Abstract—Rapid growth of modern technologies such as
internet and mobile computing are bringing dramatically
increased e-commerce payments, as well as the explosion in
transaction fraud. Meanwhile, fraudsters are continually
refining their tricks, making rule-based fraud detection
systems difficult to handle the ever-changing fraud patterns.
Many data mining and artificial intelligence methods have
been proposed for identifying small anomalies in large
transaction data sets, increasing detecting efficiency to some
extent. Nevertheless, there is always a contradiction that most
methods are irrelevant to transaction sequence, yet sequence-
related methods usually cannot learn information at single-
transaction level well. In this paper, a new “within→between→within” sandwich-structured sequence
learning architecture has been proposed by stacking an
ensemble method, a deep sequential learning method and
another top-layer ensemble classifier in proper order.
Moreover, attention mechanism has also been introduced in to
further improve performance. Models in this structure have
been manifested to be very efficient in scenarios like fraud
detection, where the information sequence is made up of
vectors with complex interconnected features.

Keywords—fraud detection; model stacking; recurrent neural
network; attention mechanism;

I. INTRODUCTION

Occurrence of fraudulent transactions has been growing
rapidly with the booming development of e-commerce. It
costs consumers and financial institutions billions of dollars
annually. According to the Nilson Report, global card fraud
cost in 2016 has reached $22.80 billion. The fraud rate in
2016 has reached 7.15 BP (1 BP = 0.01%), which increased
by 60% compare to that of 2010 [1]. Therefore, fraud
detection has become the vital activity to reduce the fraud
impact on service quality, costs and reputation of a company
or institute. Traditional anti-fraud method relying on manual
audit is unable to deal with explosively growing information
data. Rule engines have already been widely involved in
many transaction systems. Meanwhile, criminals are keeping
on finding new tricks by avoiding known rules to commit
fraud actions. It makes the rule-based fraud detection method
hard to handle the ever-changing fraud patterns.

Consequently, machine learning methods have been
introduced into fraud detection area. Supervised models like
logistic regression (LR), support vector machine (SVM) and
random forest (RF) are estimated by labeled historical
transaction data [2, 3]. They use the trained model to predict
whether a new transaction is fraudulent or legitimate.
Unsupervised methods like isolation forest (IF) usually
identify outliers as potential fraudulent cases [4]. It can help
detect some new fraud patterns which have not been found
previously. Nevertheless, most of these methods treat each
transaction as an independent individual and ignore the
associations between them. However, these sequence-related
factors may have significant influences on the outcome of
fraud detection model. For instance, criminals may try some
small amount tentative deals before carrying out large
amount transactions. Some of these patterns can be
artificially calculated as candidate features, but it depends
too much on expert experiences and lacks due
comprehensive consideration.

Some behavior-based algorithms such as hidden markov
model (HMM) and peer group analysis (PGA) have been
proposed for fraud detection by discovering anomalies
comparing to regular transaction patterns of an account [5, 6].
However, most behavior-based models need to be
constructed separately for each account. It relies on
account’s exact historical regular patterns, which are difficult
to obtain. Recently, deep learning methods based on
recurrent neural networks (RNN) have been proved to be
with good performance in sequence analysis work [7].
Dynamic temporal behaviors for various accounts can be
analyzed with help of sequence labeling skills by RNN [8].
Nevertheless, just as most sequence analysis methods,
although more sequential information between transactions
can be extracted, the feature learning ability within a single
transaction is insufficient for RNN methods. For example, an
off-site transaction with large amount happened at midnight
may be very suspicious, while the separate “off-site”, “large-
amount” and “midnight” are all common features. There are
many similar effective combinations of features, and some of
them are hard to be found artificially. These relationships
within a single transaction can be well learned by some
classification algorithms like RF, but at the expense of
attenuating the sequential learning ability.

In this paper, a comprehensive building process for
transaction fraud detection model has been presented.
Feature engineering work with rich expert experiences was
first done on distributed computing platform of Spark. A
new “within→between→within” (WBW) sandwich-
structured sequence learning architecture has been proposed
by combining ensemble and deep learning methods. In
addition, attention mechanism has also been involved for
enhancing model performance. Model in similar structure
will show an exciting performance particularly in the
scenario like transaction fraud detection, where the sequence
is made up of vectors with complex interconnected features.
The whole model has been validated on the actual
transaction data of Unionpay and has achieved very good results.

