A Time Attention based Fraud Transaction Detection Framework

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ABSTRACT
With online payment platforms being ubiquitous and important, fraud transaction detection has become the key for such platforms, to ensure user account safety and platform security. In this work, we present a novel method for detecting fraud transactions by leveraging patterns from both users’ static profiles and users’ dynamic behaviors in a unified framework. To address and explore the information of users’ behaviors in continuous time spaces, we propose to use time attention based recurrent layers to embed the detailed information of the time interval, such as the durations of specific actions, time differences between different actions and sequential behavior patterns, etc., in the same latent space. We further combine the learned embeddings and users’ static profiles altogether in a unified framework. Extensive experiments validate the effectiveness of our proposed methods over state-of-the-art methods on various evaluation metrics, especially on recall at top percent which is an important metric for measuring the balance between service experiences and risk of potential losses.

KEYWORDS
Time Attention, Fraud transaction, Sequence, RNN

1 INTRODUCTION
Online payment platforms have been playing an increasingly important role in our daily life, as we are heading towards a cashless society. The major online payment platforms, such as Alipay, PayPal and Paytm, are currently serving hundreds of millions of users around the world and processing millions of cashless transactions each day. To provide a credible service, a crucial and challenging issue is to ensure the safety of all the transactions, among which the detection and prevention for the fraud transactions is a critical task.

To handle this task, a key issue is how to construct the detection system. In recent years, machine learning based methods have been applied, in which the detection of fraud transaction is formulated as a classification problem and a model is trained with the collected labeled data. When deployed, a score can be obtained for each transaction to measure the fraud risk with the trained model. Then a threshold is set so that those transactions whose scores are higher than the threshold will be suspended for further verifications, which include different authentication methods, such as face recognition, Short Messaging Services (SMS) and verification emails. However, these are some awkward problems.

When building a model, another important issue is that the features in this task are much complicated, and specific consideration and a more effective model is needed. Roughly speaking, there are two different kinds of features in this task. On the one hand, the users’ static profiles, such as users’ demographics and average spendings, are basic features to describe one user, and to indicate the risk of the account. Thus, we claim that the model should pay enough attention to the dynamic features, and effective method should be explored to reduce the expense of computing and storage.

To handle sequence data, deep learning based methods, such as long short-term memory (LSTM) and convolutional neural network (CNN), and their variant algorithms have been developed in recent years, and significant improvement has been achieved in various applications, such as speech recognition, natural language processing, video processing, etc. However, most of these methods only address the sequence information of the data, while the detailed information of the time intervals are not considered. In fact, the time regularity is informative and the time interval information is meaningful in real-world applications. One example is that a person who trades in the same frequency is quite different from the one who trades irregularly. Another example is that the person who takes a short time between two operations is quite different from the one that takes a long time. Thus, the detailed information of the time interval is a key point which should be valued.

To address the problem above, we proposed to introduce the attention mechanism to handle it. Attention mechanisms have been proven to be a very powerful mechanism, and have brought improvement in many areas, such as natural language translation, speech recognition, and their variants have been developed to integrate the extra sources of information, and guide the extraction of embeddings which are highly correlated to the specific tasks. As we discussed, detailed time information (not only the sequence information) is of great value, which will play crucial role in our task. In this paper, inspired by [12, 15], we propose to use time attention based recurrent layers to embed the detailed information of the time interval, such as the durations of specific actions, time differences between different actions and sequential behavior patterns in the same latent space, etc., and we further combine the learned embeddings and users’ static profiles altogether in a unified framework for the final training of the fraud transactions detection model. The main contributions of this paper are summarized as follows.

- We propose a novel time attention based recurrent layer which can operate sequential data in continuous time spaces with the detailed information of the time interval addressed.

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1https://en.wikipedia.org/wiki/Cashless_society
2https://www.paypal.com
3https://www.paytm.com
4https://intl.alipay.com/
where \( x_t \) controls the ratio of the duration of the open phase to the full period.

The rest of this paper is organized as follows. We summarize the related literature in Section 2, and describe the detailed architecture of the proposed approach in Section 3. We report and discuss experimental results in Section 4, and conclude in Section 5.

2 BACKGROUND

In this section, we will introduce the related literature that formed the basis of our work.

