# ML Report Phase V: Credit Card Transaction Fraud Detection\*

Model & Utility Application Implementation

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#### **ABSTRACT**

Fraud detection is a critical application of machine learning that helps businesses and organizations identify and prevent fraudulent activities. In this report, we outline our implementation choices, APIs, preprocessing components, and retraining method for our model and application.

#### **CCS CONCEPTS**

• Computing methodologies → Machine learning.

#### **KEYWORDS**

financial fraud detection, report, machine learning, Server-client, online training, preprocessing

#### 1 The model

As discussed in the previous phase, I tuned my hyperparameters on the data and chose the model that performed the best in terms of recall on the validation set.

Unfortunately, hyperband search only managed to find a local optimum for our model while random search managed to luckily find a model with better performance than the model chosen by hyperband.

A summary of the results can be found in the notebook.

The model was then saved using keras' ability to save a model. The only addition we had to add was a method to serialize and store our custom focal loss function into our model.

Here is the top 3 models found by random search: Results summary

Results in Random\_tuner\_2\_layer/fraud\_detection\_tuning\_with\_r ecall objective

Showing 10 best trials

Objective(name="val\_recall", direction="max")

Trial 065 summary
Hyperparameters:

num\_layers: 1 units\_0: 256 activation: tanh

loss\_function: focal\_loss

learning rate: 0.0044791885334340125

units\_1: 160 alpha: 0.9 gamma: 4.0 pos weight: 6.0

Score: 0.9383260011672974

Trial 123 summary
Hyperparameters:

num\_layers: 1 units\_0: 256 activation: tanh

loss function: focal loss

learning\_rate: 0.00595824198225588

units\_1: 256

alpha: 0.7000000000000001

gamma: 5.0

pos\_weight: 7.0

Score: 0.9136564135551453

Trial 021 summary

Hyperparameters: num\_layers: 2

units\_0: 192 activation: tanh

loss\_function: focal\_loss

learning\_rate: 0.0022820322663096213

units\_1: 224 alpha: 0.8 gamma: 3.5

pos weight: 3.0

Score: 0.8387665152549744

Here are the top 3 models found by Hyperband:

Results summary

Results in Hyperband 2 layer/fraud\_detection\_tuning\_with\_recall

objective

Showing 10 best trials

Objective(name="val\_recall", direction="max")

Trial 0208 summary

Hyperparameters:

num\_layers: 1 units\_0: 224

activation: tanh

loss\_function: focal\_loss

learning rate: 0.0029110238976895516

alpha: 0.7000000000000001

gamma: 4.5 units 1: 160

pos\_weight: 1.0

tuner/epochs: 100

tuner/initial\_epoch: 34

tuner/bracket: 3

tuner/round: 3

tuner/trial\_id: 0206

Score: 0.8872246742248535

Trial 0206 summary

Hyperparameters:

num\_layers: 1

units\_0: 224

activation: tanh

loss\_function: focal\_loss

learning\_rate: 0.0029110238976895516

alpha: 0.7000000000000001

gamma: 4.5

units\_1: 160

pos\_weight: 1.0

tuner/epochs: 34

tuner/initial\_epoch: 12

tuner/bracket: 3

tuner/round: 2

tuner/trial id: 0190

Score: 0.8731277585029602

Trial 0209 summary

Hyperparameters:

num\_layers: 1

units\_0: 160

activation: tanh

loss\_function: focal\_loss

learning\_rate: 0.004079042565506928

alpha: 0.5

gamma: 4.0

units\_1: 256

pos\_weight: 8.0

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tuner/epochs: 100 tuner/initial epoch: 34

tuner/bracket: 3 tuner/round: 3 tuner/trial id: 0205

Score: 0.8590308427810669

#### 2 Client and Server

I decided to settle on using a Reactjs frontend and a flask backend for their simplicity

\*This phase was done alone due to my partner withdrawing

### 2.1 The client

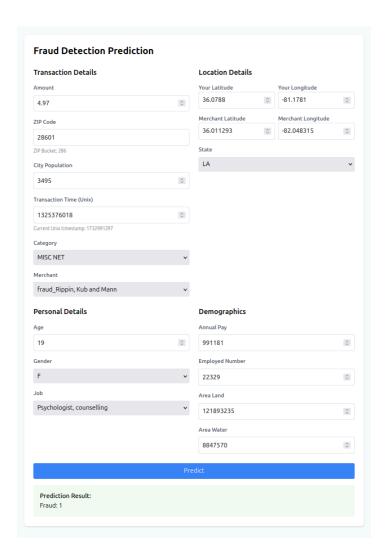
The client provides a simple User interface for the user to use to enter their data.

To simplify the input process the program will query the US census to retrieve information that is hard for a user to know such as the land area, water area, employee number, and average income.

The program will only accept data that the model is trained on i.e. any data that is not present in the one hot encoding of the model cannot be used.

The frontend provides a drop down box for categorical data to restrict the inputs to valid items.

After the user has inputted their data they will be able to click predict to receive the model's prediction.



#### 2.2 The server

The server was implemented using flask and follows the following flow:

Loads all categorical data from local files in order to be aware of the possible rows and correctly form our data row

The model is then loaded and our feature counts are verified.

A retraining thread is started that will check every hour if there are more than 100 new entries, at which point it will retrain and load the new model.

#### 2.2 **APIs**

## 2.2.1 /predict

This api is the most essential of our APIs. Its responsible for taking the data sent by the client, preforming preprocessing, then sending the data to the

model, and replying with whether or not the model predicted fraud.

Preprocessing involves using our distributions and fits to map it to the corresponding distribution. These fits are updated every 100 new items during the retraining of the model. Categorical data is also mapped into its one hot encoding format.

# 2.2.2 /feedback

Takes the label the user provided and adds it to the training data produced so far.

#### 2.2.3 /status

Returns the training samples so far and the timestamp of the last training time.

## 2.2.3 /get\_metadata

Gets the domain for each categorical data so that the client can use them in its drop down menus.

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