II. DESIGN AND IMPLEMENTATION

A. Artificial Feature Engineering

Each transaction should first be mapped into a row vector based on original transaction fields. Additional feature engineering is necessary for these vectors. According to our previous experiences, more derivative variables can be calculated using statistical methods combining some skills like rolling-window and recency-frequency-monetary (RFM) framework [9]. For example, the amount for current deal, last deal and the variance between them should both be treated as features for current transaction. Total amount over different time periods are also computed as different features. Some trusted characteristics can also be used as features according to our analysis or blacklists. For instance, if many fraud cases happen in a specific location according to historical transactions, then the customized feature “is_high_risk_loc” for this location is 1, otherwise 0.

Some continuous numerical variables like money amount and transaction moment can be directly accepted by the following model, while further artificial analysis on them can enhance the efficiency. We can use weight of evidence (WOE) method to discretize them into more distinguishable features. By the way, with the help of Spark libraries like ML and MLlib, the quality of the features can be further improved. For instance, the “VectorIndexer” API can automatically identify categorical features like location and merchant type, then index them into discrete numeric variables. Moreover, the “StringIndexer” API not only discretize categorical features, but also order them by frequencies, which help improve the model performance commendably, although it takes some time.

B. Feature Optimization Based on GBDT

Now each transaction is mapped into a vector at $n_A$ dimension. The above experience-based feature engineering work is indispensable because it can help the subsequent model to learn the inherent characteristics more quickly and accurately. However, artificial experience still encounters omissions inevitably. To make up for the lack of manual experience, researchers from FaceBook have tried to use gradient boost decision tree (GBDT) method to help discover latent combinations between features automatically before using LR classifier [10]. GBDT prefers generating features with more overall discriminability before generating distinguishing features for few samples. It is why they choose GBDT feature learning rather than RF. In addition, the trained GBDT model needs to be saved for feature conversion during subsequent fraud detection phases.

After the transaction been transformed by GBDT into a vector at $n_G$ dimension, we concentrate the original vector of $n_A$ dimension with the GBDT vector into a new vector $V_{sg}$, with the dimension at $n = n_A + n_G$. The reason why we use the concentrated vector of n dimension instead using GBDT vector directly for the following transformations is because more deep information could be obtained if original features are also involved in sequential learning using the gated recurrent unit (GRU) method.

C. Sequential Features Learning Based on RNN

a) Introduction of GRU model

Traditional machine learning methods cannot handle relationships between transactions well. RNN is a kind of neural networks who maintain a hidden state which can remember certain aspects of the sequence it has seen. However, the magnitude of weights in transition matrix can have strong impacts on the learning process during gradient back-propagation phase of basic RNN, which may lead to situations called vanishing or exploding gradients. Long short term memory (LSTM) method introduces a new structure called memory cell to enable the capability of learning long-term dependencies [11]. On top of this, the GRU method modifies 3 gates (input/forget/output) of LSTM into 2 gates (update/reset), and merges the unit output into one state [12]. It reduces the matrix multiplication to some extent. Thus the GRU method is adopted here considering the relative large training data.

![Fig. 1. Diagram for a single hidden node unit in GRU](image)

As can be seen from Fig. 1, supposing there are $j$ hidden node units. The formulas for each unit are as follows:

$$r^j_t = \sigma(W_r x_t + U_r h_{t-1})^j$$
$$z^j_t = \sigma(W_z x_t + U_z h_{t-1})^j$$
$$\hat{n}^j_t = \tanh(W x_t + U (r^j_t \odot h_{t-1}))^j$$
$$h^j_t = z^j_t h_{t-1} + (1 - z^j_t)\hat{n}^j_t$$

Here, $r^j_t$ is reset gate, which allows model to drop information that is irrelevant in the future. $z^j_t$ is update gate, which controls how much of past state should matter now. $\hat{n}^j_t$ is new memory and $h^j_t$ is current hidden state. $\odot$ means element-wise multiplication, $\sigma$ represents sigmoid function. $[.]^j$ means the No. $j$ element for a vector. $W_r, U_r, W_z, U_z, W$ and $U$ are matrix weights to be learned. It can be
found that the new memory is generated by previous hidden states and current input. Previous hidden state will be ignored when $r^1_t$ is close to 0. $z^{(D)}_t$ determines the influences of $h_{t-1}^l$ and $\tilde{h}_t^l$ to current hidden state $h_t^l$.

b) Generate sequential samples

Current samples need to be transformed into sequential ones whose format the GRU algorithm can handle. Supposing we have 2 datasets: the first set $D_T$ stores the labeled normal transactions, while the second set $D_F$ stores the labeled fraud transactions. We extract and group the samples as follows:

1. Group the transactions by account and count the number of transactions for each account.
2. Separate the accounts into k sets according to their transaction counts. This can be done according to business requirements artificially or using clustering methods.
3. For each set $i$, count the minimum transaction counts for a single account $S_i$ and the maximum $E_i$. Clusters can be sorted in ascending order of average count as: $[S_1,E_1], [S_2,E_2], \ldots, [S_k,E_k]$.

After transactions have been grouped into corresponding sets, sort the transactions by time for each account belong to set $i$. Current vector $V_{sg}$ for the No. $r$ transaction now is $X_r = \{x_{r1}, x_{r2}, \ldots, x_{rn}\}$. Each transaction can be then extended into a sequential vector sample with a fixed dimension at $n * E_i + 1$. It means the parameter “timesteps” (TS) for this set is $E_i$. For the earliest transaction of the account, the front $n * (E_i - 1)$ elements are all filled with 0 because there is no previous transaction recorded. By appending the “fraud or normal” label $Y_i$ of current transaction, the first sequential sample can be described as $\{0 \ldots 0, X_r, Y_i\}$. For the No. $r$ transaction ($r < E_i$), the previous $r - 1$ transactions are arranged before current one, and the sequential sample for this transaction can be described as $\{0 \ldots 0, X_{r-1}, X_r, Y_r\}$ by appending the current label $Y_r$. The dimension of elements filled with 0 is $n^*(E_i - 2)$. And if $r$ is the last transaction for this account, stop generating sequential samples for it. If the last transaction happens to be $E_i$, the last sequential sample for this account can be $\{X_1, \ldots, X_{E_i-1}, \tilde{X}_{E_i}, \tilde{Y}_{E_i}\}$, with no elements filled with 0. A typical sample extension process is shown in Fig. 2.

Detail division of TS should also be modified according to actual situations. For instance, a threshold of maximum transaction counts $E_M$ can be defined. Accounts with transaction count exceed $E_M$ can be categorized into the last set $\{S_E, E_M\}$. And for the No. $t$ transaction ($t > E_M$) of an account, only the previous $E_M - 1$ transactions will be involved to generate the sequential sample using the moving window with size of $E_M$, which can be described as $\{X_{t-(E_M-1)}, \ldots, X_{t-1}, X_t, Y_t\}$.

c) Sequential Features Learning using “WB” Structure

After generating sequential samples, we construct sequential feature optimization model for each of the k sets. GRU model could be trained to detect fraud directly by appending a 2-dimensional output of softmax layer, yet we do not intend to do so. Although RNN model can learn relevance between sequential items well, the learning ability for features inside a single transaction is only equivalent to a basic shallow network considering the generally small layer numbers. Engineers from Google have raised a “wide & deep” framework by combing LR method with basic deep neural networks (DNN) to improve feature learning ability [13]. Analogously, we first proposed a “within & between” (WB) structure by combining the GBDT and GRU method to intermingle their advantages. GBDT method here is applied for extracting more potential sequential optimized features based on previous GBDT learning process. In fact, a recent literature has already shown a relatively good structure by using the output of LSTM as the input for another classifier like LR. This can be taken as a forerunner for “between & within” (WB) structure [14].

Detail for sequential features learning model in WB structure is shown in Fig. 3. As can be seen, the blue dots represent the $n_A$ dimensional vector after artificial feature engineering, the purple dots represent vectors optimized by GBDT. These two vectors are merged into $V_{sg}$, which is the eigenvector for a single transaction. The sequential samples are reshaped into a tensor with dimension of $(E_i, n)$, and this tensor is the input of GRU model.

Supposing the number of layers is $N_{layer}$ and the output dimension is $n_O$ for GRU. These parameters can be adjusted according to actual demands and effects. Here
we take $N_{\text{layer}} = 2$ as an example. After the GRU model has been trained, the output of the last node could be the sequential feature vector $V_{sq}$.

