Homework 3

Part 1: Imbalanced Dataset

- In this homework, you will be working with an imbalanced Dataset.
- The dataset is Credit Card Fraud Detection dataset which was hosted on Kaggle.
- The aim is to detect fraudlent transactions.

Instructions

1) Please push the .ipynb and .pdf to Github Classroom prior to the deadline, .py file is optional (not needed).
2) Please include your Name and UNI below.

Name: Shruti Agarwal

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Setup

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Feel free to import any other packages you need
from sklearn.model_selection import train_test_split, cross_validate
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_auc_score, average_precision_score

# !pip install imbalanced-learn
from imblearn.over_sampling import RandomOverSampler
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import SMOTE
from sklearn.metrics import confusion_matrix, plot_confusion_matrix
from sklearn.metrics import roc_curve
```

Data Preprocessing and Exploration.

- Download the Kaggle Credit Card Fraud data set.
- Features V1, V2, … V27, V28 are the principal components obtained with PCA, the only features which have not been transformed with PCA are 'Time' and 'Amount'.
- Feature 'Time' contains the seconds elapsed between each transaction and the first transaction in the dataset.
- The feature 'Amount' is the transaction Amount, this feature can be used for example-dependant cost-sensitive learning.
- Feature 'Class' is the response variable and it takes value 1 in case of fraud and 0 otherwise.

In [3]:
```
raw_df = pd.read_csv('https://storage.googleapis.com/download.tensorfl
raw_df.head(10)
```

Out[3]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533
5	2.0	-0.425966	0.960523	1.141109	-0.168252	0.420987	-0.029728	0.476201	0.260314
6	4.0	1.229658	0.141004	0.045371	1.202613	0.191881	0.272708	-0.005159	0.081213
7	7.0	-0.644269	1.417964	1.074380	-0.492199	0.948934	0.428118	1.120631	-3.807864
8	7.0	-0.894286	0.286157	-0.113192	-0.271526	2.669599	3.721818	0.370145	0.851084
9	9.0	-0.338262	1.119593	1.044367	-0.222187	0.499361	-0.246761	0.651583	0.069539

10 rows × 31 columns

Examining the class Imbalance

1.1 How many observations are in this dataset? How many are positive and negative?
(Note: Positive labels are labeled as 1)

In [4]:
```
# Your Code Here

num_obs = raw_df.shape[0]
obs = raw_df.groupby(['Class']).size()
pos_obs = obs[1]
neg_obs = obs[0]
print(f"There are {num_obs} observations in the dataset with {pos_obs}
```

```
There are 284807 observations in the dataset with 492 positive and 28
4315 negative observations.
```

1.2 Cleaning and normalizing the data

The raw data has a few issues.
Since we are unsure what the time column actually means so drop the Time column. The Amount column also has a wide range of values covered so we take the log of the Amount column to reduce its range.

The below is already done for you.

In [5]:
```
cleaned_df = raw_df.copy()

# You don't want the 'Time' column. Pop it off
cleaned_df.pop('Time')

# The 'Amount' column covers a huge range. Convert it to log-space.
eps = 0.001
cleaned_df['Log Ammount'] = np.log(cleaned_df.pop('Amount') + eps)
```

1.2.1 Split the dataset into development and test sets. Set test size as 20% and random state as 42. Print the shape of your development and test features

In [6]:
```
# Your Code Here

X = cleaned_df.drop('Class', axis=1)
y = cleaned_df['Class']

# split the dataset into development and test sets
X_dev, X_test, y_dev, y_test = train_test_split(X, y, test_size=0.2, r

# print the shape of the development and test sets
print("Development set features shape:", X_dev.shape)
print("Test set features shape:", X_test.shape)
```

```
Development set features shape: (227845, 29)
Test set features shape: (56962, 29)
```

1.2.2 Normalize the features using Standard Scaler from Sklearn.

In [7]:
```
# Your Code Here

scaler = StandardScaler()
X_dev_scaled = scaler.fit_transform(X_dev)
X_test_scaled = scaler.transform(X_test)
```

Default Baseline

1.3.1 First, let us fit a default Decision tree classifier (use max_depth=10 and random_state=42). Print the AUC and Average Precision values of 5 Fold Cross Validation

In [8]:
```
# Your Code Here

dt_def = DecisionTreeClassifier(max_depth=10, random_state=42)

auc_scores = cross_val_score(dt_def, X_dev_scaled, y_dev, cv=5, scorir
ap_scores = cross_val_score(dt_def, X_dev_scaled, y_dev, cv=5, scoring

# print the AUC and Average Precision scores
print("AUC scores:", auc_scores)
print("Average Precision scores:", ap_scores)
print("Average AUC:", auc_scores.mean())
print("Average Average Precision:", ap_scores.mean())
```

```
AUC scores: [0.86957634 0.82799822 0.83798122 0.88266235 0.90893353]
Average Precision scores: [0.64646286 0.6763446  0.61677062 0.6831771
6 0.68281098]
Average AUC: 0.8654303324923142
Average Average Precision: 0.6611132453729376
```

Random Oversampling

1.3.2 Perform random oversampling on the development dataset.

- How many positive and negative labels do you observe after random oversampling?
- What is the shape of your development dataset?

(Note: Set random state as 42 when performing oversampling)

In [9]:
```
# Your Code Here

ros = RandomOverSampler(random_state=42)
X_dev_ros, y_dev_ros = ros.fit_resample(X_dev_scaled, y_dev)

print("Number of positive labels:", sum(y_dev_ros == 1))
print("Number of negative labels:", sum(y_dev_ros == 0))
print("Shape of the resampled development set:", X_dev_ros.shape)
```

```
Number of positive labels: 227451
Number of negative labels: 227451
Shape of the resampled development set: (454902, 29)
```

1.3.3 Repeat 1.3.1 using the dataset you created in the above step (1.3.2 Random oversampling).
(Make sure you use the same hyperparameters as 1.3.1. i.e., max_depth=10, random_state=42 and 5 Fold Cross Validation)
This will help us to compare the models.

In [10]:
```
# Your Code Here

dt_ros = DecisionTreeClassifier(max_depth=10, random_state=42)

auc_scores = cross_val_score(dt_ros, X_dev_ros, y_dev_ros, cv=5, scori
ap_scores = cross_val_score(dt_ros, X_dev_ros, y_dev_ros, cv=5, scorin

# print the AUC and Average Precision scores
print("AUC scores:", auc_scores)
print("Average Precision scores:", ap_scores)
print("Average AUC:", auc_scores.mean())
print("Average Average Precision:", ap_scores.mean())
```

```
AUC scores: [0.99840012 0.9983086  0.99847279 0.99847804 0.99857557]
Average Precision scores: [0.99786268 0.99767719 0.9978636  0.9978744
4 0.99807898]
Average AUC: 0.9984470244132799
Average Average Precision: 0.9978713776423949
```

Random Undersampling

1.3.4 Perform Random undersampling on the development dataset.

- How many positive and negative labels do you observe after random undersampling?
- What is the shape of your development dataset?

(Note: Set random state as 42 when performing undersampling)

In [11]:
```
# Your Code Here

rus = RandomUnderSampler(random_state=42)
X_dev_rus, y_dev_rus = rus.fit_resample(X_dev_scaled, y_dev)
```

In [12]:
```
print("Number of positive labels:", sum(y_dev_rus == 1))
print("Number of negative labels:", sum(y_dev_rus == 0))
```

```
Number of positive labels: 394
Number of negative labels: 394
```

In [13]:
```
print("Shape of the resampled development set:", X_dev_rus.shape)
```

```
Shape of the resampled development set: (788, 29)
```

1.3.5 Repeat 1.3.1 using the dataset you created in the above step(1.3.4 Random undersampling).
(Make sure you use the same hyperparameters as 1.3.1. i.e., max_depth=10, random_state=42 and 5 Fold Cross Validation)
This will help us to compare the models

In [14]:
```
# Your Code Here

dt_rus = DecisionTreeClassifier(max_depth=10, random_state=42)

auc_scores = cross_val_score(dt_rus, X_dev_rus, y_dev_rus, cv=5, scori
ap_scores = cross_val_score(dt_rus, X_dev_rus, y_dev_rus, cv=5, scorir

# print the AUC and Average Precision scores
print("AUC scores:", auc_scores)
print("Average Precision scores:", ap_scores)
print("Average AUC:", auc_scores.mean())
print("Average Average Precision:", ap_scores.mean())
```

```
AUC scores: [0.8852748  0.86388399 0.89873418 0.91731581 0.94790652]
Average Precision scores: [0.82838644 0.81661392 0.86683544 0.8753102
5 0.92073059]
Average AUC: 0.9026230592566116
Average Average Precision: 0.8615753308133469
```

SMOTE

1.3.6 Perform Synthetic Minority Oversampling Technique (SMOTE) on the development dataset

- How many positive and negative labels do you observe after performing SMOTE?
- What is the shape of your development dataset?

(Note: Set random state as 42 when performing SMOTE)

In [15]:
```
# Your Code Here

smote = SMOTE(random_state=42)
X_dev_smote, y_dev_smote = smote.fit_resample(X_dev_scaled, y_dev)
```

In [16]:
```
print("Number of positive labels:", sum(y_dev_smote == 1))
print("Number of negative labels:", sum(y_dev_smote == 0))
```

```
Number of positive labels: 227451
Number of negative labels: 227451
```

In [17]:
```
print("Shape of the resampled development set:", X_dev_smote.shape)
```

```
Shape of the resampled development set: (454902, 29)
```

1.3.7 Repeat 1.3.1 using the dataset you created in the above step(1.3.4 SMOTE). (Make sure you use the same hyperparameters as 1.3.1. i.e., max_depth=10, random_state=42 and 5 Fold Cross Validation)
This will help us to compare the models

In [18]:
```
# Your Code Here

dt_smote = DecisionTreeClassifier(max_depth=10, random_state=42)

auc_scores = cross_val_score(dt_smote, X_dev_smote, y_dev_smote, cv=5,
ap_scores = cross_val_score(dt_smote, X_dev_smote, y_dev_smote, cv=5,

# print the AUC and Average Precision scores
print("AUC scores:", auc_scores)
print("Average Precision scores:", ap_scores)
print("Average AUC:", auc_scores.mean())
print("Average Average Precision:", ap_scores.mean())
```

```
AUC scores: [0.99729603 0.99747394 0.99713467 0.99703584 0.99724342]
Average Precision scores: [0.99658165 0.99656764 0.99603047 0.9959331
7 0.99618909]
Average AUC: 0.9972367791948902
Average Average Precision: 0.996260402041384
```

Balanced Weight

1.3.8 Train a balanced default Decision tree classifier.
[use max_depth=10 and random_state=42 and balance the class weights with 5 Fold Cross Validation]
Print the AUC and average precision on dev set

In [19]:
```
# Your Code Here

dt_balanced = DecisionTreeClassifier(max_depth=10, random_state=42, cl
cv_results = cross_validate(dt_balanced, X_dev_scaled, y_dev, cv=5, sc

# print the AUC and average precision on the development set
print("AUC on development set:", cv_results['test_roc_auc'].mean())
print("Average precision on development set:", cv_results['test_averag
```

```
AUC on development set: 0.9070005244195443
Average precision on development set: 0.623661060432623
```

Model Prediction & Evaluation

1.4.1 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)

In [20]:
```
# Your Code Here

dt_def.fit(X_dev_scaled, y_dev)
dt_ros.fit(X_dev_ros, y_dev_ros)
dt_rus.fit(X_dev_rus, y_dev_rus)
dt_smote.fit(X_dev_smote, y_dev_smote)
dt_balanced.fit(X_dev_scaled, y_dev)

# make predictions on the test set and compute AUC scores
y_pred_def = dt_def.predict_proba(X_test_scaled)[:, 1]
auc_def = roc_auc_score(y_test, y_pred_def)

y_pred_ros = dt_ros.predict_proba(X_test_scaled)[:, 1]
auc_ros = roc_auc_score(y_test, y_pred_ros)

y_pred_rus = dt_rus.predict_proba(X_test_scaled)[:, 1]
auc_rus = roc_auc_score(y_test, y_pred_rus)

y_pred_smote = dt_smote.predict_proba(X_test_scaled)[:, 1]
auc_smote = roc_auc_score(y_test, y_pred_smote)

y_pred_balanced = dt_balanced.predict_proba(X_test_scaled)[:, 1]
auc_balanced = roc_auc_score(y_test, y_pred_balanced)

