ML_Project_32

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ML MID TERM PROJECT - TEAM 32

Project Topic 6 (Hiring Decision)

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

[ ]:
```
df= pd.read_csv('recruitment_data.csv')
df.head()
df.columns
```

[ ]:
```
Index(['Age', 'Gender', 'EducationLevel', 'ExperienceYears',
       'PreviousCompanies', 'DistanceFromCompany', 'InterviewScore',
       'SkillScore', 'PersonalityScore', 'RecruitmentStrategy',
       'HiringDecision'],
      dtype='object')
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1500 entries, 0 to 1499
Data columns (total 11 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Age                  1500 non-null   int64
 1   Gender               1500 non-null   int64
 2   EducationLevel       1500 non-null   int64
 3   ExperienceYears      1500 non-null   int64
 4   PreviousCompanies    1500 non-null   int64
 5   DistanceFromCompany  1500 non-null   float64
 6   InterviewScore       1500 non-null   int64
 7   SkillScore           1500 non-null   int64
```

```
 8   PersonalityScore     1500 non-null   int64
 9   RecruitmentStrategy  1500 non-null   int64
 10  HiringDecision       1500 non-null   int64
dtypes: float64(1), int64(10)
memory usage: 129.0 KB
```

[ ]:
```
df.describe()
```

[ ]:
```
               Age       Gender  EducationLevel  ExperienceYears  \
count  1500.000000  1500.000000     1500.000000      1500.000000
mean     35.148667     0.492000        2.188000         7.694000
std       9.252728     0.500103        0.862449         4.641414
min      20.000000     0.000000        1.000000         0.000000
25%      27.000000     0.000000        2.000000         4.000000
50%      35.000000     0.000000        2.000000         8.000000
75%      43.000000     1.000000        3.000000        12.000000
max      50.000000     1.000000        4.000000        15.000000

       PreviousCompanies  DistanceFromCompany  InterviewScore   SkillScore  \
count         1500.00000          1500.000000     1500.000000  1500.000000
mean             3.00200            25.505379       50.564000    51.116000
std              1.41067            14.567151       28.626215    29.353563
min              1.00000             1.031376        0.000000     0.000000
25%              2.00000            12.838851       25.000000    25.750000
50%              3.00000            25.502239       52.000000    53.000000
75%              4.00000            37.737996       75.000000    76.000000
max              5.00000            50.992462      100.000000   100.000000

       PersonalityScore  RecruitmentStrategy  HiringDecision
count       1500.000000          1500.000000     1500.000000
mean          49.387333             1.893333        0.310000
std           29.353201             0.689642        0.462647
min            0.000000             1.000000        0.000000
25%           23.000000             1.000000        0.000000
50%           49.000000             2.000000        0.000000
75%           76.000000             2.000000        1.000000
max          100.000000             3.000000        1.000000
```

[ ]:
```
df.isnull().sum()
```

[ ]:
```
Age                    0
Gender                 0
EducationLevel         0
ExperienceYears        0
PreviousCompanies      0
DistanceFromCompany    0
InterviewScore         0
SkillScore             0
```

```
PersonalityScore       0
RecruitmentStrategy    0
HiringDecision         0
dtype: int64
```

[ ]:
```
X_=df.drop("HiringDecision",axis=1) 0.8966666666666666
Y_=df["HiringDecision"]
df.head()
```

[ ]:
```
   Age  Gender  EducationLevel  ExperienceYears  PreviousCompanies  \
0   26       1               2                0                  3
1   39       1               4               12                  3
2   48       0               2                3                  2
3   34       1               2                5                  2
4   30       0               1                6                  1

   DistanceFromCompany  InterviewScore  SkillScore  PersonalityScore  \
0            26.783828              48          78                91
1            25.862694              35          68                80
2             9.920805              20          67                13
3             6.407751              36          27                70
4            43.105343              23          52                85

   RecruitmentStrategy  HiringDecision
0                    1               1
1                    2               1
2                    2               0
3                    3               0
4                    2               0
```