Preferably, a mean pooling layer can be applied on top of the last GRU layer to learn more sequential information among transactions, as shown in Fig. 4. It means the average result of all $E_n$ nodes is taken as $V_{sq}$. Note that although there are $k$ different sequential optimization models for $k$ sets, the output dimension for each model only depends on the parameter $n_p$ for GRU model. It means the format of sequential features is consistent for all transactions if parameter $n_p$ stays the same. But one fixed parameter $n_p$ may not have good performance for all $k$ models. So it is suggested to append an additional multi-layer perceptron (MLP) on top of current GRU output or the mean pooling layer, with the dimension for the last layer of MLP keep the same value of $n_M$ for all $k$ models. Here, a single-layered dense is also acceptable instead of MLP. Then we can concentrate the $V_{sq}$ of current transaction and sequential feature vector $V_{sq}$ into a new vector with dimension at $n_{op} = n + n_M$, which is the final optimized eigenvectors $V_{op}$ for current transaction.

As a special case, no division work will be done. All transactions will be processed by one sequential model with a same TS parameter at $ts$. It means only previous $ts$ transactions would be taken into consideration when building the sequential model for one account even if there are more transactions before. Sequential information can then be learned in a more simple way at the expense of a little approximation loss. Better solution is to introduce the so called “attention mechanism” into our GRU model, whose output is weighted average of sequential inputs [15]. A sketch-map for model combined with attention mechanism is shown in Fig. 5. Each GRU cell is paired with one attention model (AM). As can be seen from the insert of Fig. 5 that the AM unit first compute each $m_i$ with a tanh layer as:

$$m_{ij} = v^T \tanh(W_m h_{i-1} + U_m V_{sqi})$$

Here $v^T$, $W_m$ and $U_m$ are learnable parameters. Each weight $s_{ij}$ is computed by softmax function as:

$$s_{ij} = \frac{\exp(m_{ij})}{\sum_{k=1}^{TS} \exp(s_{ik})}$$

At last, the output $z_i$ can be computed as the weighted average of all $V_{sqi}$:

$$z_i = \sum_{j=1}^{TS} s_{ij} V_{sqi}$$

Note that the architecture illustrated in Fig. 5 is about the feature-level attention [16]. The mean polling layer can also be replaced by another attention model, which could be the component-level attention. This work will be tried in future work. Anyway, by using attention mechanism, it is possible to focus on the interesting part of sequences regardless of the size of input sequence. Models with different TS can also include attention mechanism respectively in the same way.

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**D. Entire Fraud Detection Model Based on “WBW” Sequence Learning Architecture**

Final fraud detection model can then be trained using a top-layer classifier based on the optimized eigenvectors $V_{op}$. The classifier can be chosen from some common algorithms, but suggested ones are ensemble methods such as RF, GBDT and extreme gradient boosting (XGBoost) which have been proved to be very effective in fraud detection area. To synthesize the advantages of multi methods, boosting ensemble methods will no longer be selected because GBDT has already been involved in previous feature learning steps. So RF method is selected here as the top-layer classifier, which is one of the best bagging ensemble methods and can be implemented in parallel well.
Let’s review the whole model training process. First, the GBDT method is used to expand effective features within single transaction. Then the GRU method is implemented to learn sequential features between transactions. At last, the RF method is applied to relearn more potential features within the optimized eigenvectors $V_{op}$ for each transaction. Similar structures can be unified into a “WBB” sandwich-structured sequence learning architecture. The advantage of the WBB architecture is intuitively interpretable. The features obtained from ensemble methods like GBDT could be sequentially dependent between transactions besides artificial calculated features. For example, “a large amount off-site transaction at midnight” would happen after some tentative “small amount off-site transactions at midnight”. Similar suspicious fraud patterns in deeper levels with sequential dependencies can be well learned automatically by the first WB structure. Meanwhile, newly learned sequential features again may have potential associations with others within a transaction. For instance, a “current large amount transaction happens after some small tentative ones” pattern would be more suspicious if combined with other patterns like “current transaction location is different from the previous tentative ones”. It means the sequential features may be recombined into new features within a single transaction for exposing deeper information. Similar information can be learned intelligently by the second “between → within” (BW) structure. The typical processing flow for entire WBB framework is shown in Fig. 6.

III. EXPERIMENTS AND RESULTS

Our original data are stored in Hive tables among clusters based on Cloudera CDH-5.9.0. Feature engineering is implemented on Spark-2.1.0. The experimental cluster consists of 100 nodes, where each node contains an Intel Xeon CPU E5-2620 at 2.00GHz CPU and 8 GB RAM. Data in Hive tables can be directly read by Spark SQL into Spark Dataset for further processing. The GRU related methods are carried out on the Tensorflow-1.2.0. Spark ML library was tried for the ensemble methods like RF and GBDT at first, but the performance is very poor in seriously imbalanced situations. This may be caused by some approximation in the process of algorithm parallelization. So the Python Scikit-learn library is selected for these ensemble methods.

