AML_HW3_Solutions_amp2365-4

March 23, 2024

0.1 Homework 3: Imbalanced Datasets

0.1.1 Submission Instructions:

1. Submit a PDF File on GradeScope:

- Please prepare your solutions neatly and compile them into a single PDF file.
- Submit this PDF file on GradeScope before the specified deadline.
- Ensure that your submission is clearly labeled with your UNI ID
- Ensure that your solutions are entirely original and free from any form of plagiarism.

2. Submit a .ipynb File + PDF File on Courseworks:

- Alongside the PDF submission on GradeScope, also submit your Notebook (.ipynb) file and its corresponding PDF version on the Courseworks platform.
- The Notebook should contain your code, explanations, and any additional details necessary for understanding your solutions.

Please try to name your soltution file in the following format - AML_HW3_Solutions_UNI

Dataset Location - The dataset you will be using for this assignment is called 'onlinefraud.csv'. You can find it in coursworks 'Files' section under the 'datasets' folder.

0.1.2 GIST:

The goal of this assignment is to build a model that can reliably classify online payments into two categories - fraudulent and non-fradulent. You will notice that, without much effort, you can build a model that gives you a very high 'accuracy' score for the given dataset. However, this metric is misleading since the model cannot correctly classify instances of the minority class ('1' in this case). This can be attributed to the inherent imbalance present in the target class of the dataset.

To solve this issue, you will need to employ certain ML techniques that are designed to counter class imbalance. Hence, the focus of this assignment will be towards addressing class imbalance and testing the model using different evaluation metrics other than just accuracy.

0.2 Name: Apurva Patel

0.3 UNI: amp2365

[2]:

```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[3]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

#Import below any other package you need for your solution
```

[4]:

```
!pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in
/usr/local/lib/python3.10/dist-packages (0.10.1)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-
packages (from imbalanced-learn) (1.25.2)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-
packages (from imbalanced-learn) (1.11.4)
Requirement already satisfied: scikit-learn>=1.0.2 in
/usr/local/lib/python3.10/dist-packages (from imbalanced-learn) (1.2.2)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-
packages (from imbalanced-learn) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from imbalanced-learn) (3.3.0)
```

[5]:

```
from sklearn.preprocessing import StandardScaler, OrdinalEncoder
# from category_encoders import OrdinalEncoder
```

[6]:

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
```

0.3.1 Data Exploration & Cleaning

- The dataset has been downloaded from Kaggle. You are encouraged to check this link to learn more about the dataset you are going to work with.
- *OPTIONAL* : By now, you should be comfortable with data cleaning. Employ all necessary techniques you feel would help improve your dataset. This includes handling missing values, outliers, datatype discrepancies, etc. Other 'preprocessing' techniques have been included later in the assignment. This part is just about cleaning your dataset (data-munging) and will not be graded.

[7]:

```
#import the dataset
```

[8]:

```
frauddf=pd.read_csv('/content/drive/MyDrive/AML_3/onlinefraud.csv')
```

[9]:

```
frauddf
```

[9]:

```
          step      type      amount     nameOrig  oldbalanceOrg  \
0            1   PAYMENT     9839.64  C1231006815      170136.00
1            1   PAYMENT     1864.28  C1666544295       21249.00
```

```
2           1  TRANSFER      181.00  C1305486145         181.00
3           1  CASH_OUT      181.00   C840083671         181.00
4           1   PAYMENT    11668.14  C2048537720       41554.00
…       …       …         …          …            …
6362615   743  CASH_OUT   339682.13   C786484425      339682.13
6362616   743  TRANSFER  6311409.28  C1529008245     6311409.28
6362617   743  CASH_OUT  6311409.28  C1162922333     6311409.28
6362618   743  TRANSFER   850002.52  C1685995037      850002.52
6362619   743  CASH_OUT   850002.52  C1280323807      850002.52

         newbalanceOrig     nameDest  oldbalanceDest  newbalanceDest  isFraud  \
0             160296.36  M1979787155            0.00            0.00        0
1              19384.72  M2044282225            0.00            0.00        0
2                  0.00   C553264065            0.00            0.00        1
3                  0.00    C38997010        21182.00            0.00        1
4              29885.86  M1230701703            0.00            0.00        0
…                 …          …             …             …      …
6362615            0.00   C776919290            0.00       339682.13        1
6362616            0.00  C1881841831            0.00            0.00        1
6362617            0.00  C1365125890        68488.84      6379898.11        1
6362618            0.00  C2080388513            0.00            0.00        1
6362619            0.00   C873221189      6510099.11      7360101.63        1

         isFlaggedFraud
0                     0
1                     0
2                     0
3                     0
4                     0
…                 …
6362615               0
6362616               0
6362617               0
6362618               0
6362619               0

[6362620 rows x 11 columns]
```

```
[10]: frauddf.head()
```

```
[10]:    step      type    amount     nameOrig  oldbalanceOrg  newbalanceOrig  \
      0     1   PAYMENT   9839.64  C1231006815       170136.0       160296.36
      1     1   PAYMENT   1864.28  C1666544295        21249.0        19384.72
      2     1  TRANSFER    181.00  C1305486145          181.0            0.00
      3     1  CASH_OUT    181.00   C840083671          181.0            0.00
      4     1   PAYMENT  11668.14  C2048537720        41554.0        29885.86
      nameDest  oldbalanceDest  newbalanceDest  isFraud  isFlaggedFraud
0  M1979787155             0.0             0.0        0               0
1  M2044282225             0.0             0.0        0               0
2   C553264065             0.0             0.0        1               0
3    C38997010         21182.0             0.0        1               0
4  M1230701703             0.0             0.0        0               0
```

[11]:

```
missing_values = frauddf.isnull().sum()

print("Missing values in each column:")
print(missing_values)
```

```
Missing values in each column:
step              0
type              0
amount            0
nameOrig          0
oldbalanceOrg     0
newbalanceOrig    0
nameDest          0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
isFlaggedFraud    0
dtype: int64
```

- There are no missing values in the dataset.

0.3.2 1. Examining Class Imbalance.

a. Identify the correct target column. A single line comment for the answer is sufficient.
b. Examine the class imbalance in the target column. What is its class distribution? Show this information visually using an appropriate scale.
c. What is the degree of imbalance? (Mild/Moderate/Extreme)

[12]:

```
frauddf.describe()
```

[12]:

```
               step        amount  oldbalanceOrg  newbalanceOrig  \
count  6.362620e+06  6.362620e+06   6.362620e+06    6.362620e+06
mean   2.433972e+02  1.798619e+05   8.338831e+05    8.551137e+05
std    1.423320e+02  6.038582e+05   2.888243e+06    2.924049e+06
min    1.000000e+00  0.000000e+00   0.000000e+00    0.000000e+00
25%    1.560000e+02  1.338957e+04   0.000000e+00    0.000000e+00
50%    2.390000e+02  7.487194e+04   1.420800e+04    0.000000e+00
75%    3.350000e+02  2.087215e+05   1.073152e+05    1.442584e+05
max    7.430000e+02  9.244552e+07   5.958504e+07    4.958504e+07

       oldbalanceDest  newbalanceDest       isFraud  isFlaggedFraud
```

```
count    6.362620e+06    6.362620e+06   6.362620e+06    6.362620e+06
mean     1.100702e+06    1.224996e+06   1.290820e-03    2.514687e-06
std      3.399180e+06    3.674129e+06   3.590480e-02    1.585775e-03
min      0.000000e+00    0.000000e+00   0.000000e+00    0.000000e+00
25%      0.000000e+00    0.000000e+00   0.000000e+00    0.000000e+00
50%      1.327057e+05    2.146614e+05   0.000000e+00    0.000000e+00
75%      9.430367e+05    1.111909e+06   0.000000e+00    0.000000e+00
max      3.560159e+08    3.561793e+08   1.000000e+00    1.000000e+00
```

[13]:
```
colnames = frauddf.columns
colnames
```

[13]:
```
Index(['step', 'type', 'amount', 'nameOrig', 'oldbalanceOrg', 'newbalanceOrig',
       'nameDest', 'oldbalanceDest', 'newbalanceDest', 'isFraud',
       'isFlaggedFraud'],
      dtype='object')
```

[14]:
```
frauddf['isFraud'].value_counts()
```

[14]:
```
0    6354407
1       8213
Name: isFraud, dtype: int64
```

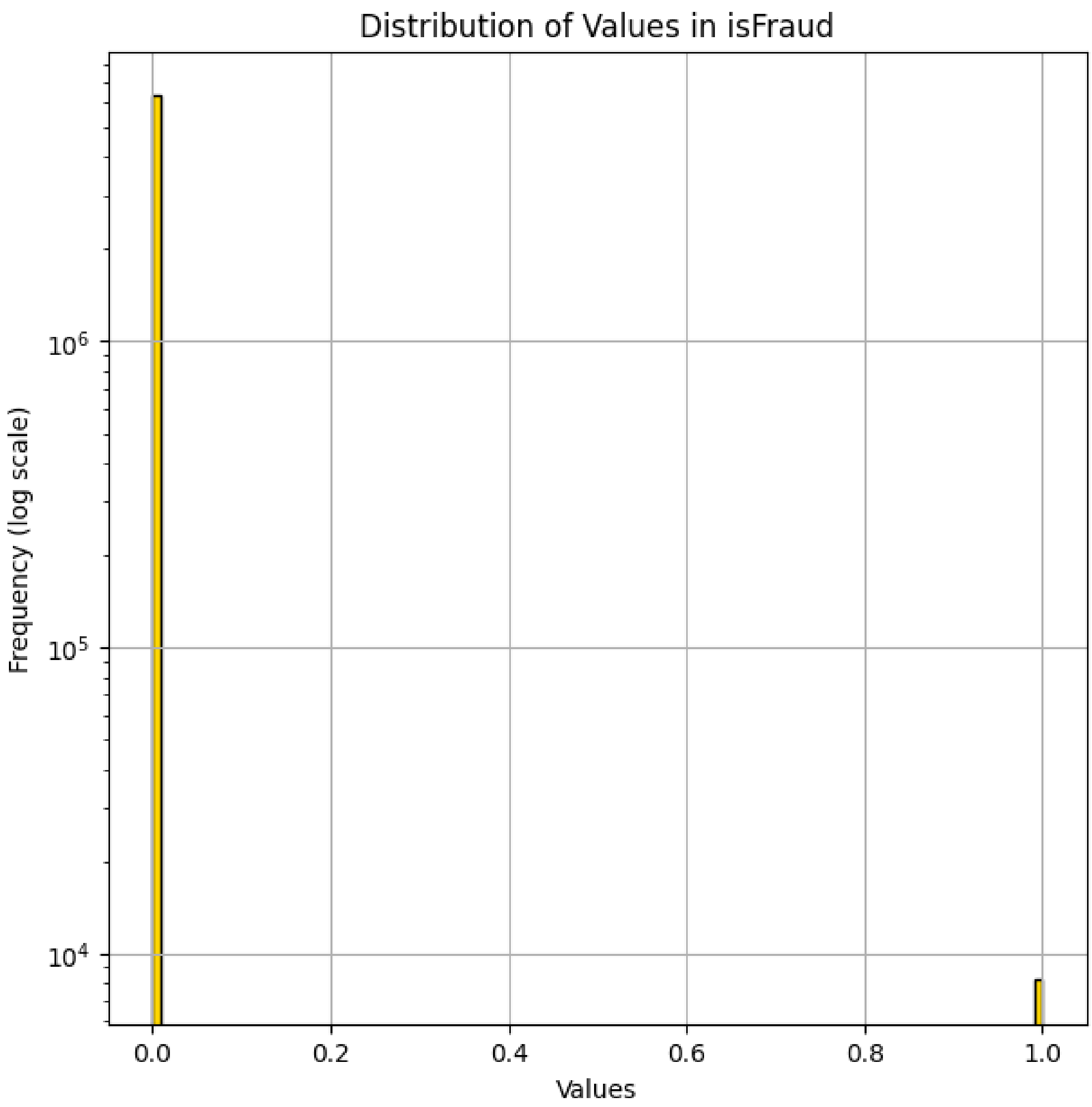
(a) I feel the correct target column is the column with name isFraud.

[15]:
```
print(f'Percentage of minority class: {(8213 / (8213 + 6354407)) * 100:.5f}%')
```

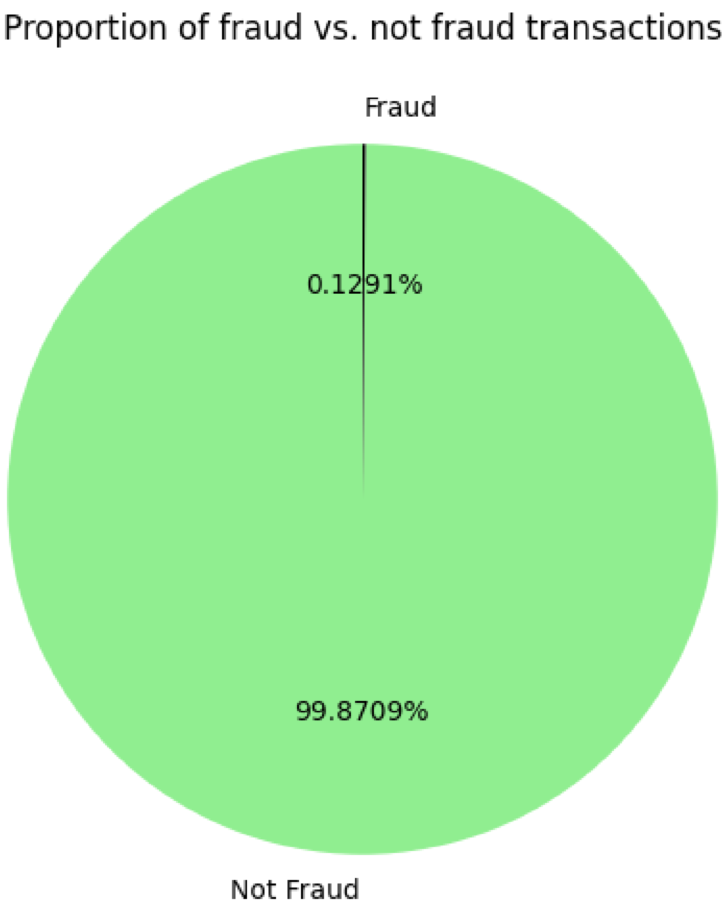
```
Percentage of minority class: 0.12908%
```

(b) Class Imbalance visualization using a logscale on y-axis

[16]:
```
#Your code here
coi = 'isFraud'

