machine learning lab homework 5

February 8, 2024

1 Machine Learning Lab HW 5

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3 02/08/2024

4 0.) Import the Credit Card Fraud Data From CCLE

[4]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

[5]:
```python
df = pd.read_csv("fraudTest.csv")
```

[6]:
```python
df.head()
```

[6]:
```
   Unnamed: 0 trans_date_trans_time            cc_num  \
0           0   2020-06-21 12:14:25  2291163933867244
1           1   2020-06-21 12:14:33  3573030041201292
2           2   2020-06-21 12:14:53  3598215285024754
3           3   2020-06-21 12:15:15  3591919803438423
4           4   2020-06-21 12:15:17  3526826139003047

                              merchant        category    amt   first  \
0                fraud_Kirlin and Sons   personal_care   2.86    Jeff
1                 fraud_Sporer-Keebler   personal_care  29.84  Joanne
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28  Ashley
3                    fraud_Haley Group        misc_pos  60.05   Brian
4                fraud_Johnston-Casper          travel   3.19  Nathan

       last gender                       street  …      lat      long  \
0   Elliott      M            351 Darlene Green  …  33.9659  -80.9355
1  Williams      F           3638 Marsh Union  …  40.3207 -110.4360
2     Lopez      F         9333 Valentine Point  …  40.6729  -73.5365
3  Williams      M  32941 Krystal Mill Apt. 552  …  28.5697  -80.8191
4    Massey      M     5783 Evan Roads Apt. 465  …  44.2529  -85.0170
```

```
   city_pop                      job         dob  \
0    333497      Mechanical engineer  1968-03-19
1       302  Sales professional, IT  1990-01-17
2     34496        Librarian, public  1970-10-21
3     54767             Set designer  1987-07-25
4      1126       Furniture designer  1955-07-06

                          trans_num   unix_time  merch_lat  merch_long  \
0  2da90c7d74bd46a0caf3777415b3ebd3  1371816865  33.986391  -81.200714
1  324cc204407e99f51b0d6ca0055005e7  1371816873  39.450498 -109.960431
2  c81755dbbbea9d5c77f094348a7579be  1371816893  40.495810  -74.196111
3  2159175b9efe66dc301f149d3d5abf8c  1371816915  28.812398  -80.883061
4  57ff021bd3f328f8738bb535c302a31b  1371816917  44.959148  -85.884734

   is_fraud
0         0
1         0
2         0
3         0
4         0

[5 rows x 23 columns]
```

[7]:
```python
df_select = df[["trans_date_trans_time", "category", "amt", "city_pop", "is_fraud"]]

df_select["trans_date_trans_time"] = pd.to_datetime(df_select["trans_date_trans_time"])
df_select["time_var"] = [i.second for i in df_select["trans_date_trans_time"]]

X = pd.get_dummies(df_select, ["category"]).drop(["trans_date_trans_time", "is_fraud"], axis = 1)
y = df["is_fraud"]
```

```
C:\Users\12282\AppData\Local\Temp\ipykernel_22492\2282180580.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_select["trans_date_trans_time"] =
pd.to_datetime(df_select["trans_date_trans_time"])
C:\Users\12282\AppData\Local\Temp\ipykernel_22492\2282180580.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_select["time_var"] = [i.second for i in df_select["trans_date_trans_time"]]
```

5 1.) Use scikit learn preprocessing to split the data into 70/30 in out of sample

[8]:
```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

[9]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = .3)
```

[10]:
```python
X_test, X_holdout, y_test, y_holdout = train_test_split(X_test, y_test,
 ↪test_size = .5)
```

[11]:
```python
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
X_holdout = scaler.transform(X_holdout)
```

6 2.) Make three sets of training data (Oversample, Undersample and SMOTE)

[12]:
```python
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import SMOTE
```

[13]:
```python
ros = RandomOverSampler()
over_X, over_y = ros.fit_resample(X_train, y_train)

rus = RandomUnderSampler()
under_X, under_y = rus.fit_resample(X_train, y_train)

smote = SMOTE()
smote_X, smote_y = smote.fit_resample(X_train, y_train)
```

7 3.) Train three logistic regression models

[14]:
```python
from sklearn.linear_model import LogisticRegression
```

[15]:
```python
over_log = LogisticRegression().fit(over_X, over_y)

under_log = LogisticRegression().fit(under_X, under_y)
```

```
smote_log = LogisticRegression().fit(smote_X, smote_y)
```

8 4.) Test the three models

[16]:
```
over_log.score(X_test, y_test)
```

[16]: 0.9271815542599391

[17]:
```
under_log.score(X_test, y_test)
```

[17]: 0.91931188368243

[18]:
```
smote_log.score(X_test, y_test)
```

[18]: 0.9233426905635932

[ ]:
```
# We see SMOTE performing with higher accuracy but is ACCURACY really the best␣
↪measure?
```

9 5.) Which performed best in Out of Sample metrics?

