Report

Assignment 2

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GRUOP | 11

Objective

We want to use machine learning models to identify fake tasks.

Import the libraries

```
[36] !pip install plotly
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: plotly in /usr/local/lib/python3.7/dist-packages (5.5.0)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from plotly) (1.15.0)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.7/dist-packages (from plotly) (8.0.1)
```

```
[37] import pandas as pd

     from sklearn.model_selection import train_test_split
     from sklearn.naive_bayes import GaussianNB
     from sklearn.ensemble import RandomForestClassifier
     from sklearn.ensemble import AdaBoostClassifier
     from sklearn.metrics import classification_report, ConfusionMatrixDisplay, accuracy_score, confusion_matrix
     from sklearn.ensemble import VotingClassifier
     from imblearn.over_sampling import RandomOverSampler

     import plotly.express as express
```

1. Read the dataset

```
[38] data = pd.read_csv("MCSDatasetNEXTCONLab.csv")
```

```
[39] data
```

	ID	Latitude	Longitude	Day	Hour	Minute	Duration	RemainingTime	Resources	Coverage	OnPeakHours	GridNumber	Ligitimacy
0	1	45.442142	-75.303369	1	4	13	40	40	9	91	0	131380	1
1	1	45.442154	-75.304366	1	4	23	40	30	9	91	0	131380	1
2	1	45.442104	-75.303963	1	4	33	40	20	9	91	0	121996	1
3	1	45.441868	-75.303577	1	4	43	40	10	9	91	0	121996	1
4	2	45.447727	-75.147722	2	15	49	30	30	5	47	0	140784	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
14479	3999	45.445303	-75.165596	2	1	18	20	20	10	80	0	131397	1
14480	3999	45.445574	-75.165168	2	1	28	20	10	10	80	0	131397	1
14481	4000	45.436682	-75.152416	0	12	21	30	30	4	63	0	122015	1
14482	4000	45.436978	-75.153278	0	12	31	30	20	4	63	0	122015	1
14483	4000	45.436983	-75.153240	0	12	41	30	10	4	63	0	122015	1

14484 rows × 13 columns

Splitting the dataset to features and label

Features

```
[40] x = data.iloc[:,:-1]
     y = data.iloc[:,-1:]
```

```
[41] x
```

	ID	Latitude	Longitude	Day	Hour	Minute	Duration	RemainingTime	Resources	Coverage	OnPeakHours	GridNumber
0	1	45.442142	-75.303369	1	4	13	40	40	9	91	0	131380
1	1	45.442154	-75.304366	1	4	23	40	30	9	91	0	131380
2	1	45.442104	-75.303963	1	4	33	40	20	9	91	0	121996
3	1	45.441868	-75.303577	1	4	43	40	10	9	91	0	121996
4	2	45.447727	-75.147722	2	15	49	30	30	5	47	0	140784
...	...	...	...	...	...	...	...	...	...	...	...	...
14479	3999	45.445303	-75.165596	2	1	18	20	20	10	80	0	131397
14480	3999	45.445574	-75.165168	2	1	28	20	10	10	80	0	131397
14481	4000	45.436682	-75.152416	0	12	21	30	30	4	63	0	122015
14482	4000	45.436978	-75.153278	0	12	31	30	20	4	63	0	122015
14483	4000	45.436983	-75.153240	0	12	41	30	10	4	63	0	122015

14484 rows × 12 columns

Label

```
[42] y
```

	Ligitimacy
0	1
1	1
2	1
3	1
4	1
...	...
14479	1
14480	1
14481	1
14482	1
14483	1

14484 rows × 1 columns

From the documentation of the dataset, we will see that there is data imbalance. The legitimate tasks have 12,578 row and the fake tasks have only 1,897 rows, so we will do oversampling to try to balance the data.

```
[43] ov = RandomOverSampler(sampling_strategy= 'minority')
     X_res, y_res = ov.fit_resample(x, y)
```

```
[44] X_res
```

	ID	Latitude	Longitude	Day	Hour	Minute	Duration	RemainingTime	Resources	Coverage	OnPeakHours	GridNumber
0	1	45.442142	-75.303369	1	4	13	40	40	9	91	0	131380
1	1	45.442154	-75.304366	1	4	23	40	30	9	91	0	131380
2	1	45.442104	-75.303963	1	4	33	40	20	9	91	0	121996
3	1	45.441868	-75.303577	1	4	43	40	10	9	91	0	121996
4	2	45.447727	-75.147722	2	15	49	30	30	5	47	0	140784
...	...	...	...	...	...	...	...	...	...	...	...	...
25169	2633	45.550732	-75.187319	4	11	31	50	30	10	91	0	309691
25170	1836	45.567417	-75.231940	1	8	56	50	20	1	56	1	347221
25171	2327	45.406017	-75.236216	5	11	2	40	40	10	30	0	65701
25172	1755	45.461136	-75.147407	0	12	36	60	50	7	76	0	159552
25173	1513	45.552153	-75.188054	0	20	3	60	60	8	94	0	319075