[ ]:
```
X_.head()
```

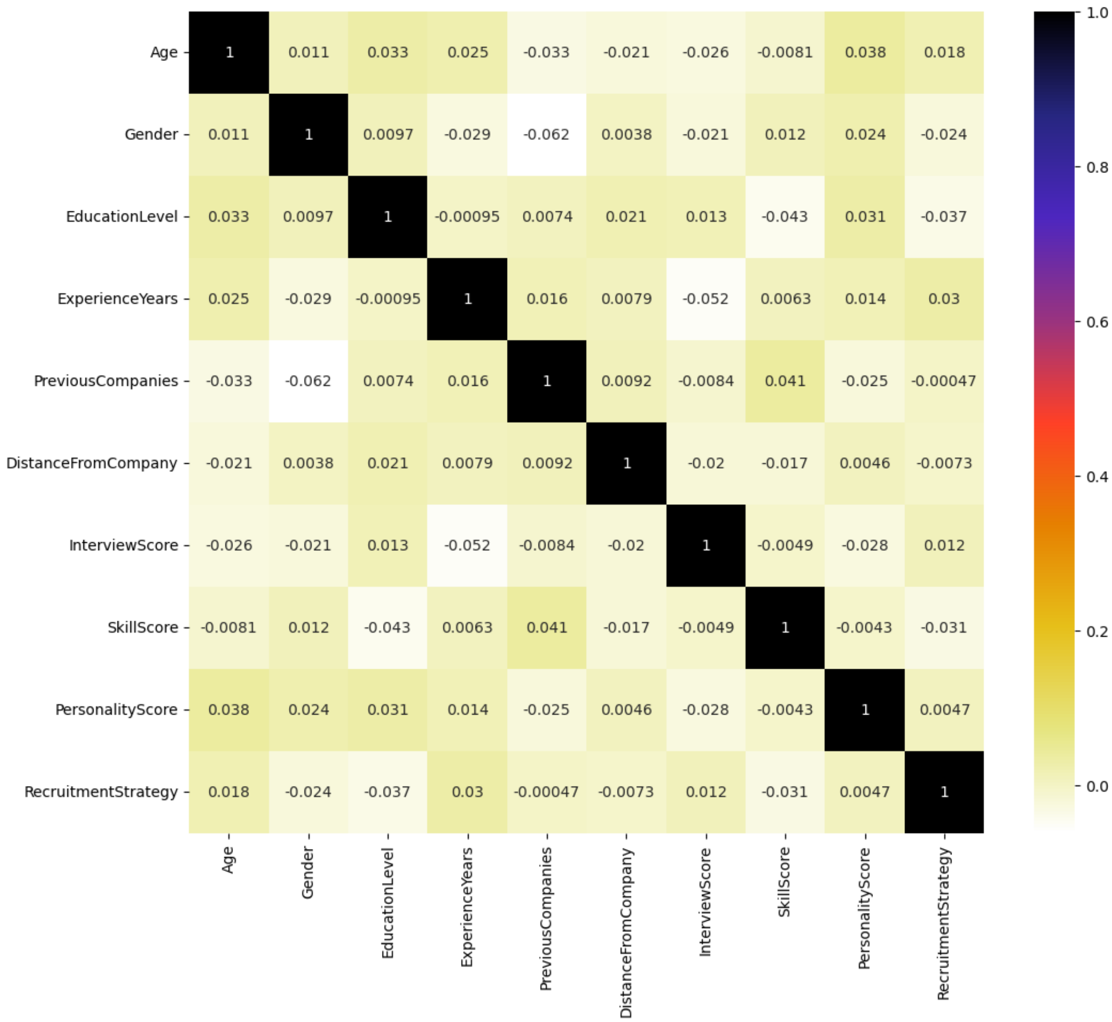
[ ]:
```
   Age  Gender  EducationLevel  ExperienceYears  PreviousCompanies  \
0   26       1               2                0                  3
1   39       1               4               12                  3
2   48       0               2                3                  2
3   34       1               2                5                  2
4   30       0               1                6                  1

   DistanceFromCompany  InterviewScore  SkillScore  PersonalityScore  \
0            26.783828              48          78                91
1            25.862694              35          68                80
2             9.920805              20          67                13
3             6.407751              36          27                70
4            43.105343              23          52                85

   RecruitmentStrategy
```

```
0                    1
1                    2
2                    2
3                    3
4                    2
```

[ ]:
```
Y_.head()
```

[ ]:
```
0    1
1    1
2    0
3    0
4    0
Name: HiringDecision, dtype: int64
```

[ ]:
```
import seaborn as sns
plt.figure(figsize=(12,10))
cor=X_.corr()
sns.heatmap(cor,annot=True,cmap=plt.cm.CMRmap_r)
plt.show()
```