plt.figure(figsize=(7, 7))
plt.hist(frauddf[coi], bins=100, color='gold', edgecolor='black')

plt.yscale('log')

plt.xlabel('Values')
plt.ylabel('Frequency (log scale)')
plt.title('Distribution of Values in ' + coi)

plt.grid(True)


plt.show()
```



[17]:
```
fraudval = frauddf['isFraud'].value_counts()
labels = ['Not Fraud', 'Fraud']

plt.figure(figsize=(6, 6))
plt.pie(fraudval, labels=labels, autopct='%1.4f%%', colors=['lightgreen',␣
  ↪'black'], startangle=90)
plt.title('Proportion of fraud vs. not fraud transactions')
plt.show()
```



(b) Class imabalnce distribution in target column `isFraud`.

[18]:
```
#Your code here
noFraud, Fraud = np.bincount(frauddf['isFraud'])
total = noFraud + Fraud
print('Total: {}\nFraud detected: {} ({:.4f}% of total)\n'.format(
    total, Fraud, 100 * Fraud / total))
```

```
Total: 6362620
Fraud detected: 8213 (0.1291% of total)
```

(c) This is an extreme case of class imbalance with *0.1291%* being in minority class

[19]:
```
#Your code here
```

0.3.3 2. Pre-processing

a. Encode categorical columns, and scale numerical columns. Drop irrelevant features (if any).

b. How did you make this decision about whom to drop? Since there are only 10 features (other than the target column), should we consider including them all?
c. Split the dataset into development and test sets. What splitting methodology did you choose, and why?
d. Print the shape of the development and test set.

[20]:

```
#Your code here
for column_name in colnames:
    counts = frauddf[column_name].nunique()
    print(f"Unique values and their frequencies for column '{column_name}':")
    print(counts)
    print()
```

```
Unique values and their frequencies for column 'step':
743

Unique values and their frequencies for column 'type':
5

Unique values and their frequencies for column 'amount':
5316900

Unique values and their frequencies for column 'nameOrig':
6353307

Unique values and their frequencies for column 'oldbalanceOrg':
1845844

Unique values and their frequencies for column 'newbalanceOrig':
2682586

Unique values and their frequencies for column 'nameDest':
2722362

Unique values and their frequencies for column 'oldbalanceDest':
3614697

Unique values and their frequencies for column 'newbalanceDest':
3555499

Unique values and their frequencies for column 'isFraud':
2

Unique values and their frequencies for column 'isFlaggedFraud':
2
```

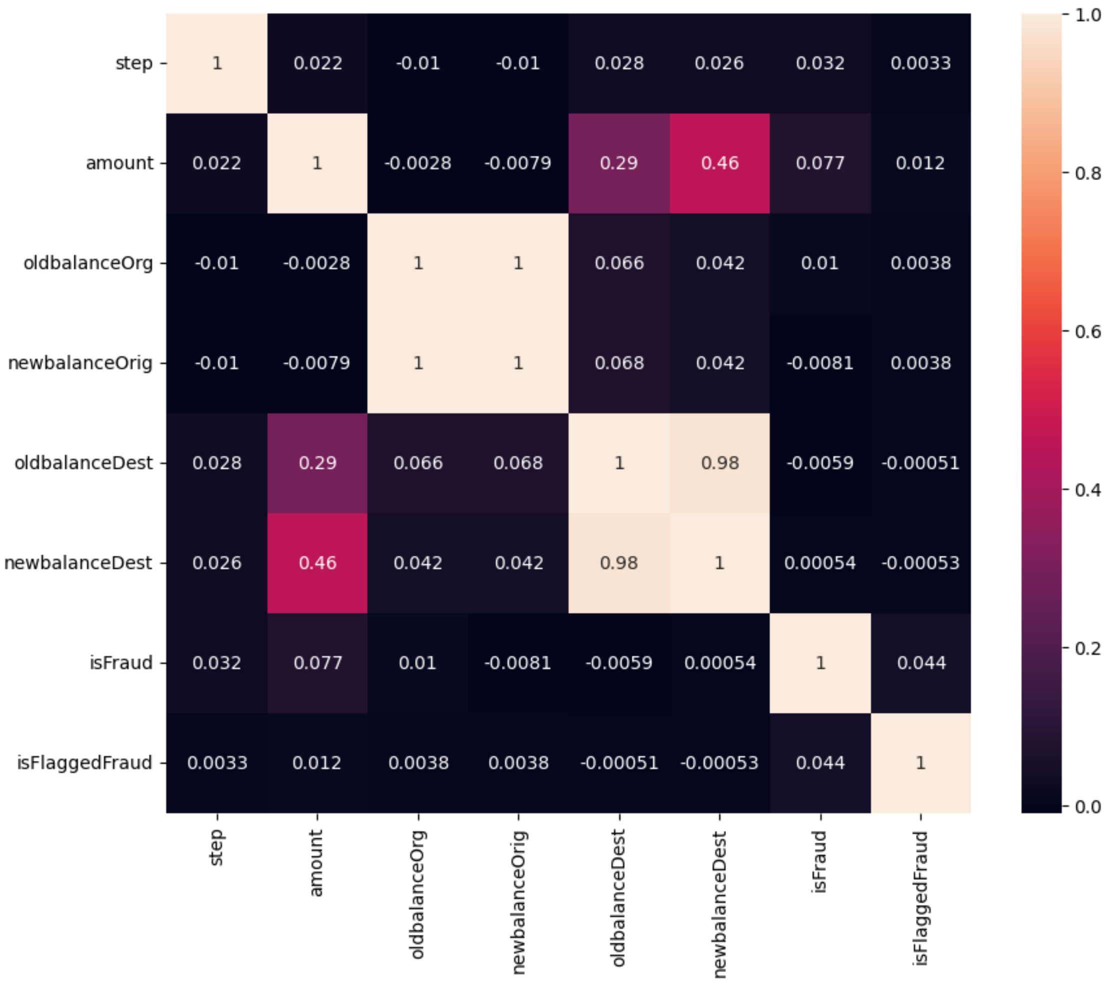
[21]:
```
#Your code here
frauddf.corr()
```

```
<ipython-input-21-2d8d4c304d50>:2: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  frauddf.corr()
```

[21]:
```
                    step    amount  oldbalanceOrg  newbalanceOrig  \
step            1.000000  0.022373      -0.010058       -0.010299
amount          0.022373  1.000000      -0.002762       -0.007861
oldbalanceOrg  -0.010058 -0.002762       1.000000        0.998803
newbalanceOrig -0.010299 -0.007861       0.998803        1.000000
oldbalanceDest  0.027665  0.294137       0.066243        0.067812
newbalanceDest  0.025888  0.459304       0.042029        0.041837
isFraud         0.031578  0.076688       0.010154       -0.008148
isFlaggedFraud  0.003277  0.012295       0.003835        0.003776

                oldbalanceDest  newbalanceDest   isFraud  isFlaggedFraud
step                  0.027665        0.025888  0.031578        0.003277
amount                0.294137        0.459304  0.076688        0.012295
oldbalanceOrg         0.066243        0.042029  0.010154        0.003835
newbalanceOrig        0.067812        0.041837 -0.008148        0.003776
oldbalanceDest        1.000000        0.976569 -0.005885       -0.000513
newbalanceDest        0.976569        1.000000  0.000535       -0.000529
isFraud              -0.005885        0.000535  1.000000        0.044109
isFlaggedFraud       -0.000513       -0.000529  0.044109        1.000000
```

[22]:
```
#Your code here
plt.figure(figsize=(10, 8))
ax = sns.heatmap(frauddf.corr(), annot=True)
plt.show()
```

```
<ipython-input-22-fdfeec9d38c7>:3: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  ax = sns.heatmap(frauddf.corr(), annot=True)
```



[23]:

```
#Your code here: Dropping nameOrigin and nameDestination columns as identifier␣
↪columns are irrelevant

frauddf_processed = frauddf.drop(columns=['nameOrig', 'nameDest',␣
↪'isFlaggedFraud'])

encoder = LabelEncoder()
frauddf_processed['type'] = encoder.fit_transform(frauddf_processed['type'])

scaler = StandardScaler()
numerical_columns = ['step', 'amount', 'oldbalanceOrg', 'newbalanceOrig',␣
↪'oldbalanceDest', 'newbalanceDest']
frauddf_processed[numerical_columns] = scaler.
↪fit_transform(frauddf_processed[numerical_columns])
```

(b) I dropped *isFlaggedFraud*, *nameOrig* and *nameDest* becasue those are indicator and identifier columns respectively and dont really matter if we include them in the model

training as they serve no purpose. Also the origin and destination of the transaction doesn't determine the nature of transaction and hence can be removed.

Less features doesn't necesasarily mean we should include them all. We want all the features for EDA but only the relevant features for the model training and selection which will not overfit the model.

[24]:

```
# splitting dev and test

X = frauddf_processed.drop(columns=['isFraud'])
y = frauddf_processed['isFraud']

X_dev, X_test, y_dev, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)
```

I used stratified splitting as this is a highly imbalanced dataset and we want to maintain the ratio of samples.

- Also inheritently this can be done using structured splitting with stratify as true to maintain the order of time asa given by ***step*** feature.

[25]:

```
print("Development set shape:", X_dev.shape, y_dev.shape)
print("Test set shape:", X_test.shape, y_test.shape)
```

```
Development set shape: (5090096, 7) (5090096,)
Test set shape: (1272524, 7) (1272524,)
```

0.3.4 3.1 Default Dataset

Use the Decision tree classifier (use max_depth=10 and random_state=42) model and print the AUC and Average Precision values of 5 Fold Cross Validation

[26]:

```
from sklearn.tree import DecisionTreeClassifier, plot_tree
```

[27]:

```
#Your Code Here
model = DecisionTreeClassifier(max_depth=10, criterion='entropy',␣
 ↪random_state=42)
model.fit(X_dev, y_dev)

print('Training performance: ', model.score(X_dev, y_dev))
print('Testing performance: ', model.score(X_test, y_test))
```

```
Training performance:  0.9996956835391709
Testing performance:  0.9996448004124088
```

[28]:

```
from sklearn.model_selection import cross_val_score, StratifiedKFold
from sklearn.metrics import roc_auc_score, average_precision_score
```

[29]:
```
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

auc_scores_default = cross_val_score(model, X_dev, y_dev, cv=cv,␣
 ↪scoring='roc_auc')
ap_scores_default = cross_val_score(model, X_dev, y_dev, cv=cv,␣
 ↪scoring='average_precision')
```

[30]:
```
print("AUC scores for each fold:", auc_scores_default)
print("AP scores for each fold:", ap_scores_default)

print("Average AUC:", np.mean(auc_scores_default))
print("Average AP:", np.mean(ap_scores_default))
```

```
AUC scores for each fold: [0.99451094 0.98727335 0.99019815 0.99585243
0.99190921]
AP scores for each fold: [0.87541948 0.83606963 0.85766722 0.87010247
0.85139786]
Average AUC: 0.991948815465746
Average AP: 0.8581313331353269
```

0.3.5 3.2 Balanced Weight

a. Here, we are going to use a ‘balanced’ decision tree clasifier on the same dataset. Use max_depth=10 and random_state=42, and then print the AUC and Average Precision values of 5 Fold Cross Validation.

[31]:
```
#Your Code Here
model_balanced = DecisionTreeClassifier(max_depth=10, random_state=42,␣
 ↪class_weight='balanced')
model_balanced.fit(X_dev, y_dev)
```

[31]:
```
DecisionTreeClassifier(class_weight='balanced', max_depth=10, random_state=42)
```

[32]:
```
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

auc_scores_balanced = cross_val_score(model_balanced, X_dev, y_dev, cv=cv,␣
 ↪scoring='roc_auc')
ap_scores_balanced = cross_val_score(model_balanced, X_dev, y_dev, cv=cv,␣
 ↪scoring='average_precision')
```

[33]:
```
print("AUC scores for each fold with balanced class weights:",␣
 ↪auc_scores_balanced)
print("AP scores for each fold with balanced class weights:",␣
 ↪ap_scores_balanced)

print("Average AUC with balanced class weights:", np.mean(auc_scores_balanced))
print("Average AP with balanced class weights:", np.mean(ap_scores_balanced))
```