25174 rows × 12 columns

2. Splitting the dataset to train and test

```
[45] x_train, x_test, y_train, y_test = train_test_split(X_res, y_res, train_size = 0.8)
```

```
[46] x_train
```

	ID	Latitude	Longitude	Day	Hour	Minute	Duration	RemainingTime	Resources	Coverage	OnPeakHours	GridNumber
14717	3706	45.406574	-75.234980	0	16	0	60	60	8	53	0	65701
11932	3310	45.409624	-75.221576	2	3	29	40	30	6	44	0	75086
10063	2799	45.434667	-75.241940	1	2	40	60	30	4	47	0	112620
8106	2255	45.435958	-75.272037	0	19	20	40	10	3	79	0	112616
14417	3982	45.473836	-75.180982	2	5	38	50	20	7	63	0	178315
...	...	...	...	...	...	...	...	...	...	...	...	...
12297	3420	45.491785	-75.204770	5	10	32	60	20	3	95	1	215848
8570	2388	45.551339	-75.189458	0	12	13	20	20	10	68	0	319074
23516	2892	45.469613	-75.156274	3	17	1	40	10	6	63	0	178319
9722	2706	45.508950	-75.207398	0	12	34	40	30	10	77	0	244000
3922	1069	45.444158	-75.302739	1	11	56	40	10	1	49	0	131380

20139 rows × 12 columns

3. Apply models

Our first model is Random Forest

```
[47] RF_model = RandomForestClassifier(random_state=42)
     RF_model = RF_model.fit(x_train, y_train)
     y_pred_RF = RF_model.predict(x_test)
     y_pred_train_RF = RF_model.predict(x_train)
```

4. Prediction of Random Forest

```
[48] y_pred_RF

     array([1, 0, 0, ..., 0, 0, 0])
```

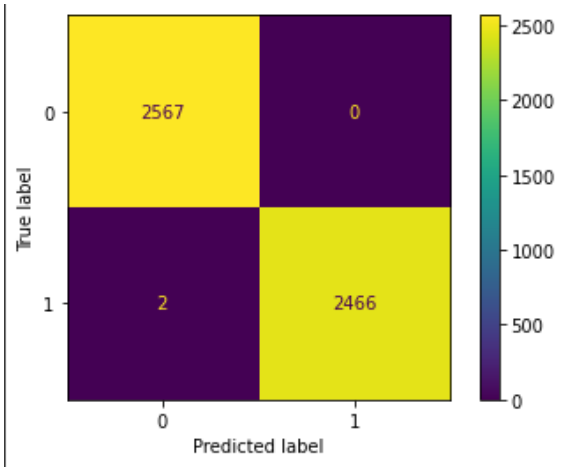
Classification Report for Random Forest

```
[49] print('\nClassification Report:\n')
     print(classification_report(y_test, y_pred_RF, target_names = ["Class 0", "legit Class 1"]))
     print('\nConfusion Matrix:\n')
     cm = confusion_matrix(y_test, y_pred_RF)
     print(cm)
     print('\nAccuracy Score:\n')
     RF_accuracy = accuracy_score(y_test, y_pred_RF)
     print(RF_accuracy)
     print('\Confusion Matrix Display:\n')
     print(ConfusionMatrixDisplay(cm).plot())
```

Classification Report

```
Classification Report:

              precision    recall  f1-score   support

     Class 0       1.00      1.00      1.00      2567
legit Class 1       1.00      1.00      1.00      2468

    accuracy                           1.00      5035
   macro avg       1.00      1.00      1.00      5035
weighted avg       1.00      1.00      1.00      5035


Confusion Matrix:

[[2567    0]
 [   2 2466]]

Accuracy Score:

0.9996027805362463
```

Confusion Matrix



Our second model is AdaBoost

```
[50] AD_model  = AdaBoostClassifier(n_estimators=100, random_state=42)
     AD_model = AD_model.fit(x_train, y_train)
     y_pred_AB = AD_model.predict(x_test)
     y_pred_train_AD = AD_model.predict(x_train)
```

