Machine Learning Prediction of Money Laundering Customers

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Overview

I present a machine learning model which the client, an online gambling platform, can use to detect customers (players) using their infrastructure to launder money. Although limited to a sample containing only 1752 suspect players, a mean accuracy of $\approx 80\%$ in the prediction of a player engaging in suspect activity is attained. The model requires only seven of the 17 available features, potentially increasing its applicability to more players, as well as possibly providing a much larger training sample which could increase the model accuracy. Given the small training sample, deep learning methods are not suited to this task.

Contents

1 Introduction

The client, an online gambling platform, requires a machine learning model with which to detect customers (players) who use the client's infrastructure for laundering money through apparent gambling activities. The findings are summarised above, with the following report containing the specific details regarding the building of the model.

2 Analysis

2.1 Pre-processing

2.1.1 The data

The client has supplied five datasets:

1. `details.csv` – the 207 398 players' basic details. The file is known to have formatting issues.
2. `payments.csv` – the payment activities of the players over the last 30 days.
3. `profiling.csv` – additional information regarding the players' activity over the same period.
4. `suspect.csv` – a list of 1752 players already flagged for suspect activity.

The fields are (in order of appearance):

`ID`	the unique ID of the player
`Life_Time`	how many years the player has been a client
`Age`	the client's age in years
`Is_Retail`	whether the player is also a retailer
`Is_CRM_Email`	whether the player has been contacted by us
`CountDeposit`	number of deposits
`CountWithdrawal`	number of withdrawals
`TotalDeposits`	value of deposits
`TotalWithdrawal`	value of withdrawals
`CountPaymentMethod`	number of different deposit/withdrawal methods
`DifferentMethodWithdrawals`	value of different deposit/withdrawal methods
`Multi_Device`	0 flags < 3 devices and 1 flags ≥ 3 devices used for payment
`IP_Counts`	number of different IP addresses used for transactions
`e_11234, e_23456, e_34454 e_43568, e_64645`	aggregated variables describing the players' activity

2.1.2 Cleaning

Using pre-process.py, it is seen that details.csv does indeed have formatting issues:

```
                                ID|Life_Time|Age|Is_Retail|Is_CRM_Email
NaN db=123 | 25 | 100001096=id     | | 1 )| | | 33 | | )| 1 | | | 0 |
    db=123 | 25 | 100002057=id     | | 1 )| | | 44 | | )| 0 | | | 0 |
 ...                                                                ...
    db=123 | 25 | 899994603=id     | | 3 )| | | 35 | | )| 0 | | | 0 |
    db=123 | 25 | 899998254=id     | | 0 )| | | 39 | | )| 0 | | | 0 |
[207398 rows x 1 columns]
```

This was easily fixed in the emacs editor[1] and saved as details_fixed.csv

```
               ID  Life_Time  Age  Is_Retail  Is_CRM_Email
0       100001096          1   33          1             0
1       100002057          1   44          0             0
...           ...        ...  ...        ...           ...
207396  899994603          3   35          0             0
207397  899998254          0   39          0             0

[207398 rows x 5 columns]
                 ID      Life_Time            Age      Is_Retail   Is_CRM_Email
count  2.073980e+05  207398.000000  207398.000000  207398.000000  207398.000000
mean   5.008909e+08       2.603342      41.490410       0.410023       0.418042
std    2.306288e+08       3.122641      13.123745       0.491839       0.493238
min    1.000011e+08       0.000000      18.000000       0.000000       0.000000
max    8.999983e+08      21.000000     120.000000       1.000000       1.000000
```

Looking at payments.csv,

```
               ID  CountDeposit  ...  CountPaymentMethod  DifferentMethodWithdrawals
0       100001096            86  ...                   1                      2359.8
1       100002057            26  ...                   1                         0.0
...           ...           ...  ...                 ...                         ...

207396  899994603             1  ...                   1                         0.0
207397  899998254             5  ...                   1                         0.0
```

this has the customer ID (ID) in common with details.csv, as does profiling.csv.

[1] Command line methods such as sed, awk, etc. could also have been used.

```
               ID  Multi_Device  IP_Counts   e_11234   e_23456   e_34454   e_43568  e_64645
0       100001096             1          3   5599.89    986.36    283.05    662.98     0.40
1       100002057             1          1   9669.93  17181.08  20905.39  38635.13     3.22
...           ...           ...        ...       ...       ...       ...       ...      ...
207396  899994603             1          2   7522.49  16485.09  37475.16  37475.16     3.15
207397  899998254             1          1   9229.69   3589.55    578.35  31473.88     1.22
```

ID was therefore used to merge these datasets and, checking the merged data, no missing values were found.

```
             Life_Time            Age  ...        e_34454        e_43568        e_64645
count    207398.000000  207398.000000  ...  207398.000000  207398.000000  207398.000000
mean          2.603342      41.490410  ...   14666.698999   18722.672481       1.516427
std           3.122641      13.123745  ...   13152.810961   15426.545697       1.101400
min           0.000000      18.000000  ...       0.000000       0.000000       0.000000
25%           0.000000      31.000000  ...    3454.317500    3320.920000       0.490000
50%           1.000000      39.000000  ...   10207.420000   14811.630000       1.350000
75%           4.000000      51.000000  ...   25097.677500   34063.392500       2.670000
max          21.000000     120.000000  ...   70086.760000   56891.910000       4.310000
[8 rows x 18 columns]
```

Finally, looking at suspect.csv, this contains only two fields, the player ID and a positive flag (Target_ml = 1) for suspected laundering activity.

```
                 ID  Target_ml
count  1.752000e+03     1752.0
mean   4.995049e+08        1.0
std    2.322098e+08        0.0
min    1.000955e+08        1.0
max    8.997882e+08        1.0
```

All 1752 of these players were also in the merged file, which was absent a suspect activity flag. These flags were added to the merged file and, assuming that the $207\,389 - 1752 = 205\,637$ remaining players are non-suspect, these were flagged as Target_ml = 0.