2.1 Phased LSTM

Phased LSTM [15] is a RNN architecture for modeling event-based sequential data. It extends LSTM by adding the time gate \( k_t \in \mathbb{R} \). \( k_t \) is controlled by three parameters: \( r, r_{on} \) and \( s \), where \( r \) is the total period of the model, \( s \) is the phase shift and \( r_{on} \) is the ratio which controls the ratio of the duration of the open phase to the full period. \( r, r_{on} \) and \( s \) are learned during the training process. \( k_t \) is formally defined as:

\[
\phi_m = \frac{(t - s) \mod r}{r} \tag{1}
\]

\[
k_t = \begin{cases} 
2 \frac{\phi_t}{r_{on}} & \text{if } \phi_t < \frac{1}{2} r_{on}, \\
2 - 2 \frac{\phi_t}{r_{on}} & \text{if } \frac{1}{2} r_{on} < \phi_t < r_{on}, \\
\alpha \phi_m, & \text{otherwise}, 
\end{cases} \tag{2}
\]

where \( t \) is the time stamp and \( \phi_t \) is an auxiliary variable. And the modified model can be described as follows:

\[
f_t = f_t \odot c_{t-1} + i_t \odot \delta_c \left( x_t + W_{hc} h_{t-1} + b + c \right) \tag{3}
\]

\[
c_t = k_t \odot f_t + (1 - k_t) \odot c_{t-1} \tag{4}
\]

\[
h_{t}^{\prime} = o_t \odot \delta_h (\hat{c}_t) \tag{5}
\]

\[
h_t = k_t \odot \hat{h}_t + (1 - k_t) \odot h_{t-1} \tag{6}
\]

where \( x_t \in \mathbb{R}^d \) denotes input features at timestamps \( t \), \( h_t \in \mathbb{R}^k \) denotes the \( k \)-dimensional hidden units, and \( c_t \in \mathbb{R}^k \) denotes the cell memory. However, this method is designed for high-frequency sampling scenes, which is quite different from our task.

2.2 Time LSTM

Time LSTM [24] adds specific inner gated units in LSTM to maintain the long term and short term effects on current actions in the sequence, such gates are controlled by the time interval between two actions. The model can be described as follows:

\[
T_m = \sigma (x_m W_{x_t} + \sigma_{m} (\Delta t_m W_{t_t} + b_t)),
\]

\[
c_m = f_m \odot c_{m-1} + i_m \odot T_m \odot \sigma_c (x_m W_{xc} + h_{m-1} W_{hc} + b_c) \tag{7}
\]

\[
o_m = \sigma_o (x_m W_{xo}) + \Delta t_m W_{t_o} + h_{m-1} W_{ho} + w_{co} \odot c_m + b_o,
\]

where \( \Delta t_m \) is the time interval between two states. Such a method has been successfully applied in predicting users’ next actions in recommendation systems (RS), which is quite similar to our task. As mentioned in [2], by using the last hidden state of such models as the representation of the sequence, it’s difficult to use a fixed length vector to represent a long sequence.

3 TIME ATTENTION BASED HETEROGENEOUS NETWORK

The proposed heterogeneous network’s architecture is shown in Fig 1. In this section, we will introduce the components of our architecture.

3.1 Representation of Static Features

According to one’s transaction and shopping records in the platform, we can collect one’s profiles, such as working places, living places, credit scores (similar with FICO score\(^2\)), trading amounts, etc., which demonstrate a person’s consuming ability and habits. The rationale for using such features is that an unusual transaction amount or location may be suspicious.

As many continuous features are static ones, before feeding such features into a neural network, data preprocessing, such as normalization and discretization, are needed. For example, different normalization, discretization methods are needed. But for tree-based models, the raw features can be directly used, as the model is able to split the numerical values accordingly. This property and the strong representation power of tree-based models make them widely adopted in the industries. Despite this, RandomForest(RF) or Gradient Boosting Decision Tree(GBDT) is a linear combination of separate trees, which can be observed from Eq. (8).

\[
F(x) = \sum_{i=1}^{n} y_i h_i(x) + \text{const.}, \tag{8}
\]

where \( y_i \) is the weight of the \( i \)-th tree, and \( h_i(x) \) is the output of \( i \)-th tree.