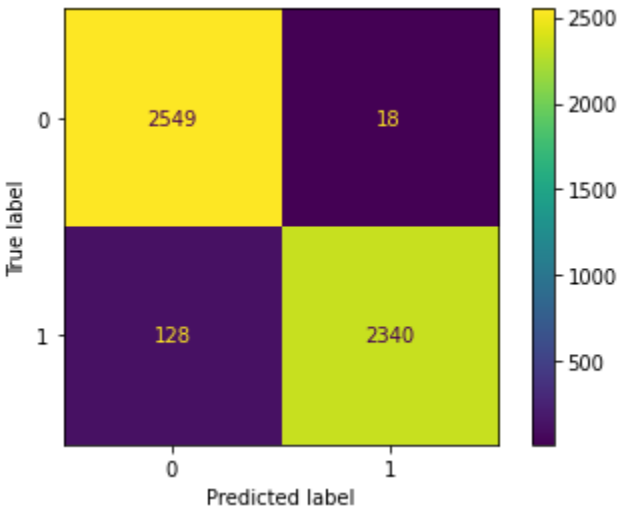
Prediction of Adaboost

```
[51] y_pred_AB

     array([1, 0, 0, ..., 0, 0, 0])
```

Classification Report for AdaBoost

```
Classification Report:

              precision    recall  f1-score   support

     Class 0       0.95      0.99      0.97      2567
legit Class 1      0.99      0.95      0.97      2468

    accuracy                           0.97      5035
   macro avg       0.97      0.97      0.97      5035
weighted avg       0.97      0.97      0.97      5035


Confusion Matrix:

[[2549   18]
 [ 128 2340]]

Accuracy Score:

0.9710029791459781
```

Confusion Matrix



Our third model is Naïve Bayes

```
[53] NB_model = GaussianNB()
     NB_model = NB_model.fit(x_train, y_train)
     y_pred_NB = NB_model.predict(x_test)
     y_pred_train_NB = NB_model.predict(x_train)
```

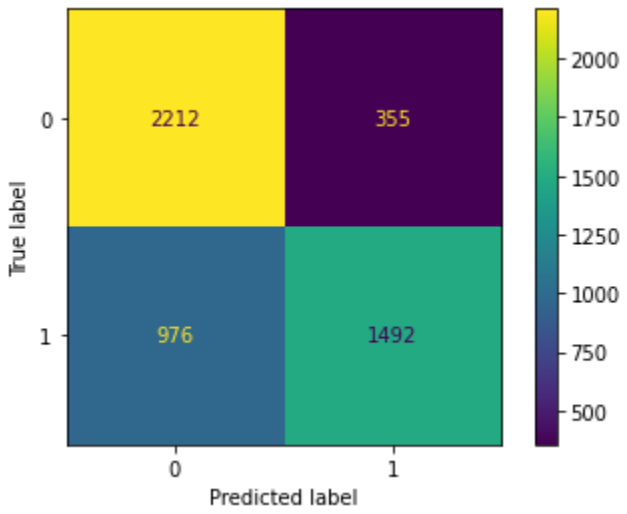
Prediction of Naïve Bayes

```
[54] y_pred_NB

     array([0, 0, 0, ..., 1, 1, 0])
```

Classification Report for Naïve Bayes

```
Classification Report:

              precision    recall  f1-score   support

     Class 0       0.69      0.86      0.77      2567
legit Class 1      0.81      0.60      0.69      2468

    accuracy                           0.74      5035
   macro avg       0.75      0.73      0.73      5035
weighted avg       0.75      0.74      0.73      5035


Confusion Matrix:

[[2212  355]
 [ 976 1492]]

Accuracy Score:

0.7356504468718967
```

Confusion Matrix



5. Voting Majority

We implemented a loop along the predictions of the three models to measure if at least two of them equal to 1, it will be 1 and 0 otherwise.

```
[57] y_majority = []

     for i in range(len(y_pred_RF)):
       if (y_pred_RF[i] + y_pred_AB[i] + y_pred_NB[i]) >= 2:
         y_majority.append(1)
       else:
         y_majority.append(0)

     len(y_majority)
```

Classification Report for voting majority

```
Classification Report:

              precision    recall  f1-score   support

     Class 0       0.96      0.99      0.98      2567
legit Class 1      0.99      0.96      0.98      2468

    accuracy                           0.98      5035
   macro avg       0.98      0.98      0.98      5035
weighted avg       0.98      0.98      0.98      5035


Accuracy Score:

0.9781529294935452
```