# print the AUC scores
print("AUC for Default Baseline:", auc_def)
print("AUC for Random Oversampling:", auc_ros)
print("AUC for Random Undersampling:", auc_rus)
print("AUC for Smote:", auc_smote)
print("AUC for Balanced Weights:", auc_balanced)
```

```
AUC for Default Baseline: 0.871912253224306
AUC for Random Oversampling: 0.8609190528349776
AUC for Random Undersampling: 0.9050787485787788
AUC for Smote: 0.8893473364303515
AUC for Balanced Weights: 0.8432507780827582
```

1.4.2 Plot Confusion Matrices for all the five models on the test set. Comment your results and share your observations of the confusion matrices in detail

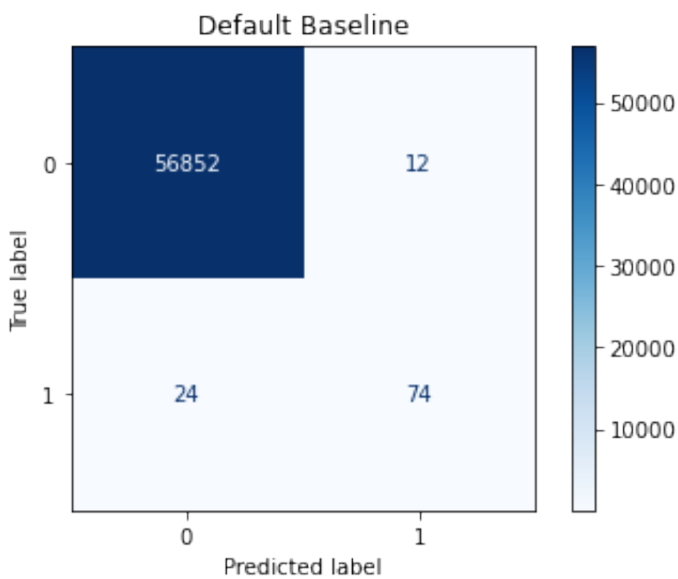
(Five models include models from - Default Baseline, Random Undersampling, Random Oversampling, SMOTE & Balanced Weight)

In [21]:

```python
titles = ['Default Baseline', 'Random Oversampling', 'Random Undersamp
classifiers = [dt_def, dt_ros, dt_rus, dt_smote, dt_balanced]


for clf, title in zip(classifiers, titles):
    # predict the target variable for the test set
    y_pred = clf.predict(X_test_scaled)
    # calculate the confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    # plot the confusion matrix
    plot_confusion_matrix(clf, X_test_scaled, y_test, cmap=plt.cm.Blue
    plt.title(title)
    plt.show()
```

```
/Users/shrutiagarwal/opt/anaconda3/lib/python3.9/site-packages/sklear
n/utils/deprecation.py:87: FutureWarning: Function plot_confusion_mat
rix is deprecated; Function `plot_confusion_matrix` is deprecated in
1.0 and will be removed in 1.2. Use one of the class methods: Confusi
onMatrixDisplay.from_predictions or ConfusionMatrixDisplay.from_estim
ator.
  warnings.warn(msg, category=FutureWarning)
```

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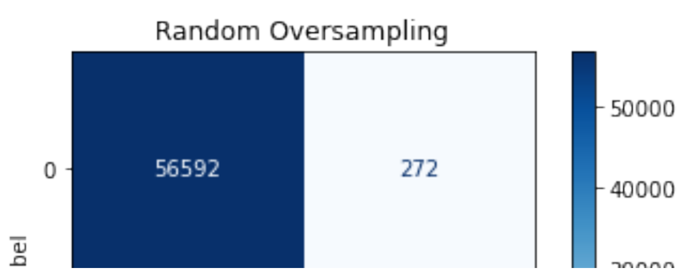
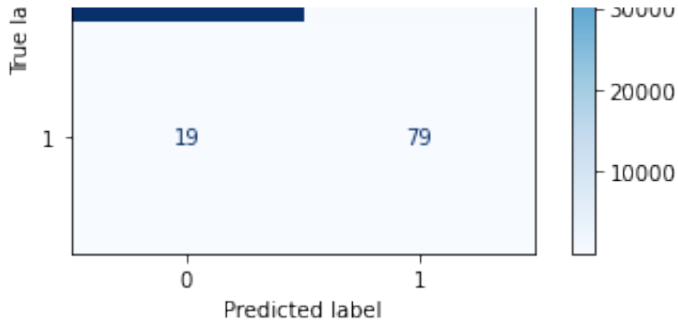
```



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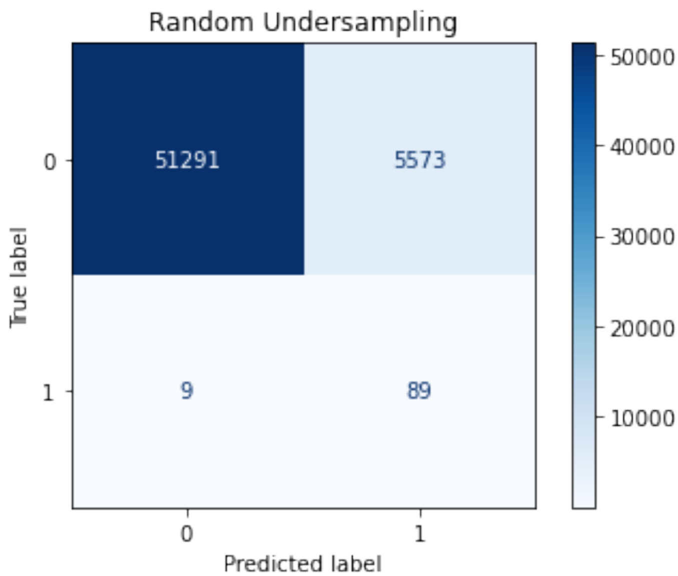
```

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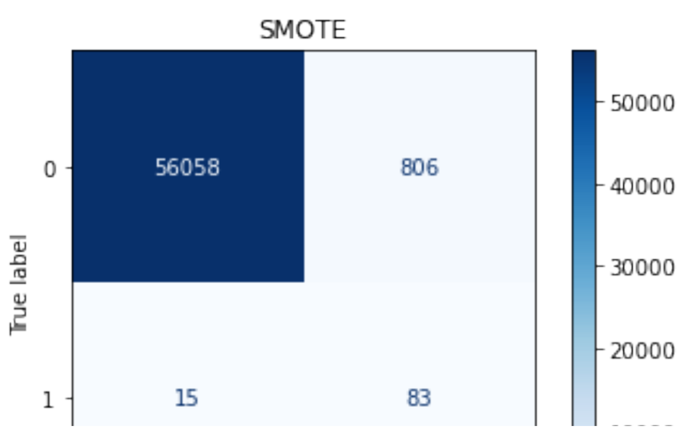
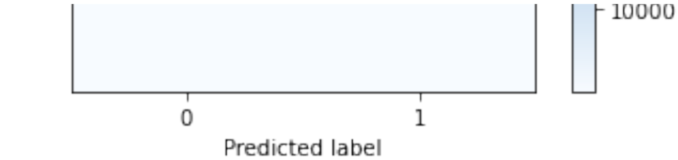
ator.
  warnings.warn(msg, category=FutureWarning)
```



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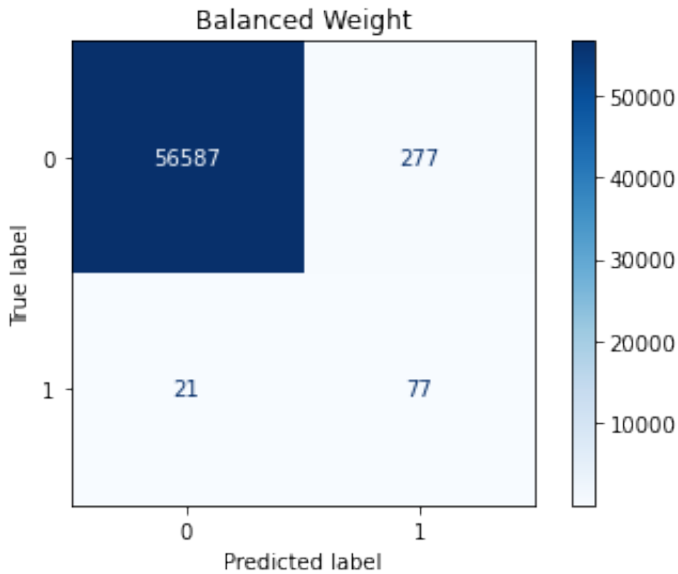


1.4.3 Plot ROC for all the five models on the test set in a single plot. Make sure you label axes and legend properly. Comment on your results and share your observations in detail

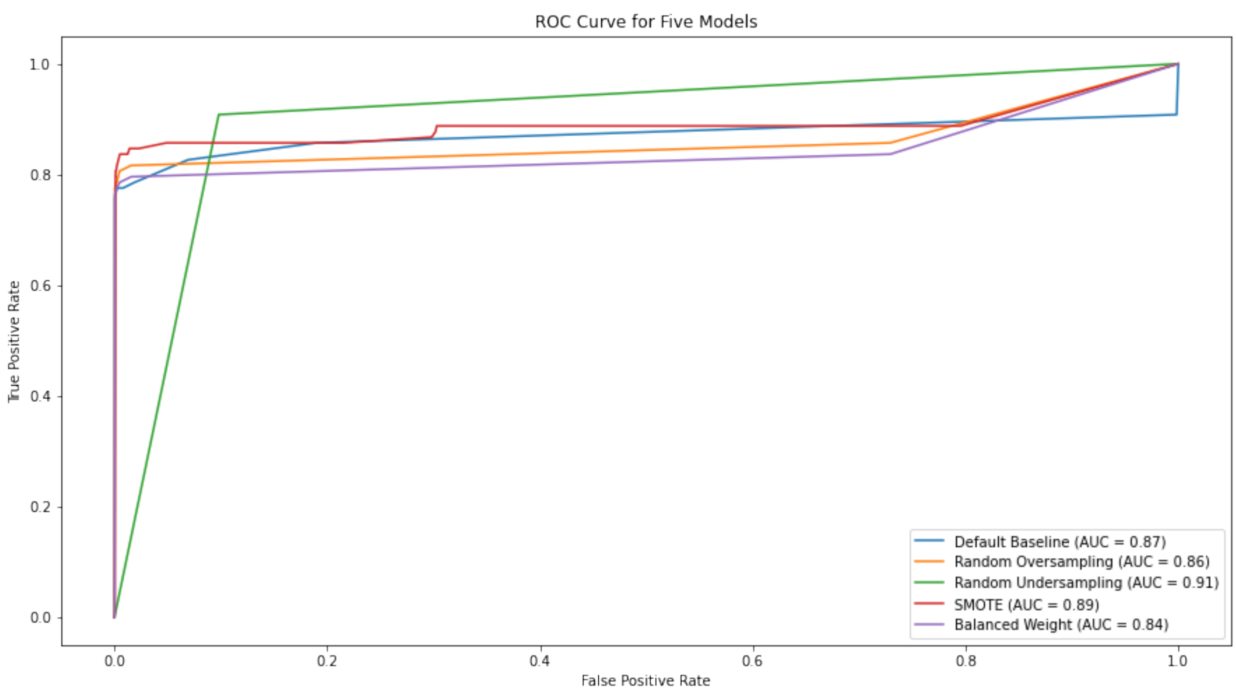
(Five models include models from - Default Baseline, Random Undersampling, Random Oversampling, SMOTE & Balanced Weight)

In [22]:
```
# Your Code Here

titles = ['Default Baseline', 'Random Oversampling', 'Random Undersamp
classifiers = [dt_def, dt_ros, dt_rus, dt_smote, dt_balanced]

plt.figure(figsize=(15, 8))
for clf, title in zip(classifiers, titles):
    y_prob = clf.predict_proba(X_test_scaled)[:, 1]
    fpr, tpr, thresholds = roc_curve(y_test, y_prob)
    auc = roc_auc_score(y_test, y_prob)
    plt.plot(fpr, tpr, label=f'{title} (AUC = {auc:.2f})')

# add labels and legend
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Five Models')
plt.legend()
plt.show()
```



In [ ]: