HR ATTRIBUTION

In [1]:
```
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
```

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

In [2]:
```
df = pd.read_csv("HR_Analytics.csv")
```

In [3]:
```
df.head()
```

Out[3]:

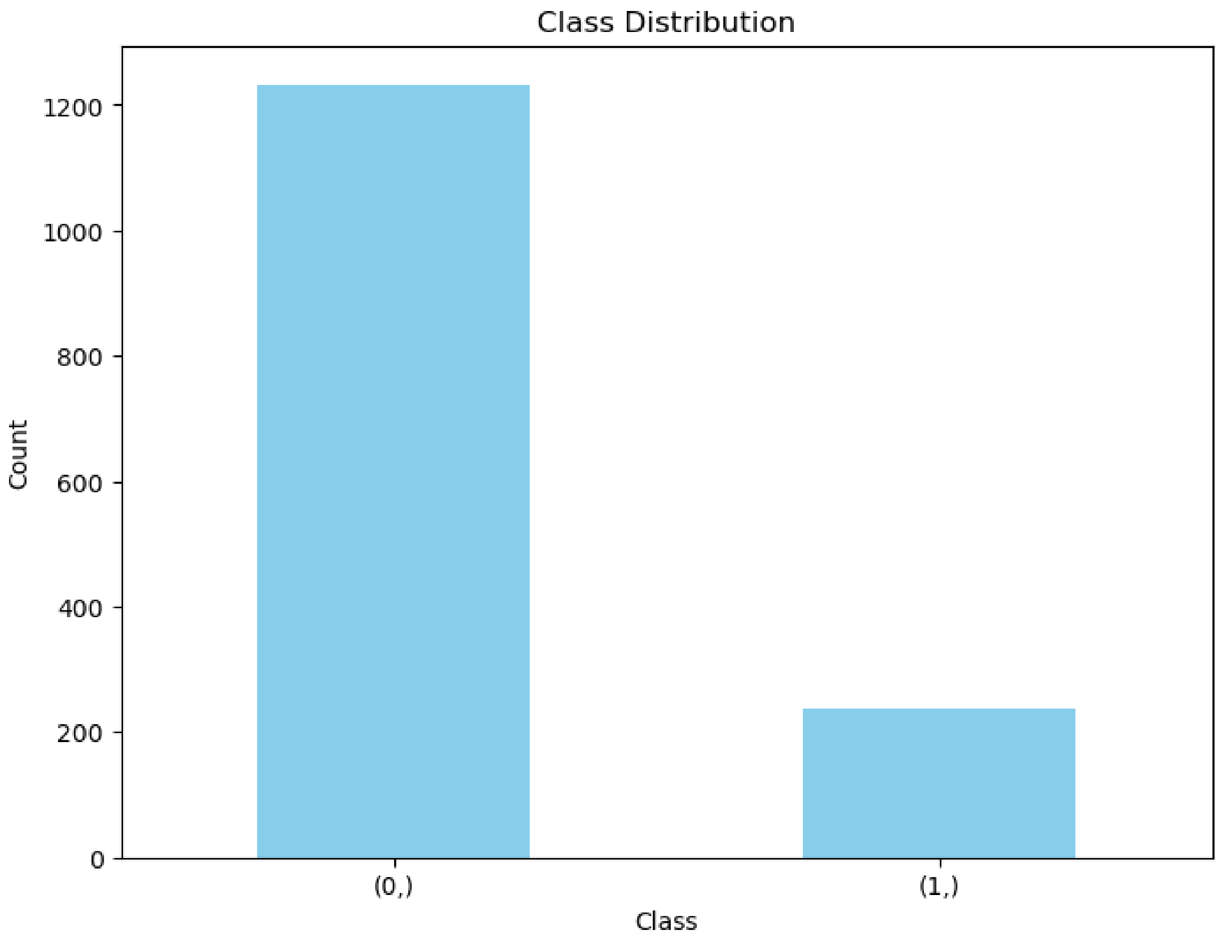
	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Education
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Scie
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Scie
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	(
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Scie
4	27	No	Travel_Rarely	591	Research & Development	2	1	Me

5 rows × 35 columns

In [4]:
```
y = df[["Attrition"]].copy()
X = df.drop("Attrition", axis = 1)
```

In [5]:
```
y["Attrition"] = [1 if i == "Yes" else 0 for i in y["Attrition"]]
```

In [6]:
```
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()
```



In [7]:
```
# 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)
```

In [8]:
```
x_train,x_test,y_train,y_test=train_test_split(X,
 y, test_size=0.20, random_state=42)
```

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

In [9]:
```
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 :  0.77
```

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

In [10]:
```
# 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=sco

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)
```

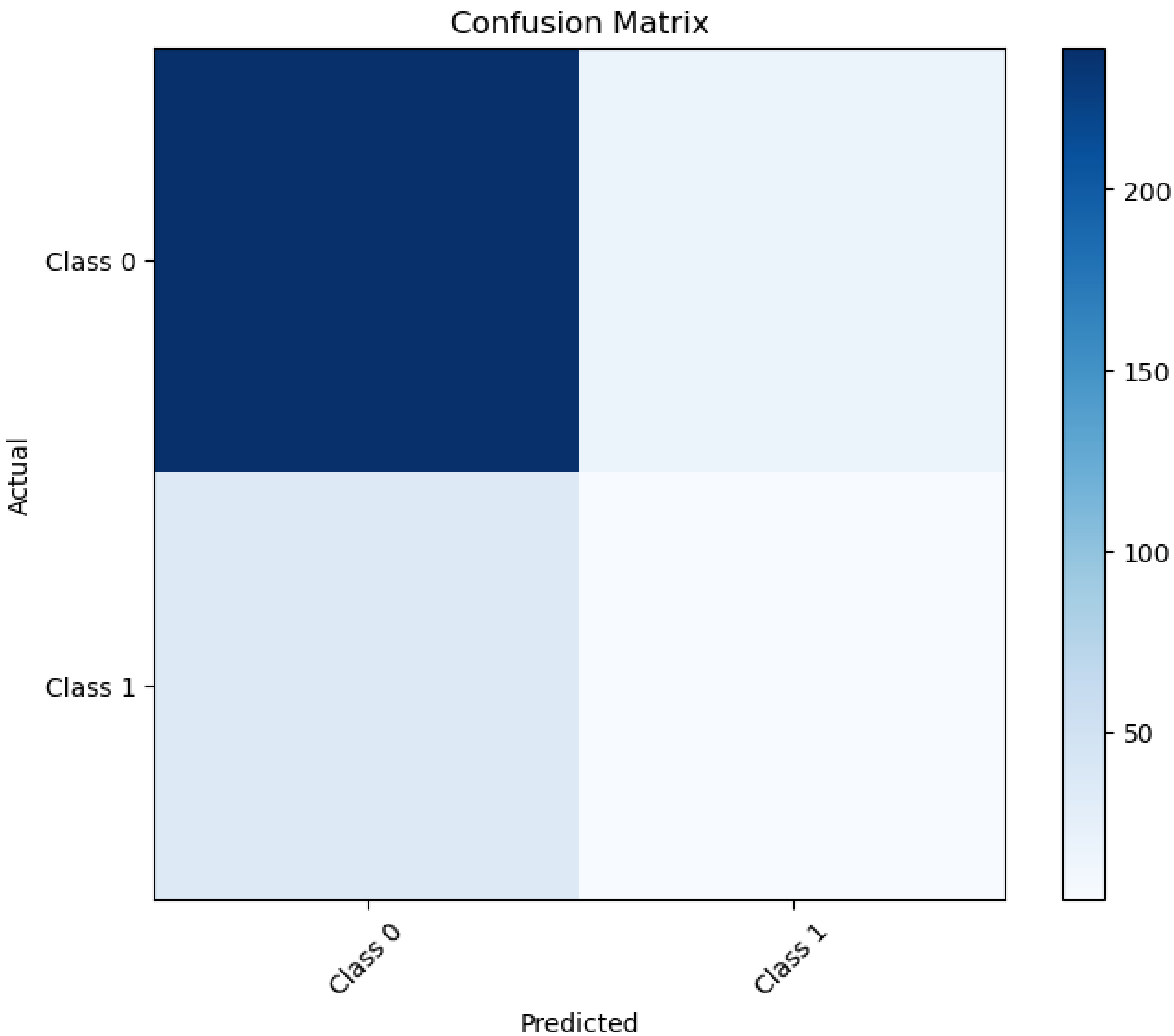
```
Best Parameters: {'criterion': 'gini', 'max_depth': 6, 'min_samples_leaf': 2, 'min_sa
mples_split': 2}
Best F1-Score: 0.8214764475510983
```

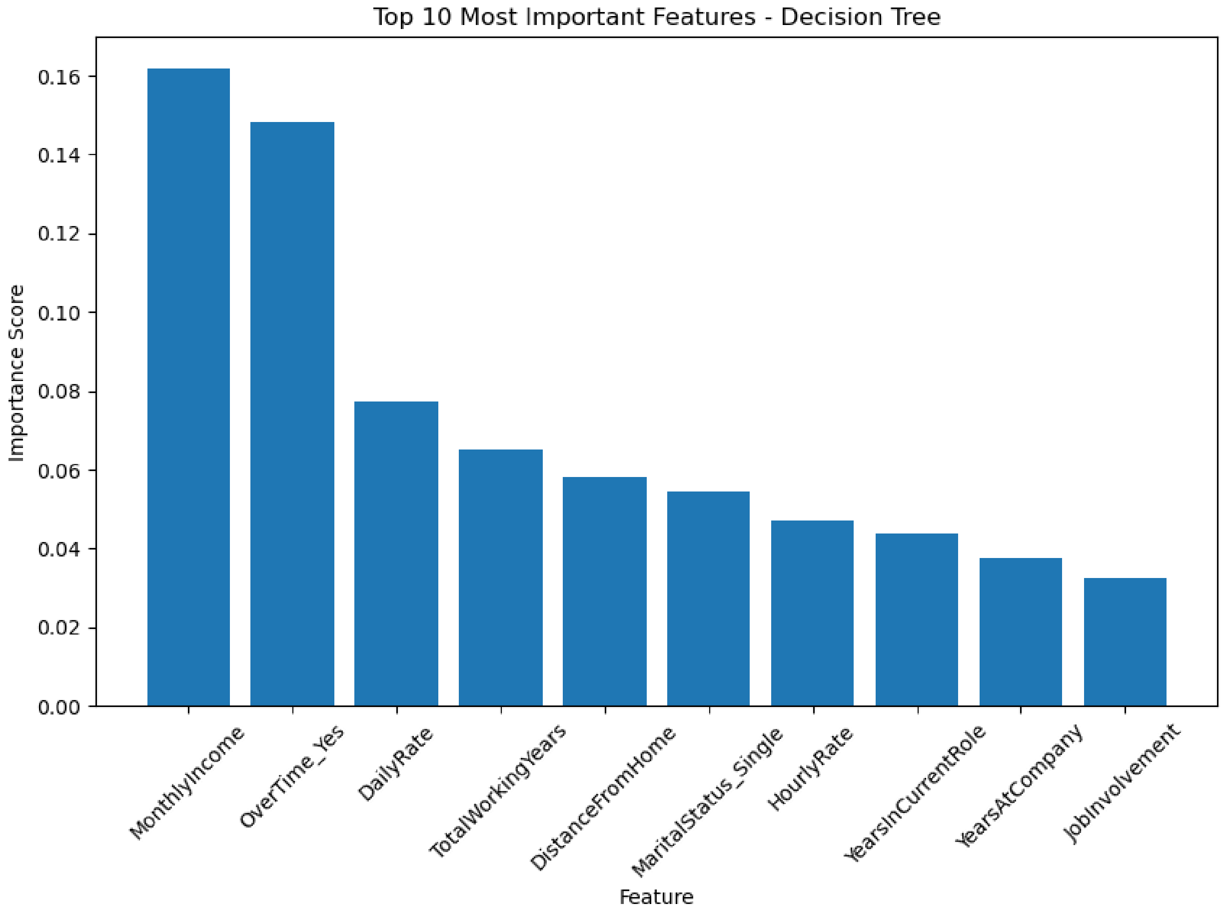
In [11]:
```
clf = tree.DecisionTreeClassifier(**best_params, random_state =42)
clf.fit(x_train,y_train)
y_pred=clf.predict(x_train)
acc=accuracy_score(y_train,y_pred)
print("IN SAMPLE ACCURACY : " , round(acc,2))

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

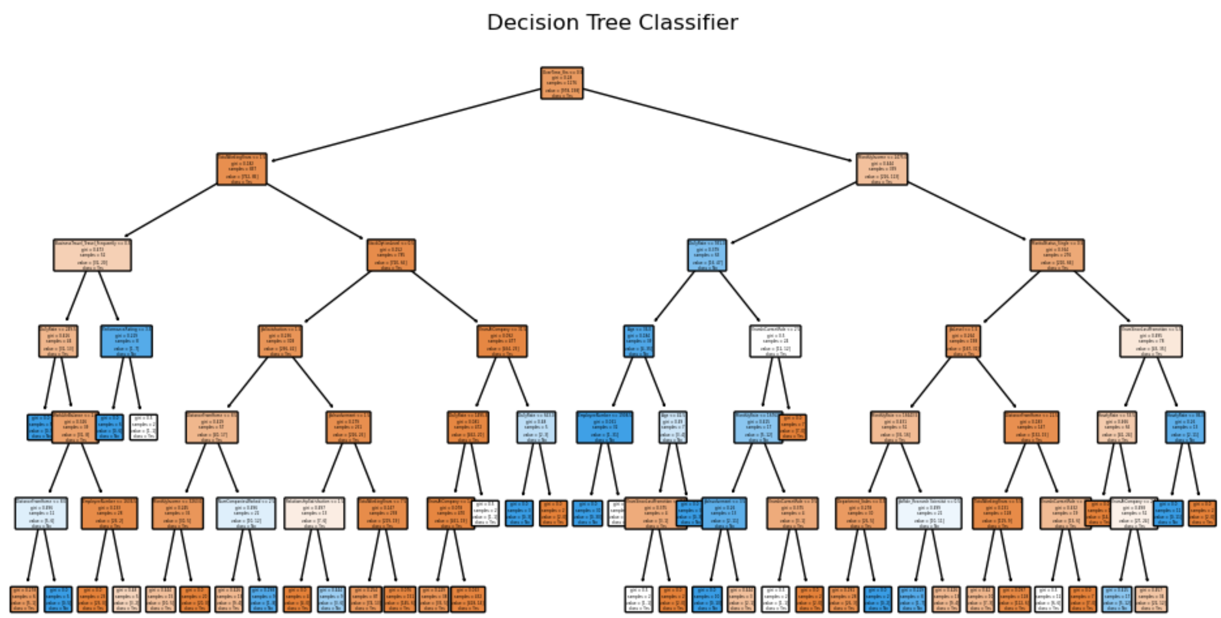
```
IN SAMPLE ACCURACY :  0.91
OUT OF SAMPLE ACCURACY :  0.83
```

4.) Plot ......

In [12]:
```python
# 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=list(X.columns), class_names=["Yes", "No"],
plt.title('Decision Tree Classifier')
plt.show()
```


Confusion Matrix
Class 0
Class 1
Actual
Class 0
Class 1
Predicted
200
150
100
50





In [ ]:

In [ ]:

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.

ANSWER :

In [14]:
```
np.corrcoef(np.array(X['OverTime_Yes']),y['Attrition'])
```

Out[14]:
```
array([[1.        , 0.24611799],
       [0.24611799, 1.        ]])
```

In [ ]:
```

```

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

In [29]:
```
x_train_exper = x_train.copy()
```

In [30]:
```
x_train_exper['OverTime_Yes'] = 0.
```

In [31]:
```
y_pred_exper = clf.predict(x_train_exper)
y_pred = clf.predict(x_train)
```

In [34]:
```
sum(y_pred - y_pred_exper)
```

Out[34]:
```
59
```

Stopping overtime would lead to a loss of 59

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

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

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

What do you suggest to maximize company profits?

In [35]:
```
x_train_exper['Y'] = y_pred
x_train_exper['Y_exp'] = y_pred_exper
x_train_exper['Ret_Change'] = x_train_exper['Y'] - x_train_exper['Y_exp']
```

In [36]:
```
sav = x_train_exper['Ret_Change'] * 2.8 * x_train_exper['MonthlyIncome']
```

In [45]:
```
sum(sav)
```

Out[45]:
```
560406.0000000002
```

In [41]:
```
cost = 2000 * len(x_train[x_train['OverTime_Yes'] == 1.])
```

In [47]:
```
cost
```

Out[47]:
```
678000
```

In [49]:
```
sum(sav) - cost
```

Out[49]:
```
-117593.99999999977
```

I would reccomend maintaining or even expanding overtime as the cost of removing overtime at present exceeds the benefits if provides

ANSWER :

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.

In [83]:
```
raise_amount = 500
```

In [84]:
```
x_train_exper = x_train.copy()
```

In [85]:
```
x_train_exper['MonthlyIncome'] += raise_amount
```

In [86]:
```
y_pred_exper = clf.predict(x_train_exper)
y_pred = clf.predict(x_train)
```

In [87]:
```
x_train_exper['Y'] = y_pred
x_train_exper['Y_exp'] = y_pred_exper
x_train_exper['Ret_Change'] = x_train_exper['Y'] - x_train_exper['Y_exp']
```

In [88]:
```
sav = x_train_exper['Ret_Change'] * 2.8 * x_train_exper['MonthlyIncome']
```

In [89]:
```
cost = raise_amount* len(x_train)
cost
```

Out[89]:
```
1176000
```

In [90]:
```
sum(sav) - cost
```

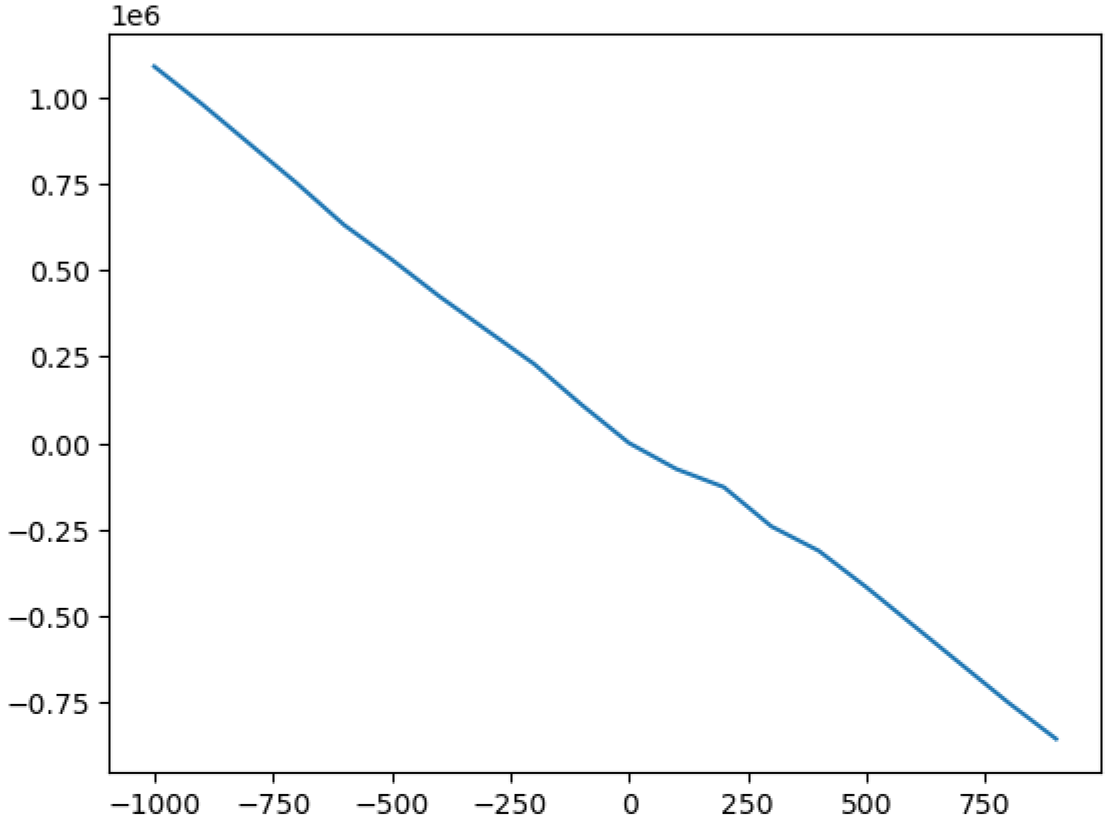
Out[90]:
```
-966159.6000000001
```

In [97]:
```
profits = []
for raise_amount in range(-1000,1000,100):
    x_train_exper = x_train.copy()
    x_train_exper['MonthlyIncome'] += raise_amount
    y_pred_exper = clf.predict(x_train_exper)
    y_pred = clf.predict(x_train)
    x_train_exper['Y'] = y_pred
    x_train_exper['Y_exp'] = y_pred_exper
    x_train_exper['Ret_Change'] = x_train_exper['Y'] - x_train_exper['Y_exp']
    sav = x_train_exper['Ret_Change'] * 2.8 * x_train_exper['MonthlyIncome']
    cost = raise_amount* len(x_train)
    print('Profits is ,' , sum(sav) - cost)
    profits.append(sum(sav) - cost)
```

```
Profits is , 1087584.4
Profits is , 979524.0
Profits is , 864992.8
Profits is , 750738.8
Profits is , 629778.8
Profits is , 530138.0
Profits is , 424200.0
Profits is , 326096.4
Profits is , 228440.8
Profits is , 110714.8
Profits is , 0.0
Profits is , -75328.40000000001
Profits is , -127503.60000000002
Profits is , -240914.8
Profits is , -311586.80000000005
Profits is , -416449.6000000001
Profits is , -527889.6000000001
Profits is , -639329.6000000001
Profits is , -750769.6000000001
Profits is , -854999.6000000001
```

In [99]:
```
plt.plot(range(-1000,1000,100), profits)
```

Out[99]: [<matplotlib.lines.Line2D at 0x204f98cda90>]



ANSWER :

Following the model, to maximize profits, reducing the monthly income / wage of the employees as the cost of wages is higher than training/layoff costs