relation-based methods help the relational domains and focus on the the relation mapping between the domains [13]–[15]. Model-based methods assume that the source model can contribute to the target model and they share parameters between the domains [16]–[18]. Common approaches including adapting models with the biased regularizers [19]–[22], ensemble strategies [23]–[26] and utilizing source model as priors [27]–[29].

Model-based methods, which we adopt in this work, stand out in the situation where the source domain is referential but the samples are not available to the target domain. There are attempts for different models in this field. Zhao et al. proposes TransEMDT that integrates a decision tree and the k-means clustering algorithm to build a personalized activity recognition model [17]. A decision tree is trained offline and unlabeled samples from a new user are then used to adapt the model. Another similar work is based on extreme learning machine [30]. SVM is a popular base model. ASVM(Adapted SVM) [31] and its extension [32] train a Gaussian kernel SVM as source model and regularize it with target samples. Many recent researches integrate neural network into transfer learning in order to learn the feature representation or share the model parameters. The adaptation layers and domain related losses are introduced to design customized neural network architectures [33]–[36]. Though the deep neural networks get fruitful results in natural language, audio and image data, tree models are more competitive when the features are well-constructed in limited feature dimensions. Considering the tree models are easy to train and interpretate, we select tree model as the base learner.

The tree-based transfer learning is widely explored for streaming data mining. The methods are designed to process massive, high-speed streams and modify the decision tree with new samples. In [37]–[39], the decision tree is constructed on the streaming data and proved to be asymptotically nearly identical to the tree of a conventional learner. The algorithm is optimized in both time(worst-case proportional to the number of attributes) and space(proportional to the size of the tree and associated sufficient statistics). Núñez et al. proposes an incremental decision tree that automatically adjusts its internal parameters [40]. Target concepts in streaming data change over time and a time window with adaptive size is introduced to solve the problem. A local performance measure is calculated and when the performance on a leaf decreases, the size of its local window is reduced. These methods process the changing batch data rather than a constant target dataset.

The model-based transfer learning framework raised by Segev et al. [41] is similar to this work, in that it also consists of several revise strategies operating on the transfered model. Two algorithms are applied to revise the tree structures of the random forest trained in the source domain. The SER(structure expansion/reduction) algorithm first expands the leaf node by utilizing the samples falling into it. Then the reduction operates on the intermediate nodes in a bottom-up order and generalizes the rules by pruning. In order to prune the tree, two types of errors are recorded: subtree error on a node is the empirical error of the its descendants and leaf error is the error when the node is regarded as a leaf node. If the leaf error is smaller than subtree error, the subtree dominated by this node is then pruned into a leaf node. The STRUT(structure transfer) algorithm is designed from a new perspective. The scales of features are observed to be quite different between the domains, so the associated decision thresholds should be modified. A final MIX method is employed to combine the two result forests generated by SER and STRUT as a voting ensemble. This framework is different from ours because of the different essence of base models. Random forest is a typical bagging model and a bunch of decision trees vote together to get the prediction. Boosting tree models outperforms random forest and could be utilized differently in transfer learning.

A well-known transfer learning algorithm based on boosting tree models is the TrAdaBoost [42]. It inherits the key idea of AdaBoost [43] and adjusts the weights of training samples. The wrongly predicted samples in source domain are regard as misleading data and their effects are weaken in the following iterations. Besides the normal AdaBoost adopted in target domain, TrAdaBoost defines a multiplier to decrease the weights of misclassified source samples. After several iterations, the most helpful diff-distribution data are picked out as supplement for the same-distribution data. AdaBoost is

[3]https://github.com/dmlc/xgboost

[4]https://github.com/microsoft/LightGBM

equivalent to GBDT with exponential loss function. We choose the more generic GBDT as base model and carry out the work under a model-based transfer learning paradigm.

III. Preliminary

Our method serves the scarce dataset as a transfer learning framework in order to provide a usable machine learning model. We take the gradient boosting tree algorithm as the basis of this framework. In this section, we briefly introduce some necessary notations and concepts used in the algorithm.

A. Transfer Learning Settings

The key definition *domain* in transfer learning consists of 3 factors: $\mathcal{D} = (\mathcal{X}, \mathcal{Y}, P)$, where $\mathcal{X}$ and $\mathcal{Y}$ stands for the d-dimension feature space and label space respectively. P represents the probability distribution of the data, which is a virtual oracle without the explicit representation. There are 2 basic domains in transfer learning. Source domain contains abundant labeled data and target domain, on the contrary, provides scarce information. The transfer learning tasks attempt to transfer the knowledge included in source domain data to the target domain.

We introduce s and t as subscript to represent the source domain and target domain as $\mathcal{D}_s$ and $\mathcal{D}_t$. There are various data hypotheses for different transfer learning algorithms. Obeying our real-world scenario, we follow the restriction that the source domain and target domain share the same feature space $\mathcal{X}$ and label space $\mathcal{Y}$, i.e. we have $\mathcal{X}_s = \mathcal{X}_t = \mathcal{X}$ and $\mathcal{Y}_s = \mathcal{Y}_t = \mathcal{Y}$.

