(SEC1) 4 - Classwork

February 2, 2024

1 HR ATTRIBUTION

[34]:
```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer, f1_score
import numpy as np
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score, auc
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import numpy as np
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer, roc_auc_score
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import accuracy_score
```

2 1.) Import, split data into X/y, plot y data as bar charts, turn X categorical variables binary and tts.

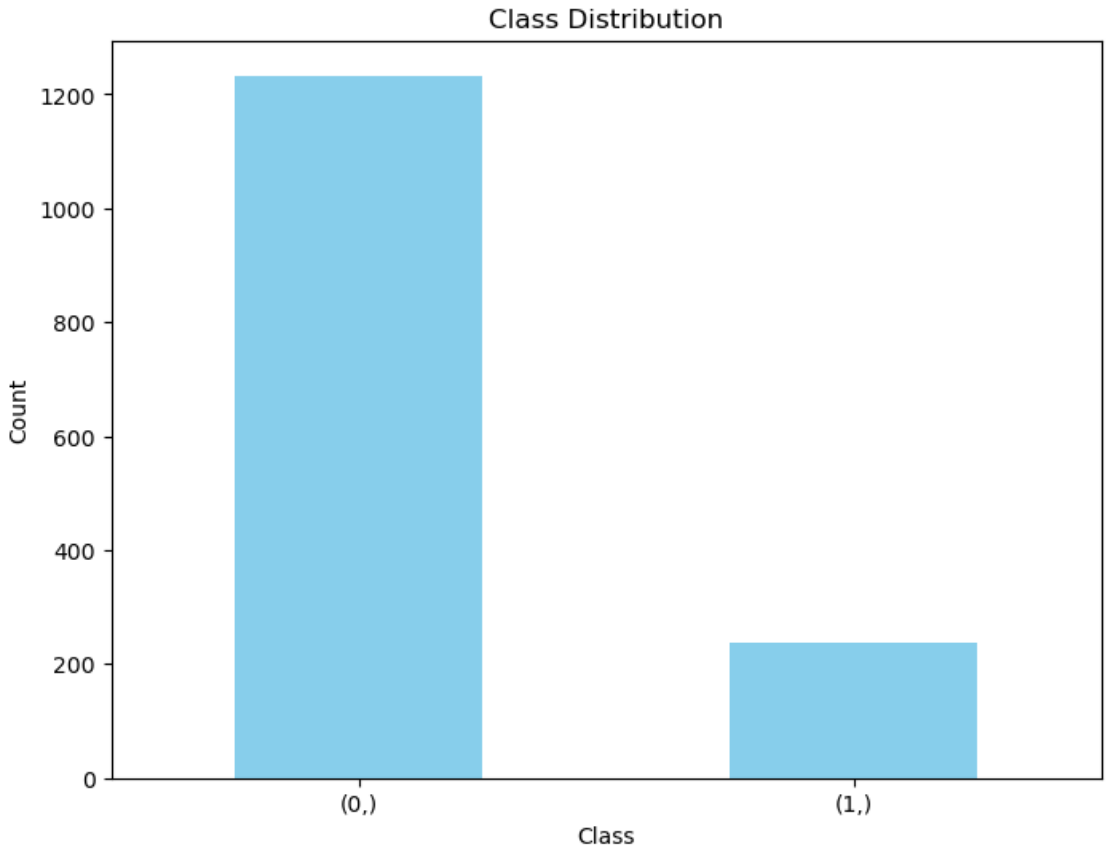
[35]:
```
df = pd.read_csv("HR_Analytics.csv")
```

[36]:
```
y = df[["Attrition"]].copy()
X = df.drop("Attrition", axis = 1)
```

[37]:
```
y["Attrition"] = [1 if i == "Yes" else 0 for i in y["Attrition"]]
```

[38]:
```
class_counts = y.value_counts()


plt.figure(figsize=(8, 6))
class_counts.plot(kind='bar', color='skyblue')
plt.xlabel('Class')
plt.ylabel('Count')
plt.title('Class Distribution')
```

```
plt.xticks(rotation=0)  # Remove rotation of x-axis labels
plt.show()
```



[39]:
```
# Step 1: Identify string columns
string_columns = X.columns[X.dtypes == 'object']

# Step 2: Convert string columns to categorical
for col in string_columns:
    X[col] = pd.Categorical(X[col])

# Step 3: Create dummy columns
X = pd.get_dummies(X, columns=string_columns,␣
 ↪prefix=string_columns,drop_first=True)
```

[40]:
```
x_train,x_test,y_train,y_test=train_test_split(X,
 y, test_size=0.20, random_state=42)
```

3 2.) Using the default Decision Tree. What is the IN/Out of Sample accuracy?

[41]:
```
clf = DecisionTreeClassifier()
clf.fit(x_train,y_train)
y_pred=clf.predict(x_train)
acc=accuracy_score(y_train,y_pred)
print("IN SAMPLE ACCURACY : " , round(acc,2))

y_pred=clf.predict(x_test)
acc=accuracy_score(y_test,y_pred)
print("OUT OF SAMPLE ACCURACY : " , round(acc,2))
```

```
IN SAMPLE ACCURACY :  1.0
OUT OF SAMPLE ACCURACY :  0.76
```

4 3.) Run a grid search cross validation using F1 score to find the best metrics. What is the In and Out of Sample now?

[42]:
```
# Define the hyperparameter grid to search through
param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': np.arange(1, 11),  # Range of max_depth values to try
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}


dt_classifier = DecisionTreeClassifier(random_state=42)

scoring = make_scorer(f1_score, average='weighted')

grid_search = GridSearchCV(estimator=dt_classifier, param_grid=param_grid,␣
 ↪scoring=scoring, cv=5)

grid_search.fit(x_train, y_train)

# Get the best parameters and the best score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

print("Best Parameters:", best_params)
print("Best F1-Score:", best_score)
```

```
Best Parameters: {'criterion': 'gini', 'max_depth': 6, 'min_samples_leaf': 2,
'min_samples_split': 2}
Best F1-Score: 0.8214764475510983
```

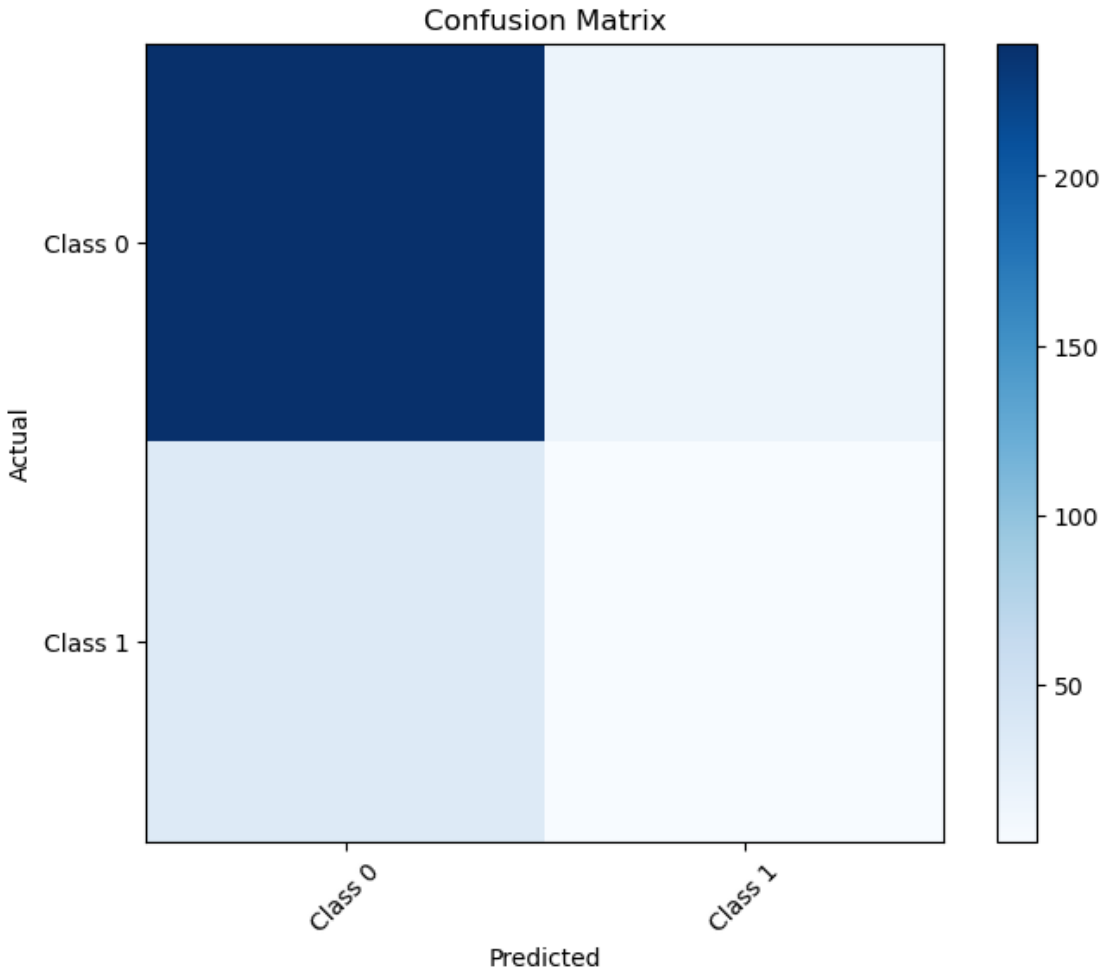
[43]:
```
clf = tree.DecisionTreeClassifier(**best_params, random_state =42)
clf.fit(x_train,y_train)
y_pred=clf.predict(x_train)
acc=accuracy_score(y_train,y_pred)
print("IN SAMPLE ACCURACY : " , round(acc,2))

y_pred=clf.predict(x_test)
acc=accuracy_score(y_test,y_pred)
print("OUT OF SAMPLE ACCURACY : " , round(acc,2))
```

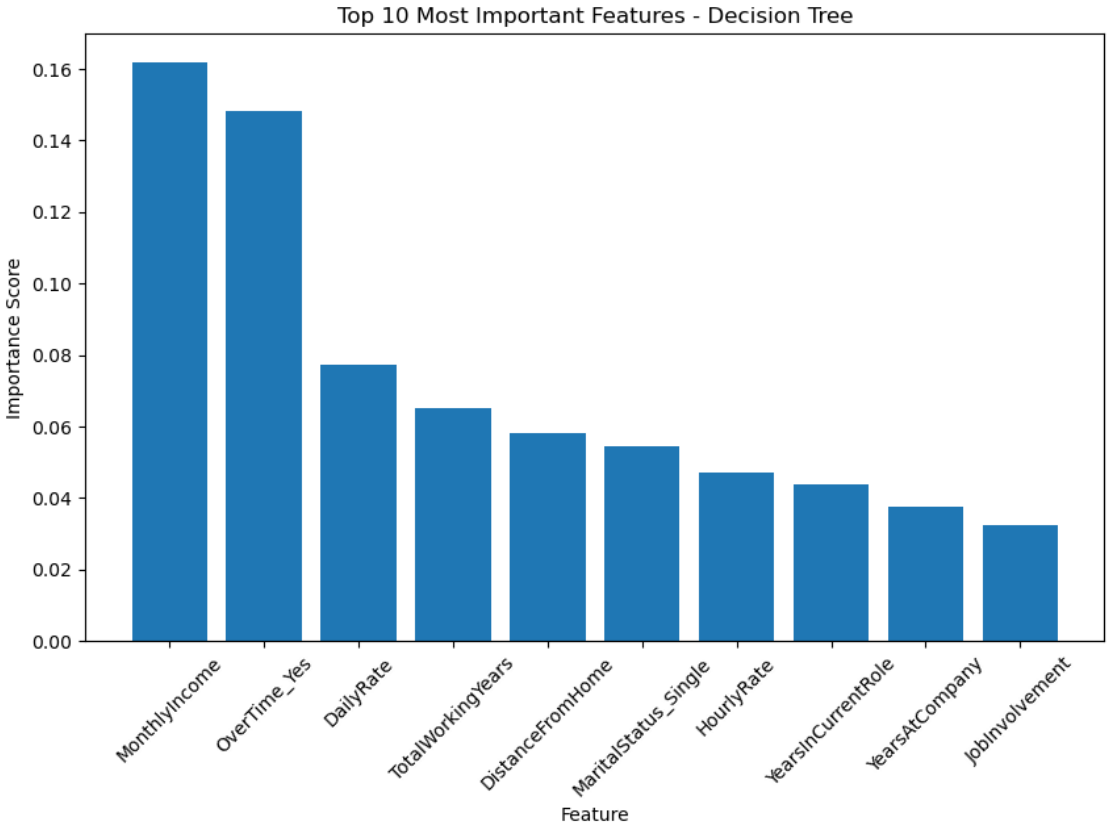
```
IN SAMPLE ACCURACY :  0.91
OUT OF SAMPLE ACCURACY :  0.83
```

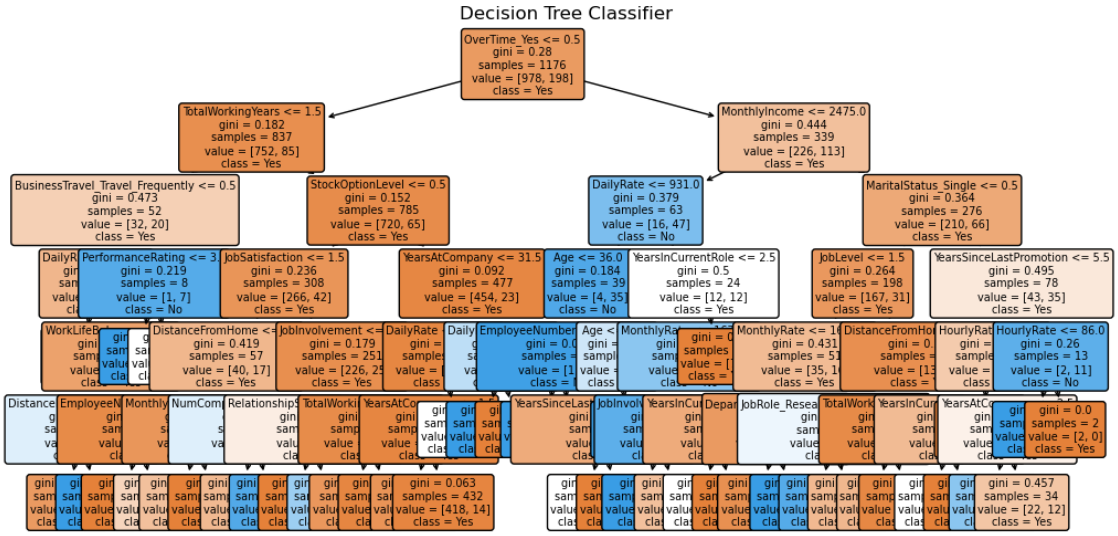
5 4.) Plot .....

[44]:
```
# Make predictions on the test data
y_pred = clf.predict(x_test)
y_prob = clf.predict_proba(x_test)[:, 1]

# Calculate the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(8, 6))
plt.imshow(conf_matrix, interpolation='nearest', cmap=plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()
tick_marks = np.arange(len(conf_matrix))
plt.xticks(tick_marks, ['Class 0', 'Class 1'], rotation=45)
plt.yticks(tick_marks, ['Class 0', 'Class 1'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()




feature_importance = clf.feature_importances_

# Sort features by importance and select the top 10
top_n = 10
top_feature_indices = np.argsort(feature_importance)[::-1][:top_n]
top_feature_names = X.columns[top_feature_indices]
top_feature_importance = feature_importance[top_feature_indices]

# Plot the top 10 most important features
plt.figure(figsize=(10, 6))
```

```
plt.bar(top_feature_names, top_feature_importance)
plt.xlabel('Feature')
plt.ylabel('Importance Score')
plt.title('Top 10 Most Important Features - Decision Tree')
plt.xticks(rotation=45)
plt.show()

# Plot the Decision Tree for better visualization of the selected features
plt.figure(figsize=(12, 6))
plot_tree(clf, filled=True, feature_names=X.columns, class_names=["Yes", "No"],␣
↪rounded=True, fontsize=7)
plt.title('Decision Tree Classifier')
plt.show()
```




Top 10 Most Important Features - Decision Tree
Importance Score
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
MonthlyIncome
OverTime_Yes
DailyRate
TotalWorkingYears
DistanceFromHome
MaritalStatus_Single
HourlyRate
YearsInCurrentRole
YearsAtCompany
JobInvolvement
Feature