```
AUC scores for each fold with balanced class weights: [0.99117479 0.98337159
0.99091018 0.99541539 0.98599213]
AP scores for each fold with balanced class weights: [0.8123268  0.7926297
0.76804995 0.79762453 0.80370554]
Average AUC with balanced class weights: 0.9893728148144187
Average AP with balanced class weights: 0.794867303636605
```

0.3.6 3.3 Random Oversampling**

a. Perform random oversampling on the development dataset. (Please set random state to 42 while doing this). Examine the target column again. What is its class distribution now? Print the shape of the development set.

b. Repear part 3.1 again. Use the Decision tree classifier (use max_depth=10 and random_state=42) model and print the AUC and Average Precision values of 5 Fold Cross Validation

[34]:

```python
import imblearn
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import SMOTE
```

[35]:

```python
#Your Code Here
ros = RandomOverSampler(random_state=42)
X_dev_os, y_dev_os = ros.fit_resample(X_dev, y_dev)

print('Dev set shape before Oversapmpling', X_dev.shape, y_dev.shape)
print('Dev set shape after Oversapmpling', X_dev_os.shape, y_dev_os.shape)
```

```
Dev set shape before Oversapmpling (5090096, 7) (5090096,)
Dev set shape after Oversapmpling (10167052, 7) (10167052,)
```

[36]:

```python
print('No of samples before OS in target: \n \n', y_dev.value_counts())
print('\n\n No of samples after OS in target: \n \n', y_dev_os.value_counts())
```

```
No of samples before OS in target:

 0    5083526
1       6570
Name: isFraud, dtype: int64


 No of samples after OS in target:

 0    5083526
1    5083526
Name: isFraud, dtype: int64
```

[37]:

```
model_os = DecisionTreeClassifier(max_depth=10, criterion='entropy',␣
 ↪random_state=42)
model_os.fit(X_dev_os, y_dev_os)

print('Training performance: ', model_os.score(X_dev_os, y_dev_os))
print('Testing performance: ', model_os.score(X_test, y_test))
```

```
Training performance:  0.9965978338657066
Testing performance:  0.9933164325387969
```

[38]:

```
#Your Code Here
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

auc_scores_os = cross_val_score(model_os, X_dev_os, y_dev_os, cv=cv,␣
 ↪scoring='roc_auc')
ap_scores_os = cross_val_score(model_os, X_dev_os, y_dev_os, cv=cv,␣
 ↪scoring='average_precision')
```

[39]:

```
print("AUC scores for each fold after OS:", auc_scores_os)
print("AP scores for each fold after OS:", ap_scores_os)

print("Average AUC after OS:", np.mean(auc_scores_os))
print("Average AP after OS:", np.mean(ap_scores_os))
```

```
AUC scores for each fold after OS: [0.99964644 0.99963077 0.99963044 0.99963454
0.99962974]
AP scores for each fold after OS: [0.99958381 0.99956136 0.99956076 0.99956333
0.99956096]
Average AUC after OS: 0.9996343850690332
Average AP after OS: 0.9995660442524503
```

0.3.7 3.4 Random Undersampling

a. Perform random undersampling on the development dataset. (Please set random state to 42 while doing this). Examine the target column again. What is its class distribution now? Print the shape of the development set.

b. Repear part 3.1 again. Use the Decision tree classifier (use max_depth=10 and random_state=42) model and print the AUC and Average Precision values of 5 Fold Cross Validation

[40]:

```
#Your Code Here
rus = RandomUnderSampler(random_state=42)
X_dev_us, y_dev_us = rus.fit_resample(X_dev, y_dev)

print('Dev set shape before Undersampling', X_dev.shape, y_dev.shape)
print('Dev set shape after Undersampling', X_dev_us.shape, y_dev_us.shape)
```

```
Dev set shape before Undersampling (5090096, 7) (5090096,)
Dev set shape after Undersampling (13140, 7) (13140,)
```

[41]:

```
print('No of samples before US in target: \n \n', y_dev.value_counts())
print('\n\n No of samples after US in target: \n \n', y_dev_us.value_counts())
```

```
No of samples before US in target:

 0    5083526
1       6570
Name: isFraud, dtype: int64


 No of samples after US in target:

 0    6570
1    6570
Name: isFraud, dtype: int64
```

[42]:

```
#Your Code Here
model_us = DecisionTreeClassifier(max_depth=10, criterion='entropy',␣
 ↪random_state=42)
model_us.fit(X_dev_us, y_dev_us)

print('Training performance: ', model_us.score(X_dev_us, y_dev_us))
print('Testing performance: ', model_us.score(X_test, y_test))
```

```
Training performance:  0.9975646879756469
Testing performance:  0.989853236559782
```

[43]:

```
#Your Code Here
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

auc_scores_us = cross_val_score(model_us, X_dev_us, y_dev_us, cv=cv,␣
 ↪scoring='roc_auc')
ap_scores_us = cross_val_score(model_us, X_dev_us, y_dev_us, cv=cv,␣
 ↪scoring='average_precision')
```

[44]:

```
print("AUC scores for each fold after US:", auc_scores_us)
print("AP scores for each fold after US:", ap_scores_us)

print("Average AUC after US:", np.mean(auc_scores_us))
print("Average AP after US:", np.mean(ap_scores_us))
```

```
AUC scores for each fold after US: [0.99352251 0.98769747 0.99603816 0.99376953
0.99297404]
AP scores for each fold after US: [0.98949547 0.98188489 0.9930825  0.99038334
0.9879989 ]
```

```
Average AUC after US: 0.9928003424078359
Average AP after US: 0.988569021346079
```

0.3.8 3.5 SMOTE

a. Perform Synthetic Minority Oversampling Technique (SMOTE) on the development dataset. (Please set random state to 42 while doing this). Examine the target column again. What is its class distribution now? Print the shape of the development set.

b. Repear part 3.1 again. Use the Decision tree classifier (use max_depth=10 and random_state=42) model and print the AUC and Average Precision values of 5 Fold Cross Validation

[45]:

```
#Your Code Here
smote = SMOTE(random_state=42)
X_dev_smote, y_dev_smote = smote.fit_resample(X_dev, y_dev)

print('Dev set shape before SMOTE', X_dev.shape, y_dev.shape)
print('Dev set shape after SMOTE', X_dev_smote.shape, y_dev_smote.shape)
```

```
Dev set shape before SMOTE (5090096, 7) (5090096,)
Dev set shape after SMOTE (10167052, 7) (10167052,)
```

[46]:

```
print('No of samples before US in target: \n \n', y_dev.value_counts())
print('\n\n No of samples after US in target: \n \n', y_dev_smote.
 ↪value_counts())
```

```
No of samples before US in target:

 0    5083526
1       6570
Name: isFraud, dtype: int64


 No of samples after US in target:

 0    5083526
1    5083526
Name: isFraud, dtype: int64
```

[47]:

```
#Your Code Here
model_smote = DecisionTreeClassifier(max_depth=10, criterion='entropy',␣
 ↪random_state=42)
model_smote.fit(X_dev_smote, y_dev_smote)

print('Training performance: ', model_smote.score(X_dev_smote, y_dev_smote))
print('Testing performance: ', model_smote.score(X_test, y_test))
```

```
Training performance:  0.9947540348962511
```

```
Testing performance:  0.9930280293338278
```

[48]:

```
#Your Code Here
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

auc_scores_smote = cross_val_score(model_smote, X_dev_smote, y_dev_smote,␣
 ↪cv=cv, scoring='roc_auc')
ap_scores_smote = cross_val_score(model_smote, X_dev_smote, y_dev_smote, cv=cv,␣
 ↪scoring='average_precision')
```

[49]:

```
print("AUC scores for each fold after SMOTE:", auc_scores_smote)
print("AP scores for each fold after SMOTE:", ap_scores_smote)

print("Average AUC after SMOTE:", np.mean(auc_scores_smote))
print("Average AP after SMOTE:", np.mean(ap_scores_smote))
```

```
AUC scores for each fold after SMOTE: [0.99958403 0.99957896 0.99957771
0.99957808 0.99957023]
AP scores for each fold after SMOTE: [0.99951825 0.99951117 0.99951148
0.99950789 0.99950576]
Average AUC after SMOTE: 0.9995778037298211
Average AP after SMOTE: 0.9995109124081033
```

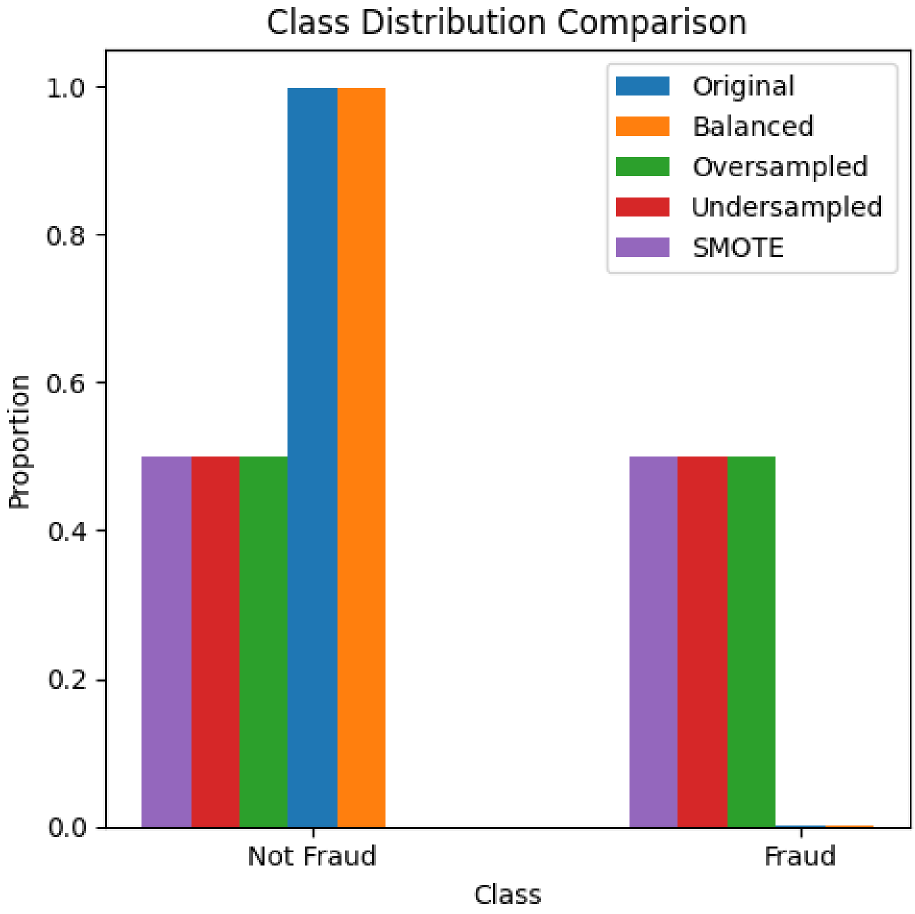
0.3.9 3.6 Visual Comparison

Prepare a plot comparing the class distribtion of the target column for each of the imbalance techiques used above. Use the default class split as well.

[50]:

```
#Your Code Here

class_distribution_original = y.value_counts(normalize=True)
class_distribution_balanced = y_dev.value_counts(normalize=True)
class_distribution_os = y_dev_os.value_counts(normalize=True)
class_distribution_us = y_dev_us.value_counts(normalize=True)
class_distribution_smote = y_dev_smote.value_counts(normalize=True)

bar_width = 0.1
index = np.arange(2)

plt.figure(figsize=(5, 5))
plt.bar(index, class_distribution_original.values, bar_width, alpha=1,␣
 ↪label='Original')
plt.bar(index + bar_width, class_distribution_balanced.values, bar_width,␣
 ↪alpha=1, label='Balanced')
plt.bar(index - bar_width, class_distribution_os.values, bar_width, alpha=1,␣
 ↪label='Oversampled')
plt.bar(index - 2*bar_width, class_distribution_us.values, bar_width, alpha=1,␣
 ↪label='Undersampled')
```

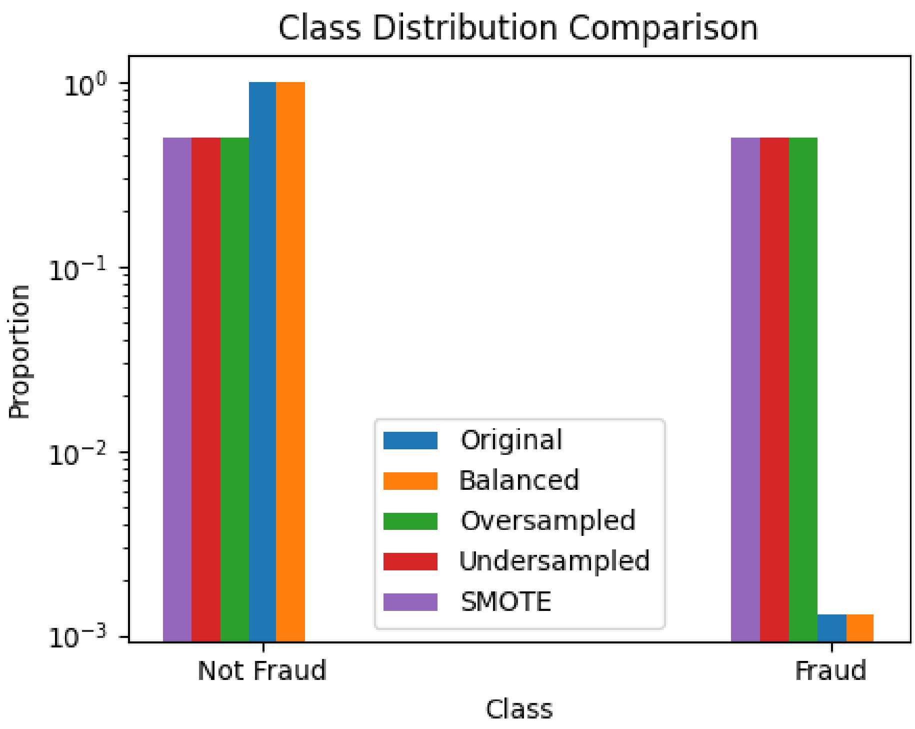
```
plt.bar(index - 3*bar_width, class_distribution_smote.values, bar_width,␣
 ↪alpha=1, label='SMOTE')

plt.xlabel('Class')
plt.ylabel('Proportion')
plt.title('Class Distribution Comparison')
plt.xticks(index, ['Not Fraud', 'Fraud'])
plt.legend()

plt.tight_layout()
plt.show()
```



[51]:

```
#Your Code Here

class_distribution_original = y.value_counts(normalize=True)
class_distribution_balanced = y_dev.value_counts(normalize=True)
class_distribution_os = y_dev_os.value_counts(normalize=True)
class_distribution_us = y_dev_us.value_counts(normalize=True)
```

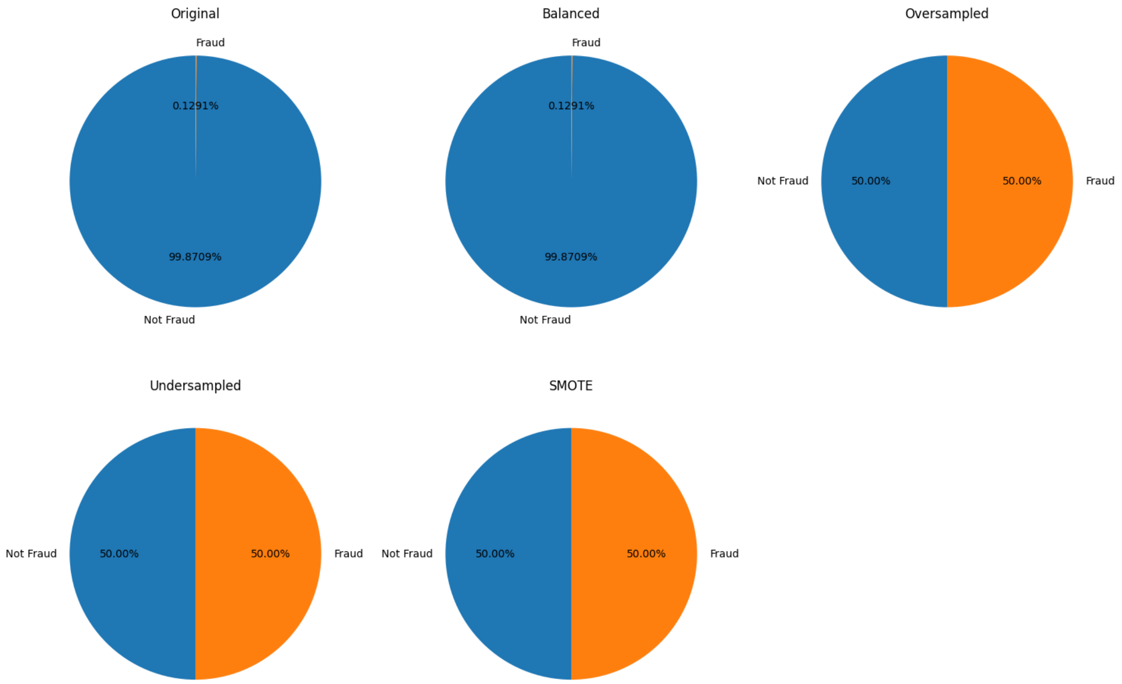
```
class_distribution_smote = y_dev_smote.value_counts(normalize=True)

bar_width = 0.05
index = np.arange(2)

plt.figure(figsize=(5, 4))
plt.bar(index, class_distribution_original.values, bar_width, alpha=1, label='Original')
plt.bar(index + bar_width, class_distribution_balanced.values, bar_width, alpha=1, label='Balanced')
plt.bar(index - bar_width, class_distribution_os.values, bar_width, alpha=1, label='Oversampled')
plt.bar(index - 2*bar_width, class_distribution_us.values, bar_width, alpha=1, label='Undersampled')
plt.bar(index - 3*bar_width, class_distribution_smote.values, bar_width, alpha=1, label='SMOTE')

plt.yscale('log')

plt.xlabel('Class')
plt.ylabel('Proportion')
plt.title('Class Distribution Comparison')
plt.xticks(index, ['Not Fraud', 'Fraud'])
plt.legend()
plt.tight_layout()
plt.show()
```



[52]:

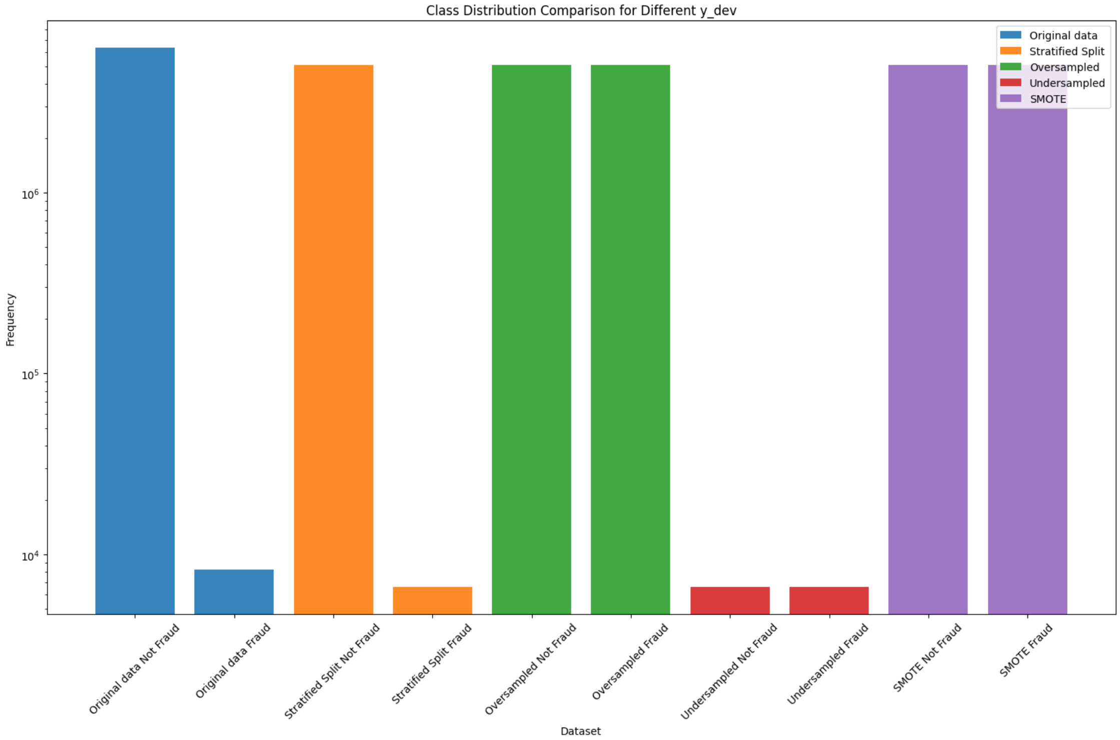
```python
labels = ['Not Fraud', 'Fraud']
original_sizes = class_distribution_original.values
balanced_sizes = class_distribution_balanced.values
os_sizes = class_distribution_os.values
us_sizes = class_distribution_us.values
smote_sizes = class_distribution_smote.values

fig, axs = plt.subplots(2, 3, figsize=(15, 10))

axs[0, 0].pie(original_sizes, labels=labels, autopct='%1.4f%%', startangle=90)
axs[0, 0].set_title('Original')

axs[0, 1].pie(balanced_sizes, labels=labels, autopct='%1.4f%%', startangle=90)
axs[0, 1].set_title('Balanced')

# OS
axs[0, 2].pie(os_sizes, labels=labels, autopct='%1.2f%%', startangle=90)
axs[0, 2].set_title('Oversampled')

# US
axs[1, 0].pie(us_sizes, labels=labels, autopct='%1.2f%%', startangle=90)
axs[1, 0].set_title('Undersampled')
```

```
# SMOTE
axs[1, 1].pie(smote_sizes, labels=labels, autopct='%1.2f%%', startangle=90)
axs[1, 1].set_title('SMOTE')

# hideing empty subplot
axs[1, 2].axis('off')

plt.tight_layout()
plt.show()
```



[53]:
```
# List of y_dev variables and their corresponding labels
y_dev_list = [y, y_dev, y_dev_os, y_dev_us, y_dev_smote]
labels = ['Original data', 'Stratified Split', 'Oversampled', 'Undersampled',␣
 ↪'SMOTE']

# Unpack value counts for each y_dev variable, taking only the first two values
class_counts = [(nf, f) for y_dev in y_dev_list for nf, f in [y_dev.
 ↪value_counts()[:2]]]

# Plot
plt.figure(figsize=(15, 10))

bars = []
```

```
legend_handles = []

for i, (nf, f) in enumerate(class_counts):
    bars.extend(plt.bar([f'{labels[i]} Not Fraud', f'{labels[i]} Fraud'], [nf,␣
 ↪f], alpha=0.9))
    legend_handles.append(bars[i])

plt.yscale('log')
plt.xticks(rotation=45)
plt.xlabel('Dataset')
plt.ylabel('Frequency')
plt.title('Class Distribution Comparison for Different y_dev')
plt.legend(labels)
plt.tight_layout()
plt.show()
```



0.3.10 4: Model Prediction & Evaluation - AUC Scores

4.1 Make predictions on the test set using the five models that you built and report their AUC values (Five models include models from - Default Baseline, Random Undersampling, Random Oversampling, SMOTE & Balanced Weight). Did the models with high AUC scores on the development set exhibit similar performance on the test set? Explain.

[54]:

```
from sklearn.metrics import roc_auc_score
```

AUC scores on DEV set

[55]:

```
print("Average AUC :", np.mean(auc_scores_default))
print("Average AUC (balanced weights):", np.mean(auc_scores_balanced))
print("Average AUC after OS:", np.mean(auc_scores_os))
print("Average AUC after US:", np.mean(auc_scores_us))
print("Average AUC after SMOTE:", np.mean(auc_scores_smote))
```

```
Average AUC : 0.991948815465746
Average AUC (balanced weights): 0.9893728148144187
Average AUC after OS: 0.9996343850690332
Average AUC after US: 0.9928003424078359
Average AUC after SMOTE: 0.9995778037298211
```

Making predictions on Test set

[56]:

```
from sklearn.metrics import roc_auc_score
```

[57]:

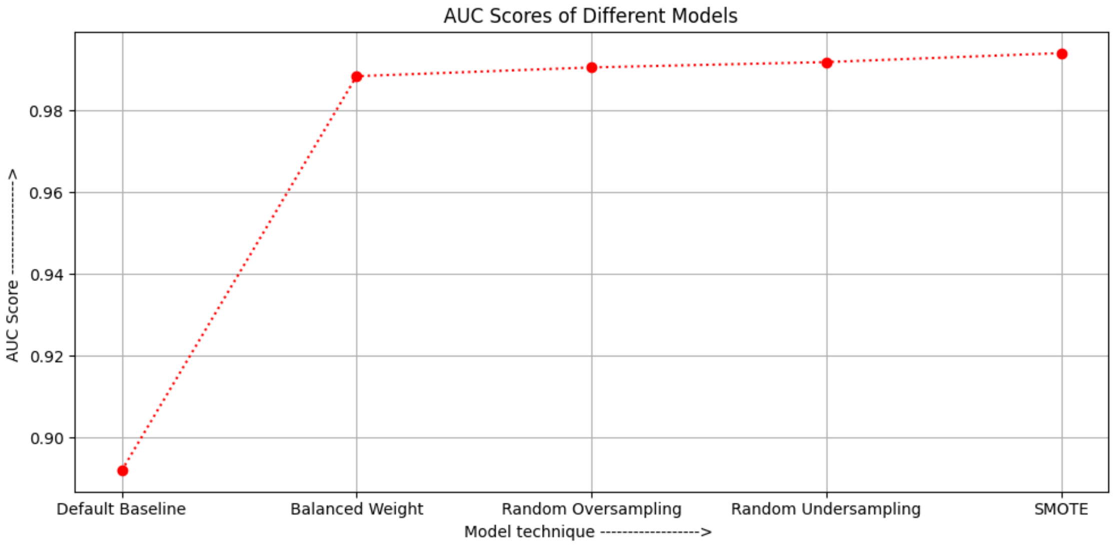
```
#Your Code Here

models = [model, model_balanced, model_os, model_us, model_smote]
model_names = ['Default Baseline', 'Balanced Weight', 'Random Oversampling',␣
 ↪'Random Undersampling', 'SMOTE']

auc_scores_test = {}

for model, name in zip(models, model_names):
    y_pred = model.predict(X_test)
    auc = roc_auc_score(y_test, y_pred)
    auc_scores_test[name] = auc

for name, auc in auc_scores_test.items():
    print(f"AUC for {name}: {auc:.4f}")
```

```
AUC for Default Baseline: 0.8919
AUC for Balanced Weight: 0.9884
AUC for Random Oversampling: 0.9906
AUC for Random Undersampling: 0.9919
AUC for SMOTE: 0.9941
```

[58]:

```
plt.figure(figsize=(10, 5))
plt.plot(model_names, auc_scores_test.values(), marker='o', linestyle='dotted',␣
 ↪color='r')
plt.xlabel('Model technique ------------------> ')

# plt.xticks(rotation=45)
```

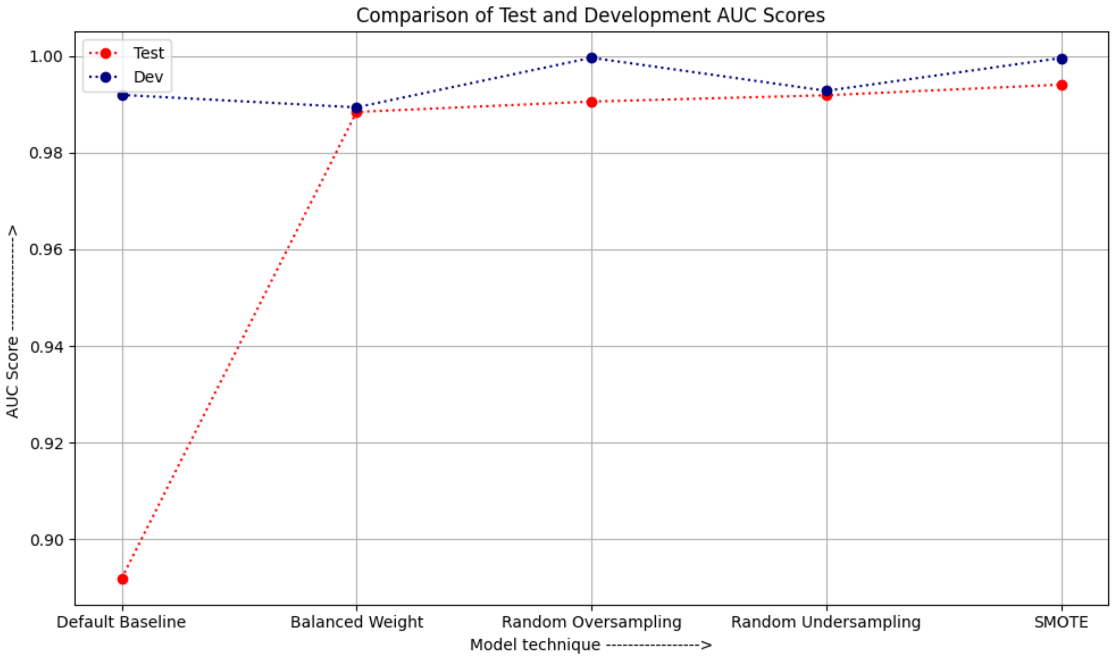
```
plt.ylabel('AUC Score -----------------> ')
plt.title('AUC Scores of Different Models')
plt.grid(True)
plt.tight_layout()
plt.show()
```



[59]:

```
dev_auc_scores = [np.mean(auc_scores_default), np.mean(auc_scores_balanced),
                  np.mean(auc_scores_os), np.mean(auc_scores_us), np.
 ↪mean(auc_scores_smote)]

test_auc_scores = [auc_scores_test['Default Baseline'],␣
 ↪auc_scores_test['Balanced Weight'],
                   auc_scores_test['Random Oversampling'],␣
 ↪auc_scores_test['Random Undersampling'], auc_scores_test['SMOTE']]

model_names = ['Default Baseline', 'Balanced Weight', 'Random Oversampling',␣
 ↪'Random Undersampling', 'SMOTE']

plt.figure(figsize=(10, 6))

plt.plot(model_names, test_auc_scores, marker='o', label='Test',␣
 ↪linestyle='dotted', color='red')
plt.plot(model_names, dev_auc_scores, marker='o',␣
 ↪label='Dev',linestyle='dotted',  color='navy')

plt.xlabel('Model technique ----------------->')
plt.ylabel('AUC Score -----------------> ')
plt.title('Comparison of Test and Development AUC Scores')
```

```python
# plt.xticks(rotation=45)

plt.legend()
plt.tight_layout()
plt.grid(True)
plt.show()
```



- **Yes the models with high AUC values performed higher on Test set except the default model where we used the minority class as it is.**
- **In my opinion this led to overfitting and the model couldn't generalize well on the test set when presented.**

0.3.11 4: Model Prediction & Evaluation - Confusion Matrix

4.2a.Plot Confusion Matrices for all the five models on the test set. Comment on your results and share in detail. Consider precision, recall and f1 scores. 4.2b. For the dataset at hand, which evaluation metric matters most according to you?

[60]:

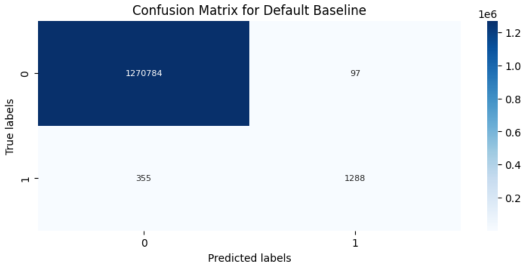
```python
from sklearn.metrics import confusion_matrix
import seaborn as sns
```

[61]:

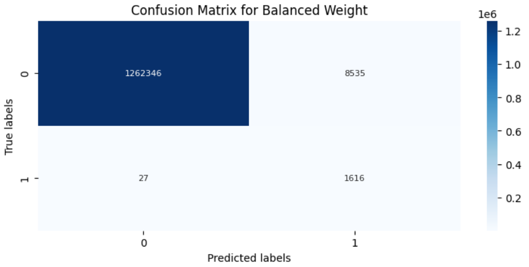
```python
def plot_confusion_matrix(y_true, y_pred, model_name, ax):
    cm = confusion_matrix(y_true, y_pred)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', annot_kws={"size": 8},␣
  ↪ax=ax)
```

```
    ax.set_xlabel('Predicted labels')
    ax.set_ylabel('True labels')
    ax.set_title(f'Confusion Matrix for {model_name}')
    ax.text(0, -0.5, f'\n\n Confusion Matrix: \n{cm}', fontsize=10, ha='left',␣
 ↪wrap=True)

fig, axes = plt.subplots(3, 2, figsize=(15, 15))
axes = axes.flatten()

for model, model_name, ax in zip(models, model_names, axes.flatten()):
    y_pred = model.predict(X_test)
    plot_confusion_matrix(y_test, y_pred, model_name, ax)

for ax in axes[len(model_names):]:
    ax.axis('off')

plt.tight_layout()
plt.show()
```

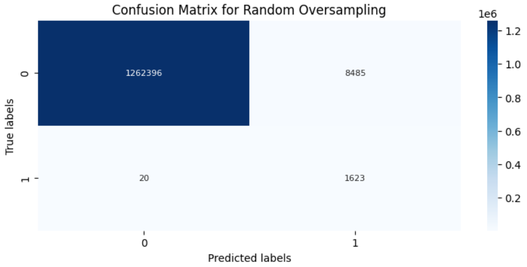
```
Confusion Matrix:
[[1270784      97]
 [    355    1288]]
```



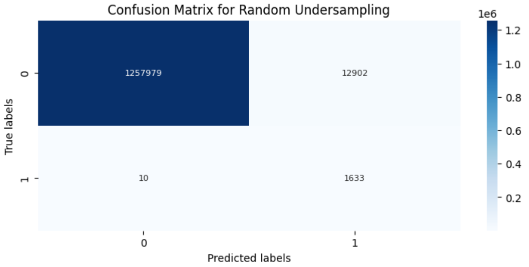
```
Confusion Matrix:
[[1262346    8535]
 [     27    1616]]
```



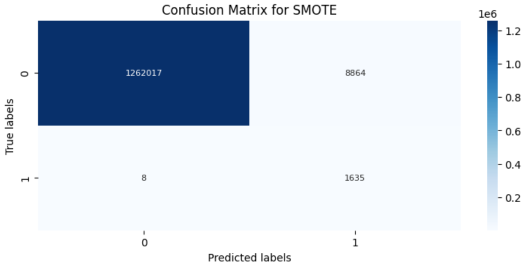
```
Confusion Matrix:
[[1262396    8485]
 [     20    1623]]
```



```
Confusion Matrix:
[[1257979   12902]
 [     10    1633]]
```



```
Confusion Matrix:
[[1262017    8864]
 [      8    1635]]
```



4.2 (b) - For the given dataset we have to choose precision as the coerrect measure of performance as we want the values of FP as high as possible and FN as low as possible. - We cannot afoord scenarios where its actually a fraud and it isnt classified as a fraud (FN). - Here the precision for SMOTE is the highest and Recall is highest for Undersampling. F1 score is the highest fro SMOTE. This happens because the number of FN is the lowest in Undersamplling case.

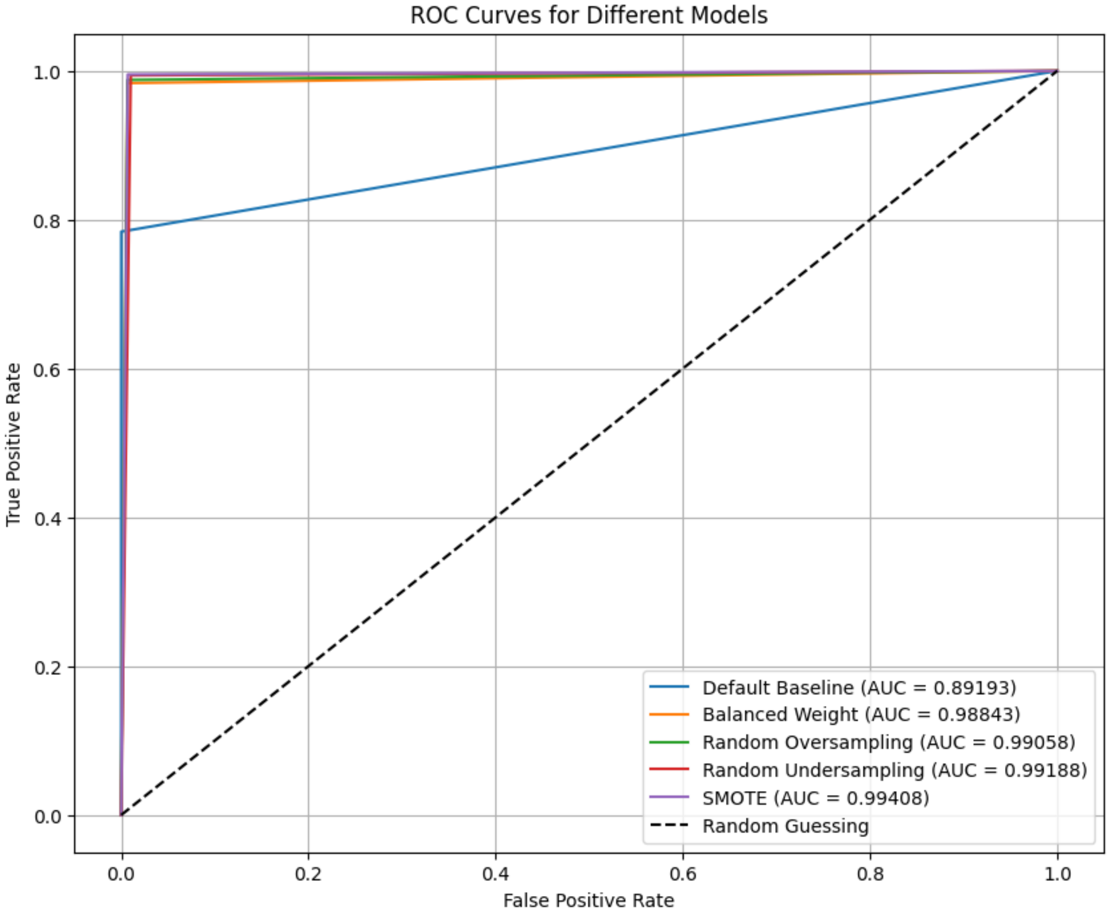
0.3.12 4: Model Prediction & Evaluation - ROC Curves

4.3 Plot ROC for all the five models on the test set in a single plot. Recomment which technique is most appropriate and why.

[62]:
```python
from sklearn.metrics import roc_curve
```

[63]:

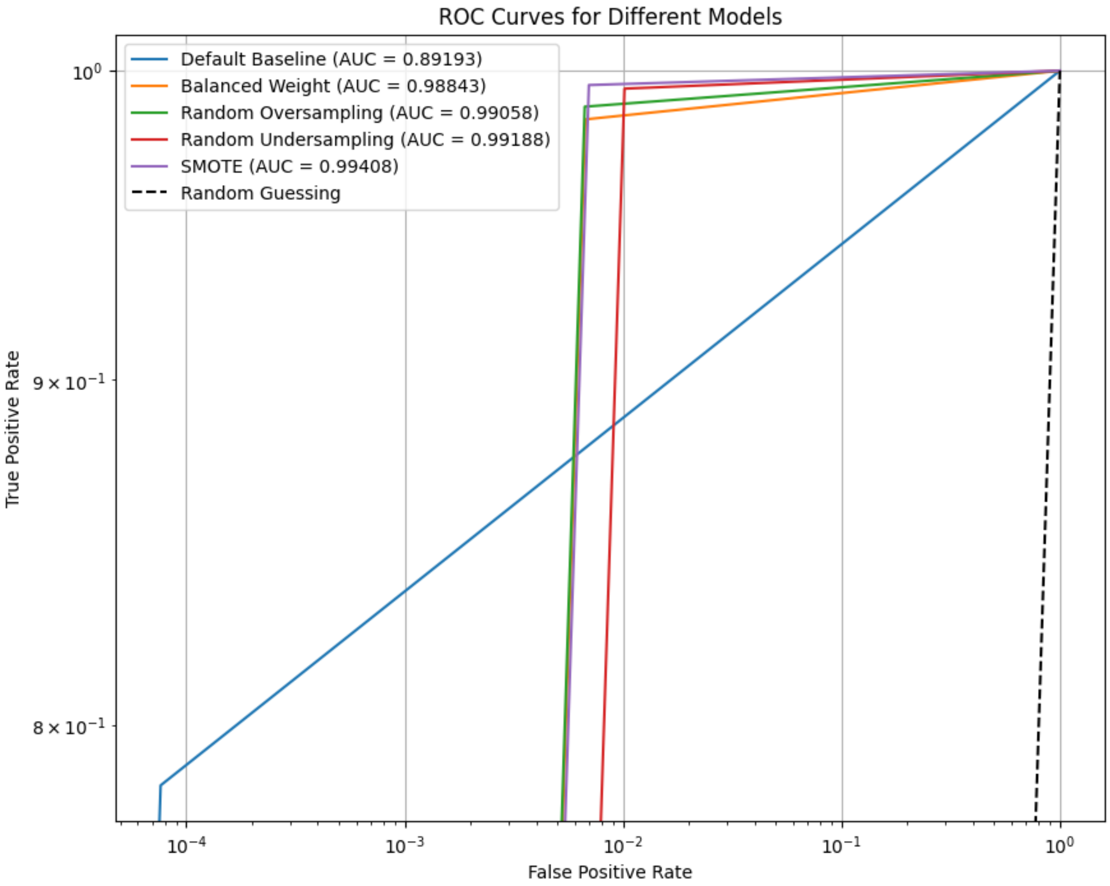
```python
plt.figure(figsize=(10, 8))