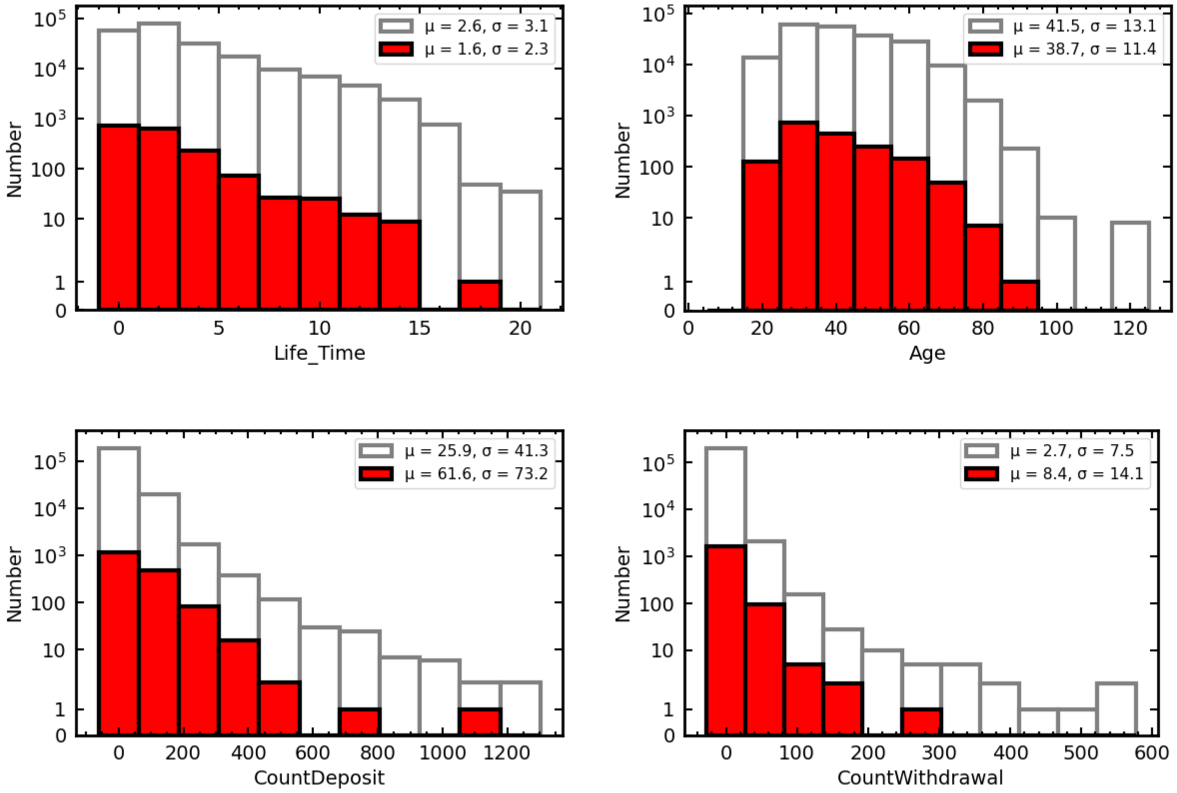
```
               ID  Life_Time  Age    ...   e_23456   e_34454   e_43568  e_64645  Target_ml
0       100001096          1   33    ...    986.36    283.05    662.98     0.40          0
1       100002057          1   44    ...  17181.08  20905.39  38635.13     3.22          0
...           ...        ...  ...    ...       ...       ...       ...      ...        ...
207396  899994603          3   35    ...  16485.09  37475.16  37475.16     3.15          0
207397  899998254          0   39    ...   3589.55    578.35  31473.88     1.22          0

[207398 rows x 19 columns]
```

```
            Life_Time          Age  ...       e_43568       e_64645      Target_ml
count   207398.000000  207398.000000  ...  207398.000000  207398.000000  207398.000000
mean         2.603342      41.490410  ...   18722.672481       1.516427       0.008448
std          3.122641      13.123745  ...   15426.545697       1.101400       0.091522
min          0.000000      18.000000  ...       0.000000       0.000000       0.000000
max         21.000000     120.000000  ...   56891.910000       4.310000       1.000000
```

