Incremental Feature Learning for Fraud Data Stream

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Abstract: Our research addresses the actual behavior of the credit-card fraud detection environment where financial transactions containing sensitive data must not be amassed in a considerable amount to train robust classifiers. We introduce an adaptive learning approach that adjusts frequently and efficiently to new transaction chunks; each chunk is discarded after each training step. Our approach combines transfer learning and incremental feature learning. The former improves the feature relevancy for subsequent chunks, and the latter increases performance during training by dynamically determining the optimal network architecture for each new chunk. We show the effectiveness and efficiency of our approach experimentally on an actual fraud dataset.

1 INTRODUCTION

A tremendous volume of credit card transactions is conducted daily, especially with COVID-19. Nevertheless, this e-commerce activity attracted many fraudsters and led to monetary losses for credit card holders. For instance, for 2019, the Nelson Report estimated the worldwide financial loss from Credit Card Fraud (CCF) to $28.65 billion (Worldwide Credit Card Fraud Statistics 2019, 2020). Over the last ten years, users that revealed at least one CCF soared by 71% in Canada (Credit Card Fraud Statistics In Canada 2021, 2021). Detecting fraudulent payments necessities vital resources, such as powerful processing, ample data storage, and human expertise. CCF detection is complex to address due to the following challenges: **(1)** Transactions are generated continuously and speedily. In this data stream context, fraud must be detected in real-time to avoid losses on the users' side; **(2)** Conventional Machine Learning Algorithms (MLAs), including deep learning, require storing many transactions to conduct training. However, financial data must not be accumulated in a large quantity by the learned models because of data sensitivity and confidentiality; and **(3)** MLAs cannot adapt previous knowledge to newly available data to improve their accuracy, making the fraud detection models obsolete and unreliable in the long run. Most of the studies on CCF detection employed conventional MLAs (non adaptive) that are inadequate for the CCF learning environment. Additionally, in the industry, a new fraud prediction system is created from scratch for every number of days to learn the new behavior from incoming transactions (Lebichot et al., 2020). However, re-training for each new data is time-consuming, and the past learned knowledge is lost.

To overcome the above challenges, we develop a new adaptive learning algorithm that adjusts frequently and efficiently to new transaction data, grouped in chunks or mini-batches. We decide how much data to collect in each chunk depending on the incremental training frequency (i.e., every day or every week). More the frequency is shorter, less sensitive data is accumulated. In our study, a chunk contains the payment transactions of one day, which is still enough for a robust adaptation. We process one chunk at a time in the short-term memory and discard it after each model's adaptation, without the necessity of storing it. The proposed adaptive approach combines transfer learning and incremental feature learning. Thanks to transfer learning, we extract more valuable features from the original ones and reuse the new features for the subsequent transaction chunks. For instance, in the image processing area, the first layers of the neural network extract more representative features that can be reused in another image processing task. Following the same reasoning, we use the first layers to collect more beneficial features and then add a new network to utilize those features. By doing so, we take advantage of the previous chunks' knowledge.

Our Incremental Feature Learning (IFL) algorithm adapts gradually to the new transaction chunks

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by **(1)** preserving the previously learned knowledge and **(2)** dynamically adjusting the network architecture for each new chunk to achieve the highest performance during training. IFL expands the network topology by adding new hidden layers and new units during each adaptation phase. Determining the most suitable model's architecture leading to the best performance is a complex problem. Our IFL approach adds hidden units one by one until the model does not converge anymore. Nevertheless, as we are changing the network architecture to increase the performance, we may over-fit the resulted model. Hence, we utilize a validation chunk during training to avoid over-fitting after each extension. More precisely, only the weights of the new hidden units are updated each time and the previous units are frozen to store the previous knowledge. Thus, less computational time is needed to conduct learning for each new chunk. In this way, our IFL approach will always outperform other incremental learning approaches as the former continuously adapts its architecture to reach optimal accuracy. Most of the architecture of past incremental learning approaches is permanently fixed (Anowar and Sadaoui, 2021), and the accuracy may not improve when new chunks are fed to the model. Implementing the IFL algorithm is challenging, requiring a deep investigation of the building blocks and libraries of MLA toolkits, such as creating a new hidden unit, adding a new connection, and freezing the weights of a old connection (not to be re-optimized). Moreover, using a real CCF dataset, we create training, testing, and validation data chunks and handle the highly imbalanced chunks. For a robust validation of our IFL algorithm, we develop four fraud classifiers, trained on different chunks, and then compare their predictive performances on unseen data. The experimental results show the efficiency of the proposed learning approach.