[ ]:
```
def correlation(dataset, threshold):
    col_corr = set()  # Set of all the names of correlated columns
    corr_matrix = dataset.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i, j]) > threshold: # we are interested in absolute coeff value
                colname = corr_matrix.columns[i]  # getting the name of column
                col_corr.add(colname)
    return col_corr
corr_feature=correlation(X_,0.7)
len(set(corr_feature))
```

[ ]: 0

```
[ ]: def standardize_column(column):
         mean = np.mean(column)
         std_dev = np.std(column)
         return (column - mean) / std_dev
```

```
[ ]: df_standardized = df.copy()  # Make a copy of the original DataFrame
     for column in df.columns:
         df_standardized[column] = standardize_column(df[column])
     print("Original Data:")
     print(df)
     print("\nStandardized Data (Z-score normalization):")
     print(df_standardized)
```

```
Original Data:
      Age  Gender  EducationLevel  ExperienceYears  PreviousCompanies  \
0      26       1               2                0                  3
1      39       1               4               12                  3
2      48       0               2                3                  2
3      34       1               2                5                  2
4      30       0               1                6                  1
…     …       …               …                …                  …
1495   48       0               2                3                  4
1496   27       1               2               10                  3
1497   24       1               1                1                  2
1498   48       0               2                4                  4
1499   34       1               2               11                  5

      DistanceFromCompany  InterviewScore  SkillScore  PersonalityScore  \
0               26.783828              48          78                91
1               25.862694              35          68                80
2                9.920805              20          67                13
3                6.407751              36          27                70
4               43.105343              23          52                85
…                     …              …           …               …
1495             9.183783              66           3                80
1496            14.847731              43          97                 7
1497             4.289911              31          91                58
1498            36.299263               9          37                44
1499            12.910472              63          40                26

      RecruitmentStrategy  HiringDecision
0                       1               1
1                       2               1
2                       2               0
3                       3               0
4                       2               0
…                     …              …
1495                    3               1
```

```
1496                    2              0
1497                    1              1
1498                    2              1
1499                    2              1

[1500 rows x 11 columns]

Standardized Data (Z-score normalization):
           Age    Gender  EducationLevel  ExperienceYears  PreviousCompanies  \
0    -0.989083  1.016130       -0.218057        -1.658237          -0.001418
1     0.416376  1.016130        2.101694         0.928044          -0.001418
2     1.389387 -0.984126       -0.218057        -1.011667          -0.710538
3    -0.124185  1.016130       -0.218057        -0.580620          -0.710538
4    -0.556634 -0.984126       -1.377932        -0.365097          -1.419657
…          …         …              …                …                  …
1495  1.389387 -0.984126       -0.218057        -1.011667           0.707701
1496 -0.880971  1.016130       -0.218057         0.496997          -0.001418
1497 -1.205308  1.016130       -1.377932        -1.442714          -0.710538
1498  1.389387 -0.984126       -0.218057        -0.796144           0.707701
1499 -0.124185  1.016130       -0.218057         0.712520           1.416821

      DistanceFromCompany  InterviewScore  SkillScore  PersonalityScore  \
0                0.087792       -0.089598    0.916174          1.418126
1                0.024537       -0.543879    0.575386          1.043255
2               -1.070200       -1.068049    0.541307         -1.240051
3               -1.311444       -0.508934   -0.821844          0.702463
4                1.208598       -0.963215    0.030126          1.213651
…                     …               …           …                 …
1495            -1.120812        0.539406   -1.639734          1.043255
1496            -0.731866       -0.264321    1.563671         -1.444526
1497            -1.456877       -0.683657    1.359198          0.293513
1498             0.741221       -1.452440   -0.481056         -0.183596
1499            -0.864899        0.434572   -0.378820         -0.797022

      RecruitmentStrategy  HiringDecision
0               -1.295790        1.491914
1                0.154721        1.491914
2                0.154721       -0.670280
3                1.605233       -0.670280
4                0.154721       -0.670280
…                     …               …
1495             1.605233        1.491914
1496             0.154721       -0.670280
1497            -1.295790        1.491914
1498             0.154721        1.491914
1499             0.154721        1.491914

[1500 rows x 11 columns]
```

[ ]:
```
def min_max_normalize_column(column):
    min_val = np.min(column)
    max_val = np.max(column)
    return (column - min_val) / (max_val - min_val)

# Apply Min-Max normalization to each feature column
df_min_max = df.copy()  # Make a copy of the original DataFrame
for column in df.columns:
    df_min_max[column] = min_max_normalize_column(df[column])

print("\nMin-Max Normalized Data (0-1 range):")
print(df_min_max)
```

```
Min-Max Normalized Data (0-1 range):
           Age  Gender  EducationLevel  ExperienceYears  PreviousCompanies  \
0     0.200000     1.0        0.333333         0.000000               0.50
1     0.633333     1.0        1.000000         0.800000               0.50
2     0.933333     0.0        0.333333         0.200000               0.25
3     0.466667     1.0        0.333333         0.333333               0.25
4     0.333333     0.0        0.000000         0.400000               0.00
…          …     …            …                …                 …
1495  0.933333     0.0        0.333333         0.200000               0.75
1496  0.233333     1.0        0.333333         0.666667               0.50
1497  0.133333     1.0        0.000000         0.066667               0.25
1498  0.933333     0.0        0.333333         0.266667               0.75
1499  0.466667     1.0        0.333333         0.733333               1.00

      DistanceFromCompany  InterviewScore  SkillScore  PersonalityScore  \
0                0.515450            0.48        0.78              0.91
1                0.497013            0.35        0.68              0.80
2                0.177927            0.20        0.67              0.13
3                0.107611            0.36        0.27              0.70
4                0.842135            0.23        0.52              0.85
…                    …              …          …                …
1495             0.163175            0.66        0.03              0.80
1496             0.276542            0.43        0.97              0.07
1497             0.065221            0.31        0.91              0.58
1498             0.705907            0.09        0.37              0.44
1499             0.237767            0.63        0.40              0.26

      RecruitmentStrategy  HiringDecision
0                     0.0             1.0
1                     0.5             1.0
2                     0.5             0.0
3                     1.0             0.0
4                     0.5             0.0
…                    …              …
```

```
1495                1.0              1.0
1496                0.5              0.0
1497                0.0              1.0
1498                0.5              1.0
1499                0.5              1.0

[1500 rows x 11 columns]
```

[ ]:
```
X = df_min_max.drop("HiringDecision",axis=1)
Y = df_min_max["HiringDecision"]
df_min_max.head()
```

[ ]:
```
        Age  Gender  EducationLevel  ExperienceYears  PreviousCompanies  \
0  0.200000     1.0        0.333333         0.000000               0.50
1  0.633333     1.0        1.000000         0.800000               0.50
2  0.933333     0.0        0.333333         0.200000               0.25
3  0.466667     1.0        0.333333         0.333333               0.25
4  0.333333     0.0        0.000000         0.400000               0.00

   DistanceFromCompany  InterviewScore  SkillScore  PersonalityScore  \
0             0.515450            0.48        0.78              0.91
1             0.497013            0.35        0.68              0.80
2             0.177927            0.20        0.67              0.13
3             0.107611            0.36        0.27              0.70
4             0.842135            0.23        0.52              0.85

   RecruitmentStrategy  HiringDecision
0                  0.0             1.0
1                  0.5             1.0
2                  0.5             0.0
3                  1.0             0.0
4                  0.5             0.0
```

0.1 Train Test Split

[ ]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.20)
```

[ ]:
```
print(X_train.shape)
print(Y_train.shape)
```

```
(1200, 10)
(1200,)
```

0.2 Logistric Regression

[ ]:
```python
import numpy as np

# Sigmoid function (maps values between 0 and 1)
def sigmoid(z):
    return 1 / (1 + np.exp(-z))

# Logistic Regression model from scratch
class LogisticRegressionScratch:
    def __init__(self, learning_rate=0.01, iterations=10000):
        self.learning_rate = learning_rate
        self.iterations = iterations
        self.weights = None
        self.bias = None

    def fit(self, X, y):
        # Number of samples and features
        n_samples, n_features = X.shape

        # Initialize weights and bias
        self.weights = np.zeros(n_features)
        self.bias = 0

        # Gradient descent
        for _ in range(self.iterations):
            # Linear model (z = wX + b)
            linear_model = np.dot(X, self.weights) + self.bias
            # Apply sigmoid function to get predictions
            y_predicted = sigmoid(linear_model)

            # Compute gradients for weights and bias
            dw = (1 / n_samples) * np.dot(X.T, (y_predicted - y))
            db = (1 / n_samples) * np.sum(y_predicted - y)

            # Update weights and bias using gradient descent
            self.weights -= self.learning_rate * dw
            self.bias -= self.learning_rate * db

    def predict(self, X):
        # Linear model (z = wX + b)
        linear_model = np.dot(X, self.weights) + self.bias
        # Apply sigmoid function
        y_predicted = sigmoid(linear_model)
        # Convert probabilities to binary classes (0 or 1)
        y_predicted_class = [1 if i > 0.5 else 0 for i in y_predicted]
        return np.array(y_predicted_class)
```

```python
# Example usage
if __name__ == "__main__":
    # Create a dataset (replace with your actual data)
    x_train = X_train
    y_train = Y_train

    # Initialize the logistic regression model
    model = LogisticRegressionScratch(learning_rate=0.01, iterations=10000)
    # Train the model
    model.fit(x_train, y_train)
    # Make predictions
    predictions = model.predict(x_train)

    print("Predicted classes:", predictions)
```

```
Predicted classes: [1 1 0 … 0 0 1]
```

0.3 Decision trees

[ ]:
```python
class Node():
    def __init__(self, feature_index=None, threshold=None, left=None,␣
↪right=None, info_gain=None, value=None):
        ''' constructor '''

        # for decision node
        self.feature_index = feature_index
        self.threshold = threshold
        self.left = left
        self.right = right
        self.info_gain = info_gain

        # for leaf node
        self.value = value
```

[ ]:
```python
class DecisionTreeClassifier():
    def __init__(self, min_samples_split=2, max_depth=4):
        ''' constructor '''

        # initialize the root of the tree
        self.root = None

        # stopping conditions
        self.min_samples_split = min_samples_split
        self.max_depth = max_depth

    def build_tree(self, dataset, curr_depth=0):
```

```python
        ''' recursive function to build the tree '''

        X, Y = dataset[:,:-1], dataset[:,-1]
        num_samples, num_features = np.shape(X)

        # split until stopping conditions are met
        if num_samples>=self.min_samples_split and curr_depth<=self.max_depth:
            # find the best split
            best_split = self.get_best_split(dataset, num_samples, num_features)
            # check if information gain is positive
            if best_split["info_gain"]>0:
                # recur left
                left_subtree = self.build_tree(best_split["dataset_left"], curr_depth+1)
                # recur right
                right_subtree = self.build_tree(best_split["dataset_right"], curr_depth+1)
                # return decision node
                return Node(best_split["feature_index"], best_split["threshold"],
                            left_subtree, right_subtree, best_split["info_gain"])

        # compute leaf node
        leaf_value = self.calculate_leaf_value(Y)
        # return leaf node
        return Node(value=leaf_value)
    def get_best_split(self, dataset, num_samples, num_features):
        ''' function to find the best split '''

        # dictionary to store the best split
        best_split = {}
        max_info_gain = -float("inf")

        # loop over all the features
        for feature_index in range(num_features):
            feature_values = dataset[:, feature_index]
            possible_thresholds = np.unique(feature_values)
            # loop over all the feature values present in the data
            for threshold in possible_thresholds:
                # get current split
                dataset_left, dataset_right = self.split(dataset, feature_index, threshold)
                # check if childs are not null
                if len(dataset_left)>0 and len(dataset_right)>0:
                    y, left_y, right_y = dataset[:, -1], dataset_left[:, -1], dataset_right[:, -1]
```

```
                    # compute information gain
                    curr_info_gain = self.information_gain(y, left_y, right_y,␣
↪"gini")
                    # update the best split if needed
                    if curr_info_gain>max_info_gain:
                        best_split["feature_index"] = feature_index
                        best_split["threshold"] = threshold
                        best_split["dataset_left"] = dataset_left
                        best_split["dataset_right"] = dataset_right
                        best_split["info_gain"] = curr_info_gain
                        max_info_gain = curr_info_gain