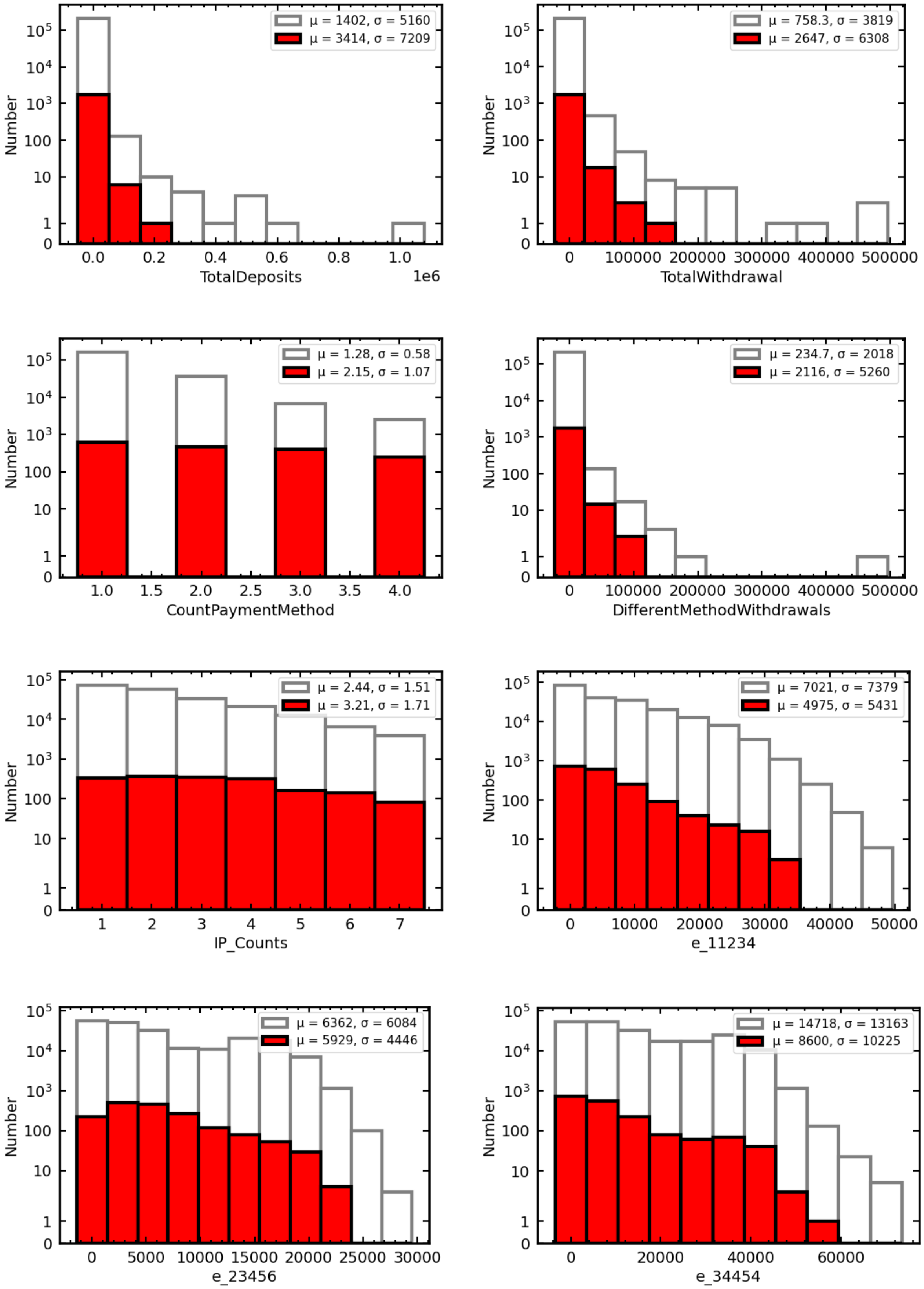
The data were then saved to `all_data.csv` to be used in the machine learning.

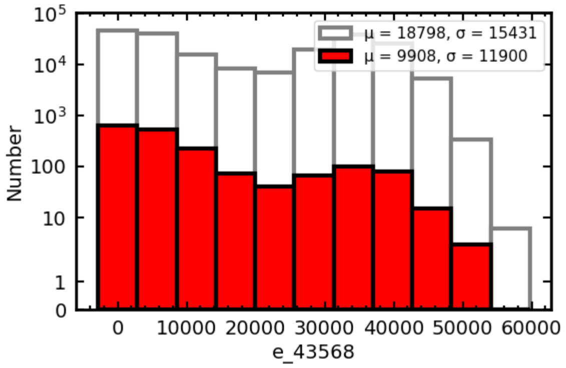
2.1.3 Exploratory Analysis

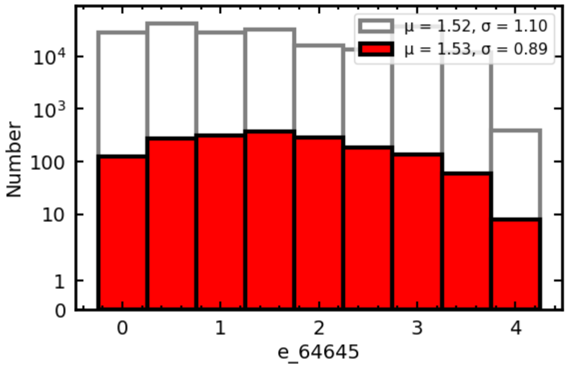
In order to visualise the data and eyeball any obvious differences between the suspect and non-suspect players, the distributions of the non-binary features are plotted below.



It is seen that the suspect players features (filled histograms) mostly overlap with the non-suspect plays (unfilled histograms), demonstrating that these would be difficult to distinguish from one another based the distributions alone. Note also that some of the non-suspect players are suspiciously long-lived.