The study (Guan and Li, 2001) was the first one to develop an IFL approach. This approach, which is elementary, adopted a network topology that is not common because the input layer is directly connected to the output layer. During training, it freezes all the weights connected to the output unit. Although freezing these weights can speed up training, it will however reduce the model's performance. Also, this paper does not provide details on the algorithm design and its implementation. Our paper presents all the stages of our IFL algorithm that learns progressively from newly available chunks. Through a concrete example, based on constructive neural networks, we illustrate step by step the sophisticated behavior of our adaptive approach.

2 RELATED WORK

We review recent research on detecting CCF and highlight its weaknesses. The majority of studies conducted batch learning, such as (Hassan et al., 2020) that explored deep learning, like BiLSTM and BiGRU, and classical learning, such as Decision Tree, Ada Boosting, Logistic Regression, Random Forest, Voting and Naive Base. Since the fraud dataset is highly imbalanced, the authors adopted random under-sampling, over-sampling and SMOTE. The hybrid of over-sampling, BiLSTM and BiGRU lead to the highest accuracy. Another work (Nguyen et al., 2020) also assessed several MLAs, including LSTM, 2-D CNN, 1-D CNN, Random Forest, ANN and SVM, using different data sampling methods on three credit-card datasets. LSTM and 1-D CNN combined with SMOTE returned the best results. We believe LSTM can be a good option for incremental learning since this algorithm can remember past data and therefore creates predictions using the current inputs and past data, leading to a better response to the environmental changes. In both papers, LSTMs and the other models were trained on very large datasets, requiring storing sensitive information forever. Nevertheless, since user transactions are available incrementally, conventional MLAs are inappropriate for streaming data. Our proposed method aims to address the real CCF classification context.

In (Anowar and Sadaoui, 2020), the authors first utilized SMOTE-ENN to handle a highly imbalanced CCF dataset and then divided the dataset into multiple training chunks to simulate incoming data. They proposed an ANN-based incremental learning approach that learns gradually from new chunks using an incremental memory model. For adjusting the model each time, the memory consists of one past chunk (so that data are not forgotten immediately) and one recent chunk (to conduct the model adaptation). The authors demonstrated that incremental learning is superior to static learning. However, using two chunks every time can be expensive computationally. Also, since the ANN topology is fixed, the model cannot adapt to significant changes in the chunk patterns. In our study, the ANN architecture is dynamic to build an optimal fraud detection model. Instead of using two chunks simultaneously, leading to storing more data, we use only one chunk. With transfer learning, we take advantage of the previous chunk without storing it.

In (Bayram et al., 2020), the authors introduced a Gradient Boosting Trees (GBT) approach, which is just an ensemble of decision trees, to minimize the loss function gradually. The ensemble is updated for

Table 1: Original and Re-Sampled Training and Testing Chunks.

(a) Highly Imbalanced Chunks

Original Dataset			
Fraud		Normal	
473		283253	
Chunk 1: transactions of day1			
Train	Ratio	Test	Ratio
101352	1:532	43437	1:529
Chunk 2: transactions of day2			
Train	Ratio	Test and Validation	Ratio
97255	1:689	41682	1:694

(b) Re-balanced Chunks

Train Chunk1		
Fraud	Normal	Total
33383	101162	134545
Test Chunk1		
Fraud	Normal	Total
14307	43355	57662

Train Chunk2		
Fraud	Normal	Total
32047	97114	129161
Test Chunk2		
Fraud	Normal	Total
6867	20811	27678
Validation Chunk2		
Fraud	Normal	Total
6867	20811	27678

each new group of transactions by appending a new Decision Tree to create a more robust GBT model. The authors developed three models: static GBT (batch learning), re-trained GBT (re-training all the transactions by including the investigated ones), and incremental GBT (ensemble). All these methods necessitate storing a tremendous quantity of user transactions. The authors divided the credit-card dataset into several sub-datasets w.r.t time (month) and evaluated the three models for each month (four months in total). Although the re-trained GBT (performed with 1.6 million transactions) achieved the best performance, it is 3000 times slower than the incremental approach. Since re-training is too time-consuming, we aim to improve the accuracy and training time for learning incrementally.