The boosted decision trees have shown to be a powerful model to transform the original features of an instance [8], which can then be utilized by other models to further get even higher accuracy. Specifically, we use each learned individual tree as a categorical feature, where the value is set as the index of the leaf node the instance falls in. As a result, if there are \( n \) trees in the GBDT model, the transformed feature of an instance is given in terms of a structured vector \( \bar{x} = (\bar{e}_1, ..., \bar{e}_n) \), where \( \bar{e}_k \) is the \( k \)-th unit vector with the dimension of \( d_k \), where \( d_k \) is the number of leaf nodes at \( k \)-th tree, and \( i_k \) is the index of the leaf node where the current instance falls into at \( k \)-th tree.

\(^2\)http://www.fico.com/
3.2 Dynamic Behaviors

3.2.1 Click Behavior. When users use services provided by Ali-pay, there will be a record describing the service the user had used, which is quite similar to the click history used in the recommendation system. We can formulate the user behavior sequence as a tuple $(u_j, a_i, t_i)$, where the $U = \{u_1, \ldots, u_j, \ldots, u_{|U|}\}$ is the user set, $A = \{a_1, \ldots, a_i, \ldots, a_{|A|}\}$ is the action set, $T = \{t_1, \ldots, t_i, \ldots, t_{|T|}\}$ is the time stamp of user $u_j$ done the action $a_i$. For a user $u$, his/her click behaviors can be represented as $B = \{(a_i, t_i) | i = 1, \ldots, m\}$. In order to involve the time effect, we separate the click behaviors into two parts, the first part is the click history $B_h = \{a_i | i = 1, \ldots, m\}$, and the second part is the time behavior $B_t = \{t_i | i = 1, \ldots, m\}$. For the time behavior, we pay more attention to the interval between two actions, so we transform the time behavior as $B_t = \{\Delta t_i | \Delta t_i = t_i - t_{i-1}\}$. However, since the $B_t$’s values fall into a large range, some values appear rarely, which makes the network hard to convergence, so a discretization process is needed.

3.2.2 Transaction Behavior. When users make a transaction, a lot of information will be saved, which contain abundant aspects of this transaction, for example, an event will contain the scene, the location, and the time user does such transaction, at the same time the formal transaction place and the registered place are included in the event, which can demonstrate if the user is trading in an abnormal place. For time data, we use the same notation as mentioned in Section 3.2.1.

3.3 Time Attention based Recurrent Layers

Since our attention mechanism is added upon RNN layers, so we will introduce the basic LSTM and GRU first, and followed by our proposed time attention mechanism.

3.3.1 LSTM. Using LSTM to model sequential data has many successful applications. Compared with Recurrent Neural Network(RNN), LSTM is comprised of forget gate, input gate, output gate, and a memory cell. Standard LSTM equations can be described as follow:

\[
i_t = \delta(W_i \ast x_t + U_i \ast h_{t-1} + b_i),
\]

\[
f_t = \delta(W_f \ast x_t + U_f \ast h_{t-1} + b_f),
\]

\[
o_t = \delta(W_o \ast x_t + U_o \ast h_{t-1} + b_o),
\]

\[
g_t = \phi(W_g \ast x_t + U_g \ast h_{t-1} + b_g),
\]

\[
m_t = f_t \odot m_{t-1} + i_t \odot g_t,
\]

\[
h_t = o_t \odot \phi(m_t),
\]

where the $W, U$ and $b$ are parameters of the LSTM. $x_t$ represents the input vector of the LSTM at timestamps $t$, $\delta$ is the sigmoid function, $\phi$ is the hyperbolic tangent function.

3.3.2 Time Attention. Assuming we have a sequence consists of $n$ actions, represented in a sequence of embeddings:

\[
S = (x_1, x_2, \ldots, x_n),
\]

where $x_1$ is a vector in dimension $d$, $S$ is a 2-D matrix, whose is $n$-by-$d$. The hidden states of RNN at time $i$ can be given by:

\[
h_i = \text{RNN}(x_i, h_{i-1}),
\]

where $h_i$ is a $k$ dimension vector, $k$ is the hidden unit number of the RNN. All the $n$ $h_i$s are denoted as $H$, whose shape is $n$-by-$k$ when RNN is the single direction architecture, or $n$-by-$2k$ if of a bi-direction architecture.