Supposing that there are n_s instances in source domain and n_t instances in target domain. X_s is employed to denote the feature matrix in source domain where X_s is an $n_s \times d$ matrix and $X_s = \{x_i\}_{i=1}^{n_s}$. Dataset D_s consists of feature matrixes and related label vectors $D_s = \{X_s, Y_s\}$. Similarly, we have the feature matrix in target domain $X_t = \{x_j\}_{j=1}^{n_t}$ and $D_t = \{X_t, Y_t\}$.

The marginal distributions of features are always different between $\mathcal{D}_s$ and $\mathcal{D}_t$ in transfer learning, $P_s(x_s) \neq P_t(x_t)$. Further, the conditional probability distribution of labels are different in our settings, $Q_s(y_s|x_s) \neq Q_t(y_t|x_t)$. Further, We apply the model-based transfer method. Our final goal is to get a classifier for target domain $F_t : x_t \mapsto y_t$. To reach the goal, a model is first built in the source domain $F_s : x_s \mapsto y_s$. We then take F_s as the knowledge transferred from the source domain and make some adaptations to guide the model building in target domain.

B. Gradient Boosting Decision Tree

The machine learning tasks are generally solved as function estimation problems. A proper loss function $L(y, F(x))$ is defined to measure the difference between the labels and the predictions. Then the optimization goal of function estimation is minimizing the expected value over the joint distribution of all training samples.

$$F^* = \arg\min_F E_{x,y} L(y, F(x)) \tag{1}$$

GBDT carries out the estimation in a nonparametric way and applies numerical optimization in function space [44]. The prediction $F(x)$ at each point x is regarded as a parameter and the minimizing objective is deduced as follows directly with respect to $F(x)$.

$$\begin{aligned} \phi(F(x)) &= \arg\min_{F(x)} E_{x,y} L(y, F(x)) \\ &= \arg\min_{F(x)} E_x[E_y(L(y, F(x))|x)] \\ &= \arg\min_{F(x)} E_y[L(y, F(x))|x] \end{aligned} \tag{2}$$

The optimal F^* is solved as a numerical optimization. The gradient descent method is applied and F^* is denoted in an additive form. Where f_0 is the initial value and followed by M boosting values$\{f_m\}_1^M$. At each step, the descent direction is determined by the gradient g_m, which is in infinite-dimensional space. Then the step size ρ_m is computed by minimizing the objective in the negative gradient direction.

$$F^* = \sum_{m=0}^{M} f_m \tag{3}$$

$$g_m = \{g_{im}\} = \{\frac{\partial E_y[L(y, F(x))|x_i]}{\partial F}|_{F=F_{m-1}}\} \tag{4}$$

$$\rho_m = \arg\min_{\rho} E_{x,y} L(y, F_{m-1} - \rho g_m) \tag{5}$$

$$f_m = -\rho_m g_m \tag{6}$$

However, real-world datasets contain finite training samples and F^* cannot be estimated at each x_i. In order to smooth the estimation among the samples and generalize to the data beyond training set, a function h with parameter α is introduced to fit the gradients at each step.

$$g_{im} = g_m(x_i) \simeq h(x_i; \alpha_m) \tag{7}$$

The optimization turns into finding the best $h_m = \{h(x_i; \alpha_m)\}_1^N$ that most parallel to $-g_m \in R^N$, where N is the number of samples. The parameter α_m is obtained by solving that:

$$\alpha_m = \arg\min_{\alpha,\beta} \sum_{i=1}^{N} [-g_m(x_i) - \beta h(x_i; \alpha)]^2 \tag{8}$$

With the direction $h(x_i; \alpha_m)$ and finite dataset, the step size in (5) and optimal estimation in (1) is updated:

$$\rho_m = \arg\min_{\rho} \sum_{i=1}^{N} L(y_i, F_{m-1}(x_i) + \rho h(x_i; \alpha_m)) \tag{9}$$

$$F_m(x) = F_{m-1}(x) + \rho_m h(x_i; \alpha_m) \tag{10}$$

Function h is also called the base learner. F^* is searched in the function space which is restricted by $h(x_i; \alpha)$. GBDT chooses decision tree as the base learner. A tree model is parameterized by each leaf node region R_j and its weight b_j, then a tree model with J leaf nodes is represented as

$$h(x; \{b_j, R_j\}_{j=1}^{J}) = \sum_{j=1}^{J} b_j \mathbb{I}(x \in R_j) \tag{11}$$

where the function $\mathbb{I}$ indicates whether a sample x falls into the leaf node j.