3 DATA CHUNK PREPARATION

We utilize a public, anonymized CCF dataset consisting of 284807 users' purchasing transactions that occurred during two days in September 2013 (Credit Card Fraud Detection, Anonymized credit card transactions labeled as fraudulent or genuine, 2016). It is worth mentioning that CCF datasets are lacking in the literature due to data confidentiality. The 2-class fraud dataset possesses 29 predictive features obtained with the feature extraction method PCA. However, the two features Time and Amount as kept as is, because their actual values are essential for training. Time represents the seconds passed between the current and the first transactions in the dataset. After examining the dataset, only 0.172% (492) of the transactions is fraudulent. We found duplicated fraud data (19) that we eliminated. We are in the presence of a highly imbalanced dataset where the count of legitimate data is much higher than the count of fraudulent data. In this case, classifiers will be biased towards the Normal class and will wrongly classify the Fraud class.

We split the fraud dataset into two chunks using the transaction's time: the first chunk is related to the first day and the second chunk to the second day. We use the first chunk to perform transfer learning and the second chunk IFL. In Table 1 (a), using the stratified method, we divide the first chunk into 70% training and 30% testing, and the second chunk into 70% training, 15% validation and 15% testing. As observed, the training chunks are highly imbalanced. Hence, we adopt the successful over-sampling method SMOTE using the new class distribution ratio of Normal instances to Fraud instances equals 1.3. We over-sample the Fraud class to keep all of them as they are rare events. For example, the training chunk2 has a highly imbalanced class ratio of 1:689 that we re-balance with the new ratio of 1.3. Table 1 (b) exposes the re-sampled training, validation and testing chunks.

4 INCREMENTAL FEATURE LEARNING

For our fraud classification problem, we first build the initial model on the first chunk and then utilize the transformed features to train on the second chunk using the optimal number of hidden units. Instead of retraining from scratch the entire model for each new chunk, we only train the newly added units and freeze all the previous layers. This strategy will significantly decrease the training time so that the classifier identifies fraud activities much faster. The most difference of incremental learning from conventional learning is that the former does not assume the availability of sufficient training data, as data are available over time (Guan and Li, 2001). So, based on these facts, improving learning for each newly supplied chunk is an excellent approach.

Algorithm 1 conducts transfer learning and then IFL. We first build the initial network with four fully connected layers, where the first layer has the input features, the first hidden layer 500 units, the second hidden layer ten units, and the output layer one unit for the binary classification. The study (Anowar and Sadaoui, 2020), which validated an incremental learning approach with the same credit-card dataset, determined that 500 units as the best number for the first hidden layer. Hence, we train this first network on the first chunk. Then, after removing the output unit, we refit the initial model using previous knowledge and the second chunk. Now, the second hidden layer represents the transformed features (called tSubset) i.e., the new dimensional space more relevant to the target class because it is obtained with previous knowledge. Here, tSubset contains the values corresponding to the transformed features. For example, assume we have 100,000 transactions in the second chunk. Using the refitted model, we convert each transaction of 29 values to ten new values. So, our transformed tSubset will contain 100,000 new data with 10 new features. With transfer learning (Weiss et al., 2016), our model takes information from a previously learned task and uses it to learn a related task. The model can extract useful features from the input features, and instead of learning this knowledge again, we use it via the past network.