μ = 1402, σ = 5160
μ = 3414, σ = 7209
Number
TotalDeposits
1e6
0.0
0.2
0.4
0.6
0.8
1.0
μ = 758.3, σ = 3819
μ = 2647, σ = 6308
TotalWithdrawal
0
100000
200000
300000
400000
500000
μ = 1.28, σ = 0.58
μ = 2.15, σ = 1.07
CountPaymentMethod
1.0
1.5
2.0
2.5
3.0
3.5
4.0
μ = 234.7, σ = 2018
μ = 2116, σ = 5260
DifferentMethodWithdrawals
μ = 2.44, σ = 1.51
μ = 3.21, σ = 1.71
IP_Counts
1
2
3
4
5
6
7
μ = 7021, σ = 7379
μ = 4975, σ = 5431
e_11234
0
10000
20000
30000
40000
50000
μ = 6362, σ = 6084
μ = 5929, σ = 4446
e_23456
0
5000
10000
15000
20000
25000
30000
μ = 14718, σ = 13163
μ = 8600, σ = 10225
e_34454
0
20000
40000
60000
0
1
10
100
10^3
10^4
10^5





```
Maximum suspect age is 89, above which there are 63 non-suspect players (oldest is 120)
```

2.2 Machine Learning

2.2.1 Initial models and tests

In ML.py four common, but varied, ML classifiers were initially tested:

1. *Logistic Regression* (LR): This is analogous to multi-variable linear regression, but instead of a fit yields a binary result. Thus, it is particularly suited to this problem where we are classifying a player as suspect or not. The algorithm compresses a linear combination of several variables (features) with a logistics sigmoid to yield a value of between 0 and 1. For the binary model, the prediction is labelled with one of these two end values, depending upon its probability $(0 \rightarrow 1)$, or odds $(0 \rightarrow \infty)$

2. *k-Nearest Neighbour* (kNN): This algorithm maps the variables to a feature space and then compares the Euclidean distance between a test point and its k nearest neighbours. It then assigns a weighted combination of the target values with the nearest neighbours in order to place the test object in a group. kNN is especially suited when the number of features is small. If there are too many these can be reduced via Principal Component Analysis.

3. *Support Vector Classifier* (SVC): This constructs a hyperplane in a high dimensional space in order to perform classification, regression and outlier detection. Support vectors are points that reside closest to the hyperplane and in binary classification the training maximises the distance between the two categories. Further data are transformed into the same space and assigned a category based upon where in the space the are located. Although the support vector machine classifier is computationally fast, it is not suitable for noisy data (overlapping features) nor large data sets.

4. *Decision Tree Classifier* (DTC): Like the other algorithms, decision trees can be used for both classification and regression. The algorithm builds a classification model based upon a tree structure, which branches the data-set (top node) into smaller subsets (child nodes), according to a predefined decision boundary. With one node on either side of the boundary, the process is iterated through

further branching until a predefined stopping criterion in reached. DTC has the advantage that it is not as sensitive to outliers as some of the other algorithms, although the tree choices can be biased due to the sequential nature of the algorithm. Over-fitting can also be a problem, which can be mitigated by limiting the maximum tree depth.

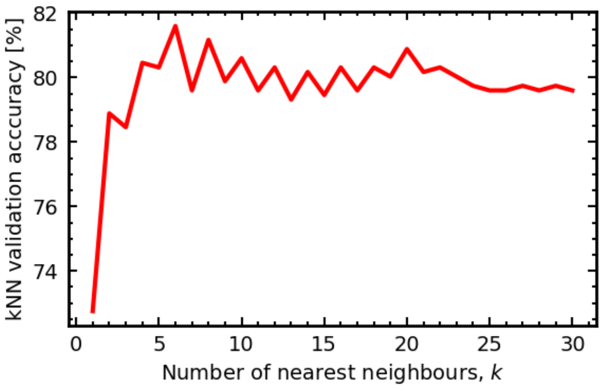
As stated above, there are only 1752 suspect players and so from raw statistics alone we can ascertain that there is a probability of $100 \times 1752/207\,389 = 0.84\%$ of the player being suspect. In order to prevent the ML blindly yielding an apparent $100 - 0.84 \approx 99\%$ accuracy based upon the probability alone, 1752 of the remaining 205 637 non-suspect players were randomly selected for the binary testing.

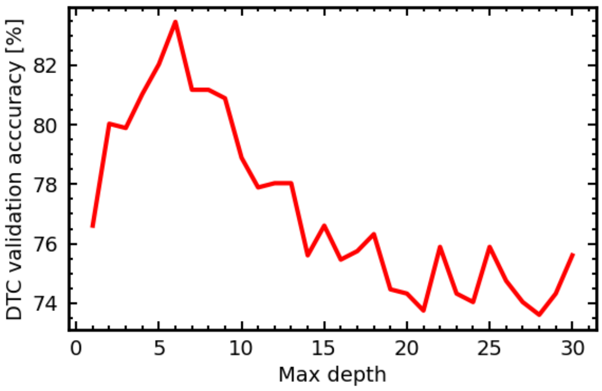
Training on 80% of the 2×1752 strong sample (2803 players) and testing on the other 20% (701), using the default values of the algorithms,training scores of $\gtrsim 75\%$ and validation scores $\gtrsim 70\%$ were obtained.

2.2.2 Model optimisation

Each models was then optimised via:

- *Logistic regression* – using `sklearn GridSearchCV` in `LR.py`, giving `C=0.0886`, `solver='newton-cg'`.
- *Support Vector Classifier* – using `sklearn GridSearchCV` in `SVC.py`, giving `C=1, gamma=0.1`.
- *k-Nearest Neighbour & Decision Tree Classifier* – the number of nearest neighbours and maximum depths were iterated (in `kNN.py` & `DTC.py`), giving `n_neighbors` ≈6 and `max_depth` ≈7, respectively.





Re-running `ML.py`, with these parameters the results were similar to previous.

```
For a 0.2 test fraction (2803 train & 701 test) LR training score = 75.135 percent
Validation accuracy of LR is 78.60 percent
```

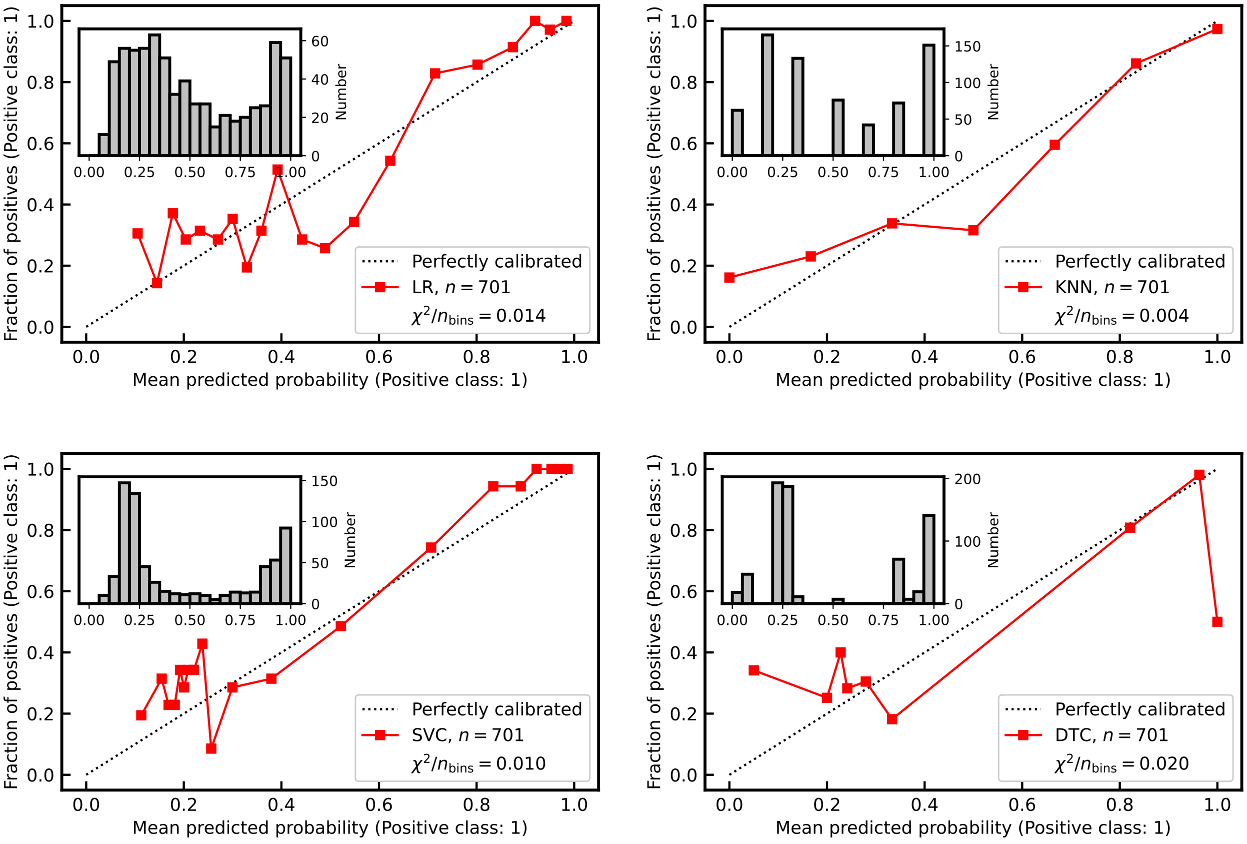
```
For a 0.2 test fraction (2803 train & 701 test) KNN training score = 78.131 percent
Validation accuracy of KNN is 80.17 percent
```

```
For a 0.2 test fraction (2803 train & 701 test) SVC training score = 80.093 percent
Validation accuracy of SVC is 82.17 percent

For a 0.2 test fraction (2803 train & 701 test) DTR training score = 78.879 percent
Validation accuracy of DTR is 77.89 percent
```

The confusion matrix for a run of the SV classifier is shown to the right. From the validation of the model, TP is the number of true positives, FP – false positives, FN – false negatives and TN – true negatives.

	Predicted			
	Good	**Bad**		
Actual good	323	103	TP	FP
Actual bad	22	253	FN	TN

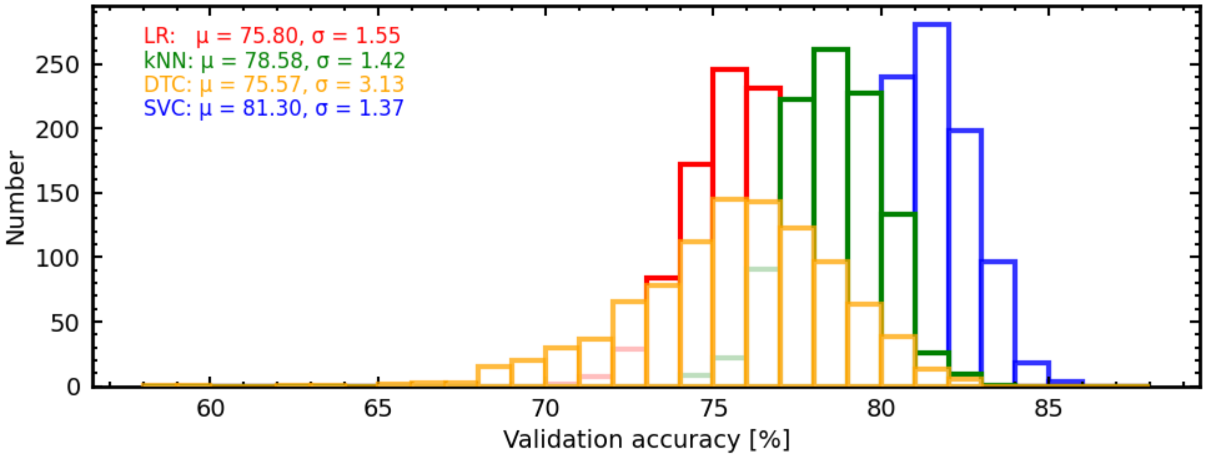
The validation data yield 323 true positives (suspect) and 253 true negatives (non-suspect), compared to 22 false positives and 103 false negatives. This gives a test score of (323 + 253)/(323 + 253 +22 + 103) = 0.8217.



However, from the calibration plots it appears that the kNN classification may be the best, with the least straying from perfect calibration ($\chi^2/n_{\rm bins} = 0.004$ in this instance). This is also reflected in the histogram, which is fairly even distributed, whereas the SV classifier tends to push extreme probabilities (≈ 0.2 or ≈ 1).

Furthermore, these tests are based upon a single instance of the models and, given the small sample, could be subject to the choice of the 1752 non-suspect players. Using `ML-loop.py`, this is tested by running 1000 trials, randomising the sample of non-suspect players from the pool of 205 646 each time.[2]

Summarising the results in the histograms below, averaging a validation score of $81.3 \pm 1.4\%$ it is seen that the SV classifier outperforms the others. The kNN classifier comes in at a close second and, given the calibration plots above, may be the preferred model.



2.2.3 Feature importance

In descending order, from a single run the importance of the features are:

```
LogisiticRegression score = 76.524         Support Vector Classifier score = 81.55
                   Feature  Importance                        Feature  Importance
        CountPaymentMethod    0.053086                        e_23456    0.067499
                   e_64645    0.024331                        e_64645    0.055369
                   e_43568    0.022975                        e_43568    0.051445
                 IP_Counts    0.016625                      IP_Counts    0.017838
                   e_23456    0.010275                      Is_Retail    0.017339
                   e_34454    0.009989                        e_34454    0.016768
                 Is_Retail    0.006136             CountPaymentMethod    0.015912
 DifferentMethodWithdrawals    0.005066     DifferentMethodWithdrawals    0.012986
              Multi_Device    0.003568                        e_11234    0.012772
                 Life_Time    0.003211                      Life_Time    0.011559
              CountDeposit    0.001570                  TotalDeposits    0.010917
           CountWithdrawal    0.001284                   CountDeposit    0.008919
                   e_11234    0.000357                TotalWithdrawal    0.008205
              Is_CRM_Email    0.000214                CountWithdrawal    0.006778
                       Age    0.000143                   Multi_Device    0.006422
             TotalDeposits   -0.000571                   Is_CRM_Email    0.005351
           TotalWithdrawal   -0.001070                            Age    0.005351

KNearest score = 78.843                      DecisionTreeClassifier score = 78.701
```

[2] From 207 398 total minus the 1752 suspect players.

Feature	Importance
e_64645	0.043453
e_23456	0.038673
e_43568	0.035391
CountPaymentMethod	0.026543
Is_Retail	0.026258
e_11234	0.016054
e_34454	0.014413
IP_Counts	0.012558
Is_CRM_Email	0.009704
Age	0.009633
Multi_Device	0.008348
Life_Time	0.008063
CountDeposit	0.005280
CountWithdrawal	0.003068
TotalDeposits	0.002426
TotalWithdrawal	0.001927
DifferentMethodWithdrawals	0.001213

Feature	Importance
CountWithdrawal	0.231038
TotalDeposits	0.140564
DifferentMethodWithdrawals	0.070781
CountDeposit	0.068783
e_23456	0.048519
e_64645	0.040314
IP_Counts	0.022333
e_43568	0.020407
TotalWithdrawal	0.018480
e_34454	0.012130
Life_Time	0.010560
e_11234	0.001998
Age	0.000999
Is_CRM_Email	0.000999
Multi_Device	0.000000
Is_Retail	0.000000
CountPaymentMethod	0.000000

In the following table, these are seen to be roughly consistent, although there was some variation between different runs. Focusing on the best performing (SV) classifier, the training score remains above 80% if only the top seven features are retained. From the training scores, using only the seven most important features, it is seen that the top features between the LR, SV and kNN classifiers are similar, with only e_64645 being common to all classifiers.

However, this is based on the single run shown above. Again, running 1000 trials, where *all* top seven features are used for each classifier (`ML-loop_feat.py`), it is seen that the results are largely insensitive to the choice of the seven features, suggesting that the most important features are a subset of those above.

The LR remains the worst performing classifier for these data, with the SV classifier being best performer, although at the same level (within uncertainties) as the kNN classifier.

Feature	Top Seven Classifier Features				Number of
	LR	SVC	kNN	DTC	Occurrences
e_11234			✓		1
e_23456	✓	✓	✓		3
e_34454	✓	✓	✓		3
e_43568	✓	✓	✓		3
e_64645	✓	✓	✓	✓	4
CountDeposit				✓	1
CountPaymentMethod	✓	✓	✓		3
CountWithdrawal				✓	1
DifferentMethodWithdrawals	✓			✓	2
Is_Retail	✓	✓	✓		3
IP_Counts		✓		✓	2
TotalDeposits				✓	1
Training score [%]					**All features**
LR	74.95 ± 0.62	74.92 ± 0.62	74.93 ± 0.61	72.01 ± 0.70	76.07 ± 0.58
SVC	80.34 ± 0.46	80.33 ± 0.45	80.47 ± 0.45	79.51 ± 0.47	81.23 ± 0.46
kNN	80.44 ± 0.52	80.41 ± 0.52	81.04 ± 0.47	78.60 ± 0.57	78.92 ± 0.55
DTC	78.68 ± 0.68	78.71 ± 0.65	78.55 ± 0.65	79.72 ± 0.64	79.86 ± 0.71
Validation accuracy [%]					
LR	74.75 ± 1.63	74.75 ± 1.63	74.31 ± 1.56	73.06 ± 1.64	74.75 ± 1.75
SVC	80.37 ± 1.35	80.27 ± 1.41	80.41 ± 1.35	79.27 ± 1.41	80.85 ± 1.41
kNN	79.99 ± 1.37	79.96 ± 1.39	80.58 ± 1.30	77.99 ± 1.42	80.51 ± 1.34
DTC	78.58 ± 1.65	78.58 ± 1.56	78.46 ± 1.62	74.58 ± 3.26	77.72 ± 1.95

2.3 Deep Learning (Artificial Neural Network)

Having only 1752 suspect players available, the sample is likely too small to yield reliable predictions from a deep learning (artificial neural network) algorithm. I nevertheless test this in case any further insight can be gained.

DL-grid.py was used to estimate the best combination of hyper-parameters for the TensorFlow models. To randomly sample the hyper-parameter space, we randomly chose:

- Between 0 and 10 hidden layers.
- The number of neurons (hidden layer size) from `[10,20,50,100,200,500]`.
- Activation functions from `['relu','sigmoid','tanh','softmax']`.

Since the results were strongly dependent on the random training sample[3], each model was run 10 times, with the training data being randomised.

```
   HL_0     HL_1  HL_2  HL_3 HL_4 HL_5 HL_6 HL_7 HL_8 HL_9 HL_10  HLS     Score
0  relu  softmax  tanh  relu                                      200  0.801712
0  relu  softmax  tanh  relu                                      200  0.499287
0  relu  softmax  tanh  relu                                      200  0.513552
0  relu  softmax  tanh  relu                                      200  0.820257
0  relu  softmax  tanh  relu                                      200  0.797432
0  relu  softmax  tanh  relu                                      200  0.830243
0  relu  softmax  tanh  relu                                      200  0.805991
0  relu  softmax  tanh  relu                                      200  0.492154
0  relu  softmax  tanh  relu                                      200  0.840228
0  relu  softmax  tanh  relu                                      200  0.808845
```

The mean and standard deviation of the run were taken, as shown below.

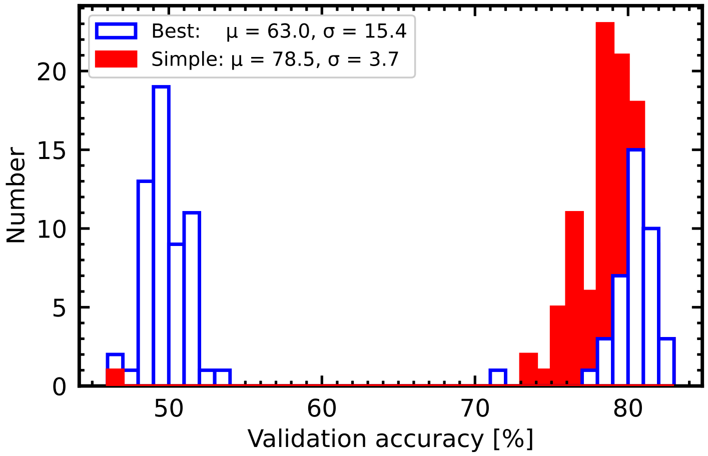
```
   HL_0     HL_1  HL_2  HL_3 HL_4 ... HL_9 HL_10  HLS   Score    Mean        SD    N
  relu  softmax  tanh  relu                      200  0.499287  0.72097  0.151972  10
```

Doing this for 100 randomly selected models, via the DL-grid.csh script, gave the top performers as

```
         HL_1     HL_2   HL_3 HL_4   HL_5   HL_6  HL_7  HL_8  HL_9 HL_10 HLS  Mean    SD
         sigmoid                                                         10   0.769  0.098
relu     tanh    relu                                                    20   0.787  0.029
softmax  tanh                                                            200 0.788  0.100
relu     sigmoid sigmoid relu tanh softmax tanh tanh                     10   0.802  0.024
```

[3] An ≈80% validation accuracy being directly followed by ≈50% for the same model was typical.

Running the `Best` performing set of hyperparameters (mean = 0.802) 100 times gives a bimodal distribution, where around half of the predictions are good (≈80% accurate) and the other half are poor (≈50% accurate, i.e. down to pure chance). In fact, this performs significantly worse than the `Simple` model, comprising just two *ReLu* layers with a 50 neurons, found quickly by trial and error. This shows that the grid search, via random hyperparameter sampling, is far from exhaustive, requiring more extensive sampling and testing.[a]



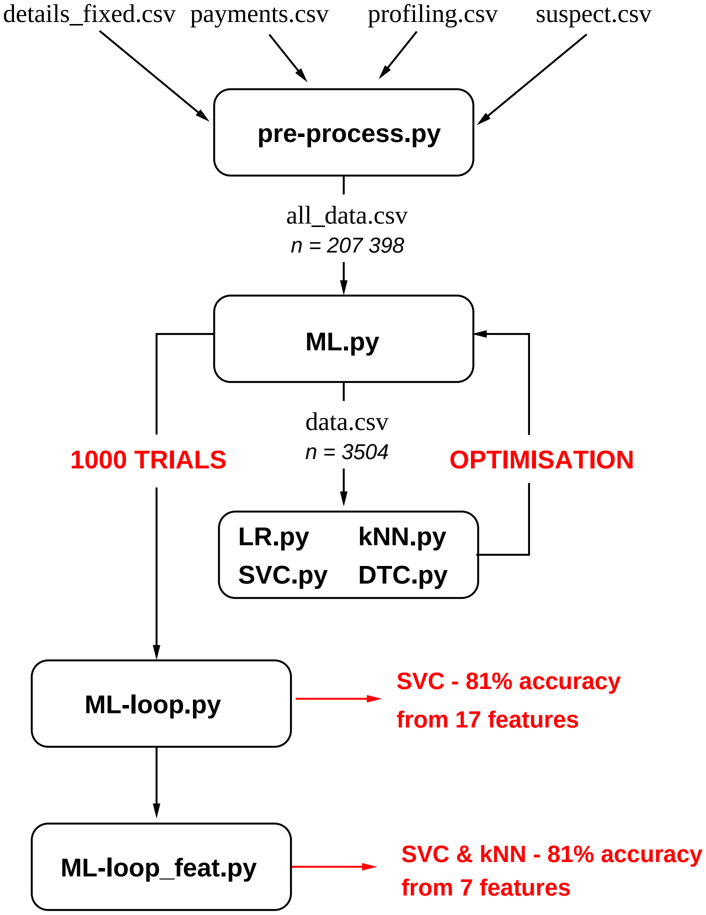
[a] Much more than 10 runs for each model.

Given that the `Simple` model also has one out of the 100 runs giving and accuracy of ≈50% and a spread of scores twice as wide as the machine learning models (σ =3.7%, cf. $\lesssim$1.5%), deep learning is not suitable for this project, mostly likely due to the small training sample.

3 Discussion

3.1 Recap

Summarising the steps taken above.



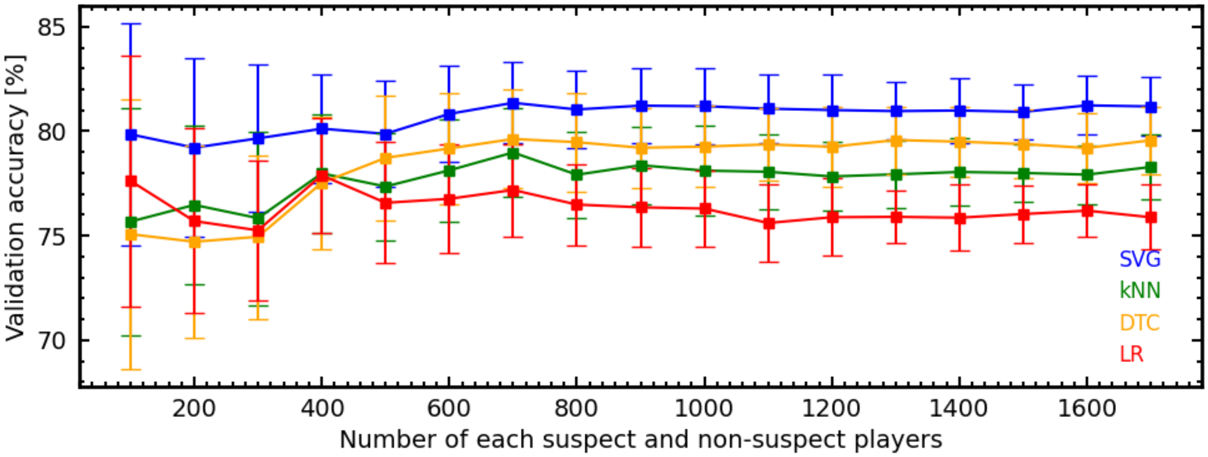
- In `pre-process.py`, the players details (`details_fixed.csv`) are combined with their payment activities (`payments.csv`) and other additional information (`profiling.csv`). Using `suspect.csv`, those with known suspect activity are then flagged.
- In `ML.py`, the 1752 suspect players, in addition to a random sample of 1752 non-suspect, are selected. Four different classification methods are tested on the sample of 3504 and then optimised.
- Selecting such a relatively small number of non-suspects from a pool of 205 646 may lead to a single trial being unrepresentative. Therefore, in `ML-loop.py`, the selection of the 1752 non-suspect players is randomised before re-running the algorithm. After 1000 runs, the Support Vector Classifier is found to be the best performer with an average validation accuracy of $80.9 \pm 1.4\%$.
- Finally, the relative importance of each feature is explored and, testing these, it is apparent that retaining only the seven most important has little detrimental effect. In the case of the SV and kNN classifiers, the performance reaches the same level as the full 17 feature SV classifier.

Note that the requirement of only seven features has the potential to vastly increase the sample sizes and number of players which can be tested for likely money laundering.[4]

[4] The SVC and kNN models, which use the top seven kNN features, have been saved in `KNN-0.818.pickle` and `SVC-0.812.pickle`, which as the names suggest, have training scores of 81.8% and 81.2%, respectively.

3.2 Prospects

Being trained on just 2×1752 players, the sample is relatively small, as is reflected in the unimpressive deep learning results. Increasing the sample size is expected to increase the accuracy and, in an attempt to quantify this, in `ML_sampled.py` 100 trials for each of the algorithms for randomly selected samples of varying size are tested.



Plotting the results (using `sampled_plot.py`), it appears that the accuracy does not increase significantly for sample sizes above $2\times \approx 500$ players, although the spread in the accuracies narrow and the DT classifier may be trending upwards. In any case, a significant increase in accuracy cannot be ruled out until much larger datasets are used for the training. We would also expect these to improve the adherence to `Perfectly calibrated` line in the calibration plots (Sect. 2.2.2).

Although all of the processing was done in the python scripts mentioned in the report, a simplified run-through is included as the Jupyter notebook `PP+ML.ipynb`