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Data Mining Final Project

A. Background

An established food retailer has introduced a self-scanning system that allows customers to scan their items using a handheld mobile scanner while shopping.

This type of payment leaves retailers opens to the risk that a certain number of customers will take advantage of this freedom to commit fraud by not scanning all of the items in their cart.

Empirical research conducted by suppliers has shown that discrepancies are found in approximately 5 % of all self-scan transactions. The research does not differentiate between actual fraudulent intent of the customer, inadvertent errors or technical problems with scanners.

B. Goal

To minimize losses, the food retailer hopes to identify cases of fraud using targeted follow-up checks. The challenge here is to keep the number of checks as low as possible to avoid unnecessary added expense as well as to avoid putting off innocent customers due to false accusations. At the same time, however, the goal is to identify as many false scans as possible.

The objective is to create a model to classify the scans as fraudulent or non-fraudulent. The classification does not take into account whether the fraud was committed intentionally or inadvertently.

C. Data Description

This dataset is a dataset from a *self-checkout* machine in a shop that is currently testing a machine that allows buyers to input the purchased items and then pay for them independently. This dataset has a *fraud* column that shows whether a transaction is included in the fraud category or not.

```
train = pd.read_csv('DMC_2019_task/train.csv', sep='|')
test = pd.read_csv('DMC_2019_task/test.csv', sep='|')
truth = pd.read_csv('DMC-2019-realclass.csv', sep='|').values.flatten()
print(train.shape)
print(test.shape)
print(truth.shape)
```

```
(1879, 10)
(498121, 9)
(498121,)
```

Train dataset has 1879 rows and Test dataset has 498121 rows. Then for the column is 10.

trustLevel: A customer's individual trust level. 6 means Highest trustworthiness *(int)*
totalScanTimeInSeconds: Total time in seconds between the first and last product scanned *(int)*
grandTotal: Grand total of products scanned *(float)*
lineItemVoids: Number of voided scans *(int)*
scansWithoutRegistration: Number of attempts to activate the scanner without actually scanning anything *(int)*

quantityModification: Number of modified quantities for one of the scanned products *(int)*
scannedLineItemsPerSecond: Average number of scanned products per second *(int)*
valuePerSecond: Average total value of scanned products per second *(float)*
lineItemVoidsPerPosition: Average number of item voids per total number of all scanned and not cancelled products *(float)*
fraud: Classification as fraud (1) or not fraud (0) *(int)*

D. Preprocess

1. Label data check

   Fact: This data is very unbalanced. Of the 1879 training data, only 5% of the data is fraudulent transaction data.

   Hypothesis: In the process of determining the model to be used in the classification process, cross validation must be carried out to ensure that the selected model is the model that has the highest performance.

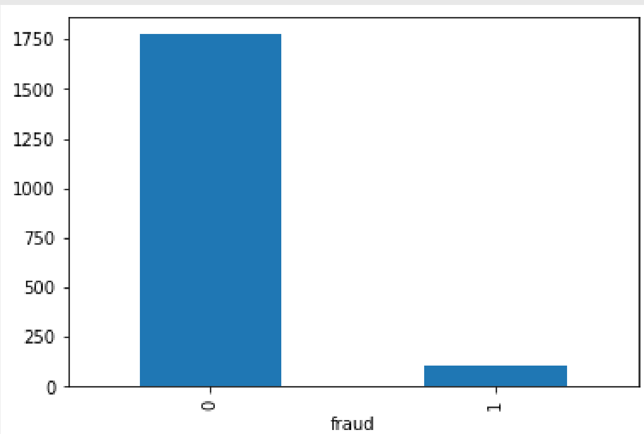
   Hypothesis: Evaluation metrics that are suitable for this data are precision, recall and f1 score in the *fraud* label.

```
pd.Series(data=[len(train),len(test)],index=['train','test'])
```

```
train      1879
test     498121
dtype: int64
```

```
train.groupby('fraud').size().plot(kind='bar')
print('fraud percent =',len(train[train.fraud == 1])/len(train)*100,'%')
```

```
fraud percent = 5.534858967535923 %
```



2. *trustLevel* feature Check
   Facts: In the training data, all data categorized as fraud have a low individual trust level, between 1 or 2 only.
   Hypothesis: Models with linear-based models can distinguish fraud well because of this fact

```
train[train.fraud == 1].trustLevel.unique()
```

```
array([1, 2], dtype=int64)
```

3. Outlier Check
   Fact: in the *lineItemVoidsPerPosition*, *valuePerSecond* and *scannedLineItemsPerSecond* columns there are outliers in this dataset. This is inferred from looking at the average, 75% and max of these columns. The mean and 75% of the columns are far from the largest data in that column.