for model, model_name in zip(models, model_names):
    y_pred = model.predict(X_test)
    auc = roc_auc_score(y_test, y_pred)
    fpr, tpr, _ = roc_curve(y_test, y_pred)
    plt.plot(fpr, tpr, label=f'{model_name} (AUC = {auc:.5f})')

plt.plot([0, 1], [0, 1], 'k--', label='Random Guessing')

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Different Models')
plt.legend()
plt.grid(True)
plt.show()
```



- **After Plotting the ROC curves, it appears almost same and close to each other.**
- **To compare effectively I plotted it on a log scale to see the minor variations near**

the escalation point so as to understand which is better

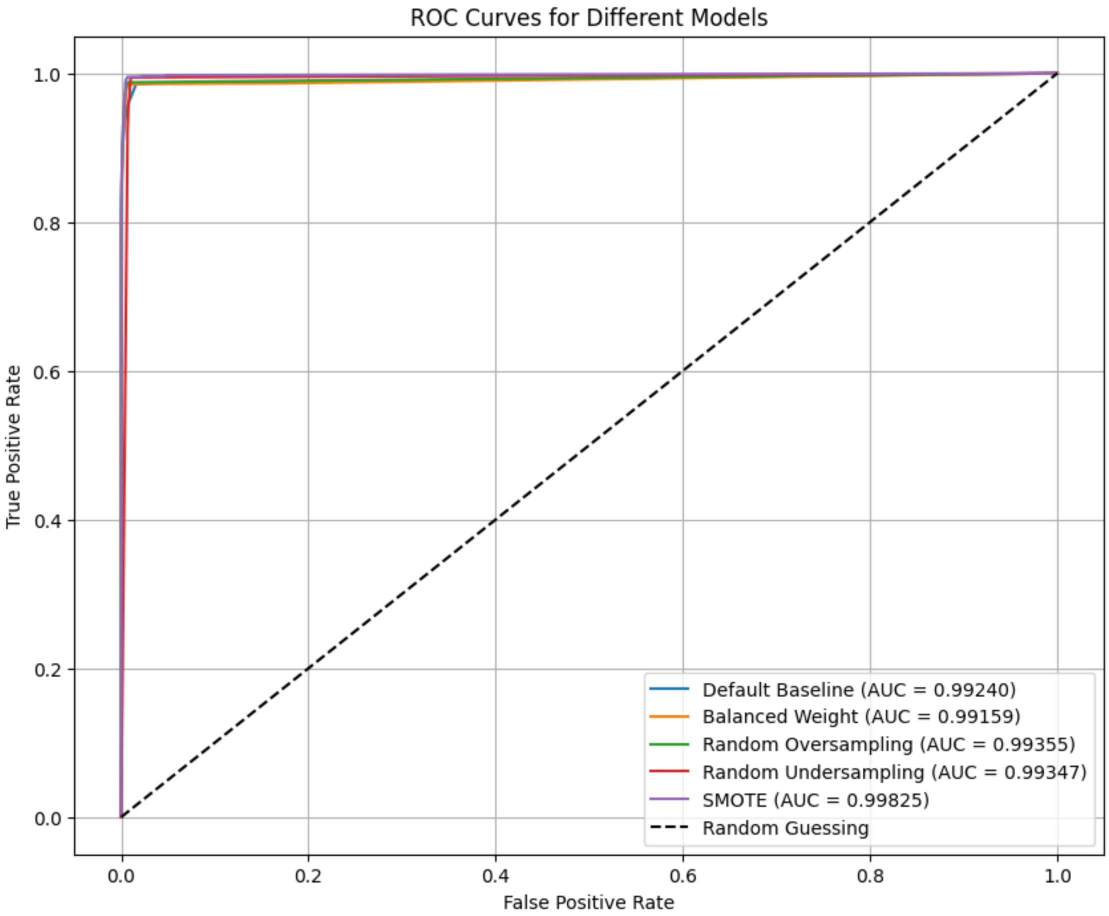
[64]:
```python
plt.figure(figsize=(10, 8))

for model, model_name in zip(models, model_names):
    y_pred = model.predict(X_test)
    auc = roc_auc_score(y_test, y_pred)
    fpr, tpr, _ = roc_curve(y_test, y_pred)
    plt.plot(fpr, tpr, label=f'{model_name} (AUC = {auc:.5f})')

plt.plot([0, 1], [0, 1], 'k--', label='Random Guessing')

plt.xscale('log')
plt.yscale('log')

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Different Models')
plt.legend()
plt.grid(True)
plt.show()
```



- **After comparong the ROC using the log scale, we clearly the technique where we used SMOTE has the maximum area under the curve (i.e. AUC value highest), so SMOTE is the most effective amongst all choices of method.**

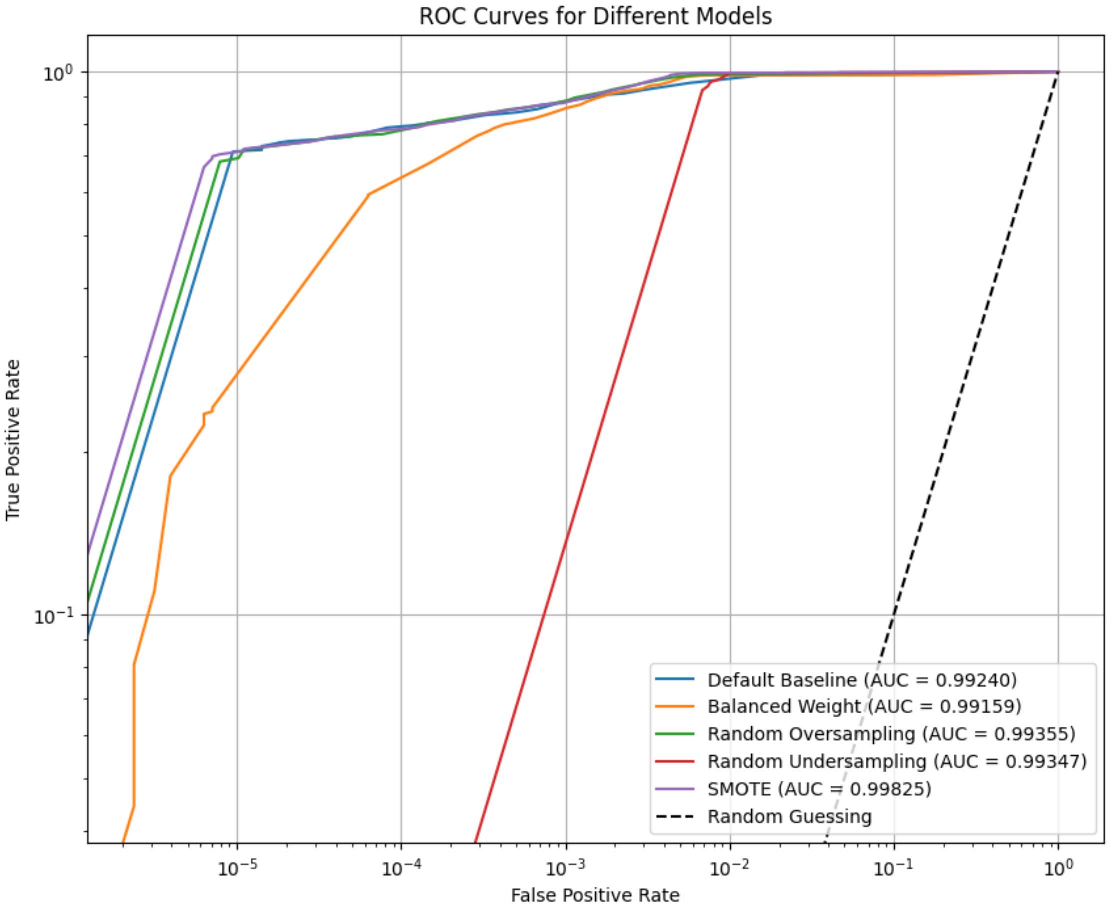
[65]:

```
#Your Code Here: Using predict_proba function

plt.figure(figsize=(10, 8))

for model, model_name in zip(models, model_names):
    y_pred_proba = model.predict_proba(X_test)[:, 1]
    fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
    auc = roc_auc_score(y_test, y_pred_proba)
    plt.plot(fpr, tpr, label=f'{model_name} (AUC = {auc:.5f})')

plt.plot([0, 1], [0, 1], 'k--', label='Random Guessing')

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Different Models')
plt.legend()
plt.grid(True)
plt.show()
```



[66]:

```
#Your Code Here

plt.figure(figsize=(10, 8))

for model, model_name in zip(models, model_names):
    y_pred_proba = model.predict_proba(X_test)[:, 1]
    fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
    auc = roc_auc_score(y_test, y_pred_proba)
    plt.plot(fpr, tpr, label=f'{model_name} (AUC = {auc:.5f})')

plt.plot([0, 1], [0, 1], 'k--', label='Random Guessing')

plt.xscale('log')
plt.yscale('log')

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Different Models')
plt.legend()
plt.grid(True)
plt.show()
```



[70]:

```
!jupyter nbconvert --to html /content/AML_HW3_Solutions_amp2365-3.ipynb
```

```
[NbConvertApp] Converting notebook /content/AML_HW3_Solutions_amp2365-3.ipynb to
html
[NbConvertApp] Writing 1874175 bytes to
/content/AML_HW3_Solutions_amp2365-3.html
```

[67]:

```
!apt-get install texlive texlive-xetex texlive-latex-extra pandoc

!pip install pypandoc
```

```
Reading package lists… Done
Building dependency tree… Done
Reading state information… Done
pandoc is already the newest version (2.9.2.1-3ubuntu2).
pandoc set to manually installed.
The following additional packages will be installed:
  dvisvgm fonts-droid-fallback fonts-lato fonts-lmodern fonts-noto-mono fonts-
texgyre
  fonts-urw-base35 libapache-pom-java libcommons-logging-java libcommons-parent-
java
  libfontbox-java libfontenc1 libgs9 libgs9-common libidn12 libijs-0.35
libjbig2dec0 libkpathsea6
  libpdfbox-java libptexenc1 libruby3.0 libsynctex2 libteckit0 libtexlua53
libtexluajit2 libwoff1
  libzzip-0-13 lmodern poppler-data preview-latex-style rake ruby ruby-net-
telnet ruby-rubygems
  ruby-webrick ruby-xmlrpc ruby3.0 rubygems-integration t1utils teckit tex-
common tex-gyre
  texlive-base texlive-binaries texlive-fonts-recommended texlive-latex-base
  texlive-latex-recommended texlive-pictures texlive-plain-generic tipa xfonts-
encodings
  xfonts-utils
Suggested packages:
  fonts-noto fonts-freefont-otf | fonts-freefont-ttf libavalon-framework-java
  libcommons-logging-java-doc libexcalibur-logkit-java liblog4j1.2-java poppler-
utils ghostscript
  fonts-japanese-mincho | fonts-ipafont-mincho fonts-japanese-gothic | fonts-
ipafont-gothic
  fonts-arphic-ukai fonts-arphic-uming fonts-nanum ri ruby-dev bundler debhelper
gv
  | postscript-viewer perl-tk xpdf | pdf-viewer xzdec texlive-fonts-recommended-
doc
  texlive-latex-base-doc python3-pygments icc-profiles libfile-which-perl
  libspreadsheet-parseexcel-perl texlive-latex-extra-doc texlive-latex-
recommended-doc
  texlive-luatex texlive-pstricks dot2tex prerex texlive-pictures-doc vprerex
default-jre-headless
  tipa-doc
The following NEW packages will be installed:
  dvisvgm fonts-droid-fallback fonts-lato fonts-lmodern fonts-noto-mono fonts-
texgyre
  fonts-urw-base35 libapache-pom-java libcommons-logging-java libcommons-parent-
java
  libfontbox-java libfontenc1 libgs9 libgs9-common libidn12 libijs-0.35
libjbig2dec0 libkpathsea6
  libpdfbox-java libptexenc1 libruby3.0 libsynctex2 libteckit0 libtexlua53
libtexluajit2 libwoff1
  libzzip-0-13 lmodern poppler-data preview-latex-style rake ruby ruby-net-
telnet ruby-rubygems
  ruby-webrick ruby-xmlrpc ruby3.0 rubygems-integration t1utils teckit tex-
common tex-gyre texlive
  texlive-base texlive-binaries texlive-fonts-recommended texlive-latex-base
```

```
texlive-latex-extra
  texlive-latex-recommended texlive-pictures texlive-plain-generic texlive-xetex
tipa
  xfonts-encodings xfonts-utils
0 upgraded, 55 newly installed, 0 to remove and 39 not upgraded.
Need to get 182 MB of archives.
After this operation, 572 MB of additional disk space will be used.
Get:1 http://archive.ubuntu.com/ubuntu jammy/main amd64 fonts-droid-fallback all
1:6.0.1r16-1.1build1 [1,805 kB]
Get:2 http://archive.ubuntu.com/ubuntu jammy/main amd64 fonts-lato all 2.0-2.1
[2,696 kB]
Get:3 http://archive.ubuntu.com/ubuntu jammy/main amd64 poppler-data all
0.4.11-1 [2,171 kB]
Get:4 http://archive.ubuntu.com/ubuntu jammy/universe amd64 tex-common all 6.17
[33.7 kB]
Get:5 http://archive.ubuntu.com/ubuntu jammy/main amd64 fonts-urw-base35 all
20200910-1 [6,367 kB]
Get:6 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libgs9-common
all 9.55.0~dfsg1-0ubuntu5.6 [751 kB]
Get:7 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libidn12 amd64
1.38-4ubuntu1 [60.0 kB]
Get:8 http://archive.ubuntu.com/ubuntu jammy/main amd64 libijs-0.35 amd64
0.35-15build2 [16.5 kB]
Get:9 http://archive.ubuntu.com/ubuntu jammy/main amd64 libjbig2dec0 amd64
0.19-3build2 [64.7 kB]
Get:10 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libgs9 amd64
9.55.0~dfsg1-0ubuntu5.6 [5,031 kB]
Get:11 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libkpathsea6
amd64 2021.20210626.59705-1ubuntu0.2 [60.4 kB]
Get:12 http://archive.ubuntu.com/ubuntu jammy/main amd64 libwoff1 amd64
1.0.2-1build4 [45.2 kB]
Get:13 http://archive.ubuntu.com/ubuntu jammy/universe amd64 dvisvgm amd64
2.13.1-1 [1,221 kB]
Get:14 http://archive.ubuntu.com/ubuntu jammy/universe amd64 fonts-lmodern all
2.004.5-6.1 [4,532 kB]
Get:15 http://archive.ubuntu.com/ubuntu jammy/main amd64 fonts-noto-mono all
20201225-1build1 [397 kB]
Get:16 http://archive.ubuntu.com/ubuntu jammy/universe amd64 fonts-texgyre all
20180621-3.1 [10.2 MB]
Get:17 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libapache-pom-java
all 18-1 [4,720 B]
Get:18 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libcommons-parent-
java all 43-1 [10.8 kB]
Get:19 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libcommons-logging-
java all 1.2-2 [60.3 kB]
Get:20 http://archive.ubuntu.com/ubuntu jammy/main amd64 libfontenc1 amd64
1:1.1.4-1build3 [14.7 kB]
Get:21 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libptexenc1
```

```
amd64 2021.20210626.59705-1ubuntu0.2 [39.1 kB]
Get:22 http://archive.ubuntu.com/ubuntu jammy/main amd64 rubygems-integration
all 1.18 [5,336 B]
Get:23 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 ruby3.0 amd64
3.0.2-7ubuntu2.4 [50.1 kB]
Get:24 http://archive.ubuntu.com/ubuntu jammy/main amd64 ruby-rubygems all
3.3.5-2 [228 kB]
Get:25 http://archive.ubuntu.com/ubuntu jammy/main amd64 ruby amd64 1:3.0~exp1
[5,100 B]
Get:26 http://archive.ubuntu.com/ubuntu jammy/main amd64 rake all 13.0.6-2 [61.7
kB]
Get:27 http://archive.ubuntu.com/ubuntu jammy/main amd64 ruby-net-telnet all
0.1.1-2 [12.6 kB]
Get:28 http://archive.ubuntu.com/ubuntu jammy/universe amd64 ruby-webrick all
1.7.0-3 [51.8 kB]
Get:29 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 ruby-xmlrpc all
0.3.2-1ubuntu0.1 [24.9 kB]
Get:30 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libruby3.0
amd64 3.0.2-7ubuntu2.4 [5,113 kB]
Get:31 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libsynctex2
amd64 2021.20210626.59705-1ubuntu0.2 [55.6 kB]
Get:32 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libteckit0 amd64
2.5.11+ds1-1 [421 kB]
Get:33 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libtexlua53
amd64 2021.20210626.59705-1ubuntu0.2 [120 kB]
Get:34 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libtexluajit2
amd64 2021.20210626.59705-1ubuntu0.2 [267 kB]
Get:35 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libzzip-0-13 amd64
0.13.72+dfsg.1-1.1 [27.0 kB]
Get:36 http://archive.ubuntu.com/ubuntu jammy/main amd64 xfonts-encodings all
1:1.0.5-0ubuntu2 [578 kB]
Get:37 http://archive.ubuntu.com/ubuntu jammy/main amd64 xfonts-utils amd64
1:7.7+6build2 [94.6 kB]
Get:38 http://archive.ubuntu.com/ubuntu jammy/universe amd64 lmodern all
2.004.5-6.1 [9,471 kB]
Get:39 http://archive.ubuntu.com/ubuntu jammy/universe amd64 preview-latex-style
all 12.2-1ubuntu1 [185 kB]
Get:40 http://archive.ubuntu.com/ubuntu jammy/main amd64 t1utils amd64
1.41-4build2 [61.3 kB]
Get:41 http://archive.ubuntu.com/ubuntu jammy/universe amd64 teckit amd64
2.5.11+ds1-1 [699 kB]
Get:42 http://archive.ubuntu.com/ubuntu jammy/universe amd64 tex-gyre all
20180621-3.1 [6,209 kB]
Get:43 http://archive.ubuntu.com/ubuntu jammy-updates/universe amd64 texlive-
binaries amd64 2021.20210626.59705-1ubuntu0.2 [9,860 kB]
Get:44 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-base all
2021.20220204-1 [21.0 MB]
Get:45 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-fonts-
```

```
recommended all 2021.20220204-1 [4,972 kB]
Get:46 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-latex-base
all 2021.20220204-1 [1,128 kB]
Get:47 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-latex-
recommended all 2021.20220204-1 [14.4 MB]
Get:48 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive all
2021.20220204-1 [14.3 kB]
Get:49 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libfontbox-java all
1:1.8.16-2 [207 kB]
Get:50 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libpdfbox-java all
1:1.8.16-2 [5,199 kB]
Get:51 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-pictures
all 2021.20220204-1 [8,720 kB]
Get:52 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-latex-extra
all 2021.20220204-1 [13.9 MB]
Get:53 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-plain-
generic all 2021.20220204-1 [27.5 MB]
Get:54 http://archive.ubuntu.com/ubuntu jammy/universe amd64 tipa all 2:1.3-21
[2,967 kB]
Get:55 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-xetex all
2021.20220204-1 [12.4 MB]
Fetched 182 MB in 13s (14.0 MB/s)
Extracting templates from packages: 100%
Preconfiguring packages …
Selecting previously unselected package fonts-droid-fallback.
(Reading database … 121753 files and directories currently installed.)
Preparing to unpack …/00-fonts-droid-fallback_1%3a6.0.1r16-1.1build1_all.deb
…
Unpacking fonts-droid-fallback (1:6.0.1r16-1.1build1) …
Selecting previously unselected package fonts-lato.
Preparing to unpack …/01-fonts-lato_2.0-2.1_all.deb …
Unpacking fonts-lato (2.0-2.1) …
Selecting previously unselected package poppler-data.
Preparing to unpack …/02-poppler-data_0.4.11-1_all.deb …
Unpacking poppler-data (0.4.11-1) …
Selecting previously unselected package tex-common.
Preparing to unpack …/03-tex-common_6.17_all.deb …
Unpacking tex-common (6.17) …
Selecting previously unselected package fonts-urw-base35.
Preparing to unpack …/04-fonts-urw-base35_20200910-1_all.deb …
Unpacking fonts-urw-base35 (20200910-1) …
Selecting previously unselected package libgs9-common.
Preparing to unpack …/05-libgs9-common_9.55.0~dfsg1-0ubuntu5.6_all.deb …
Unpacking libgs9-common (9.55.0~dfsg1-0ubuntu5.6) …
Selecting previously unselected package libidn12:amd64.
Preparing to unpack …/06-libidn12_1.38-4ubuntu1_amd64.deb …
Unpacking libidn12:amd64 (1.38-4ubuntu1) …
Selecting previously unselected package libijs-0.35:amd64.
```

```
Preparing to unpack …/07-libijs-0.35_0.35-15build2_amd64.deb …
Unpacking libijs-0.35:amd64 (0.35-15build2) …
Selecting previously unselected package libjbig2dec0:amd64.
Preparing to unpack …/08-libjbig2dec0_0.19-3build2_amd64.deb …
Unpacking libjbig2dec0:amd64 (0.19-3build2) …
Selecting previously unselected package libgs9:amd64.
Preparing to unpack …/09-libgs9_9.55.0~dfsg1-0ubuntu5.6_amd64.deb …
Unpacking libgs9:amd64 (9.55.0~dfsg1-0ubuntu5.6) …
Selecting previously unselected package libkpathsea6:amd64.
Preparing to unpack …/10-libkpathsea6_2021.20210626.59705-1ubuntu0.2_amd64.deb
…
Unpacking libkpathsea6:amd64 (2021.20210626.59705-1ubuntu0.2) …
Selecting previously unselected package libwoff1:amd64.
Preparing to unpack …/11-libwoff1_1.0.2-1build4_amd64.deb …
Unpacking libwoff1:amd64 (1.0.2-1build4) …
Selecting previously unselected package dvisvgm.
Preparing to unpack …/12-dvisvgm_2.13.1-1_amd64.deb …
Unpacking dvisvgm (2.13.1-1) …
Selecting previously unselected package fonts-lmodern.
Preparing to unpack …/13-fonts-lmodern_2.004.5-6.1_all.deb …
Unpacking fonts-lmodern (2.004.5-6.1) …
Selecting previously unselected package fonts-noto-mono.
Preparing to unpack …/14-fonts-noto-mono_20201225-1build1_all.deb …
Unpacking fonts-noto-mono (20201225-1build1) …
Selecting previously unselected package fonts-texgyre.
Preparing to unpack …/15-fonts-texgyre_20180621-3.1_all.deb …
Unpacking fonts-texgyre (20180621-3.1) …
Selecting previously unselected package libapache-pom-java.
Preparing to unpack …/16-libapache-pom-java_18-1_all.deb …
Unpacking libapache-pom-java (18-1) …
Selecting previously unselected package libcommons-parent-java.
Preparing to unpack …/17-libcommons-parent-java_43-1_all.deb …
Unpacking libcommons-parent-java (43-1) …
Selecting previously unselected package libcommons-logging-java.
Preparing to unpack …/18-libcommons-logging-java_1.2-2_all.deb …
Unpacking libcommons-logging-java (1.2-2) …
Selecting previously unselected package libfontenc1:amd64.
Preparing to unpack …/19-libfontenc1_1%3a1.1.4-1build3_amd64.deb …
Unpacking libfontenc1:amd64 (1:1.1.4-1build3) …
Selecting previously unselected package libptexenc1:amd64.
Preparing to unpack …/20-libptexenc1_2021.20210626.59705-1ubuntu0.2_amd64.deb
…
Unpacking libptexenc1:amd64 (2021.20210626.59705-1ubuntu0.2) …
Selecting previously unselected package rubygems-integration.
Preparing to unpack …/21-rubygems-integration_1.18_all.deb …
Unpacking rubygems-integration (1.18) …
Selecting previously unselected package ruby3.0.
Preparing to unpack …/22-ruby3.0_3.0.2-7ubuntu2.4_amd64.deb …
```

```
Unpacking ruby3.0 (3.0.2-7ubuntu2.4) …
Selecting previously unselected package ruby-rubygems.
Preparing to unpack …/23-ruby-rubygems_3.3.5-2_all.deb …
Unpacking ruby-rubygems (3.3.5-2) …
Selecting previously unselected package ruby.
Preparing to unpack …/24-ruby_1%3a3.0~exp1_amd64.deb …
Unpacking ruby (1:3.0~exp1) …
Selecting previously unselected package rake.
Preparing to unpack …/25-rake_13.0.6-2_all.deb …
Unpacking rake (13.0.6-2) …
Selecting previously unselected package ruby-net-telnet.
Preparing to unpack …/26-ruby-net-telnet_0.1.1-2_all.deb …
Unpacking ruby-net-telnet (0.1.1-2) …
Selecting previously unselected package ruby-webrick.
Preparing to unpack …/27-ruby-webrick_1.7.0-3_all.deb …
Unpacking ruby-webrick (1.7.0-3) …
Selecting previously unselected package ruby-xmlrpc.
Preparing to unpack …/28-ruby-xmlrpc_0.3.2-1ubuntu0.1_all.deb …
Unpacking ruby-xmlrpc (0.3.2-1ubuntu0.1) …
Selecting previously unselected package libruby3.0:amd64.
Preparing to unpack …/29-libruby3.0_3.0.2-7ubuntu2.4_amd64.deb …
Unpacking libruby3.0:amd64 (3.0.2-7ubuntu2.4) …
Selecting previously unselected package libsynctex2:amd64.
Preparing to unpack …/30-libsynctex2_2021.20210626.59705-1ubuntu0.2_amd64.deb
…
Unpacking libsynctex2:amd64 (2021.20210626.59705-1ubuntu0.2) …
Selecting previously unselected package libteckit0:amd64.
Preparing to unpack …/31-libteckit0_2.5.11+ds1-1_amd64.deb …
Unpacking libteckit0:amd64 (2.5.11+ds1-1) …
Selecting previously unselected package libtexlua53:amd64.
Preparing to unpack …/32-libtexlua53_2021.20210626.59705-1ubuntu0.2_amd64.deb
…
Unpacking libtexlua53:amd64 (2021.20210626.59705-1ubuntu0.2) …
Selecting previously unselected package libtexluajit2:amd64.
Preparing to unpack
…/33-libtexluajit2_2021.20210626.59705-1ubuntu0.2_amd64.deb …
Unpacking libtexluajit2:amd64 (2021.20210626.59705-1ubuntu0.2) …
Selecting previously unselected package libzzip-0-13:amd64.
Preparing to unpack …/34-libzzip-0-13_0.13.72+dfsg.1-1.1_amd64.deb …
Unpacking libzzip-0-13:amd64 (0.13.72+dfsg.1-1.1) …
Selecting previously unselected package xfonts-encodings.
Preparing to unpack …/35-xfonts-encodings_1%3a1.0.5-0ubuntu2_all.deb …
Unpacking xfonts-encodings (1:1.0.5-0ubuntu2) …
Selecting previously unselected package xfonts-utils.
Preparing to unpack …/36-xfonts-utils_1%3a7.7+6build2_amd64.deb …
Unpacking xfonts-utils (1:7.7+6build2) …
Selecting previously unselected package lmodern.
Preparing to unpack …/37-lmodern_2.004.5-6.1_all.deb …
```

```
Unpacking lmodern (2.004.5-6.1) …
Selecting previously unselected package preview-latex-style.
Preparing to unpack …/38-preview-latex-style_12.2-1ubuntu1_all.deb …
Unpacking preview-latex-style (12.2-1ubuntu1) …
Selecting previously unselected package t1utils.
Preparing to unpack …/39-t1utils_1.41-4build2_amd64.deb …
Unpacking t1utils (1.41-4build2) …
Selecting previously unselected package teckit.
Preparing to unpack …/40-teckit_2.5.11+ds1-1_amd64.deb …
Unpacking teckit (2.5.11+ds1-1) …
Selecting previously unselected package tex-gyre.
Preparing to unpack …/41-tex-gyre_20180621-3.1_all.deb …
Unpacking tex-gyre (20180621-3.1) …
Selecting previously unselected package texlive-binaries.
Preparing to unpack …/42-texlive-
binaries_2021.20210626.59705-1ubuntu0.2_amd64.deb …
Unpacking texlive-binaries (2021.20210626.59705-1ubuntu0.2) …
Selecting previously unselected package texlive-base.
Preparing to unpack …/43-texlive-base_2021.20220204-1_all.deb …
Unpacking texlive-base (2021.20220204-1) …
Selecting previously unselected package texlive-fonts-recommended.
Preparing to unpack …/44-texlive-fonts-recommended_2021.20220204-1_all.deb …
Unpacking texlive-fonts-recommended (2021.20220204-1) …
Selecting previously unselected package texlive-latex-base.
Preparing to unpack …/45-texlive-latex-base_2021.20220204-1_all.deb …
Unpacking texlive-latex-base (2021.20220204-1) …
Selecting previously unselected package texlive-latex-recommended.
Preparing to unpack …/46-texlive-latex-recommended_2021.20220204-1_all.deb …
Unpacking texlive-latex-recommended (2021.20220204-1) …
Selecting previously unselected package texlive.
Preparing to unpack …/47-texlive_2021.20220204-1_all.deb …
Unpacking texlive (2021.20220204-1) …
Selecting previously unselected package libfontbox-java.
Preparing to unpack …/48-libfontbox-java_1%3a1.8.16-2_all.deb …
Unpacking libfontbox-java (1:1.8.16-2) …
Selecting previously unselected package libpdfbox-java.
Preparing to unpack …/49-libpdfbox-java_1%3a1.8.16-2_all.deb …
Unpacking libpdfbox-java (1:1.8.16-2) …
Selecting previously unselected package texlive-pictures.
Preparing to unpack …/50-texlive-pictures_2021.20220204-1_all.deb …
Unpacking texlive-pictures (2021.20220204-1) …
Selecting previously unselected package texlive-latex-extra.
Preparing to unpack …/51-texlive-latex-extra_2021.20220204-1_all.deb …
Unpacking texlive-latex-extra (2021.20220204-1) …
Selecting previously unselected package texlive-plain-generic.
Preparing to unpack …/52-texlive-plain-generic_2021.20220204-1_all.deb …
Unpacking texlive-plain-generic (2021.20220204-1) …
Selecting previously unselected package tipa.
```

```
Preparing to unpack …/53-tipa_2%3a1.3-21_all.deb …
Unpacking tipa (2:1.3-21) …
Selecting previously unselected package texlive-xetex.
Preparing to unpack …/54-texlive-xetex_2021.20220204-1_all.deb …
Unpacking texlive-xetex (2021.20220204-1) …
Setting up fonts-lato (2.0-2.1) …
Setting up fonts-noto-mono (20201225-1build1) …
Setting up libwoff1:amd64 (1.0.2-1build4) …
Setting up libtexlua53:amd64 (2021.20210626.59705-1ubuntu0.2) …
Setting up libijs-0.35:amd64 (0.35-15build2) …
Setting up libtexluajit2:amd64 (2021.20210626.59705-1ubuntu0.2) …
Setting up libfontbox-java (1:1.8.16-2) …
Setting up rubygems-integration (1.18) …
Setting up libzzip-0-13:amd64 (0.13.72+dfsg.1-1.1) …
Setting up fonts-urw-base35 (20200910-1) …
Setting up poppler-data (0.4.11-1) …
Setting up tex-common (6.17) …
update-language: texlive-base not installed and configured, doing nothing!
Setting up libfontenc1:amd64 (1:1.1.4-1build3) …
Setting up libjbig2dec0:amd64 (0.19-3build2) …
Setting up libteckit0:amd64 (2.5.11+ds1-1) …
Setting up libapache-pom-java (18-1) …
Setting up ruby-net-telnet (0.1.1-2) …
Setting up xfonts-encodings (1:1.0.5-0ubuntu2) …
Setting up t1utils (1.41-4build2) …
Setting up libidn12:amd64 (1.38-4ubuntu1) …
Setting up fonts-texgyre (20180621-3.1) …
Setting up libkpathsea6:amd64 (2021.20210626.59705-1ubuntu0.2) …
Setting up ruby-webrick (1.7.0-3) …
Setting up fonts-lmodern (2.004.5-6.1) …
Setting up fonts-droid-fallback (1:6.0.1r16-1.1build1) …
Setting up ruby-xmlrpc (0.3.2-1ubuntu0.1) …
Setting up libsynctex2:amd64 (2021.20210626.59705-1ubuntu0.2) …
Setting up libgs9-common (9.55.0~dfsg1-0ubuntu5.6) …
Setting up teckit (2.5.11+ds1-1) …
Setting up libpdfbox-java (1:1.8.16-2) …
Setting up libgs9:amd64 (9.55.0~dfsg1-0ubuntu5.6) …
Setting up preview-latex-style (12.2-1ubuntu1) …
Setting up libcommons-parent-java (43-1) …
Setting up dvisvgm (2.13.1-1) …
Setting up libcommons-logging-java (1.2-2) …
Setting up xfonts-utils (1:7.7+6build2) …
Setting up libptexenc1:amd64 (2021.20210626.59705-1ubuntu0.2) …
Setting up texlive-binaries (2021.20210626.59705-1ubuntu0.2) …
update-alternatives: using /usr/bin/xdvi-xaw to provide /usr/bin/xdvi.bin
(xdvi.bin) in auto mode
update-alternatives: using /usr/bin/bibtex.original to provide /usr/bin/bibtex
(bibtex) in auto mode
```

```
Setting up lmodern (2.004.5-6.1) …
Setting up texlive-base (2021.20220204-1) …
/usr/bin/ucfr
/usr/bin/ucfr
/usr/bin/ucfr
/usr/bin/ucfr
mktexlsr: Updating /var/lib/texmf/ls-R-TEXLIVEDIST…
mktexlsr: Updating /var/lib/texmf/ls-R-TEXMFMAIN…
mktexlsr: Updating /var/lib/texmf/ls-R…
mktexlsr: Done.
tl-paper: setting paper size for dvips to a4:
/var/lib/texmf/dvips/config/config-paper.ps
tl-paper: setting paper size for dvipdfmx to a4:
/var/lib/texmf/dvipdfmx/dvipdfmx-paper.cfg
tl-paper: setting paper size for xdvi to a4: /var/lib/texmf/xdvi/XDvi-paper
tl-paper: setting paper size for pdftex to a4: /var/lib/texmf/tex/generic/tex-
ini-files/pdftexconfig.tex
Setting up tex-gyre (20180621-3.1) …
Setting up texlive-plain-generic (2021.20220204-1) …
Setting up texlive-latex-base (2021.20220204-1) …
Setting up texlive-latex-recommended (2021.20220204-1) …
Setting up texlive-pictures (2021.20220204-1) …
Setting up texlive-fonts-recommended (2021.20220204-1) …
Setting up tipa (2:1.3-21) …
Setting up texlive (2021.20220204-1) …
Setting up texlive-latex-extra (2021.20220204-1) …
Setting up texlive-xetex (2021.20220204-1) …
Setting up rake (13.0.6-2) …
Setting up libruby3.0:amd64 (3.0.2-7ubuntu2.4) …
Setting up ruby3.0 (3.0.2-7ubuntu2.4) …
Setting up ruby (1:3.0~exp1) …
Setting up ruby-rubygems (3.3.5-2) …
Processing triggers for man-db (2.10.2-1) …
Processing triggers for fontconfig (2.13.1-4.2ubuntu5) …
Processing triggers for libc-bin (2.35-0ubuntu3.4) …
/sbin/ldconfig.real: /usr/local/lib/libtbbmalloc.so.2 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbbind.so.3 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbbind_2_5.so.3 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbb.so.12 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbmalloc_proxy.so.2 is not a symbolic
link

/sbin/ldconfig.real: /usr/local/lib/libtbbbind_2_0.so.3 is not a symbolic link
```

```
Processing triggers for tex-common (6.17) …
Running updmap-sys. This may take some time… done.
Running mktexlsr /var/lib/texmf … done.
Building format(s) --all.
        This may take some time… done.
Collecting pypandoc
  Downloading pypandoc-1.13-py3-none-any.whl (21 kB)
Installing collected packages: pypandoc
Successfully installed pypandoc-1.13
```

[69]:

```
!jupyter nbconvert AML_HW3_Solutions_amp2365-3.ipynb --to latex
```

```
[NbConvertApp] Converting notebook AML_HW3_Solutions_amp2365-3.ipynb to latex
[NbConvertApp] Support files will be in AML_HW3_Solutions_amp2365-3_files/
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Making directory AML_HW3_Solutions_amp2365-3_files
[NbConvertApp] Writing 159561 bytes to AML_HW3_Solutions_amp2365-3.tex
```

[ ]:

```

```