[19]:
```
# Sensitivity here in credit fraud is more important as seen from last class
```

[20]:
```
from sklearn.metrics import confusion_matrix
```

[69]:
```
y_true = y_test
```

[70]:
```
y_pred = over_log.predict(X_test)
cm = confusion_matrix(y_true, y_pred)
cm
```

[70]:
```
array([[77065,  5991],
       [   79,   223]], dtype=int64)
```

[71]:
```
print("Over Sample Sensitivity : ", cm[1,1] /(cm[1,0] + cm[1,1]))
```

```
Over Sample Sensitivity :  0.7384105960264901
```

[72]:
```
y_pred = under_log.predict(X_test)
cm = confusion_matrix(y_true, y_pred)
cm
```

[72]:
```
array([[76409,  6647],
       [   79,   223]], dtype=int64)
```

[73]:
```
print("Under Sample Sensitivity : ", cm[1,1] /(cm[1,0] + cm[1,1]))
```

```
Under Sample Sensitivity :  0.7384105960264901
```

[74]:
```
y_pred = smote_log.predict(X_test)
cm = confusion_matrix(y_true, y_pred)
cm
```

[74]:
```
array([[76745,  6311],
       [   79,   223]], dtype=int64)
```

[75]:
```
print("SMOTE Sample Sensitivity : ", cm[1,1] /(cm[1,0] + cm[1,1]))
```

```
SMOTE Sample Sensitivity :  0.7384105960264901
```

All three models performed equally well.

10 6.) Pick two features and plot the two classes before and after SMOTE.

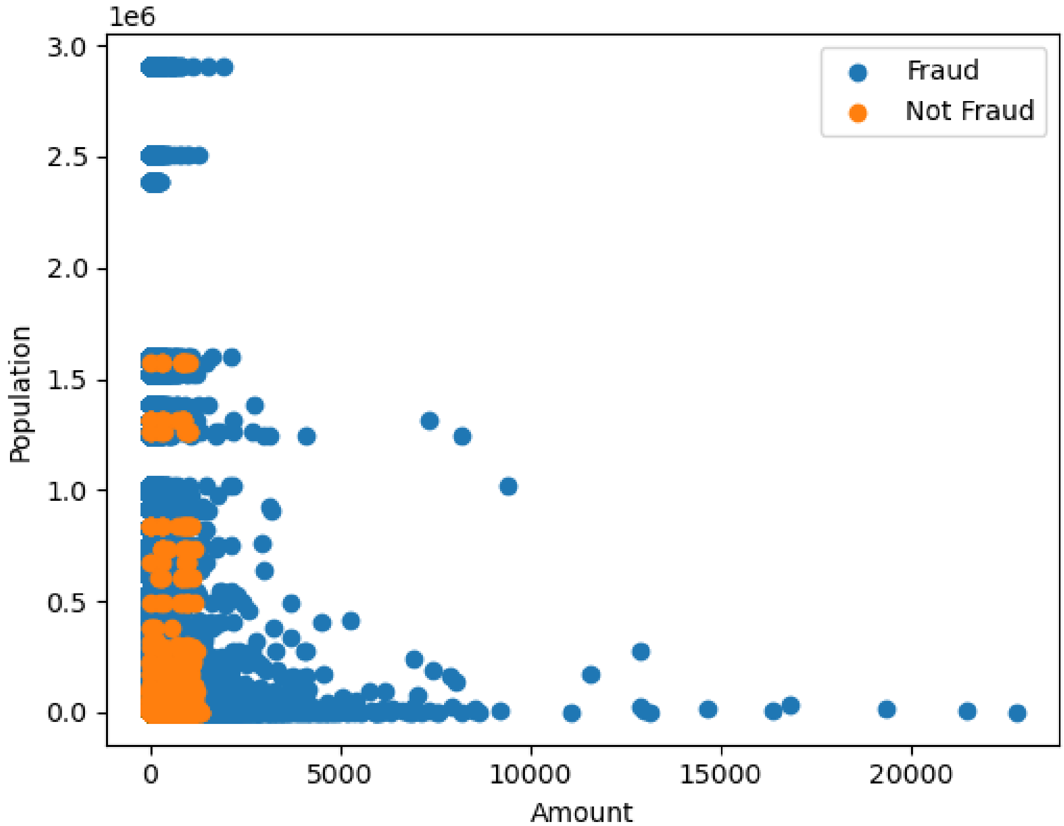
[40]:
```
X_train = pd.DataFrame(X_train)
y_train = pd.DataFrame(y_train)
raw_temp = pd.concat([X_train, y_train], axis = 1)
raw_temp
```