We actually extend the initial network with two sub-networks; the first sub-NN considers the high-level features, and the second sub-NN the low-level features. We leverage both of them to predict the output more efficiently. Also, the study (Wang et al., 2014) showed that creating sub-networks according to the features' relevancy can lead to a better outcome. We add the second sub-NN to improve more the model's performance. A similar idea is used in the incremental approach defined in (Guan and Li, 2001) by connecting the original inputs directly to the output unit with the same motivation. Another paper (Wang et al., 2021) compared the performance results of connecting the inputs to the output unit directly. These are the reasons we use high-level features for creating the first sub-NN and then low-level features for creating the second sub-NN. Thus, we can gradually improve the accuracy using newly available data without forgetting the previous knowledge (stored in the previous weights). Also, the training time will be much lower as we only train the new chunk and one unit only per epoch. Our approach can be used for any number of chunks by appending a new hidden layer to the first sub-NN.

Algorithm 2, proposed in our past study (Sadreddin and Sadaoui, 2021), shows how to extend a sub-NN with new hidden units and connections. The main challenge is determining the number of units that should be added to attain the best training performance. In transfer learning, we add a predetermined number of layers and units to the previously trained model. It can lead to fewer layers/units, but, the resulting model will return poor predictions. On the other hand, it can add unnecessary layers/units, which only increases the learning time. Since the numbers of layers and units are predetermined, all the units are trained together and not one at a time like our proposed method. So, the training time will be very time-consuming. We determine the needed number of units in our work by adding and training them one by one. This approach is highly efficient computationally.

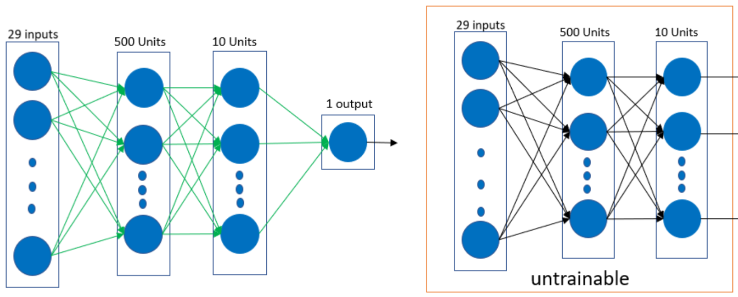
Furthermore, instead of computing the gradient descent for all the new units at once for each epoch, which is time-consuming, we utilize the "patience" parameter as the early stopping criterion. Based on the convergence threshold, this parameter checks whether the error is reducing or not in a certain number of epochs.

4.1 An Illustrative Example

Based on the CCF chunks, we illustrate the behavior of our IFL algorithm in Figures 1, 2, and 3, where the green color denotes new connections and new units and the red color the frozen part of the NN (weight are not re-learned). Figure 1 creates the initial NN and trains it on chunk1. After deleting the output unit, the algorithm utilizes previously learned weights and creates the refitted model by training with chunk2. Figure 2 first adds the first sub-NN to the initial model and then keeps training on the data of the transformed features by including new hidden units and connections and freezing past weights until the training performance is not converging anymore. Figure 3 creates the second sub-NN using the original features, connects it to the output unit of the previous model, freezes all the previous weights, and trains it on chunk2 until the model is not converging anymore.

5 VALIDATION

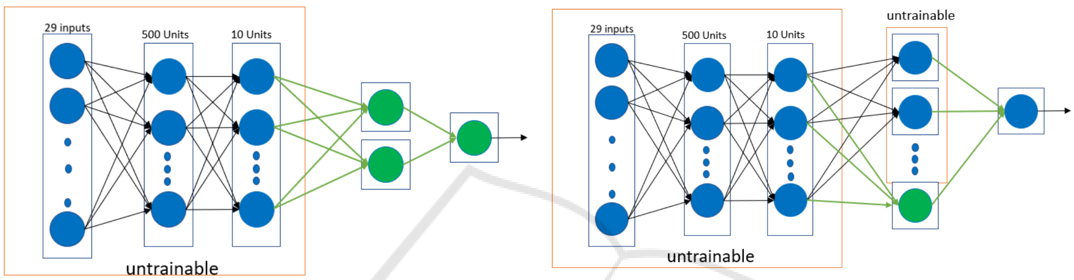
Since the CCF features have different value ranges and with significant discrepancies, we first normalize them into the same range. To this end, we train the initial network (four fully connected layers) on chunk1 using various ranges to determine the most appropriate feature scale. The range of [-5, +5] returned the best performance. Using random search, we tune the network's hyper-parameters, such as the