6. Equations

Sum of training accuracies

```
[59] x = accuracy_score(y_train, y_pred_train_RF)
     y = accuracy_score(y_train, y_pred_train_AD)
     z = accuracy_score(y_train, y_pred_train_NB)
     sum = x + y + z
```

Weights

```
[60] w_RF = x / sum
     w_AD = y / sum
     w_NB = z / sum
```

Predictions

```
[61] P_RF = y_pred_RF
     P_AB = y_pred_AB
     P_NB = y_pred_NB
```

Aggregated Output

```
[62] Agg_out = (P_RF * w_RF) + (P_AB * w_AD) + (P_NB * w_NB)

[63] Agg_out

     array([0.73128631, 0.        , 0.        , ..., 0.26871369, 0.26871369,
            0.        ])
```

Loop to apply the condition that the probability will be equal to 1 if aggregated output is larger than 0.5 and equal to 0 otherwise.

```
[64] Agg_binary = []

     for i in range(len(Agg_out)):
       if Agg_out[i] > 0.5:
         Agg_binary.append(1)
       else:
         Agg_binary.append(0)

     len(Agg_binary)
```

Classification Report for the aggregated output from equations.

```
Classification Report:

              precision    recall  f1-score   support

      Class 0       0.96      0.99      0.98      2567
legit Class 1       0.99      0.96      0.98      2468

     accuracy                           0.98      5035
    macro avg       0.98      0.98      0.98      5035
 weighted avg       0.98      0.98      0.98      5035


Accuracy Score:

0.9781529294935452
```

7. Comparing between the two ensemble frameworks

```
Classification Report:

              precision    recall  f1-score   support

      Class 0       1.00      1.00      1.00      2649
legit Class 1       1.00      1.00      1.00      2386

     accuracy                           1.00      5035
    macro avg       1.00      1.00      1.00      5035
 weighted avg       1.00      1.00      1.00      5035


Accuracy Score:

1.0
```

8. Plot the comparison between the accuracies of our models

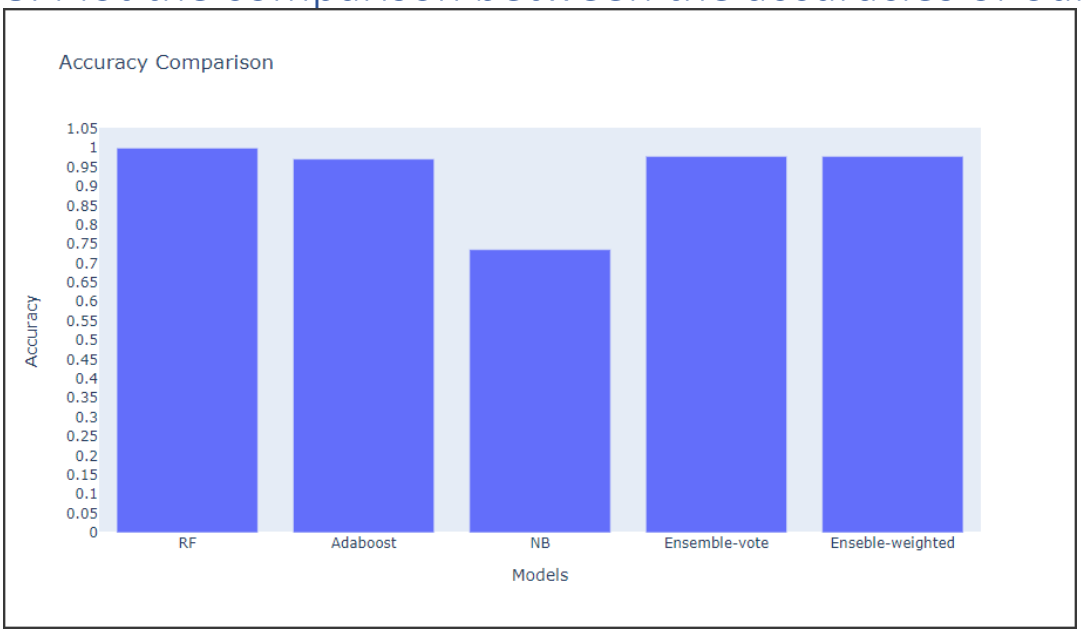


Table to compare the accuracies of all the models

Models	Accuracy
Random Forest	99.9
AdaBoost	97.1
Naïve Bayes	73.5
Majority Classifier	97.8
Aggregated Output	97.8

Conclusion

We ended up with that the random forest classifier is the best model to detect fake tasks based on its highest accuracy.

Code link

https://colab.research.google.com/drive/1IjaZublIFQtwAFnHMqVxAnbwHr4crOjz