By solving (8), the leaf weight is the weighted average of the latest gradients.

$$b_{jm} = \frac{\sum\limits_{x_i \in R_{jm}} w_i g_{im}}{\sum\limits_{x_i \in R_{jm}} w_i} = \bar{g}_m \tag{12}$$

With this weight estimation, the split operation can be evaluated by computing the gain of objective in (8). By traversing the features and values, the tree is construct node by node and the structure is finally determined. The line search multiplier ρ_m can be merged in b_{jm} and (10) is expressed as:

$$\begin{aligned} F_m(x) &= F_{m-1}(x) + \rho_m \sum_{j=1}^{J} b_{jm} \mathbb{I}(x \in R_j) \\ &= F_{m-1}(x) + \sum_{j=1}^{J} \gamma_{jm} \mathbb{I}(x \in R_j) \end{aligned} \tag{13}$$

According to (9) the leaf weight is updated as:

$$\gamma_{jm} = \arg\min_{\gamma} \sum_{x_i \in R_j} L(y_i, F_{m-1}(x_i) + \gamma) \tag{14}$$

C. XGBoost

The gradient decent in GBDT is a first-order optimization algorithm. The variants, such as XGBoost [45] and Psmart [46], add regularizer Ω to the objective and the objective at m iteration is

$$O^{(m)} = \sum_{i=1}^{N} L(y_i, F_{m-1}(x_i) + f_m(x_i)) + \Omega(f_m) \tag{15}$$

The objective takes the second-order taylor expansion approximation of objective and regularizes the number of leaf nodes J and leaf weights γ. It can be regrouped by leaf:

$$\begin{aligned} O^{(m)} &\simeq \sum_{i=1}^{N} [g_{im} f_m(x_i) + \frac{1}{2} h_{im} f_m^2(x_i)] + (\eta J + \frac{1}{2}\lambda \sum_{j=1}^{J} \gamma_{jm}) \\ &= \sum_{j=1}^{J} [(\sum_{x_i \in R_{jm}} g_{im}) \gamma_{jm} + \frac{1}{2} (\sum_{x_i \in R_{jm}} h_{im} + \lambda) \gamma_{jm}^2] + \eta J \\ &= \sum_{j=1}^{J} [G_{jm} \gamma_{jm} + \frac{1}{2} (H_{jm} + \lambda) \gamma_{jm}^2] + \eta J \end{aligned} \tag{16}$$

where G_{jm} and H_{jm} is the first-order and second-order derivative summation on leaf j.

Then the optimal weight and related objective are:

$$\gamma_{jm} = -\frac{G_{jm}}{H_{jm} + \lambda} \tag{17}$$

$$O^{(m)} = -\frac{1}{2} \sum_{j=1}^{J} \frac{G_{jm}^2}{H_{jm} + \lambda} + \eta J \tag{18}$$

Formula (18) is employed to evaluate the split and construct the tree. After that, the leaf weight is calculated by (17).

LogLoss is a common loss function for classification problem and it is calculated by label y and output probability $\hat{y}$, where $\hat{y} = \frac{1}{1+e^{F_m}}$.

$$L(y, \hat{y}) = -y ln(\hat{y}) - (1-y) ln(1-\hat{y}) \tag{19}$$

With this definition, the first-order derivative g_m and second-order derivative h_m used in the following revise algorithms can be formalized:

$$\begin{aligned} g_m &= \frac{\partial L}{\partial F_m} \\ &= y \cdot \frac{1}{1+e^{-F_m}} \cdot e^{-F_m} \cdot (-1) + (1-y) \cdot \frac{1}{1+e^{F_m}} \cdot e^{F_m} \\ &= -y \cdot (1 - 1 + e^{-F_m}) + (1-y) \cdot \frac{1}{1+e^{-F_m}} \\ &= -y + \frac{1}{1+e^{F_m}} \\ &= \hat{y} - y \\ h_m &= \frac{\partial L}{\partial^2 F_m} = (-1) \frac{e^{-F_m \cdot (-1)}}{(1+e^{-F_m})^2} = (1-\hat{y}) \cdot \hat{y} \end{aligned} \tag{20}$$

IV. Mechanism

To face the fact that there are no sufficient data to obtain practical models under new scenes. Data, especially the labels, are time-consuming and costly to collect. So it's natural to seek for some help from the accumulated data under similar scenes, namely source domain data in transfer learning. In this section, we start from our scenario and design a transfer learning framework to utilize the treasurable data based on the XGBoost.

A. Data Analysis

Both of the data in our source domain and target domain are drawn from the oversea e-commerce transactions, but in different marketplaces. Here, the features are defined based on the fraud detection expertise and describe the characteristics distinguishing the samples with different labels. Obviously, these characteristics can be shared across different fraud scenes in a degree.

However, the data distributions can be various in several ways. Different fraud groups take charge of different regions and different fraudsters may follow different fraud tricks. Another point is that their behaviors are completely related to the local risk management strategies. The region-wise strategies are formulated differently, so the fraudsters have to adjust their actions along with the strategies even for the same vulnerability.

Several drift modes show up in Fig.1, which compares the feature distributions between domains :

- Only the range of feature value is changed, while the shape of distribution remains similar(fid35)
- The shape of feature distribution changes(fid39 & fid45)
- The feature lose efficacy and is not so active under the new scene(fid18)

Additionally, we can also observe the predictive power change of the features from the IV(Information Value) metric.