For time data, there are multiple meanings, for example, how long a user stays in a session, which means the degree of interest or familiar of this user, or how long after the user uses another service, which can denote a user’s behavior. Here we use $r$ to denote the time data. Since $r \in \mathbb{R}$, where $\mathbb{R}$ is one dimension real value space, we first discrete the time data by $\theta = \left\lceil \frac{r}{\tau} \right\rceil$, and just use it as a category feature, and then we can encode the time data as:

\[
\rho_i = \text{lookup}(\theta_i),
\]

where $\rho_i$ is the embedding representation of the discrete time data, whose dimension is $q$. Then we can stack all time embeddings $\{\rho_1, \ldots, \rho_n\}$ together, and denote such matrix as $P$, which means the embedding representation of time data. Its dimension is $n$-by-$q$. Following the self-attention mechanism, we use the following equations to calculate the weight of $H$ we get from RNN:

\[
e = w_k \tanh(W_e \ast H^T + W_f \ast P^T),
\]

\[
\alpha = \text{Softmax}(e),
\]

where $W_e$ and $W_f$ are the matrices to be learned, $W_e \in \mathbb{R}^{m \times k}$, $W_f \in \mathbb{R}^{m \times q}$, $w_k$ is a vector, $w_k \in \mathbb{R}^m$. $\alpha$ is the attention weight which quantifies the relevance of features in $H$. The Softmax ensures all the computed weights sum up to 1. After getting the $\alpha$, we can use the standard attention mechanism to gather the embeddings extracted from different time states together by the following equation:

\[
\hat{h} = \sum_{i=1}^{n} \alpha_i \ast h_i,
\]

where the $\hat{h}$ demonstrates the new representation of the sequence.

3.4 Heterogeneous network

Since we have two different kinds of behavior data, and static features in our system, we want to blend the heterogeneous data into a unified architecture, which will make the whole system more compact, at the mean while reduce the work of feature engineering. According to the method we mentioned in Section 3.1, we extract tree embeddings based on the user profile. At the same time, we extract two kinds of behavior embeddings from click and transaction behavior by our time attention RNN architecture, respectively. Since the values from different parts are in different scales, directly concatenating them together will make the whole network hard to converge. So we add a batch normalization layer [10] at the top of time attention layer and tree embedding layer, then we concatenate the output of each BN layer and feed them to a multi-layer neural network. The whole architecture is shown in the Figure 1.

4 EXPERIMENTS

In this section, we will describe the comprehensive experiments that we conducted to show the effectiveness of our proposed model. We first describe the dataset we use, the comparison methods, hyperparameter settings, and evaluation metrics. We then report the comparison result and finally study model parameter effects.
4.1 Dataset
We use the real transaction data from Alipay as our experimental dataset, where both real and fraud transactions are available. Fraud detection task is quite different from the traditional classification tasks, because the execution methods of fraud transaction vary in different time periods. Thus, in order to test our model’s performance as practical as possible, we separate the original five-month transaction data into three parts according to the transaction occur time: the transaction data of the first three months are used as training set, the data of the fourth month is used as the validation set, and the data of the last month is used as test set. Meanwhile, since the whole transaction amount is extremely large and the fraud transactions are rare, we down-sample the non fraud samples of train set and the validation set to accelerate our experiments, at the same time, in order to simulate the real online situation, we sample from the original data set to build our test set which makes the fraud and non-fraud samples number is quite different from train and validation set. We report the details of the dataset after preprocessing in Table 1.

As described in section 3, the features in fraud transaction scenario are divided into three groups, i.e., user static features, user click behavior features, and transaction behavior features. User static features demonstrate a person’s consuming ability and habits. For the click behavior, we choose user’s interactions with the Alipay APP during the recent two days as click behavior features. We set the max number of interaction to 200 based on experience. If the number of interaction is bigger than 200, we only keep the latest 200 interactions. For transaction behavior, user’s trading history in Alipay during the recent ten days are selected as features. We also set the max number of trading history to 32 based on experience.

4.2 Comparison Methods
In order to study whether our proposed time attention mechanism works, we compare our time attention mechanism with the following methods by varying the building block that generates the behavior embedding.