There are also various types of fraud. Taking the statistical result of China in 2016 as an example, the most fraud type for debit cards is telecommunication fraud, while the fraud losses for credit cards are dominated by counterfeit cards. Special models should be built for different fraud types separately. Here we take the counterfeit credit card fraud detection model as an example to show the typical building process and performance. The WBB sequence learning process was trained on a real transaction collection of Unionpay within a three-month period from 2016.06 to 2016.08. The division of parameter $TS$ was implemented according to the distribution of transaction count for single accounts. As shown in Fig. 7, the histogram represents the statistics of the accounts number within special transaction count range for a single account during experimental period. The first red column represents that there are about $2 \times 10^5$ accounts whose transaction count is in range of $0$–$5$, while the second green column represents that in range of $5$–$10$. Special sequential model with corresponding $TS$ was built for accounts within these ranges with large accounts number. Whereas accounts in the range of $40$–$100$ was arranged into one sequential model with a uniform $TS$ at $40$ due to the relative less accounts number. A special sequential model with $TS$ at $100$ was also built for accounts in the range above $100$ considering the larger total number of transactions.

Performances of multiple algorithms have been compared. The precision and recall of fraudulent samples are good choices for performance evaluation in view of the highly skewed data. Fig. 8 (a) shows the precision-recall (PR) curve of test data in the following month of 2016.09 for each algorithm with the imbalance ratio between regular and fraudulent samples at $10000:1$. As can be seen, the performances for ensemble methods like RF and GBDT are better than other common classification algorithms like SVM or LR under the experimental scenario. RF combined with GBDT optimization has only a little promotion compared to separate ones. Single GRU sequential method prevails a little
over ensemble methods. Some additional improvement can be obtained by placing ensemble methods before or after GRU process. By contrast, a more distinct promotion emerges when GBDT, GRU and RF methods are stacked in order. It indicates that the “WBW” sequence learning architecture provides a better performance than that of “WWB” or “BWW” structures, let alone other simpler structures like “WB” or “BW”. Besides, from Fig. 8 (b) we can see that the predicting ability for RF model attenuates gradually as time elapses, while the effect of GRU model is declining with some irregular beatings. It means that current fraud detection patterns within a single transaction are ever-changing while the sequential patterns could be effective periodically. Nevertheless, it is suggested that all models should be trained termly in case of losing effectiveness.

![Fig. 8. (a) Comparison of PR curves in special imbalance ratio. (b) Comparison of variation trends for F1 score as time elapses](image)

In fact, RF method could be better than single GRU model when data is very balanced. As shown in Fig. 9 (a) the best F1 score is higher than that of GRU model at first, while it drops more sharply with increasing the imbalance ratio. It means GRU model can alleviate imbalance to some extent. The WBW approach inherits this advantage of GRU model, and thus can give a relatively good performance in seriously imbalanced situations. The performances of WBW models with different GRU structures have also been compared, as shown in Fig. 9 (b). It can be seen that model with GRU consists of various artificially divided TS ranges has better performance than that with fixed TS. Further improvement can be accessed by combining the attention mechanism. It can also be found that models with GRU at larger TS benefit more from attention mechanism, and the performance of model with attention model at fixed TS=20 is very close to that of model using various GRU models in different time steps. It indicates that attention-based single GRU model at a relatively large TS is also an acceptable choice for the “B” in “WBW” structure, considering the simplicity of artificial operation.

![Fig. 9. (a) Comparison of decline trends for F1 score with increasing imbalance ratio. (b) Comparison of F1 score for WBW models with different GRU structures.](image)

IV. CONCLUSIONS

In this paper, we presented a sophisticated solution to build a transaction fraud detection model. Firstly, artificial feature engineering work is carried out on the Spark distributed platform. Next, GBDT algorithm is involved to optimize the features within a single transaction. Then the GRU model is applied on the transformed sequential samples to learn the relationships between transactions better. Finally, a top-layer RF classifier is trained using the optimized transaction eigenvectors. This approach has been proved to be more efficient for detecting transaction fraud than most traditional methods. In addition, attention mechanism has also been integrated into our model for enhancing the performance. The entire process by stacking an ensemble method, a RNN deep learning method and then another ensemble method orderly can be unified as the WBW sandwich-structured sequence learning architecture. Models in similar structures could also play important roles in many other scenarios where the information sequence is made up of vectors with complex interconnected features.

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