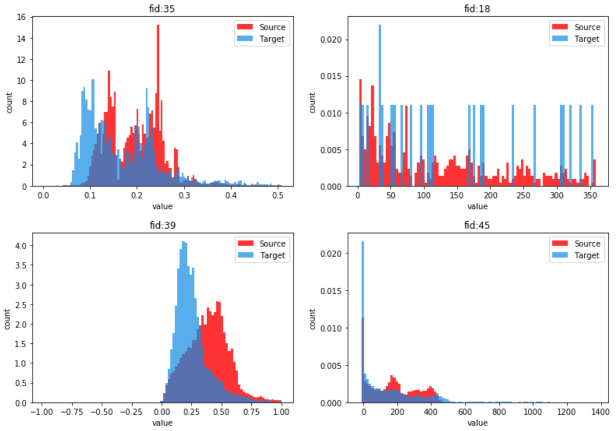

Fig. 1. Feature distribution between domains

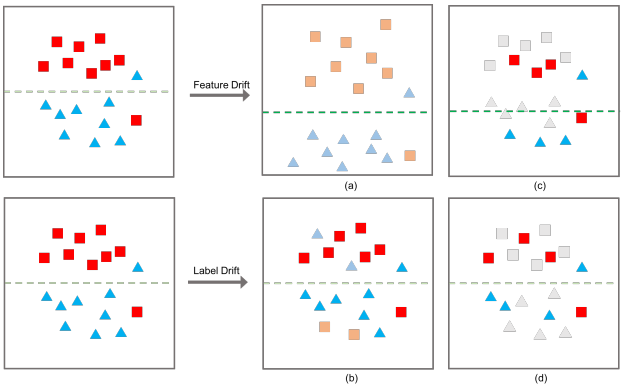

Fig. 2. Feature and label drift between domains

As shown in TABLE I, the top IV features on different domains vary a lot and one third of the top IV features on the source domain become less predicative(marked as red). Besides the relative rank, the overall value scale of IV and the IV of the same feature are also different. This reveals the relation change between the features and the labels.

TABLE I
THE IV COMPARISON OF TOP 20 FEATURES ON SOURCE DOMAIN

feat_id	IV_s	$rank_s$	IV_t	$rank_t$	rank_diff
43	1.412	1	0.9	3	2
44	1.412	2	0.9	4	2
5	1.268	3	0.374	26	23
17	1.01	4	0.629	7	3
34	0.749	5	0.5	11	6
37	0.65	6	0.283	31	25
35	0.634	7	0.488	13	6
36	0.629	8	0.341	27	19
38	0.507	9	0.565	9	0
6	0.369	10	0.384	23	13
45	0.337	11	1.024	1	10
47	0.337	12	1.024	2	10
46	0.264	13	0.797	5	8
31	0.236	14	0.449	15	1
8	0.228	15	0.232	34	19
28	0.224	16	0.423	17	1
1	0.219	17	0.38	24	7
30	0.208	18	0.428	16	2
41	0.206	19	0.596	8	11
15	0.202	20	0.271	32	12

In fact, both of the labels and features can be shifty from our analysis of the data difference between the domains. Fig.2 visualizes the typical drifting cases. The fraudsters change their operandi over time and are active at different regions. So the feature drifting in Fig.2-a often takes place from one scene to another. Meanwhile, the label drifting in figure Fig.2-b may result from the rule change in the definition of "bad" under different scenes. Sometimes, even our datasets are subsamples from the same oracle, a drift can be brought out with the limited sample counts as in Fig.2-c and Fig.2-d.

Though there are distribution changes and relation changes among the domains, the fraudsters do share similar patterns and attributes, which is in harmony with the basic supposition of transfer learning. In particular, the data experts would like to refer to mature scenes and make the defense plans under some new scenes with rare data or labels. The experts manually extract the similarities and this process works out as a good initialization of cold starting, which proves the feasibility of utilizing transfer learning methods to help with the data deficiency.

B. Model-based Transfer

In our case, we have to protect the privacy of the original data and the data are in separated projects. So we turn to model-based transfer learning, a light-weight transfer from the source domain to the target domain.

GBDT is a common choice in machine learning tasks. Besides the high performance and efficiency, GBDT and its variants also provides the model interpretability [47] and the easiness of parameter tuning. The most direct transfer is first train a model on the source dataset. Then the model is transferred to target domain and further trained based on the target dataset. The final model is a fine-tuned version, which inherits the informative patterns in source domain and fits in with the target dataset. Sharing the model directly is a good solution if the target dataset stay the same as the source dataset, but it may be fruitless due to the data drifting in previous analysis. Considering the above reasons, we choose XGBoost as the basic learner of this transfer learning framework and make adaptations to the source trees before continuing training.

Algorithm 1 shows the main workflow of our training process. Given a training dataset $\mathcal{D}$, the wrapper function $TrainXGB$ trains T trees with L levels based on a base model M. It calls the XGBoost API and takes advantage of this highly optimised toolkit. There are two strategies listed to conduct the training process, namely OneRound and MultiRound respectively. The function names indicate the number of times needed for transferring models between the domains.

- OneRound: train a batch of trees on the source domain and transfer them to the target domain in bulk. Then

on the target side, the trees are revised one by one and become the base model for further training.
- MultiRound: iteratively train on the source domain and revises on the target domain to grow each source tree. Instead of the batch process, multiple model exchanges take place during the base model training. Then continue training with only target dataset.

The main difference is how to train the source model. The OneRound strategy captures more patterns in the source domain and maintains a lower transmission cost. The Multi-Round strategy fits the target domain better and considers the statistics change after tree revising. Which strategy to apply is a hyper parameter to be decided based on the datasets.

Algorithm 1 Transfer Learning XGB

function ONEROUND($\mathcal{D}_s, \mathcal{D}_t, T_s, T_t, L_s, L_t$)
  $M_s = TrainXGB(\mathcal{D}_s, T_s, L_s, M = None)$
  // transfer M_s to the target domain
  $M'_s = [\ ]$
  for $i = 1, 2, ..., T_s$ **do**
    $tree = ReviseOneTree(M'_s, M_s[i-1], \mathcal{D}_t)$
    $M'_s.append(tree)$
  end for
  $M_t = TrainXGB(\mathcal{D}_t, T_t, L_t, M = M'_s)$
  return M_t
end function
function MULTIROUND($\mathcal{D}_s, \mathcal{D}_t, T_s, T_t, L_s, L_t$)
  $M_s = [\ ]$
  $M'_s = [\ ]$
  for $i = 1, 2, ..., T_s$ **do**
    $M_s = TrainXGB(\mathcal{D}_s, 1, L_s, M = M_s)$
    // transfer $M_s[i-1]$ to the target domain
    $tree = ReviseOneTree(M'_s, M_s[i-1], \mathcal{D}_t)$
    $M'_s.append(tree)$
    // transfer $M'_s[i-1]$ to the source domain
    $M_s[i-1] = M'_s[i-1]$
  end for
  $M_t = TrainXGB(\mathcal{D}_t, T_t, L_t, M = M'_s)$
  return M_t
end function

C. Revise Strategies

In Algorithm 1, the function $ReviseOneTree$ takes current revised model $M_s^{'}$ and next source tree $M_s[i-1]$ as input, then conduct the revise strategies based on the target dataset $\mathcal{D}_t$. In this section, we discuss some practical strategies, inspired by the data drifting analysis, and related implementation details.

1) Re-split: As shown in Fig.1 and Fig.2-a, the most common feature drifts are scale change and shape change, which fade the branches of the source model. From our observation, the original split values usually result in an unbalanced sample division and the source patterns then become useless. It's obvious that the value is no longer the best split point under the new data distribution. To maintain the efficacy, recomputation of split value is necessary.

The original split features, which construct the backbone of the valuable patterns, are reserved while re-spliting the target dataset. Reviewing the computation of split gain in XGBoost in Formula (18), the first-order and second-order derivatives rely on current predict values and labels. Firstly, the g and h of each sample could be computed, with which we get the split gain for every possible feature values. Then we traverse the whole tree in a top-down order and revise all the split values.

When the data drifting belongs to the scale change but the labels are rare, a simpler method also works out fine. We can first compute the fractile of split value in source dataset and get the same fractile in target dataset as new split value.

2) Re-weight: After getting the tree structure, XGBoost assigns a score to each leaf node with Formula (17). The leaf score is determined by the sample labels fallen into the it. To deal with the label drift problem in Fig.2-b and eliminate the effects of the distribution change, we have to re-weight the leaves. It's easy to embed the score computation in the steps of re-split.

3) Rare Branch: A common case, when we apply the revise strategies, is that some of the branches only contain a small amount of samples. We lose the statistical significance to re-split and may overfit on the these samples. In this way, the revise neither make better use of the source dataset nor result in a reasonable final model. So the sample count on every subtree should be recorded and taken into consideration while executing the strategy.

For the branches with no sufficient samples, two new operations are needed: prune and discount. Prune means that we set up a least sample threshold and drop a rare branch directly. By doing so, a intermediate node becomes a leaf node. This method can cut off the source patterns that is invalid. However, for the cases in Fig.2-c and Fig.2-d, rare branch is caused by the limited dataset and the related pattern may work well on future samples. Because we are not confident of the rare branches, a discount factor is multiplied to the original weight, as a hyper parameter to be determined. This factor reflects the confidence that a source pattern will take effect on the target domain. We tempted to maintain the original branch information, only to get a bad result. The reason is that the original scores are confused with the revised scores, but they are not comparable. With the factor, we weaken the source scores.

TABLE I shows that some features may lose efficacy and fail to be a good split feature. When we traverse the samples and compute the new split gain, no positive result could be found and the feature cannot bring information gain by dividing the samples. So we have to treat it just as the rare branches and apply the prune/discount strategies.

4) Implementation: The basic train and predict process are provided by the XGBoost toolkit. To implement the revise strategies, a data structure is in need to restore the necessary tree structure and the intermediate split statistics. A parser is designed to initialize the data structure from the dumped XGBoost model file.

In order to continue training an XGBoost model, the data structure should also support reverse model transformation. However, no API is released in XGBoost to load a dumped model. In this case, we employ the Treelite[5] to solve this problem. Treelite is compatible with the most popular GBDT toolkit, e.g. XGBoost, LightGBM and Scikit-learn[6]. It allows us to define a Treelite model and generate a mocked binary model, which XGBoost is able to load.

V. Experiment

The experimental dataset contains the card(debit card or credit card) transaction samples from one of the oversea e-commerce platform partners of Alibaba, which utilizes the risk management system of Alipay to detect the real-time transaction frauds, e.g. card-stolen cases. There are nearly 5 million successful transaction samples from 5 contries in total, which consists of basic transaction information, fraud labels and 48 well-designed features.

The features are designed to describe different risk factors. For example, whether the shipping information and device of the payment are reliable, the consistency of the user behaviors and the buyer-seller relation, etc. The fraud labels are collected in the following 3 ways:

- Chargeback from the card issuer banks: the card issuer receives claims on unauthorized charges from the card holders and report related transaction frauds to the merchants
- Third-party data: the fraud data, gathered from banks worldwide, from the venders work as a good supplement
- Label propagation: the device and card information are also utilized to mark similar transactions

A. Experiment setup

Because some scenes are new or the labels need time to be fed back, the bad rate in different contries are quite different(TABLE II). We take the mature scene with highest bad rate as the source domain and the rest scenes as the target domain. In order to simulate the common case of real-world applications, we take 30% of the target domain as training data. In this way, the training data in target domain cannot build a robust model and the evaluation is more reliable with more positive labels. To better understand the data, We run a basic XGBoost model in the dataset in advance. Because of the low bad rate, we apply the negative sampling method to get a better performance. After this, the bad rate of the training data on both domains is about 3%.

Here list the main metrics we care about:

- AUC: basic discriminability measurement for classification problem, area plotted with TPR against the FPR
- Top-Recall: recall of the samples whose scores rank on the top, in practice, the 1‰ recall is in use

While evaluating the dataset with the class imbalance problem, AUC will be high and the gap between models will be minor.

[5]https://github.com/dmlc/treelite
[6]https://scikit-learn.org/stable/

TABLE II
Experimental Dataset Statistics

scene_id	neg#	pos#	bad_rate	domain
3	1227023	1872	0.152%	Source
1	777364	368	0.047%	
2	1285753	74	0.006%	
4	371938	96	0.026%	
5	1299483	464	0.036%	
	3734538	1002	0.027%	Target

In this case, Top-Recall is a better measurement. What's more, it plays a import role in fraud detection, because the follow-up actions are taken on the most suspicious users. To provide a better user experience, it's necessary to ensure the model performance at the top.

From the description in section IV-C, the algorithm involves many parameters. One part of the parameters are related to XGBoost, we focus on the most important two: the tree number and the tree depth. And these XGBoost parameters on source and target domains should be tuned respectively. Other parameters, like learning rate and sample rate, we fix them up globally and initialize them with the aforementioned basic XGBoost model. Another part of the parameters control the revise process, e.g. whether execute the re-split, re-weight, prune and the proper discount of bare branches.

The Baseline Model 1(BM1) trains model with training set only on the target dataset. The Baseline Model 2(BM2) transfers the source model without any revise. We can conclude the gain of transfer learning and the effects of tree revision by comparing the model performance with BM1 and BM2 respectively.

B. Revise Analysis

We recorded the statistics on each tree node during training the XGBoost model on source domain and compared them with the statistics in the revising process. Here, the first tree serves as an example, we'd like to analysis our observations on the revise strategies.

1) Re-split: The intermediate nodes with more than 1 sample on the target domain are listed in TABLE III. We print out the split value, split gain and sample number on both domains. The score is calculated just as the leaf node and it reflects the label distribution in the node.

- There are nodes(marked as red) that cannot get a positive split gain. The reasons could be lacking in samples(node 12) or pattern difference between domains(node 19). It's pointless to split on and the following path should be skipped.
- Observing the nodes with statistical significance (containing more than 3000 samples), the new split values are quite different from the old ones. The original split values tend to get imbalanced samples divisions with the drifted features.
- We rank the nodes with positive re-split gains by the score difference. As we can see, the node with low

score difference(marked as green) tends to be statistically significant. It indicates our datasets have minor label drift. What's more, large score differences(marked as blue) are mainly caused by lacking of samples.

2) Re-weight: The leaf nodes are listed in TABLE IV and we ignore the nodes with no samples. Only 2 nodes are statistical significant (marked as blue) and their score difference is low. Most of the leaf nodes are effected by the limited target dataset and result in high score differences (marked as red). It's a wise choice to count more on the reasonable source model in this situation.

3) Prune or Discount: If we prune the rare branches and intermediate nodes with no gains, only 15 nodes are remained. The source patterns cannot take effect beyond doubt and the general metrics also prove this. So the discount strategy beats the prune strategy and works out better on the rare branches.

According to the above analysis, the revise strategies are determined for current scene. Both of the re-split and re-weight operations should be executed. The selection of discount value is not sensitive as long as it can differentiate the inherited source model weight and revised weight. Empirically, we set the discount value as 0.1.

C. Result

Besides the 2 baseline models, two revise mechanism mentioned in IV-B are tested, denoted as OR (OneRound) and MR (MultiRound).

We tune the models by grid search (the tree depth in target domain is fixed as 5):

- tree depth in source domain (denoted as dep in the result table): 3, 4, 5
- tree number in source domain: 2, 4, 6, 8, 10, 20, 30, 40, 60, 80
- tree number in target domain: 40, 80, 120, 160, 200, 240

For each paramater combination, the experiment was repeated 5 times and the average value was recorded. TABLE V shows the result of the models.

- All the transfer models promote the model performance on this dataset. Less than 10 trees are needed to reach the promotion.
- The AUCs are high and close due to the low bad rate. OneRound mechanism offers the best 1‰ recall value and lift the BM1 by 11.607%. The multi-round mechanism may fail to capture more source pattern information with frequent revisions.
- The BM2 gets a better result with shallower source tree depth. In this way, it keeps the patterns to be more generic. With revise operatioins, our models make reasonable changes and remain more informative source patterns.

D. Deployment

We deploy the OneRound revision algorithm as a toolkit in PAI (Platform of Artificial Intelligence)[7], which is a machine learning platform of Alibaba Group and contains a lot of large-scale data mining algorithms.

In order to access the models in both domains, PAI offers a model pool via a specific OSS(Alibaba Cloud Object Storage Service)[8], which is a cost-effective, highly secure, and highly reliable cloud storage solution.

According to the phases needed, we implement three new components:

- TLXGB-SRC-TRAIN: Call the XGBoost API to train a batch of trees and push the model to the model pool (record the returned model path for the following process).
- TLXGB-TGT-TRAIN: Fetch the source model from model pool, revise & continue train the model and push the model to the model pool(record model path)
- TLXGB-PREDICT: Load a model from model pool and call the XGBoost API to predict the samples

Fig.3 shows the workflow of the components. Only the TLXGB-SRC-TRAIN runs on the source domain and we have to change the running project to target domain after that. Because of the data isolation, TLXGB-TGT-TRAIN cannot read the output table on source domain. We add a reconstruction SQL to the output table, copy it to a SQL component in the target project and reconstruct the configs(e.g. model path). Then continue the process with TLXGB-TGT-TRAIN and TLXGB-PREDICT. Finally, we can connect the prediction result to a evaluation component BINARY-CLS-EVAL and get the performance metrics.

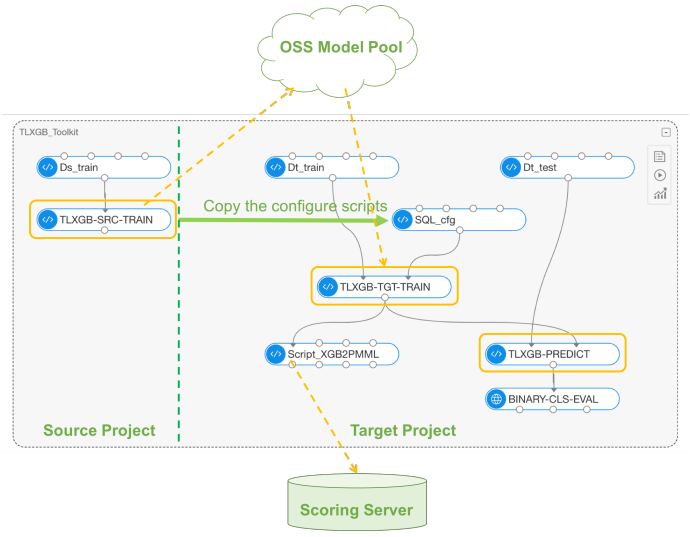

Fig. 3. Workflow of the TLXGB toolkit

The online prediction service is provided by the real-time scoring server, whose service is triggered by each payment and output a final score with the corresponding features fed. Timeliness is import for the server and the whole process is limited to 100ms. JPMML[9] is a widespread evaluator and is

[7]https://www.alibabacloud.com/press-room/alibaba-cloud-announces-machine-learning-platform-pai

[8]https://www.alibabacloud.com/help/doc-detail/31817.htm

[9]https://github.com/jpmml/jpmml-evaluator

TABLE III
RE-SPLIT STATISTICS OF INTERMEDIATE NODES

node_id	feat_id	split_val$_s$	split_gain$_s$	inst#$_s$	score$_s$	split_val$_t$	split_gain$_t$	inst#$_t$	score$_t$	Δscore
0	5	140689.5	542.19208	62400	-0.18799	**439902.5**	46.88963	10200	-0.18793	6.1646E-05
1	43	11.5	136.56732	61119	-0.19069	61.5	12.62515	10137	-0.18900	0.001692
7	34	0.23066	46.87704	9607	-0.17848	0.60413	10.84173	3464	-0.18281	0.004331
15	41	6860329	5.63867	5475	-0.19095	72	11.60792	3445	-0.18365	0.007300
3	17	4318	136.20298	10933	-0.17016	30515.5	37.96496	3635	-0.17824	0.008079
24	40	0.14558	4.19831	67	0.10423	0.31587	4.07152	25	0.11724	0.013016
5	45	26.5	170.83625	650	0.05076	4.5	2.56277	40	0.07273	0.021963
8	34	0.23045	149.07564	1326	-0.10947	0.50828	14.16933	171	-0.08343	0.026045
2	43	0.5	398.10758	1281	-0.05899	4	21.77838	63	-0.01493	0.044063
17	42	834.5	9.89684	712	-0.17151	1.5	25.89931	163	-0.09701	0.074502
23	10	5.5	27.48077	261	-0.09132	2.5	0.43209	13	0.01176	0.103085
16	5	17783.5	61.63551	4132	-0.16180	26892.5	0.32298	19	-0.02609	0.135712
11	5	770377.5	53.27773	328	-0.05060	642766	2.31006	38	0.08571	0.136317
30	36	-0.44286	5.05051	12	0.00000	-0.46204	2.42667	21	-0.15200	0.152000
18	45	77.5	93.29868	614	-0.03689	12	-0.67879	8	0.13333	0.170227
14	34	0.47958	10.55379	516	-0.18538	0.06995	-0.74462	22	-0.15385	0.031538
6	43	23.5	12.37396	631	-0.17165	25.5	-0.74872	23	-0.15556	0.016098
19	0	73687	5.37106	48096	-0.19672	5148309	-0.79935	6500	-0.19490	0.001828
9	21	281.5	10.05906	48572	-0.19640	29182	-0.79935	6501	-0.19490	0.001505
4	17	16899	57.01518	50186	-0.19515	5454684	-0.79935	6502	-0.19490	0.000249

TABLE IV
RE-WEIGHT STATISTICS OF LEAF NODES

node_id	inst#$_s$	score$_s$	inst#$_t$	score$_t$	Δscore
39	48067	-0.19678	6499	-0.19489	0.00189
32	47	-0.10588	3154	-0.18746	0.08158
31	5428	-0.19161	291	-0.14034	0.05127
36	5	0.06667	141	-0.12828	0.19494
49	21	0.02400	23	0.14074	0.11674
35	707	-0.17356	22	0.09231	0.26587
62	7	-0.09091	20	-0.16667	0.07576
33	3739	-0.16976	17	-0.00952	0.16023
37	490	-0.07611	7	0.12727	0.20339
48	137	-0.15177	7	-0.01818	0.13359
47	124	-0.02187	6	0.04	0.06187
50	46	0.13600	2	-0.06667	0.20267
34	393	-0.08514	2	-0.06667	0.01847
38	124	0.11563	1	0.04	0.07563
61	5	0.11111	1	0.04	0.07111
40	29	-0.09091	1	-0.04	0.05091

TABLE V
THE EXPERIMENT RESULT

Model	AUC	1‰ Recall	AUC Lift	1‰ Recall Lift
BM1	0.92535	0.16092	-	-
BM2-dep3	0.92951	0.17672	0.449%	9.821%
BM2-dep4	0.93057	0.17098	0.563%	6.250%
BM2-dep5	0.92825	0.16810	0.313%	4.464%
OR-dep3	0.92886	0.17098	0.379%	6.250%
OR-dep4	0.92799	0.17098	0.284%	6.250%
OR-dep5	0.92869	0.17960	0.360%	**11.607%**
MR_dep3	0.93069	0.17241	0.577%	7.143%
MR_dep4	0.92855	0.17672	0.345%	9.821%
MR_dep5	0.92999	0.17098	0.501%	6.250%

embeded in the server. The PMML (Predictive Model Markup Language)[10], an XML-based format, provides a way for analytic applications to describe and exchange predictive models produced by data mining and machine learning algorithms.

We apply the toolkit to the card-stolen fraud detection scene. Similary to the experimental dataset, the algorithm promotes the 1‰ recall impressively by 26.7%. In order to deploy the final model in the scoring server, we wrap the JPMML-XGBoost[11] and some post-process scripts to convert XGBoost models to PMML.

VI. CONCLUSION

The cold-starting problem under a new scene and data-sharing problem with privacy concerns can be solved by transfer learning algorithms. To deal with a real-world fraud detection modeling in Alipay, we proposed a set of revise strategies to expand the XGBoost as a transfer learning framework. Detailed analysis of the strategies are displayed. The experimental result prove it to be practical and this method promotes the model performance at the top. This model-based transfer learning framework is further deployed on PAI and work as an internal shared component.

There are several open issues to be investigated. A practical extension is allowing the domains to maintain different feature spaces. The process for rare branches also need futher exploration and find a better way to cope with the unconfident subtrees. The revise associated parameters control the revise strategies and the parameter values rely on the data distribution. How to determine the parameter automatically is worthwhile studying. Furthermore, if the datasets are equivalent and how to conduct a multi-task learning among the domains, which is a typical scenario in private data-sharing modeling.

[10]http://dmg.org/pmml/v4-4/GeneralStructure.html
[11]https://github.com/jpmml/jpmml-xgboost

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