- Bi-LSTM: We use bidirectional-LSTM [7] method to model the user’s behavior. We extract the last state data as user embedding, and concatenate it with tree embedding extracted from trees [22], [21].
- Phased LSTM: This method is introduced in Section 2. We use the implementation which is provided by TensorFlow [1].
- Self-attention LSTM: We add a self attention layer on the top of Bi-LSTM which is introduced in [12].
- CNN+Max pooling: We use traditional CNN with Max pooling to extract click and transaction behavior’s embedding. The window size is set from 4 to 10. For click behavior, the kernel size is set to be 32. For transaction behavior, the kernel size is set to be 16, which equals to the embedding dimension of different kinds of behaviors.
- Time LSTM: This method is introduced in Section 2, and we use the implementation available at GitHub6.

If the number of history is bigger than 32, we will only keep the latest 32 transactions. Moreover, for each transaction, we select the 28 most important attributes, e.g., the trading location, IP location, trading amount and so on. Finally, we summarize the dimensions of each feature in Table 2.
Table 1: Fraud detection dataset description

| Dataset     | #User   | #Sequences   | #Non Fraud Transaction | #Fraud Transaction |
|-------------|---------|--------------|------------------------|--------------------|
| train set   | 1,221,706 | 3,837,624    | 3,832,560              | 5,064              |
| validation set | 656,521  | 1,248,912    | 1,247,315              | 1,597              |
| test set    | 674,057  | 1,302,226    | 1,302,091              | 135                |

Table 2: Feature dimension description

| Feature Dimension               | Dimension |
|--------------------------------|-----------|
| Static feature dimension       | 89        |
| User behavior feature dimension| 2,300     |
| Transaction feature dimension  | 28        |

4.3 Hyperparameter Setting

We fix the tree model’s parameters, so that different models are using the same tree embeddings. For all the LSTM derived algorithm, we set the stack depth to 1, and use the same shape to make a fair comparison. The detailed settings are described as below.

- Tree Embedding: We choose the large-scale GBDT model implemented on KunPeng [23] as the tree model, and we set the tree number to 100 and the max depth to 5.
- Network shape: For LSTM, GRU, and the derived algorithm, we set the hidden units to 256. For MLP, the hidden layer size is set to 1, and hidden unit number is 128.
- Learning rate: We use SGD as the optimizer, and select the best learning rate in {0.1, 0.01, 0.001}.
- Embedding Dimension: For every time stamp, the transaction event contains 28 different features, and each feature contains a different number of components, each component uses a 16 dimension embedding matrix. For click behavior, the dimension of embedding matrix is set to 32. For the time dimension, we select the best value in {8, 16, 32, 64}.
- Batch Size: We set batch size to 512 for all the models.
- Regularization: We use L2 as regularization, and its value is set to be 1e-5.

Note that for each model, we use the validation set to select the best model parameters, and evaluate them on the test set.

4.4 Evaluation Metrics

We use three different kinds of evaluation metrics to measure our proposed method’s performance. We adopt two standard ranking metrics: Area Under ROC Curve (AUC) and F1-Score. At the same time, in the real fraud detection system, we cannot disturb too many people to improve the recall rate, so we use another more practical indicator to evaluate our method, i.e., Recall At Top Percent (RATP). RATP@r is the recall of the subset which consists of the instances of the top r percentage of prediction scores, for example, RATP@0.05 means only 5 transactions will be disturbed in 10000 transactions.

4.5 Comparison Results

We report the comparison results in Table 3. From it, we can see that:

1) compared with the original GBDT which uses behavior features extracted by human, after using LSTM or GRU to modeling the user behavior, our proposed model has a significant improvement in terms of RATP@r. Take RATP@0.05 for example, our proposed method has a 7% improvement compared with the GBDT, which is because by using sequence modeling method, more complex patterns can be extracted.
2) The improvements of our proposed model against other models are not significant in terms of AUC, which is because the number of Non-Fraud transaction is too many, while the number of fraud transaction is too little. Thus, the improvement at the high score part will not improve the AUC too much. (3) All the methods that consider the time influence between different action outperform the Bi-LSTM and GRU and Bi-LSTM with self-attention, which means that time is an important information in fraud detection task. (4) At the same time, LSTM, GRU with our proposed time attention mechanism outperform PLSTM and
Table 3: Experiment Results

| Method               | F1-score | AUC   | RATP@0.05 | RATP@0.01 |
|----------------------|----------|-------|-----------|-----------|
| GBDT                 | 0.701    | 0.981 | 0.807     | 0.637     |
| CNN+Max pooling      | 0.702    | 0.982 | 0.815     | 0.652     |
| GRU                  | 0.708    | 0.981 | 0.822     | 0.652     |
| Bi-LSTM              | 0.712    | 0.983 | 0.815     | 0.659     |
| Bi-LSTM+Self attention| 0.714   | 0.984 | 0.830     | 0.674     |
| PLSTM                | 0.714    | 0.986 | 0.835     | 0.689     |
| TLSTM                | 0.716    | 0.986 | 0.844     | 0.692     |
| Bi-LSTM+time attention| 0.721   | 0.99  | 0.864     | 0.706     |
| GRU+time attention   | 0.718    | 0.988 | 0.859     | 0.703     |

Figure 4: Effect of different hidden units. The vertical axes indicates test set RATP@0.05 and the horizontal axes indicates the number of RNN hidden units.

Figure 5: Effect of different time embedding dimension. The vertical axes shows RATP@0.05 on the test set and the horizontal axes is the dimension of time embedding.

4.6 Parameter Analysis

We will study the effects of the hidden units and the time embedding dimension on our model performance.

4.6.1 Effect of the hidden units. We first vary the LSTM/GRU hidden units number to study their effect on our model performance, while fixing other hyperparameters. The result is shown in Fig. 4. As we can see, with $n_h$ increases, the performance of RATP@0.01 becomes better. However, $n_h = \{1024, 512\}$ do not perform too much better than $n_h = 256$. This is because as the number of hidden unit increasing, the parameter is also increasing, which makes more data is needed to fit the model.

4.6.2 Effect of the time embedding dimension. We then vary the time data’s embedding dimension to study its effect on model performance, at the same time we fixing the other hyper-parameters. As shown in the Fig 5, with the time data embedding dimension increases, the performance does not always become better. When time embedding dimension is 32, we get the best result. That because as the time embedding dimension increasing, the feature space become sparse, which makes the model harder to converge.

5 CONCLUSIONS AND FUTURE WORK

In this paper, we proposed a framework which manipulates heterogeneous data, at the same time, we introduce a new attention mechanism which models the time aspect into the whole framework. We implemented and evaluated our proposed method against several baseline approaches, and showed that our method achieve the best results.

In the future, we will try to evaluate our model in more datasets, and we will improve the computational efficiency of our model. Moreover, we will try to deal with the users who do not have too much history information in our platform.

REFERENCES

[1] Martin Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Gregory S. Corrado, Andy Davis, Jeffrey Dean, Matthews Devin, Sanjay
Ghemawat, Ian J. Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur,Josh Levenberg, Dan Manan, Rajat Monga, Sherry Moore, Derek Gordon Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul-Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernando B. Viegas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. 2016. Tensorflow: Large-Scale Machine Learning on Heterogeneous Distributed Systems. CoRR abs/1603.04467 (2016). arXiv:1603.04467 http://arxiv.org/abs/1603.04467

[2] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2014. Neural Machine Translation by Jointly Learning to Align and Translate. CoRR abs/1409.0473 (2014). arXiv:1409.0473 http://arxiv.org/abs/1409.0473

[3] Jan Chorowski, Dzmitry Bahdanau, Dmitriy Serdyuk, Kyunghyun Cho, and Yoshua Bengio. 2015. Attention-Based Models for Speech Recognition. In Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada. 577–585. http://papers.nips.cc/paper/5847-attention-based-models-for-speech-recognition

[4] Junyoung Chung, Çağlar Gülcehre, KyungHyun Cho, and Yoshua Bengio. 2014. Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling. CoRR abs/1412.3555 (2014). arXiv:1412.3555 http://arxiv.org/abs/1412.3555

[5] Jeff Donahue, Lisa Anne Hendricks, Sergio Guadarrama, Marcus Rohrbach, Subhankar Venugopalan, Trevor Darrell, and Kate Saenko. 2015. Long-term recurrent convolutional networks for visual recognition and description. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015. 2625–2634. https://doi.org/10.1109/CVPR.2015.7299878

[6] Alex Graves, Abdelrahman Mohamed, and Geoffrey E. Hinton. 2013. Speech recognition with deep recurrent neural networks. In IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2013, Vancouver, BC, Canada, May 26-31, 2013. 6645–6649. https://doi.org/10.1109/ICASSP.2013.6638947

[7] Alex Graves and Jürgen Schmidhuber. 2009. Offline handwriting recognition with multidimensional recurrent neural networks. In Advances in neural information processing systems. 545–552.