[40]:
```
               0         1         2         3         4         5        6  \
0      -0.141414 -0.289937  1.070757 -0.278376 -0.275988 -0.336219 -0.19051
1      -0.389317 -0.276441  0.897274 -0.278376 -0.275988 -0.336219 -0.19051
2       0.039317 -0.039814  1.244240 -0.278376 -0.275988 -0.336219 -0.19051
3      -0.060003 -0.293272  1.417723 -0.278376 -0.275988  2.974253 -0.19051
4       0.120301 -0.180632  0.608135  3.592267 -0.275988 -0.336219 -0.19051
…            …        …        …        …        …        …        …
501540       NaN       NaN       NaN       NaN       NaN       NaN      NaN
440489       NaN       NaN       NaN       NaN       NaN       NaN      NaN
534484       NaN       NaN       NaN       NaN       NaN       NaN      NaN
481131       NaN       NaN       NaN       NaN       NaN       NaN      NaN
438877       NaN       NaN       NaN       NaN       NaN       NaN      NaN

               7         8         9        10        11        12        13  \
0      -0.322955 -0.266147  3.094914 -0.310211 -0.226946 -0.257458 -0.275308
1      -0.322955  3.757324 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308
2       3.096403 -0.266147 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308
3      -0.322955 -0.266147 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308
4      -0.322955 -0.266147 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308
…            …        …        …        …        …        …        …
501540       NaN       NaN       NaN       NaN       NaN       NaN       NaN
440489       NaN       NaN       NaN       NaN       NaN       NaN       NaN
534484       NaN       NaN       NaN       NaN       NaN       NaN       NaN
481131       NaN       NaN       NaN       NaN       NaN       NaN       NaN
438877       NaN       NaN       NaN       NaN       NaN       NaN       NaN
```

```
            14        15        16  is_fraud
0      -0.284894 -0.314464 -0.17929       0.0
1      -0.284894 -0.314464 -0.17929       NaN
2      -0.284894 -0.314464 -0.17929       0.0
3      -0.284894 -0.314464 -0.17929       NaN
4      -0.284894 -0.314464 -0.17929       0.0
…            …         …        …         …
501540       NaN       NaN       NaN       0.0
440489       NaN       NaN       NaN       0.0
534484       NaN       NaN       NaN       0.0
481131       NaN       NaN       NaN       0.0
438877       NaN       NaN       NaN       0.0

[505381 rows x 18 columns]
```

[42]:

```python
# not sure if this is right
plt.scatter(df[df["is_fraud"] == 0]["amt"], df[df["is_fraud"] == 0]["city_pop"])
plt.scatter(df[df["is_fraud"] == 1]["amt"], df[df["is_fraud"] == 1]["city_pop"])
plt.legend(["Fraud", "Not Fraud"])
plt.xlabel("Amount")
plt.ylabel("Population")

plt.show()
```



[45]:
```
smote_X = pd.DataFrame(smote_X)
smote_y = pd.DataFrame(smote_y)
raw_temp = pd.concat([smote_X, smote_y], axis = 1)
raw_temp
```

[45]:

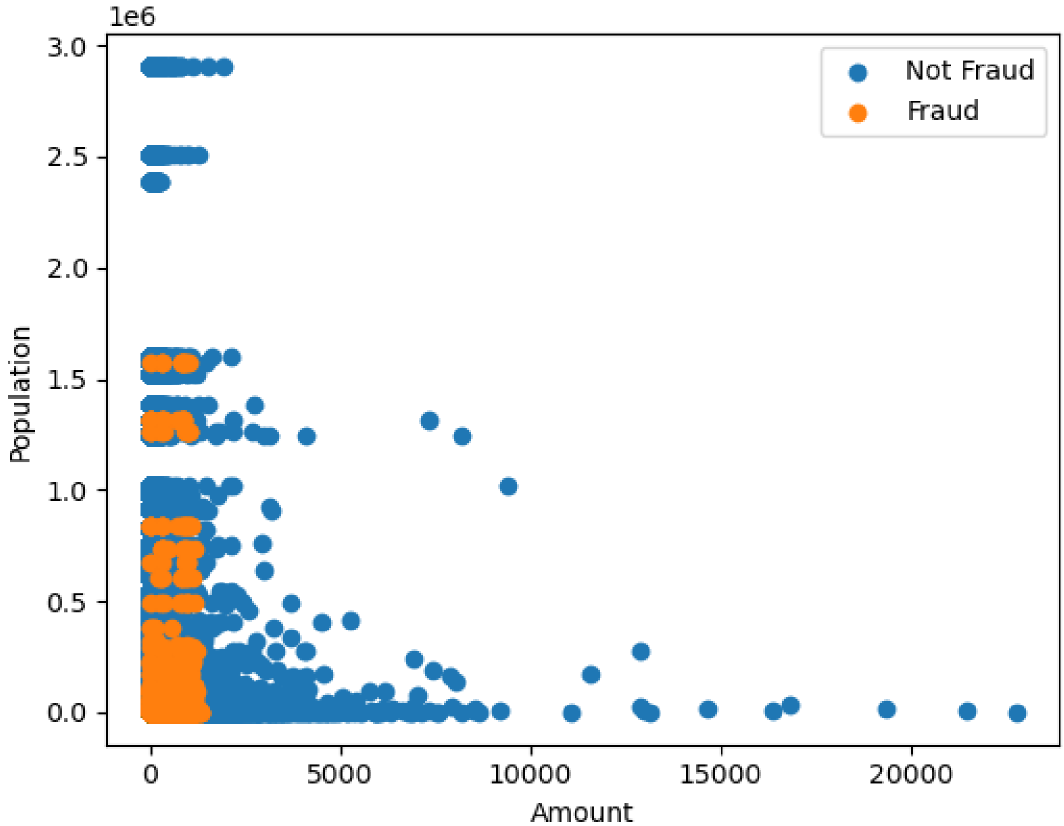
	0	1	2	3	4	5	6	\
0	-0.141414	-0.289937	1.070757	-0.278376	-0.275988	-0.336219	-0.190510	
1	-0.389317	-0.276441	0.897274	-0.278376	-0.275988	-0.336219	-0.190510	
2	0.039317	-0.039814	1.244240	-0.278376	-0.275988	-0.336219	-0.190510	
3	-0.060003	-0.293272	1.417723	-0.278376	-0.275988	2.974253	-0.190510	
4	0.120301	-0.180632	0.608135	3.592267	-0.275988	-0.336219	-0.190510	
…	…	…	…	…	…	…	…	
775013	2.928237	-0.289327	-0.192000	3.592267	-0.275988	-0.336219	-0.190510	
775014	-0.370246	-0.289225	-0.112553	-0.278376	-0.275988	-0.336219	5.249074	
775015	6.363394	0.002887	0.524250	-0.278376	-0.275988	-0.336219	-0.190510	
775016	5.009204	-0.074031	-0.873593	-0.278376	-0.275988	-0.336219	-0.190510	
775017	1.474739	-0.288638	-1.300180	-0.278376	-0.275988	-0.336219	-0.190510	

	7	8	9	10	11	12	13	\
0	-0.322955	-0.266147	3.094914	-0.310211	-0.226946	-0.257458	-0.275308	

```
1      -0.322955  3.757324 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308
2       3.096403 -0.266147 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308
3      -0.322955 -0.266147 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308
4      -0.322955 -0.266147 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308
…            …         …         …         …         …         …         …
775013 -0.322955 -0.266147 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308
775014 -0.322955 -0.266147 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308
775015 -0.322955 -0.266147 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308
775016 -0.322955 -0.266147 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308
775017  3.096403 -0.266147 -0.323111 -0.310211 -0.226946 -0.257458 -0.275308

              14        15       16  is_fraud
0      -0.284894 -0.314464 -0.17929         0
1      -0.284894 -0.314464 -0.17929         0
2      -0.284894 -0.314464 -0.17929         0
3      -0.284894 -0.314464 -0.17929         0
4      -0.284894 -0.314464 -0.17929         0
…            …         …       …         …
775013 -0.284894 -0.314464 -0.17929         1
775014 -0.284894 -0.314464 -0.17929         1
775015  3.510079 -0.314464 -0.17929         1
775016 -0.284894  3.180010 -0.17929         1
775017 -0.284894 -0.314464 -0.17929         1

[775018 rows x 18 columns]
```

[47]:

```
# not sure if this is right
plt.scatter(df[df["is_fraud"] == 0]["amt"], df[df["is_fraud"] == 0]["city_pop"])
plt.scatter(df[df["is_fraud"] == 1]["amt"], df[df["is_fraud"] == 1]["city_pop"])
plt.legend([ "Not Fraud", "Fraud"])
plt.xlabel("Amount")
plt.ylabel("Population")

plt.show()
```


1e6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Population
0
5000
10000
15000
20000
Amount
Not Fraud
Fraud

11 7.) We want to compare oversampling, undersampling and SMOTE across our 3 models (Logistic Regression, Logistic Regression Lasso and Decision Trees).

