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_sc
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
0	41	Yes	Travel_Rarely	1102	Sales	1	2
1	49	No	Travel_Frequently	279	Research & Development	8	1
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2
3	33	No	Travel_Frequently	1392	Research & Development	3	4
4	27	No	Travel_Rarely	591	Research & Development	2	1

5 rows × 35 columns

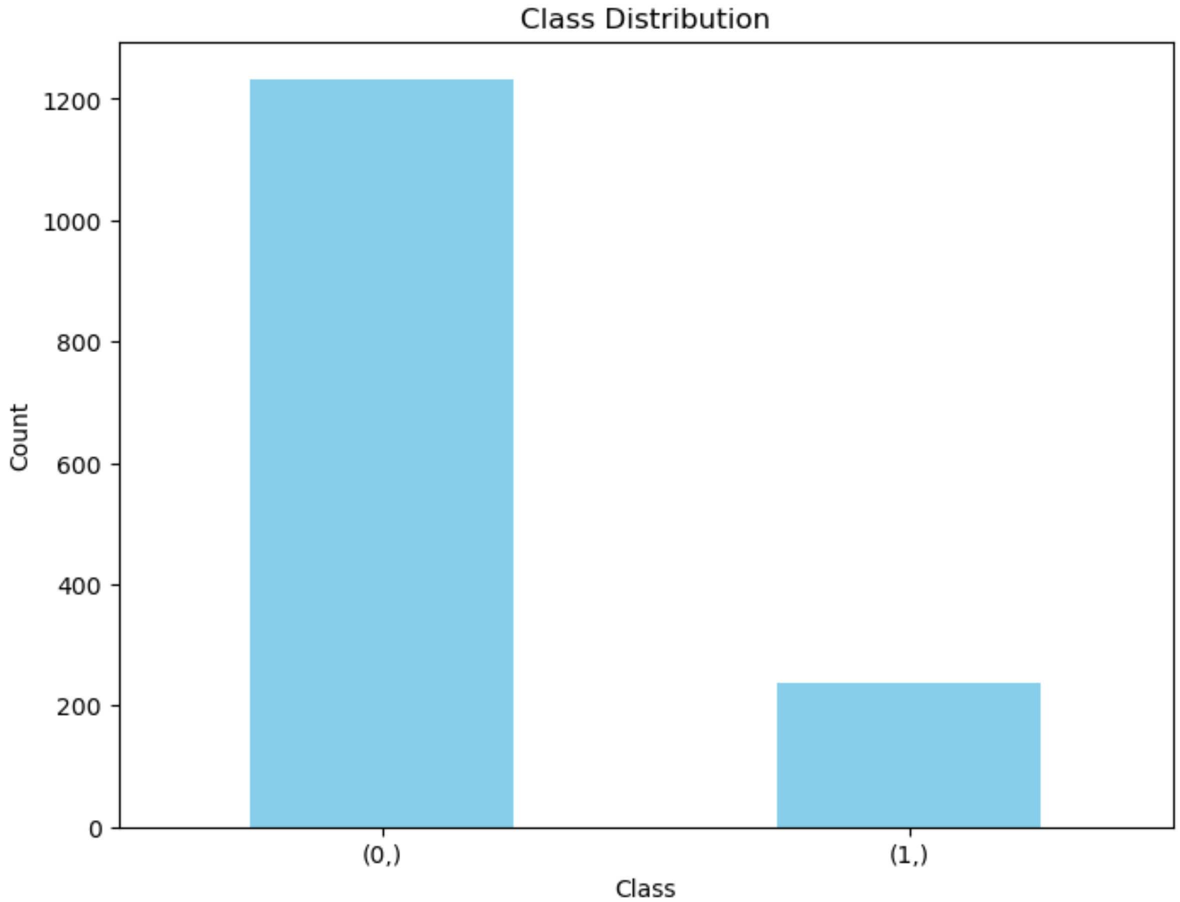
In [4]:
```
y = df[["Attrition"]].copy()
X = df.drop("Attrition", axis = 1)
```

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 is important to avoid multicollinearity
```

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 :  0.78
```

In [10]:
```
#There is some overfitting here so we can reduce the in-sample accu
```

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 [11]:
```
# Define the hyperparameter grid to search through
param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': np.arange(1, 11),  # Range of max_depth values to
    '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=para

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_sample
s_leaf': 2, 'min_samples_split': 2}
Best F1-Score: 0.8214764475510983
```

In [12]:
```
# we can take the above dictionary as parameters for the model belo
```

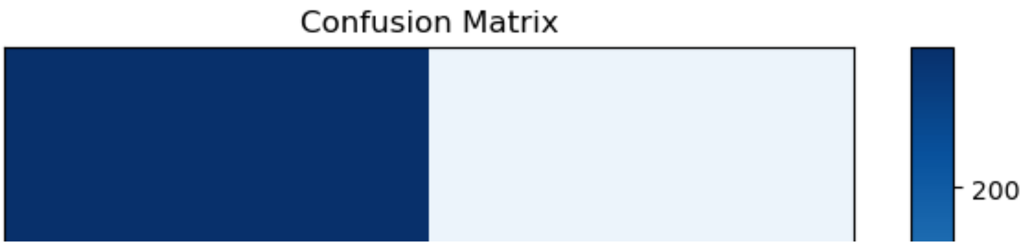
In [13]:
```
clf = tree.DecisionTreeClassifier(**best_params, random_state =42)
clf.fit(x_train,y_train)
y_pred=clf.predict(x_train)
acc=accuracy_score(y_train,y_pred)
print("IN SAMPLE ACCURACY : " , round(acc,2))

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

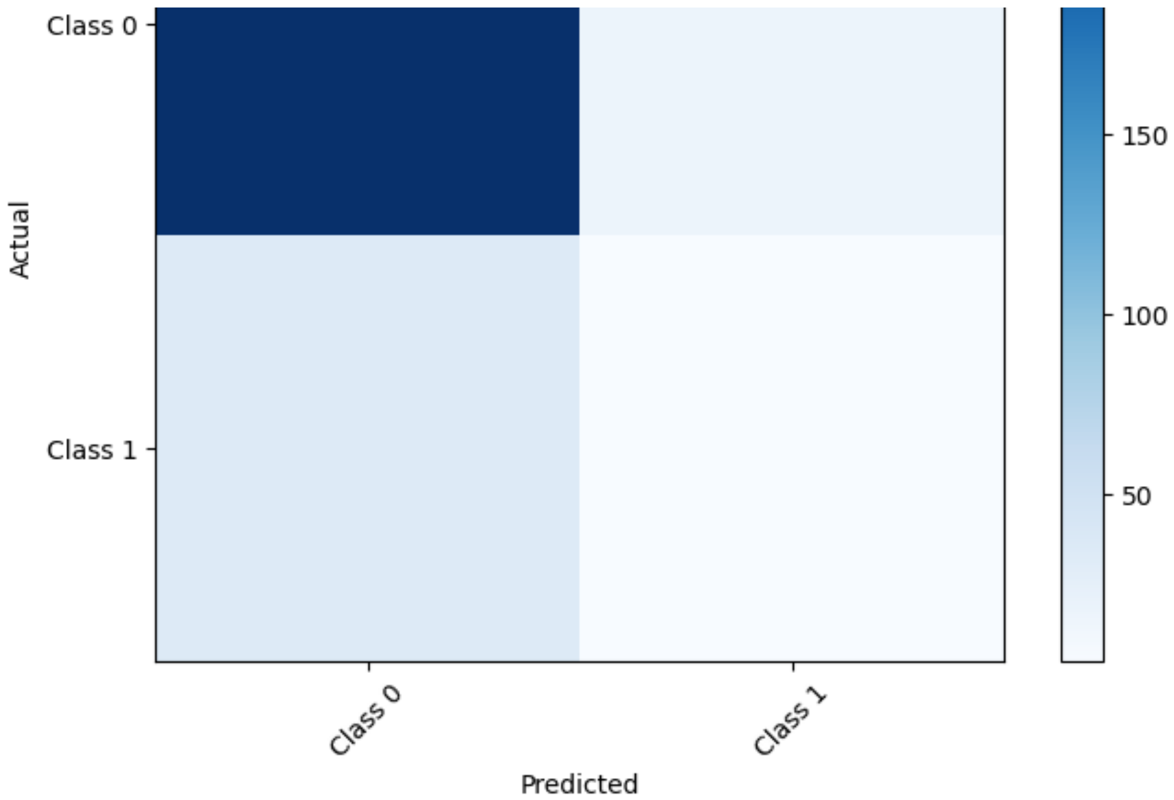
```
IN SAMPLE ACCURACY :  0.91
OUT OF SAMPLE ACCURACY :  0.83
```

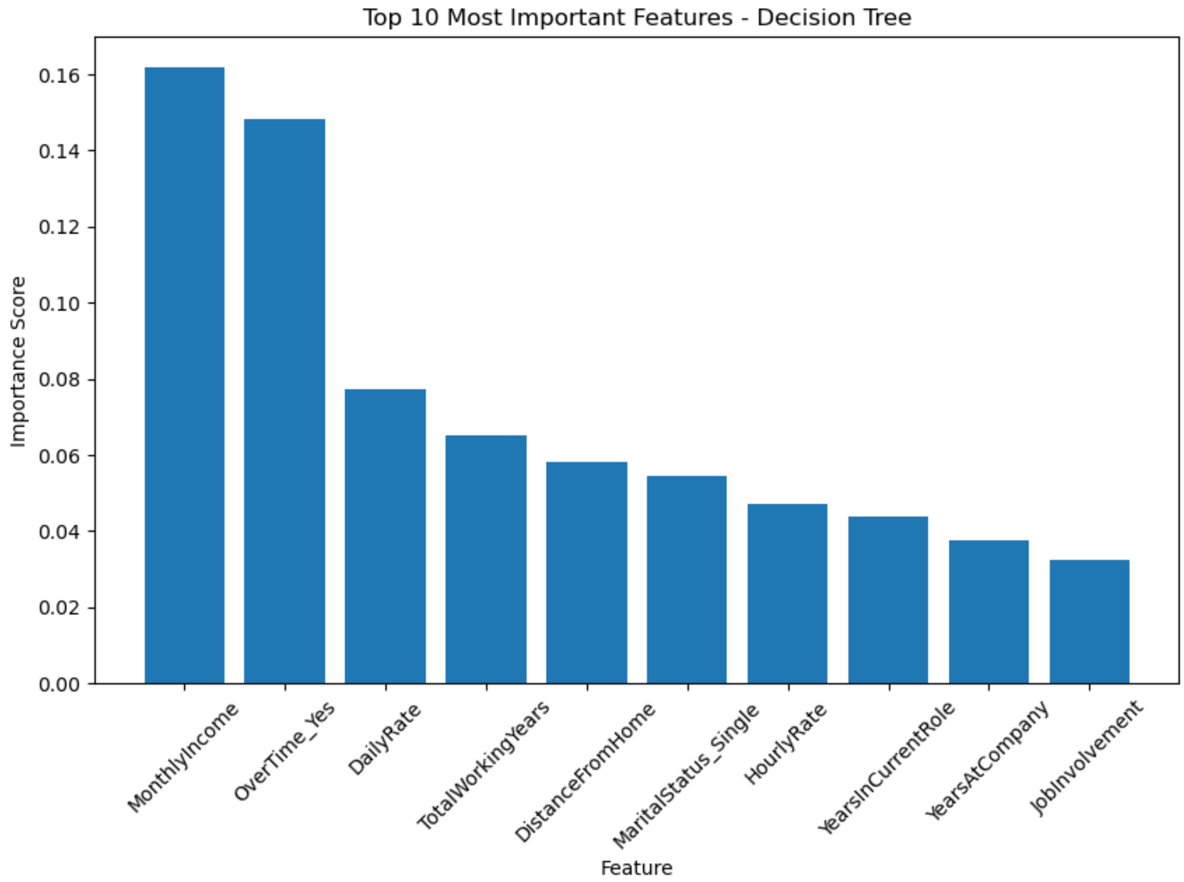
4.) Plot ......

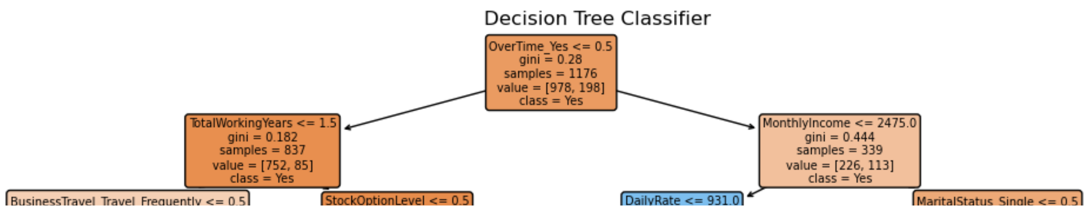
In [14]:

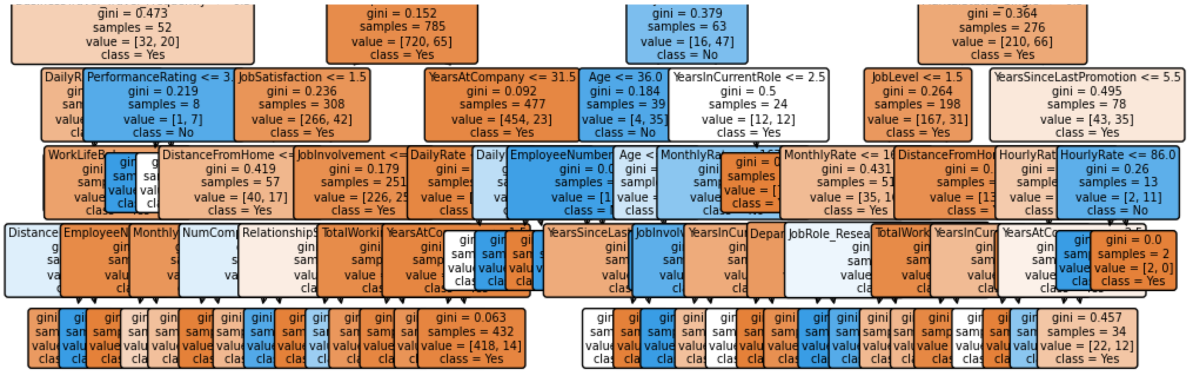
```
# Make predictions on the test data
y_pred = clf.predict(x_test)
y_prob = clf.predict_proba(x_test)[:, 1]

# 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 f
plt.figure(figsize=(12, 6))
plot_tree(clf, filled=True, feature_names=X.columns, class_names=["
plt.title('Decision Tree Classifier')
plt.show()
```




Class 0
Class 1
Actual
150
100
50
Class 0
Class 1
Predicted


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
StockOptionLevel <= 0.5
DailyRate <= 931.0
MaritalStatus_Single <= 0.5



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

ANSWER :

In [32]:
```
np.corrcoef(np.array(X['OverTime_Yes']), np.array(y['Attrition']))
```

Out[32]:
```
array([[1.        , 0.24611799],
       [0.24611799, 1.        ]])
```

In [ ]:
```
The more hours they work the more likey they are to leave, hence in
```

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

In [34]:
```
x_train_experiment = x_train.copy()

x_train_experiment["OverTime_Yes"] = 0.
```

In [35]:
```
y_pred_experiment = clf.predict(x_train_experiment)
```

In [36]:
```
y_pred = clf.predict(x_train)
```

In [37]:
```
y_pred - y_pred_experiment

retention = sum(y_pred - y_pred_experiment)
```

In [38]:
```
retention
```

Out[38]:
```
59
```

In [39]:
```
#Stopping overtime work would have prevented 59 people from leaving
```

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 [18]:
```
x_train_experiment["Y"]= y_pred
x_train_experiment["Y_exp"] = y_pred_experiment
x_train_experiment["Ret_Change"] = x_train_experiment["Y"] - x_trai
```

In [20]:
```
# Saving: Change in training cost
sav = sum(x_train_experiment["Ret_Change"]* 2.8 * x_train_experimen
```

In [21]:
```
# Cost of lost OverTime
cost = 2000 * len(x_train[x_train['OverTime_Yes'] == 1.])
```

In [22]:
```
print("Profit from this experiment:", sav - cost)
```

```
Profit from this experiment: -117593.99999999977
```

In [23]:
```
# to max profit remove overtime and train new people if required
```

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.

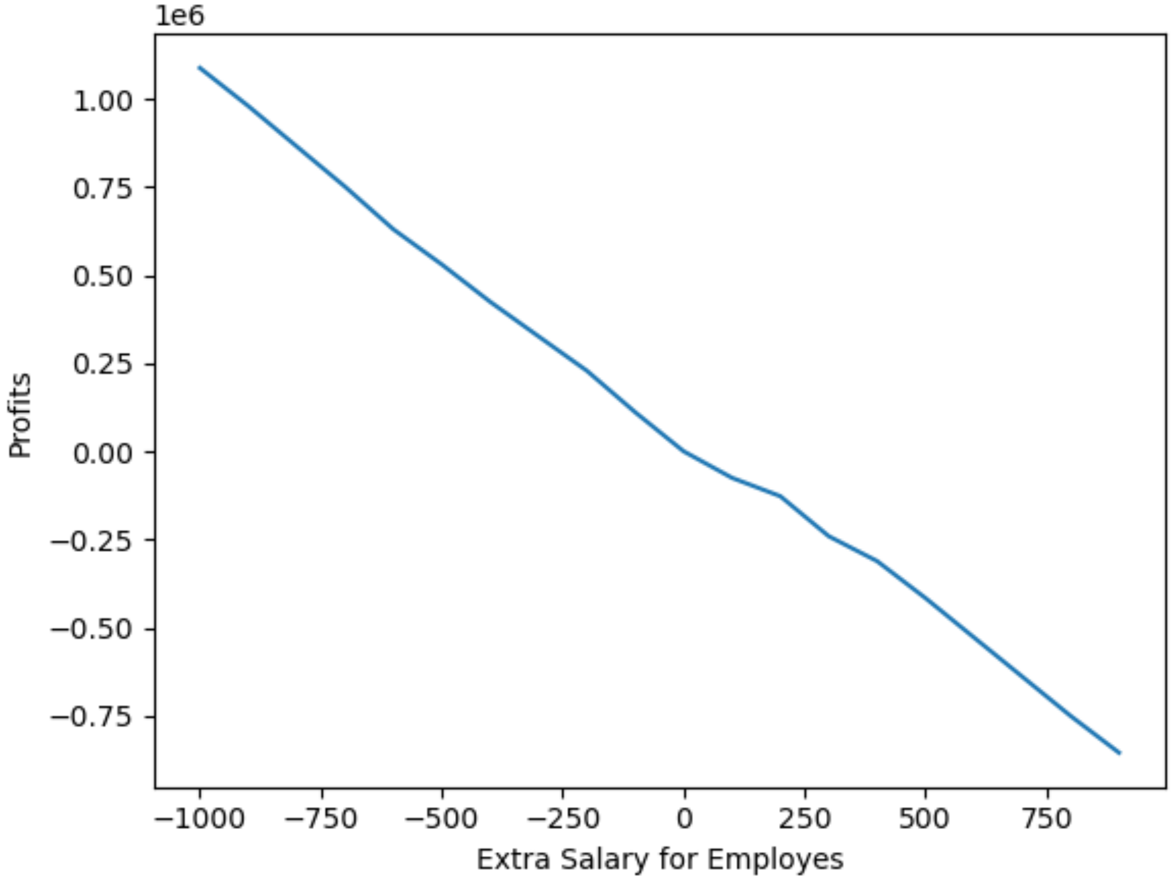
In [24]:
```
raise_amount = 500
```

In [25]:
```
profits = []
for raise_amount in range(-1000, 1000, 100):
    x_train_experiment = x_train.copy()
    x_train_experiment['MonthlyIncome'] = x_train_experiment['Month
    y_pred_experiment = clf.predict(x_train_experiment)
    y_pred = clf.predict(x_train)
    x_train_experiment["Y"] = y_pred
    x_train_experiment["Y_exp"] = y_pred_experiment
    x_train_experiment["Ret_Change"] = x_train_experiment["Y"] - x_

    # Saving: Change in Training cost
    print("Retention difference", sum(x_train_experiment["Ret_Chang
    sav = sum(x_train_experiment["Ret_Change"]* 2.8 * x_train_exper

    # Cost of lost Overtime
    cost = raise_amount * len(x_train)


    print("Profit is ", sav - cost)
    profits.append(sav - cost)
```

```
Retention difference -16
Profit is  1087584.4
Retention difference -14
Profit is  979524.0
Retention difference -13
Profit is  864992.8
Retention difference -12
Profit is  750738.8
Retention difference -12
Profit is  629778.8
Retention difference -9
Profit is  530138.0
Retention difference -7
Profit is  424200.0
Retention difference -4
Profit is  326096.4
Retention difference -1
Profit is  228440.8
Retention difference 1
```

```
Retention difference -1
Profit is  110714.8
Retention difference 0
Profit is  0.0
Retention difference 6
Profit is  -75328.40000000001
Retention difference 15
Profit is  -127503.60000000002
Retention difference 15
Profit is  -240914.8
Retention difference 21
Profit is  -311586.80000000005
Retention difference 22
Profit is  -416449.6000000001
Retention difference 22
Profit is  -527889.6000000001
Retention difference 22
Profit is  -639329.6000000001
Retention difference 22
Profit is  -750769.6000000001
Retention difference 23
Profit is  -854999.6000000001
```

In [26]:
```
plt.plot(range(-1000, 1000, 100), profits)
plt.xlabel("Extra Salary for Employes")
plt.ylabel("Profits")
plt.show()
```



ANSWER :

If you cut salaries, profit increases. However, like amazon , there would higher turnover because employees will work so much and get paid lesser

In [ ]: