# (SEC1) 4 - Classwork

January 31, 2024

## 1 HR ATTRIBUTION

[29]:
```
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
from scipy.stats import pearsonr
```

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

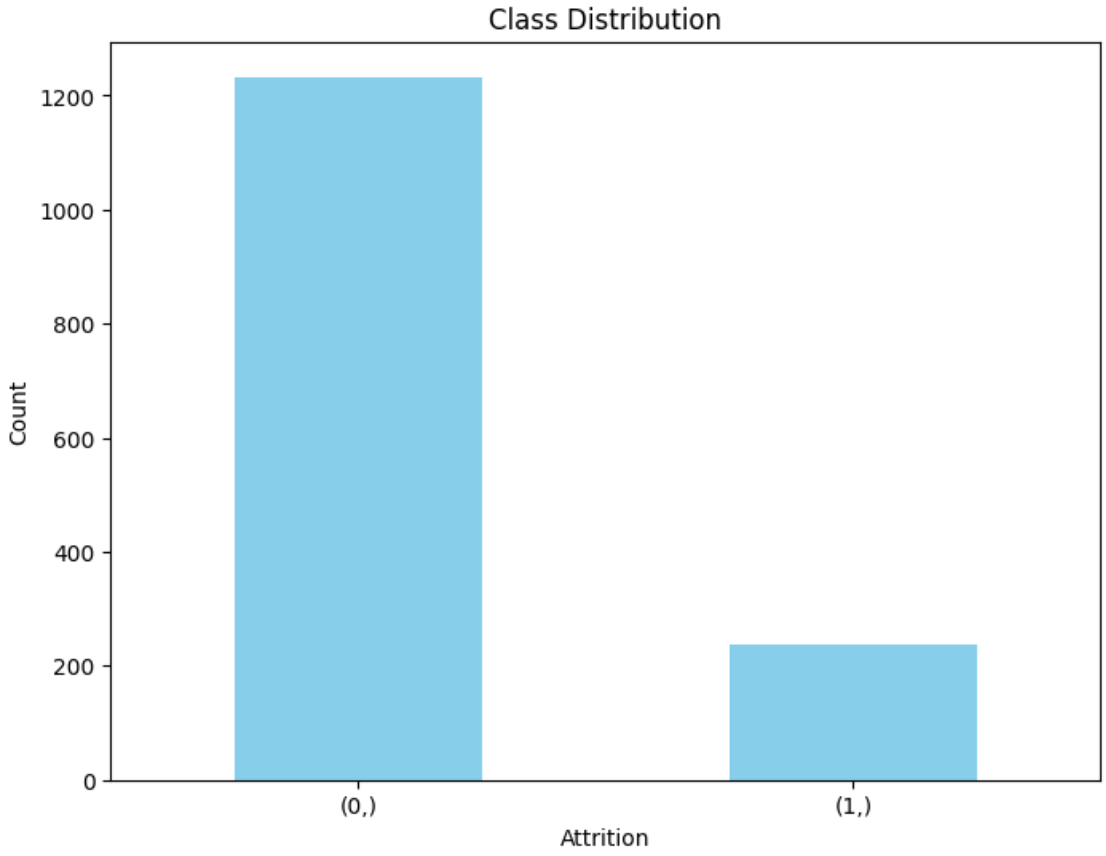
[19]:
```
df = pd.read_csv("HR_Analytics.csv")
```

[20]:
```
y = df[["Attrition"]].copy()
X = df.drop("Attrition", axis = 1)
```

[21]:
```
y["Attrition"] = [1 if i == "Yes" else 0 for i in y["Attrition"]]
```

[22]:
```
class_counts = y.value_counts()


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

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




[23]:
```
# 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)
```

[24]:
```
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?

[25]:
```
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 :  0.79
```

## 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?

[26]:
```
# 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
```

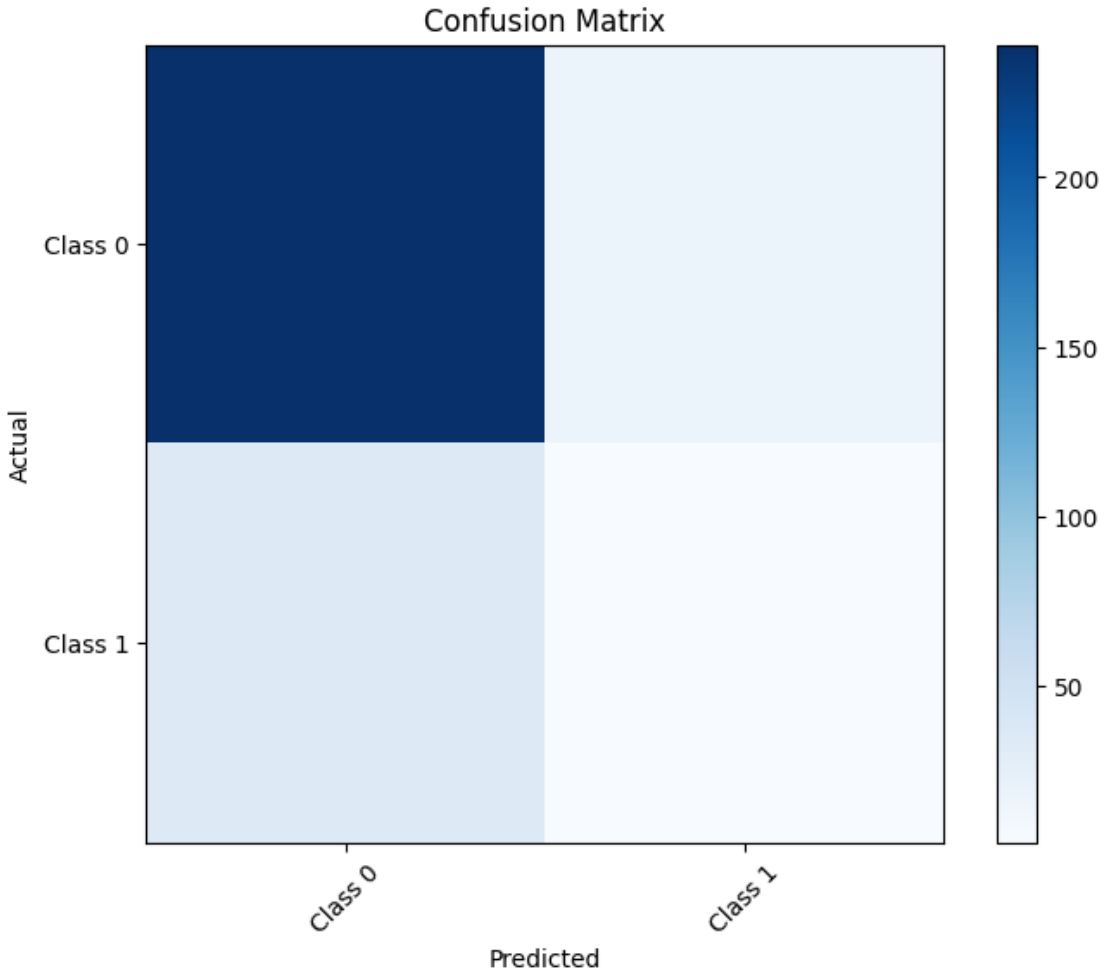
[27]:
```
clf = tree.DecisionTreeClassifier(**best_params, random_state =42)
clf.fit(x_train,y_train)
y_pred=clf.predict(x_train)
acc=accuracy_score(y_train,y_pred)
print("IN SAMPLE ACCURACY : " , round(acc,2))

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

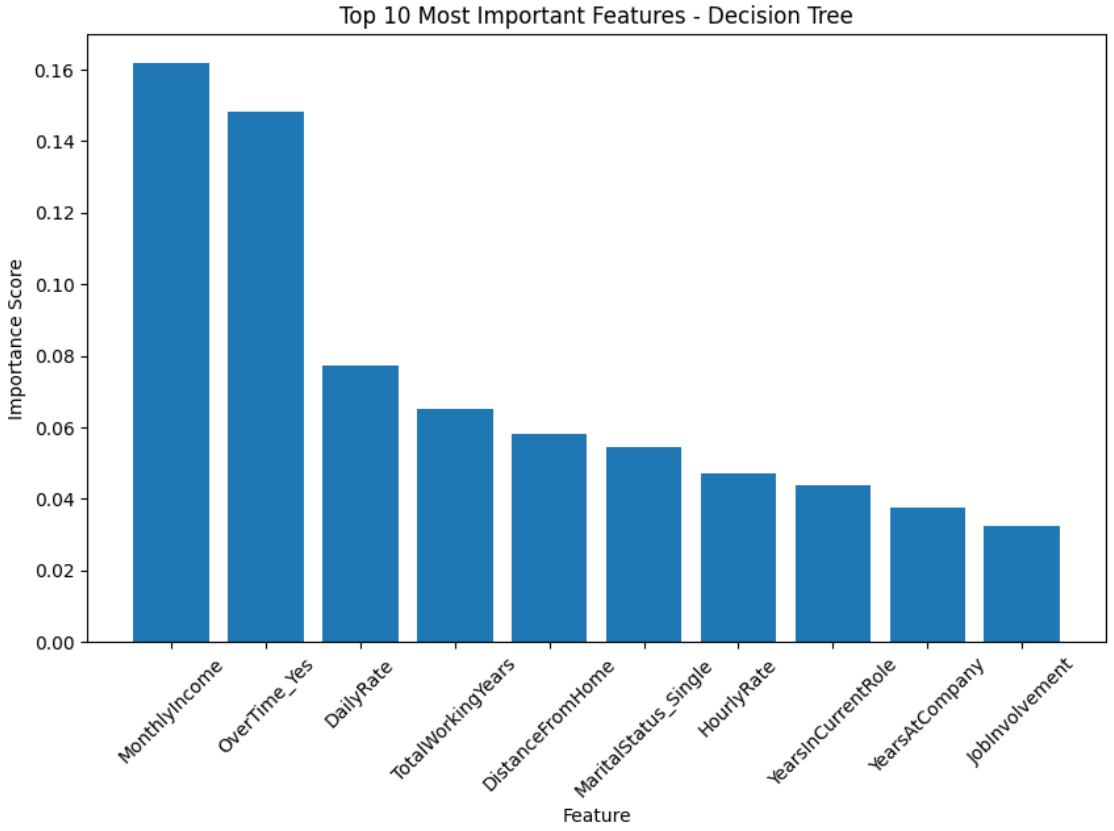
```
IN SAMPLE ACCURACY :  0.91
OUT OF SAMPLE ACCURACY :  0.83
```

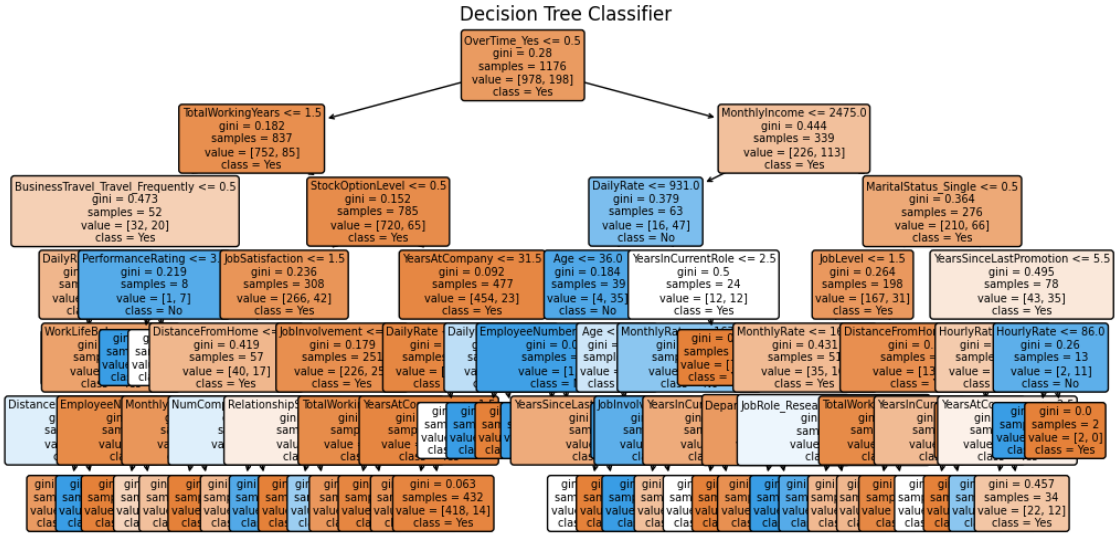
## 5 4.) Plot .....

[28]:
```
# 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
EmployeeNumber
gini = 0.0
samples = 1
class = No
MonthlyRate <= 1
gini = 0.431
samples = 51
value = [35, 1
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. Calculate anything you think would assist in your assessment.

### 6.1 ANSWER :

[50]:
```
print(pearsonr(np.array(X['MonthlyIncome']),np.array(y["Attrition"])))
print(pearsonr(np.array(X['OverTime_Yes']),np.array(y["Attrition"])))
```

```
PearsonRResult(statistic=-0.15983958238499035, pvalue=7.147363985350898e-10)
PearsonRResult(statistic=0.2461179942458061, pvalue=1.0092540336555553e-21)
```

Given the two most important features: Monthly Income, and Working Overtime, and given their correlations with attrition, we can argue that higher income makes workers stay at the company, while making them work overtime decreases the probability that the worker will stay at the company.

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

[82]:
```
x_train_experiment = x_train.copy()
x_train_experiment["OverTime_Yes"] = 0
```

[83]:
```
y_pred = clf.predict(x_train)
y_pred_experiment = clf.predict(x_train_experiment)
```

[85]:
```
diff = sum(y_pred - y_pred_experiment)
print('The expected difference in retention would be of',diff,'people staying␣
 ↪at the company.')
```

```
The expected difference in retention would be of 59 people staying at the
company.
```

## 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?

[86]:
```
x_train_experiment["Y"] = y_pred
x_train_experiment["Y_exp"] = y_pred_experiment
```

[87]:
```
x_train_experiment["RetChange"] = x_train_experiment["Y_exp"] -␣
↪x_train_experiment["Y"]
```

[88]:
```
sav = sum(-2.
↪8*x_train_experiment["RetChange"]*x_train_experiment["MonthlyIncome"])
```

[89]:
```
cost = len(x_train[x_train["OverTime_Yes"]==1])*2000
```

[90]:
```
sav-cost
```

[90]:
```
-117593.99999999977
```

Since we get a negative estimated profit, we can argue that we should keep the workers working overtime. Training a new employer is not as costly as the cost of making someone not work overtime, so it doesn't matter if they eventually leave.

### 11.1 ANSWER :

## 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.

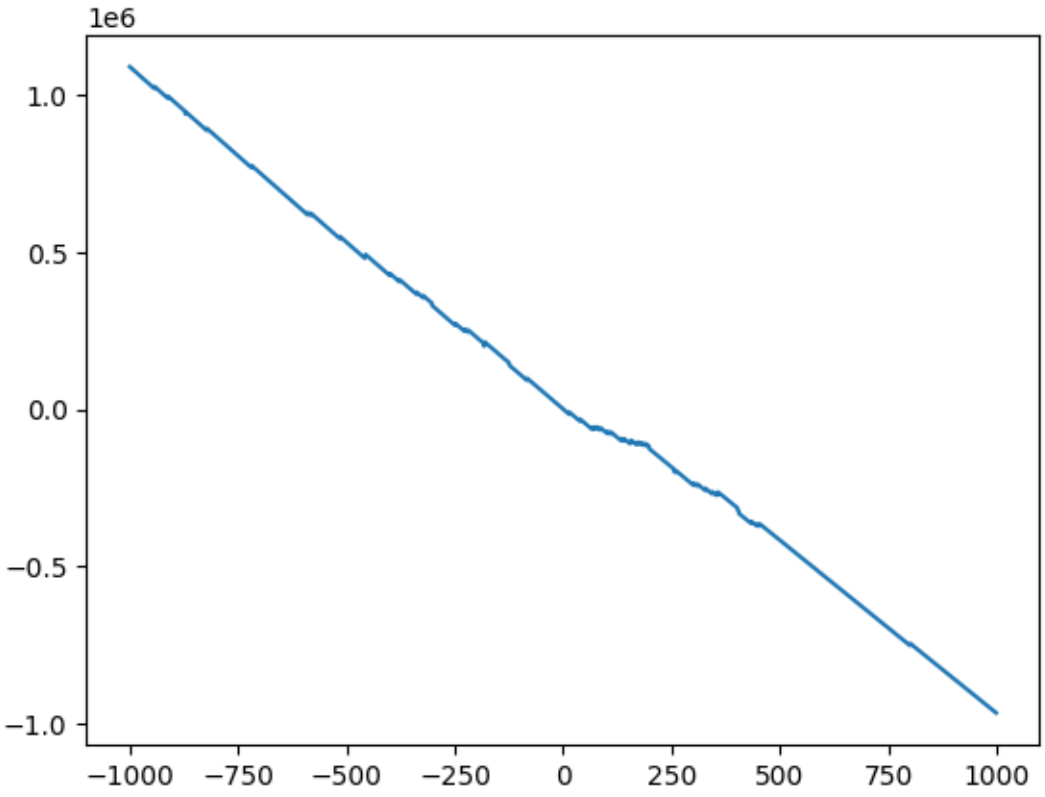
[93]:
```
profits = []

for raise_amount in range(-1000,1000):
    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)

    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

    prof = sav-cost

    profits.append(prof)
```

-75328.4000001

[94]:
```
plt.plot(range(-1000,1000),profits)
```

[94]: [<matplotlib.lines.Line2D at 0x28ca6ec90>]



### 12.1 ANSWER :

We see that the profits are maximized when we have a negative 1000 raise amount. So the intuition is that hiring new employees is actually so relatively cheap, that we should decrease our workers income without caring if they stay at the company, as we can get new workers and cover the cost with the saves from paying lower wages.