Decision Tree Classifier
OverTime_Yes <= 0.5
gini = 0.28
samples = 1176
value = [978, 198]
class = Yes
TotalWorkingYears <= 1.5
gini = 0.182
samples = 837
value = [752, 85]
class = Yes
MonthlyIncome <= 2475.0
gini = 0.444
samples = 339
value = [226, 113]
class = Yes
BusinessTravel_Travel_Frequently <= 0.5
gini = 0.473
samples = 52
value = [32, 20]
class = Yes
StockOptionLevel <= 0.5
gini = 0.152
samples = 785
value = [720, 65]
class = Yes
DailyRate <= 931.0
gini = 0.379
samples = 63
value = [16, 47]
class = No
MaritalStatus_Single <= 0.5
gini = 0.364
samples = 276
value = [210, 66]
class = Yes
PerformanceRating <= 3.
gini = 0.219
samples = 8
value = [1, 7]
class = No
JobSatisfaction <= 1.5
gini = 0.236
samples = 308
value = [266, 42]
class = Yes
YearsAtCompany <= 31.5
gini = 0.092
samples = 477
value = [454, 23]
class = Yes
Age <= 36.0
gini = 0.184
samples = 39
value = [4, 35]
class = No
YearsInCurrentRole <= 2.5
gini = 0.5
samples = 24
value = [12, 12]
class = Yes
JobLevel <= 1.5
gini = 0.264
samples = 198
value = [167, 31]
class = Yes
YearsSinceLastPromotion <= 5.5
gini = 0.495
samples = 78
value = [43, 35]
class = Yes
DistanceFromHome <=
gini = 0.419
samples = 57
value = [40, 17]
class = Yes
JobInvolvement <=
gini = 0.179
samples = 251
value = [226, 25
class = Yes
HourlyRate <= 86.0
gini = 0.26
samples = 13
value = [2, 11]
class = No
gini = 0.0
samples = 2
value = [2, 0]
class = Yes
gini = 0.063
samples = 432
value = [418, 14]
class = Yes
gini = 0.457
samples = 34
value = [22, 12]
class = Yes

6 5.) Looking at the graphs. what would be your suggestions to try to improve customer retention? What additional information would you need for a better plan. Plot anything you think would assist in your assessment.

6.1 ANSWER :

- Suggestions: Have overtime increased
- We could calculate the correlation coefficient between two variables: 'OverTime_Yes' and 'Attrition'

[45]:
```
from scipy.stats import pearsonr
```

[46]:
```
def calculate_correlation(X, feature_name, y):
    feature = X[feature_name]

    coef, _ = pearsonr(feature,y)
```

[47]:
```
np.corrcoef(np.array(X['OverTime_Yes']), np.array(y['Attrition']))
```

[47]:
```
array([[1.        , 0.24611799],
       [0.24611799, 1.        ]])
```

[ ]:

7 6.) Using the Training Data, if they made everyone work overtime. What would have been the expected difference in client retention?

[48]:
```
x_train_experiment = x_train.copy()
```

[49]:
```
x_train_experiment['OverTime_Yes'] = 0.
```

[50]:
```
y_pred = clf.predict(x_train)
y_pred_experiment = clf.predict(x_train_experiment)
```

[51]:
```
diff = sum(y_pred - y_pred_experiment)
print('expected difference', diff)
```

```
expected difference 59
```

[ ]:

8 7.) If they company loses an employee, there is a cost to train a new employee for a role ~2.8 * their monthly income.

9 To make someone not work overtime costs the company 2K per person.

10 Is it profitable for the company to remove overtime? If so/not by how much?

11 What do you suggest to maximize company profits?

[52]:
```
x_train_experiment['Y'] = y_pred
x_train_experiment['Y_exp'] = y_pred_experiment
```

[53]:
```
x_train_experiment['RetChange'] = x_train_experiment['Y_exp'] -␣
↪x_train_experiment['Y']
```

[54]:
```
sav = sum(-2.8*x_train_experiment['RetChange'] *␣
↪x_train_experiment['MonthlyIncome'])
```

[55]:
```
cost = len(x_train[x_train['OverTime_Yes']==1]) * 2000
```

[56]:
```
print("Profit from overtime: ", sav-cost)
```

```
Profit from overtime:  -117593.99999999977
```

11.1 ANSWER :

- Our savings come from not losing employees
- our cost comes from over time
- keep them working over time
- more profitable to keep employees working

12 8.) Use your model and get the expected change in retention for raising and lowering peoples income. Plot the outcome of the experiment. Comment on the outcome of the experiment and your suggestions to maximize profit.

[57]:
```
raise_amount = 100
```

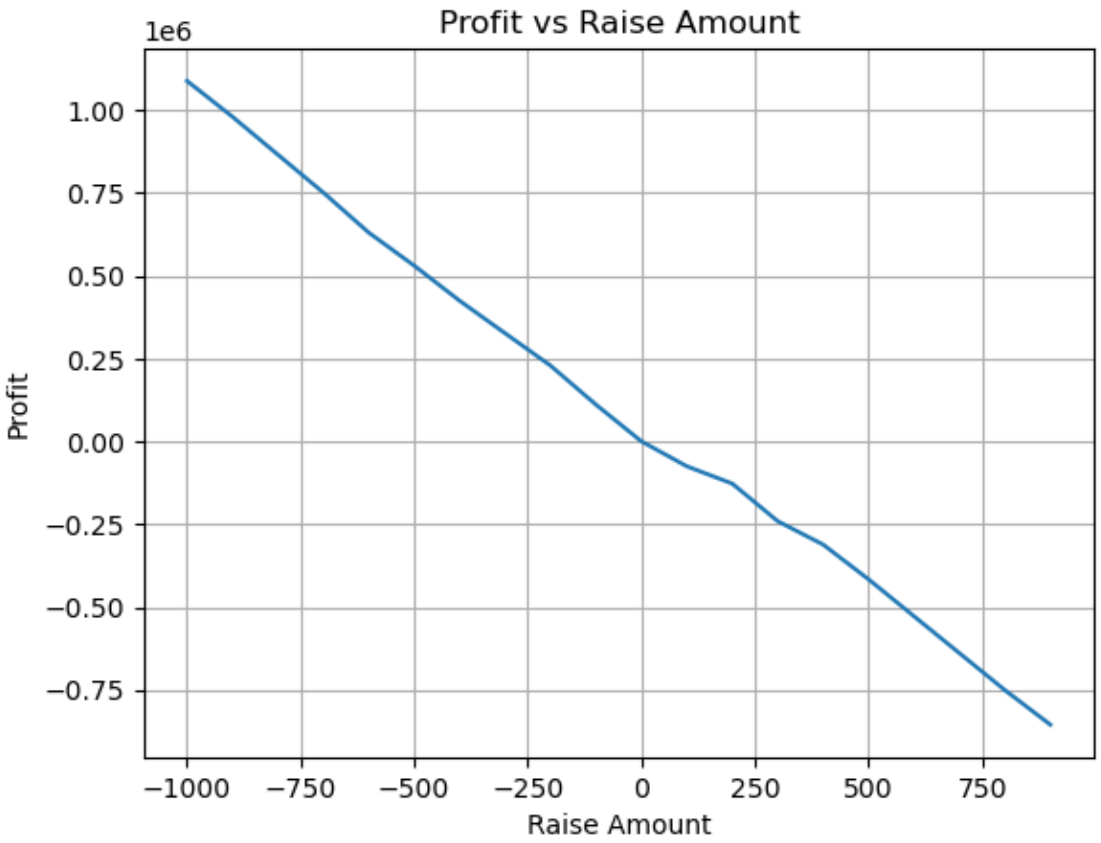
[58]:
```
profits = []
for raise_amount in range(-1000, 1000, 100):
    x_train_experiment = x_train.copy()
```

```
    x_train_experiment['MonthlyIncome'] = x_train_experiment['MonthlyIncome'] ␣
↪+ raise_amount

    y_pred = clf.predict(x_train)
    y_pred_experiment = clf.predict(x_train_experiment)

    diff = sum(y_pred - y_pred_experiment)
    print('Change in attrition', diff)

    x_train_experiment['Y'] = y_pred
    x_train_experiment['Y_exp'] = y_pred_experiment

    x_train_experiment['RetChange'] = x_train_experiment['Y_exp'] -␣
↪x_train_experiment['Y']

    sav = sum(-2.8*x_train_experiment['RetChange'] *␣
↪x_train_experiment['MonthlyIncome'])

    cost = len(x_train) * raise_amount

    profit = sav - cost

    print("Profit: {:.2f}".format(profit))

    profits.append(profit)
```

```
Change in attrition -16
Profit: 1087584.40
Change in attrition -14
Profit: 979524.00
Change in attrition -13
Profit: 864992.80
Change in attrition -12
Profit: 750738.80
Change in attrition -12
Profit: 629778.80
Change in attrition -9
Profit: 530138.00
Change in attrition -7
Profit: 424200.00
Change in attrition -4
Profit: 326096.40
Change in attrition -1
Profit: 228440.80
Change in attrition -1
Profit: 110714.80
Change in attrition 0
```

```
Profit: 0.00
Change in attrition 6
Profit: -75328.40
Change in attrition 15
Profit: -127503.60
Change in attrition 15
Profit: -240914.80
Change in attrition 21
Profit: -311586.80
Change in attrition 22
Profit: -416449.60
Change in attrition 22
Profit: -527889.60
Change in attrition 22
Profit: -639329.60
Change in attrition 22
Profit: -750769.60
Change in attrition 23
Profit: -854999.60
```

[61]:
```python
plt.plot(range(-1000, 1000, 100), profits)
plt.xlabel('Raise Amount')
plt.ylabel('Profit')
plt.title('Profit vs Raise Amount')
plt.grid(True)
plt.show()
```



12.1 ANSWER :

- raising amount hurts our profits