12 Make a dataframe that has a dual index and 9 Rows.

13 Calculate: Sensitivity, Specificity, Precision, Recall and F1 score for out of sample data.

14 Notice any patterns across perfomance for this model. Does one totally out perform the others i.e. over/under/smote or does a model perform better DT, Lasso, LR?

15 Choose what you think is the best model and why.

[50]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, precision_score, recall_score,␣
 ↪f1_score
import pandas as pd
```

[64]:
```
resampling_methods = {
    'over': RandomOverSampler(),
    'under': RandomUnderSampler(),
    'smote': SMOTE()
}

model_configs = {
    'LOG': LogisticRegression(),
    'LASSO': LogisticRegression(penalty = 'l1', C = 2, solver = 'liblinear'),
    'DTREE': DecisionTreeClassifier()
}
```

[65]:
```
# want to calculate a performance metric function
def calc_perf_metric(y_true, y_pred):
    tn, fp, fn, tp = confusion_matrix(y_true, y_pred).ravel()

    sensitivity = tp/(tp+fn)
    specificity = tn/(tn+fp)
    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)

    return(sensitivity, specificity, precision, recall, f1)
```

[66]:
```
trained_models = {}
results = []
```

[67]:
```
for resample_key, resampler in resampling_methods.items():
    resample_X, resample_y = resampler.fit_resample(X_train, y_train)

    for model_key, model in model_configs.items():
        combined_key = f'{resample_key}_{model_key}'

        m = model.fit(resample_X, resample_y)

        trained_models[combined_key] = m

        y_pred = m.predict(X_test)

        sensitivity, specificity, precision, recall, f1 =␣
↪calc_perf_metric(y_test, y_pred)

        results.append({'Model': combined_key,
                         'Sensitivity': sensitivity,
                        'Specificity': specificity,
                        'Precision': precision,
                        'Recall': recall,
                        'F1': f1})
        #####
        #results.append(calc_perf_metric(y_test, y_pred))
```

```
C:\Users\12282\anaconda3\Lib\site-packages\sklearn\utils\validation.py:1229:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
C:\Users\12282\anaconda3\Lib\site-packages\sklearn\utils\validation.py:1229:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
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C:\Users\12282\anaconda3\Lib\site-packages\sklearn\utils\validation.py:1229:
```

```
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
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  y = column_or_1d(y, warn=True)
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DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
```

[68]:

```
result_df = pd.DataFrame(results)
result_df
```

[68]:

	Model	Sensitivity	Specificity	Precision	Recall	F1
0	over_LOG	0.738411	0.927856	0.035881	0.738411	0.068436
1	over_LASSO	0.738411	0.927928	0.035916	0.738411	0.068499
2	over_DTREE	0.569536	0.998736	0.620939	0.569536	0.594128
3	under_LOG	0.738411	0.924713	0.034435	0.738411	0.065801
4	under_LASSO	0.738411	0.924172	0.034197	0.738411	0.065367
5	under_DTREE	0.953642	0.946048	0.060390	0.953642	0.113587
6	smote_LOG	0.738411	0.925014	0.034568	0.738411	0.066045
7	smote_LASSO	0.738411	0.925014	0.034568	0.738411	0.066045
8	smote_DTREE	0.692053	0.993402	0.276090	0.692053	0.394712

In the machine learning lecture, we were told that F1 is usually the best measure of the validity of a model, particularly when it comes to imbalanced datasets. With this in mind, it is important to note than the over_DTREE model has the best F1 score, and by a large margin. However, smote_DTREE has higher sensitivity and recall values. Because we are predicting whether or not a crdit card transaction is fraudulent or not, it is important to minimize the number of false negatives.

$$Recall = \frac{TP}{TP + FN}$$

With this in mind, I believe the best model is the one that maximizes recall, therefore minimizing the number of unreported fraudulent purchase (under_DTREE).