(a) create initial model on chunk1

(b) transform input features with chunk2 using past weights

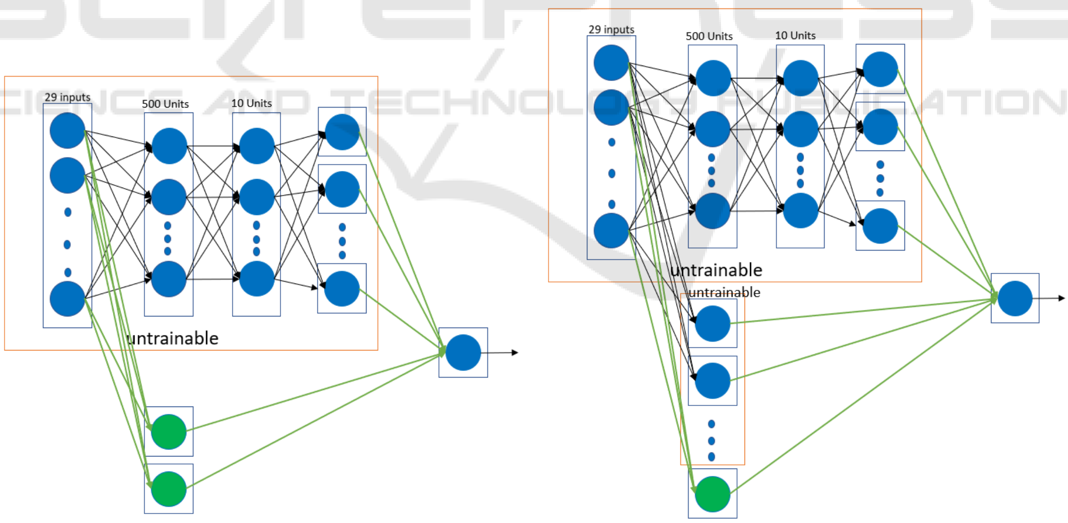
Figure 1: Transformed Features.



(a) add/train subNN1 & freeze past NN

(b) add hidden unit(s) until no convergence

Figure 2: Network training and expansion using transformed features.



(a) add/train subNN2 & freeze past NN

(b) add hidden unit(s) until no convergence

Figure 3: Network training and expansion using original features.

learning rate to 0.001, batch size to 1024, epoch to 100, convergence threshold to 0.01, and patience to 10. We employ the Adam optimizer to learn the best weights. In our experiment, we develop four main fraud classifiers: **(1)** The initial classifier trained on train chunk1 and tested on test chunk1, **(2)** The initial classifier evaluated on test chunk2, **(3)** The initial classifier re-trained on train chunk2 and tested on test chunk2, and **(4)** The optimal final classifier, produced with our IFL algorithm, trained on train chunk2 and assessed on test chunk2.

For a proper comparison, we utilize the same unseen dataset to assess the last three classifiers, based on five quality metrics for evaluating the predictive

Algorithm 1: Transfer Learning and Incremental Feature Learning.

```
Inputs: trainChunk1, trainChunk2,
validChunk2, threshold, nEpoch
Result: optimal model
(*Initial Model with Chunk1*)
iniNN ← build network with four fully
  connected layers;
iniModel ← train initNN on trainChunk1;
(*Refitted Model with Chunk2*)
refModel ← delete output unit of initModel;
refModel ← feedforward trainChunk2 using
  past weights;
(*Transformed Feature Sub-dataset*)
traSet ← extract transformed features;
traSubset ← create sub-dataset w.r.t traSet
  and trainChunk2;
(*Incremental Feature Learning*)
(*Sub-NN Training and Extension with
Transformed Features*)
subNN1 ← create network (2 hidden units
  and 1 output unit);
model1 ← train subNN1 with traSubset by
  freezing all past weights;
extModel1= Algorithm2(model1, traSubset,
  validChunk2, threshold, nEpoch);
(*Sub-NN Training and Extension with Input
Features*)
subNN2 ← create network (2 hidden units);
subNN2 ← connect hidden units to output
  unit of extModel1 ;
model2 ← freeze weights of previous units
  except hidden and output units;
model2 ← train subNN2 with trainChunk2;
extModel2 ← Algorithm2(model2,
  trainChunk2, validChunk2, threshold,
  nEpoch);
return extModel2;
```

performances: Precision, Recall, F1-score, False Negative Rate (FNR), and Time (in seconds). Due to the randomness of neural networks, we run ten training sessions for each of the four classifiers. As a result, for each classifier, we develop ten models, and test each one of them on the corresponding testing dataset. In summary, we build and assess a tally of 40 models. We consider the average of the ten testing sessions for comparing the four fraud classifiers.

5.1 Feature Transformation

Using the initial classifier's knowledge obtained with the first transaction chunk, we transform the input features by feed-forwarding the second chunk to the first classifier. Figure 4 exposes the distribution of the new features. The transformed features (10 in total) are now more relevant to the target class. After checking their correlation values with the class output, we find them much higher than the original features.

Algorithm 2: Model Extension with New Hidden Units until No Convergence.

```
Inputs: model; trainData, validData,
threshold, nEpoch
Result: extended model
preValAcc ← 0;
while True do
    curValAcc ← compute accuracy of model
      using validData;
    while (curValAcc is converging with
      patience of nEpoch) do
        model ← train non-frozen weights
          with trainData;
        curValAcc ← compute accuracy of
          model using validData;
    if (curValAcc - preValAcc < threshold)
      and (preValAcc ≠ 0) then
        Break;
    preValAcc ← curValAcc;
    model ← add new hidden unit to hidden
      layer;
    model ← freeze weights of previous units
      except new hidden and output units;
return model;
```

5.2 Performance Evaluation

1. Initial Classifier: We first build the initial classifier, trained on train chunk1 and assessed on test chunk1 (Table 2). After that, we evaluate the same classifier using test chunk2 (Table 3). According to the 10-round testing results of these two classifiers, F-score decreased by 4.6% for the second chunk. Changes in data patterns, such as concept drift, may have caused this decrease (Lebichot et al., 2020). Credit card datasets are known to contain concept drift, and as a consequence, the model's performance decreases (Abdallah et al., 2016). We reached good accuracy with the first classifier by splitting the data into chunks and normalizing and re-sampling them. Yet, when passing the second chunk to the first classifier, the performance decreased. So, our goal is to build a model capable of adapting itself to the changes in the data.

2. Re-trained Classifier: Here, we re-train from scratch the initial classifier using train chunk2 and evaluate its accuracy on test chunk2 (Table 3). In this case, F1-score decreased by 0.5% for the re-trained

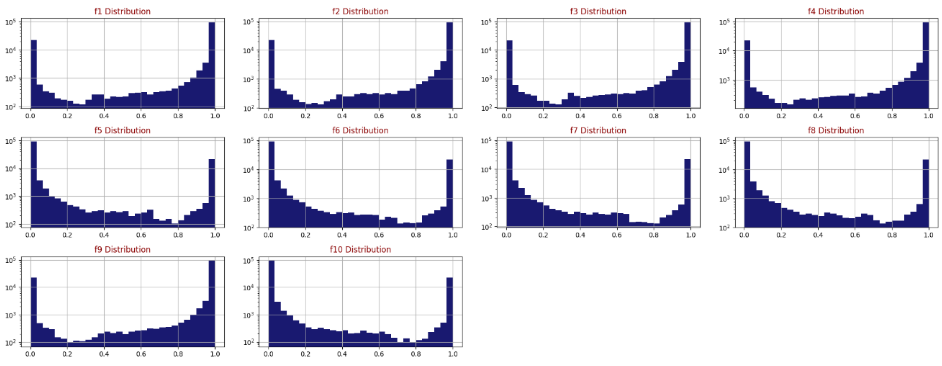


Figure 4: Distribution of the New Features.

Table 2: Training and Testing on Transaction Chunk1.

Classifier	**Metric**	**#1**	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**	**#9**	**#10**	**Aver.**
Initial	Precis	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.999
	Recall	0.87	0.87	0.93	0.84	0.85	0.83	0.84	0.87	0.77	0.84	0.851
	F1	0.93	0.93	0.96	0.91	0.92	0.91	0.91	0.93	0.87	0.91	0.918

Table 3: Training and Testing on Transaction Chunk2.

Classifier	**Metric**	**#1**	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**	**#9**	**#10**	**Aver.**
Initial	Precis	1.00	0.99	0.98	0.98	0.99	1.00	0.99	1.00	0.99	0.99	0.991
	Recall	0.71	0.77	0.84	0.84	0.81	0.75	0.76	0.85	0.67	0.81	0.781
	F1	0.83	0.87	0.90	0.90	0.89	0.86	0.86	0.92	0.80	0.89	0.872
Retrained	Precis	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Recall	0.70	0.79	0.76	0.82	0.85	0.74	0.84	0.87	0.69	0.66	0.772
	F1	0.82	0.88	0.86	0.90	0.92	0.85	0.91	0.93	0.81	0.79	0.867
	Time	23s	22s	24s	23s	22s	23s	23s	22s	22s	23s	22.7s
Optimal	Precis	0.97	0.95	0.95	0.96	0.96	0.95	0.95	0.96	0.96	0.96	0.957
	Recall	0.86	0.86	0.89	0.88	0.90	0.80	0.90	0.97	0.76	0.88	0.870
	F1	0.91	0.90	0.92	0.92	0.93	0.87	0.92	0.96	0.85	0.92	0.910
	Time	18s	15s	12s	19s	25s	16s	16s	16s	22s	19s	17.8s

classifier. This expected decrease is due to the higher number of instances in train chunk1 (60% of data) than in train chunk2 (40% of data). Therefore, re-training a model from scratch is not a good solution (as done in the industry).

3. Optimal Classifier: Lastly, in Table 3, we develop the final optimal model using our IFL algorithm. Using only one chunk, F1-score of the final classifier improved by 3.8% compared to the initial classifier (trained on chunk1). Also, Recall, an essential metric in fraud detection, is augmented with 8.9%, which means we have fewer false negatives with the second chunk. Moreover, as we are training only the new hidden units, the training time is less than the time of the re-trained classifier. We can conclude that the final classifier outperforms the initial and re-trained classifiers using only one chunk.

Another important metric for fraud detection is the False Negative Rate (FNR), which refers to the rate of fraudulent transactions detected as normal. According to the average of the ten experiments, the FNR values of the initial classifier on test chunk1 (called ICTC1) is 0.149 and on test chunk2 (ICTC2) is 0.219. The FNR of the re-trained classifier (RCTC2) is 0.228, and FNR of the optimal classifier (OCTC2) is 0.13. These values demonstrate that the final classifier caches more fraudulent cases when fed with new chunks, reducing FNR over time.

In our point of view, financial transactions should not be stored in a large quantity and for a long time by the fraud classifiers because of confidentiality issues. In this challenging situation, we train the classifier incrementally, chunk by chunk, and discard each chunk right away. In Table 3, the proposed adaptive learning algorithm can enhance the performance using one chunk at a time and with less computational cost.

6 CONCLUSION

Intending to address the actual behavior of the CCF detection environment, we introduced a new incremental classification algorithm that adjusts gradually and efficiently to new transaction chunks based on transfer learning and IFL. Transfer learning, which preserves past knowledge, transforms original features into more valuable ones. Then, our adaptive algorithm utilizes them to adapt to subsequent chunks. IFL extends the network architecture incrementally by determining the optimal number of hidden units for each new chunk. Our dynamic learning approach improves the performance during training without the necessity of accumulating and storing a large volume of data and spending too much time on learning since only the new weights are learned. The proposed approach can be employed on everyday credit card transactions to prevent the performance from decreasing by using current and past knowledge.

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