   Hypothesis: it seems that fraud data is outlier data

```
train.describe()
```

Python

	trustLevel	totalScanTimeInSeconds	grandTotal	lineItemVoids	scansWithoutRegistration	quantityModifications	scannedLineItemsPerSecond	valuePerSecond	lineItemVoidsPerPosition	fraud
count	1879.000000	1879.000000	1879.000000	1879.000000	1879.000000	1879.000000	1879.000000	1879.000000	1879.000000	1879.000000
mean	3.401809	932.153273	50.864492	5.469931	4.904204	2.525279	0.058138	0.201746	0.745404	0.055349
std	1.709404	530.144640	28.940202	3.451169	3.139697	1.695472	0.278512	1.242135	1.327241	0.228720
min	1.000000	2.000000	0.010000	0.000000	0.000000	0.000000	0.000548	0.000007	0.000000	0.000000
25%	2.000000	474.500000	25.965000	2.000000	2.000000	1.000000	0.008384	0.027787	0.160000	0.000000
50%	3.000000	932.000000	51.210000	5.000000	5.000000	3.000000	0.016317	0.054498	0.350000	0.000000
75%	5.000000	1397.000000	77.285000	8.000000	8.000000	4.000000	0.032594	0.107313	0.666667	0.000000
max	6.000000	1831.000000	99.960000	11.000000	10.000000	5.000000	6.666667	37.870000	11.000000	1.000000

   Facts: The previous hypothesis is not correct, it turns out that outliers in this dataset are not a sign that the data is fraud. Because based on the mean, 75% and max of the fraud data, there is no data that is far adrift (outliers).

   Hypothesis: removing outliers cannot affect fraud detection. But it might make it easier to detect non-fraud transactions.

```
train[train.fraud == 1].describe()
```

Python

	trustLevel	totalScanTimeInSeconds	grandTotal	lineItemVoids	scansWithoutRegistration	quantityModifications	scannedLineItemsPerSecond	valuePerSecond	lineItemVoidsPerPosition	fraud
count	104.000000	104.000000	104.000000	104.000000	104.000000	104.000000	104.000000	104.000000	104.000000	104.0
mean	1.144231	1173.913462	51.034327	6.375000	5.865385	2.519231	0.031582	0.053622	0.251412	1.0
std	0.353025	471.260881	30.298933	3.498092	3.211199	1.654536	0.034298	0.045918	0.146440	0.0
min	1.000000	91.000000	0.260000	0.000000	0.000000	0.000000	0.011692	0.000661	0.000000	1.0
25%	1.000000	819.000000	27.072500	3.000000	3.000000	1.000000	0.016411	0.026209	0.130435	1.0
50%	1.000000	1309.500000	48.670000	6.000000	7.000000	2.000000	0.020436	0.043697	0.245000	1.0
75%	1.000000	1540.500000	76.862500	10.000000	8.250000	4.000000	0.033966	0.071838	0.379721	1.0
max	2.000000	1830.000000	99.820000	11.000000	10.000000	5.000000	0.307692	0.230802	0.578947	1.0

4. Correlation Check
   Facts: The following are the feature importance of the columns in this dataset using the Pearson correlation algorithm.

   Hypothesis: Columns that have a correlation of -0.05 < x < 0.05 cannot be used because they do not significantly affect the change in the value in the fraud column.

```
train.corr().fraud
```

```
trustLevel                  -0.319765
totalScanTimeInSeconds       0.110414
grandTotal                   0.001421
lineItemVoids                0.063496
scansWithoutRegistration     0.074123
quantityModifications       -0.000864
scannedLineItemsPerSecond   -0.023085
valuePerSecond              -0.028873
lineItemVoidsPerPosition    -0.090116
fraud                        1.000000
Name: fraud, dtype: float64
```

TO-DO:

- Add column 'totalItems' which contains the number of items purchase in one transaction.

```
train['totalItems'] = [train.iloc[i].totalScanTimeInSeconds * train.iloc[i].scannedLineItemsPerSecond for i in tqdm(range(len(train)))]
test['totalItems'] = [test.iloc[i].totalScanTimeInSeconds * test.iloc[i].scannedLineItemsPerSecond for i in tqdm(range(len(test)))]
```

```
100%|██████████| 1879/1879 [00:00<00:00, 4742.56it/s]
100%|██████████| 498121/498121 [02:11<00:00, 3774.18it/s]
```

- Look for the column whose feature importance is -0.05 < x < 0.05.

```
corr = train.corr().fraud
todrop = [i for i in corr.index if corr[i] < 0.05 and corr[i] > -0.05]
todrop
```

```
['grandTotal',
 'quantityModifications',
 'scannedLineItemsPerSecond',
 'valuePerSecond']
```

- Drop the column and create variables X, X_test, y that are ready to be used for the model.

```
X = train.drop(columns=todrop+['fraud'])
X_test = test.drop(columns=todrop)
y = train.fraud.values
```

- Scale the dataset using the Standard Scaler. So that models that do not have a built-in scaler such as SVM or Logistic Regression can fit better and reach convergence more quickly.

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X = scaler.fit_transform(X)
X_test = scaler.transform(X_test)
```

E. Algorithm Analysis

So, for the model. I use various existing classifiers to find which type of classifier fits this dataset.

```
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import confusion_matrix
```

In the Data Mining Cup 2019, additional evaluation metrics in the form of reward punishment are also given that the data uses as a moral compass to determine how many false positives and false negatives are reasonable for a model. The following is the cost matrix given for the Data Mining Cup 2019:

Evaluation

The solutions submitted will be assessed and compared based on their monetary value for the food retailer. This can be calculated using the following cost matrix based on empirical observation.

Prediction	**Actual value**		
		0 (no fraud)	**1** (fraud)
	0 (no fraud)	*€ 0.0*	*€ -5.0*
	1 (fraud)	*€ -25.0*	*€ 5.0*

Thus, the food retailer receives a profit of € 5 for every correctly identified fraud attempt. However, for every fraud case that goes unexposed he loses € 5.

A costumer falsely accused of fraud, might not return to this store, which is denoted by a € 25 loss for the retailer.

An honest customer identified correctly means neither profit nor loss for the retailer.

The sum of the costs or profit of all scans is the monetary value of the submitted solution.

The winning team is the one whose solution achieves the highest monetary profit. In the event of a tie, a random draw will determine the winner.

```python
def evaluate(actual, pred, pri=True, ret='all'):
    tn, fp, fn, tp = confusion_matrix(actual, pred).ravel()
    if pri:
        print('TN =',tn,', FP =', fp,', FN =', fn,', TP =',tp)
        print((tp*5) + (tn*0) + (fp*-25) + (fn*-5),'/', len(actual[actual == 1]) * 5)
        print('current monetary profit / highest monetary profit that possible')
    if ret != None:
        if ret == 'all':
            return (tp*5) + (tn*0) + (fp*-25) + (fn*-5)
        elif ret == 'fpfn':
            return fp+fn
        elif ret == 'fp':
            return fp
        elif ret == 'fn':
            return fn
```

F. Parameter Value Analysis

```
models = {
    'Naive Bayes' : GaussianNB(), #Naive Bayes
    'Logistic Regression' : LogisticRegression(), #Linear Model
    'Linear SVC' : LinearSVC(), #Support Vector
    'SVC rbf': SVC(kernel='rbf',probability=True),#Support Vector
    'SVC poly': SVC(kernel='poly', probability=True),#Support Vector
    'Decision Tree': DecisionTreeClassifier(), #Tree
    'MLP' : MLPClassifier(random_state=12,hidden_layer_sizes=(100),max_iter=1000), #Neural Network
    'KNN' : KNeighborsClassifier(), #Nearest Neighbor
}
```

- Naïve Bayes: -
- Logistic Regression: -
- Linear SVC: -
- SVC rbf and SVC poly: (probability=True) to enable probability estimates. This must be enabled prior to calling fit, will slow down that method as it internally uses 5-fold cross-validation.
- Decision Tree: -
- MLP:
- KNN: -

G. Result/Output

```
Model : Naive Bayes
              precision    recall  f1-score   support

           0       1.00      0.97      0.98      1775
           1       0.64      0.92      0.75       104

    accuracy                           0.97      1879
   macro avg       0.82      0.95      0.87      1879
weighted avg       0.98      0.97      0.97      1879

TN = 1720 , FP = 55 , FN = 8 , TP = 96
-935 / 520
current monetary profit / highest monetary profit that possible
FP+FN = 63
============================================
Model : Logistic Regression
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      1775
           1       0.95      0.87      0.90       104

    accuracy                           0.99      1879
   macro avg       0.97      0.93      0.95      1879
weighted avg       0.99      0.99      0.99      1879

TN = 1770 , FP = 5 , FN = 14 , TP = 90
255 / 520
current monetary profit / highest monetary profit that possible
FP+FN = 19
============================================
```

```
Model : Linear SVC
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1775
           1       0.93      0.92      0.93       104

    accuracy                           0.99      1879
   macro avg       0.96      0.96      0.96      1879
weighted avg       0.99      0.99      0.99      1879

TN = 1768 , FP = 7 , FN = 8 , TP = 96
265 / 520
current monetary profit / highest monetary profit that possible
FP+FN = 15
============================================
```

```
Model : SVC rbf
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      1775
           1       0.96      0.83      0.89       104

    accuracy                           0.99      1879
   macro avg       0.97      0.91      0.94      1879
weighted avg       0.99      0.99      0.99      1879

TN = 1771 , FP = 4 , FN = 18 , TP = 86
240 / 520
current monetary profit / highest monetary profit that possible
FP+FN = 22
```

```
============================================
Model : SVC poly
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      1775
           1       0.96      0.84      0.89       104

    accuracy                           0.99      1879
   macro avg       0.97      0.92      0.94      1879
weighted avg       0.99      0.99      0.99      1879

TN = 1771 , FP = 4 , FN = 17 , TP = 87
250 / 520
current monetary profit / highest monetary profit that possible
FP+FN = 21
============================================
Model : Decision Tree
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1775
           1       0.81      0.84      0.82       104

    accuracy                           0.98      1879
   macro avg       0.90      0.91      0.91      1879
weighted avg       0.98      0.98      0.98      1879

TN = 1754 , FP = 21 , FN = 17 , TP = 87
-175 / 520
current monetary profit / highest monetary profit that possible
FP+FN = 38
============================================
```

```
Model : MLP
              precision    recall  f1-score   support

           0       0.99      1.00      1.00      1775
           1       0.94      0.91      0.93       104

    accuracy                           0.99      1879
   macro avg       0.97      0.96      0.96      1879
weighted avg       0.99      0.99      0.99      1879

TN = 1769 , FP = 6 , FN = 9 , TP = 95
280 / 520
current monetary profit / highest monetary profit that possible
FP+FN = 15
============================================
Model : KNN
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      1775
           1       0.85      0.70      0.77       104

    accuracy                           0.98      1879
   macro avg       0.92      0.85      0.88      1879
weighted avg       0.98      0.98      0.98      1879

TN = 1762 , FP = 13 , FN = 31 , TP = 73
-115 / 520
current monetary profit / highest monetary profit that possible
FP+FN = 44
============================================
```

H. Summary of the Pattern

Best Baseline Model

```
clf = LogisticRegression()
clf.fit(X,y)
pred = clf.predict(X_test)
print(classification_report(truth, pred))
print('FP+FN =',evaluate(truth,pred,ret='fpfn'))
```

```
              precision    recall  f1-score   support

           0       0.99      1.00      0.99    474394
           1       0.93      0.86      0.89     23727

    accuracy                           0.99    498121
   macro avg       0.96      0.93      0.94    498121
weighted avg       0.99      0.99      0.99    498121

TN = 472889 , FP = 1505 , FN = 3380 , TP = 20347
47210 / 118635
current monetary profit / highest monetary profit that possible
FP+FN = 4885
```

Can be concluded that:

- Logistic Regression is better than SVC poly because it can classify fraud with the highest monetary profit in the test data. Logistic Regression gets the lowest FP but high False Negative.
- MLP and Linear SVC can classify fraud with relatively stable FP and FN and can be accepted with stable reasons.
- Naive Bayes can classify data with low FN, this makes the TP value higher. This model is suitable if there is no problem when there is a False Positive. However, in this case False Positive can make customers not want to shop at this store because they are accused of cheating when they are not.

Since this model is based on monetary profit, the best baseline model is Logistic Regression with a monetary profit of €47,210 and the number of misclassifications (FP+FN) of 4,885 transactions.

I. Pattern Interpretation

Based on the part G the goal has been reached. Because from the experiment that I have done, Logistic Regression can get the highest monetary profit and has minimum number of misclassifications transactions compared to other classifiers.