[8] Xinran He, Junfeng Pan, Ou Jin, Tianbing Xu, Bo Liu, Tao Xu, Yanxin Shi, Antoine Bordes, and Jianfeng Zhang. 2015. Deep Network Training by Reducing Internal Covariate Shift. In Proceedings of the 32nd International Conference on Machine Learning, ICML 2015, Lille, France, June 7-10, 2015. 1045–1054. http://jmlr.org/proceedings/papers/v37/ioffe15.html

[9] Nader Mahmoudi and Ekrem Duman. 2015. Detecting credit card fraud using hidden Markov model. IEEE Transactions on dependable and secure computing, 3 (2008), 38–47.

[10] Nitish Srivastava, Elman Mansimov, and Ruslan Salakhutdinov. 2015. Unsupervised Learning of Video Representations using LSTMs. In Proceedings of the 32nd Conference on Machine Learning, ICML 2015, Lille, France, 6-11 July 2015. 685–693. http://jmlr.org/proceedings/papers/v37/srivastava15.html

[11] Abhinav Srivastava, Amlan Kundu, Shamik Sural, and Arun Majumdar. 2008. Credit card fraud detection using hidden Markov model. IEEE Transactions on dependable and secure computing, 5 (1), 2008), 38–47.

[12] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is All you Need. In Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, 4-9 December 2017, Long Beach, CA, USA. 6000–6010. http://papers.nips.cc/paper/7181-attention-is-all-you-need

[13] Wenpeng Yin, Hinrich Schütze, Bing Xiang, and Bowen Zhou. 2016. ABCNN: Attention-Based Convolutional Neural Network for Modeling Sentence Pairs. TACL 4 (2016), 259–272. https://taco2016.cs.columbia.edu/ijscy/index.php/tacl/article/view/831

[14] Yu-Lin Zhang, Jun Zhou, Wenhao Zheng, Ji Feng, Longfei Li, Ziqi Liu, Ming Li, Zhiqiang Zhang, Chaochao Chen, Xiaolong Li, Yuan (Alan) Qi, and Zhi-Hua Zhou. 2019. Distributed Deep Forest and its Application to Automatic Detection of Cash-Out Fraud. ACM TIST 10, 5 (2019), 55:1–55:19. https://doi.org/10.1145/3342241

[15] Jun Zhou, Qing Cui, Xiaolong Li, Peilin Zhao, Shipeng Qu, and Jun Huang. 2017. PSMART: Parameter Server based Multiple Additive Regression Trees System. In Proceedings of the 26th International Conference on World Wide Web Companion,Perth, Australia, April 3–7, 2017, Rick Barrett, Rick Cummings, Eugene Agichtein, and Evgeniy Gabrilovich (Eds.). ACM, 879–880. https://doi.org/10.1145/3041021.3054225

[16] Xinran He, Junfeng Pan, Ou Jin, Tianbing Xu, Bo Liu, Tao Xu, Yanxin Shi, Antoine Bordes, and Jianfeng Zhang. 2015. Deep Network Training by Reducing Internal Covariate Shift. In Proceedings of the 32nd International Conference on Machine Learning, ICML 2015, Lille, France, June 7-10, 2015. 1045–1054. http://jmlr.org/proceedings/papers/v37/ioffe15.html

[17] Yu-Lin Zhang, Jun Zhou, Wenhao Zheng, Ji Feng, Longfei Li, Ziqi Liu, Ming Li, Zhiqiang Zhang, Chaochao Chen, Xiaolong Li, Yuan (Alan) Qi, and Zhi-Hua Zhou. 2019. Distributed Deep Forest and its Application to Automatic Detection of Cash-Out Fraud. ACM TIST 10, 5 (2019), 55:1–55:19. https://doi.org/10.1145/3342241

[18] Yo Zhu, Hao Li, Yukang Liao, Bedou Wang, Ziyu Guan, Haifeng Liu, and Deng Cai. 2017. What to Do Next: Modeling User Behaviors by Time-LSTM. In Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017, Melbourne, Australia, August 19-25, 2017. 3662–3668. https://doi.org/10.24963/ijcai.2017/504