        # return best split
        return best_split

    def split(self, dataset, feature_index, threshold):
        ''' function to split the data '''

        dataset_left = np.array([row for row in dataset if␣
↪row[feature_index]<=threshold])
        dataset_right = np.array([row for row in dataset if␣
↪row[feature_index]>threshold])
        return dataset_left, dataset_right

    def information_gain(self, parent, l_child, r_child, mode="entropy"):
        ''' function to compute information gain '''

        weight_l = len(l_child) / len(parent)
        weight_r = len(r_child) / len(parent)
        if mode=="gini":
                       gain = self.gini_index(parent) - (weight_l*self.
↪gini_index(l_child) + weight_r*self.gini_index(r_child))
        else:
            gain = self.entropy(parent) - (weight_l*self.entropy(l_child) +␣
↪weight_r*self.entropy(r_child))
        return gain

    def entropy(self, y):
        ''' function to compute entropy '''

        class_labels = np.unique(y)
        entropy = 0
        for cls in class_labels:
            p_cls = len(y[y == cls]) / len(y)
            entropy += -p_cls * np.log2(p_cls)
        return entropy
```

```
    def gini_index(self, y):
        ''' function to compute gini index '''

        class_labels = np.unique(y)
        gini = 0
        for cls in class_labels:
            p_cls = len(y[y == cls]) / len(y)
            gini += p_cls**2
        return 1 - gini

    def calculate_leaf_value(self, Y):
        ''' function to compute leaf node '''

        Y = list(Y)
        return max(Y, key=Y.count)

    def print_tree(self, tree=None, indent=" "):
        ''' function to print the tree '''

        if not tree:
            tree = self.root

        if tree.value is not None:
            print(tree.value)

        else:
            print("X_"+str(tree.feature_index), "<=", tree.threshold, "?", tree.
↪info_gain)
            print("%sleft:" % (indent), end="")
            self.print_tree(tree.left, indent + indent)
            print("%sright:" % (indent), end="")
            self.print_tree(tree.right, indent + indent)
    def fit(self, X, Y):
        ''' function to train the tree '''

        dataset = np.concatenate((X, Y), axis=1)
        self.root = self.build_tree(dataset)

    def predict(self, X):
        ''' function to predict new dataset '''

        preditions = [self.make_prediction(x, self.root) for x in X]
        return preditions

    def make_prediction(self, x, tree):
        ''' function to predict a single data point '''
```

```
        if tree.value!=None: return tree.value
        feature_val = x[tree.feature_index]
        if feature_val<=tree.threshold:
            return self.make_prediction(x, tree.left)
        else:
            return self.make_prediction(x, tree.right)
```

0.4 Training on Both models

[ ]:
```
predictions = model.predict(X_test)
print(len(predictions))
```

```
300
```

[ ]:
```
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report
accuracy = accuracy_score(Y_test, predictions)
conf_matrix = confusion_matrix(Y_test, predictions)
class_report = classification_report(Y_test, predictions)
print("Accuracy: ", accuracy)
print("Confusion Matrix:\n", conf_matrix)
print("Classification Report:\n", class_report)
```

```
Accuracy:  0.8666666666666667
Confusion Matrix:
 [[204  11]
 [ 29  56]]
Classification Report:
               precision    recall  f1-score   support

         0.0       0.88      0.95      0.91       215
         1.0       0.84      0.66      0.74        85

    accuracy                           0.87       300
   macro avg       0.86      0.80      0.82       300
weighted avg       0.86      0.87      0.86       300
```

[ ]:
```
X = df_min_max.iloc[:, :-1].values
Y = df_min_max.iloc[:, -1].values.reshape(-1,1)
from sklearn.model_selection import train_test_split
X_train_dt, X_test_dt, Y_train_dt, Y_test_dt = train_test_split(X, Y,␣
 ↪test_size=.20, random_state=41)
```

[ ]:
```
print(X_train_dt.shape)
print(Y_train_dt.shape)
```

```
(1200, 10)
(1200, 1)
```

```
[ ]: classifier = DecisionTreeClassifier(min_samples_split=3, max_depth=6)
classifier.fit(X_train_dt, Y_train_dt)
classifier.print_tree()
```

```
X_9 <= 0.0 ? 0.14172068580101083
 left:X_7 <= 0.47 ? 0.0673748031138045
  left:X_3 <= 0.3333333333333333 ? 0.10481356777653078
    left:X_6 <= 0.79 ? 0.10587154972181712
        left:X_8 <= 0.73 ? 0.048765112141546496
                left:X_8 <= 0.0 ? 0.05124653739612173
                                left:1.0
                                right:0.0
                right:X_2 <= 0.3333333333333333 ? 0.336620644312952
                                left:X_0 <= 0.16666666666666666 ?
0.19753086419753085
                                                                left:1.0
                                                                right:0.0
                                right:1.0
        right:X_2 <= 0.3333333333333333 ? 0.14814814814814814
                left:X_8 <= 0.59 ? 0.49382716049382713
                                left:0.0
                                right:1.0
                right:1.0
    right:X_2 <= 0.3333333333333333 ? 0.06311638043195417
        left:X_8 <= 0.58 ? 0.18127940320899222
                left:X_6 <= 0.7 ? 0.43102040816326526
                                left:0.0
                                right:1.0
                right:X_7 <= 0.0 ? 0.06816568047337264
                                left:0.0
                                right:X_5 <= 0.8581793054445147 ?
0.03679999999999998
                                                                left:1.0
                                                                right:0.0
        right:X_3 <= 0.4 ? 0.023772418058132447
                left:1.0
                right:X_7 <= 0.04 ? 0.01028466483011925
                                left:X_4 <= 0.75 ? 0.31999999999999984
                                                                left:1.0
                                                                right:0.0
                                right:1.0
  right:X_3 <= 0.3333333333333333 ? 0.022031077115505032
    left:X_6 <= 0.65 ? 0.07500000000000001
        left:X_8 <= 0.52 ? 0.2049011857707509
                left:X_2 <= 0.3333333333333333 ? 0.39669421487603307
                                left:0.0
                                right:1.0
                right:X_7 <= 0.5 ? 0.07578621756315554
```

```
                              left:0.0
                              right:X_2 <= 0.0 ? 0.014049586776859371
                                                               left:1.0
                                                               right:1.0
        right:1.0
    right:X_2 <= 0.0 ? 0.007891110806042358
        left:X_5 <= 0.8192442904827852 ? 0.11932938856015768
                left:X_7 <= 0.63 ? 0.041666666666666796
                              left:X_3 <= 0.6 ? 0.4444444444444444
                                                               left:0.0
                                                               right:1.0
                              right:1.0
                right:0.0
        right:1.0
right:X_2 <= 0.3333333333333333 ? 0.020658593641384004
 left:X_6 <= 0.74 ? 0.003701210553126749
    left:X_0 <= 0.0 ? 0.0009092584064248482
        left:X_7 <= 0.66 ? 0.08357142857142866
                left:0.0
                right:X_7 <= 0.72 ? 0.48979591836734704
                              left:1.0
                              right:0.0
        right:X_6 <= 0.21 ? 0.000690975656774756
                left:X_6 <= 0.2 ? 0.012599726837922265
                              left:X_0 <= 0.9 ? 0.008895044629116652
                                                               left:0.0
                                                               right:0.0
                              right:X_0 <= 0.36666666666666664 ? 0.5
                                                               left:1.0
                                                               right:0.0
                right:X_8 <= 0.77 ? 0.0007976258462526614
                              left:X_8 <= 0.32 ? 0.0008267812083850856
                                                               left:0.0
                                                               right:0.0
                              right:X_8 <= 0.8 ? 0.03481661515687966
                                                               left:1.0
                                                               right:0.0
    right:X_8 <= 0.59 ? 0.04321229107081567
        left:X_0 <= 0.1 ? 0.003245456378361794
                left:X_3 <= 0.0 ? 0.0973183391003461
                              left:1.0
                              right:X_8 <= 0.42 ? 0.0234375
                                                               left:0.0
                                                               right:0.0
                right:X_8 <= 0.03 ? 0.006156181480856789
                              left:X_0 <= 0.7 ? 0.375
                                                               left:0.0
                                                               right:1.0
```

```
                                right:0.0
        right:X_7 <= 0.74 ? 0.14713482292141655
                left:X_8 <= 0.62 ? 0.06838238203907196
                                left:1.0
                                right:X_9 <= 0.5 ? 0.016671173363618286
                                                                left:0.0
                                                                right:0.0
                right:X_3 <= 0.26666666666666666 ? 0.26574394463667833
                                left:X_0 <= 0.0 ? 0.31999999999999984
                                                                left:1.0
                                                                right:0.0
                                right:1.0
  right:X_8 <= 0.61 ? 0.08393651806734992
    left:X_6 <= 0.71 ? 0.0439372843616922
        left:X_5 <= 0.7890827161160316 ? 0.004056068742639862
                left:X_4 <= 0.25 ? 0.003533208765075388
                                left:X_4 <= 0.0 ? 0.01387755102040833
                                                                left:0.0
                                                                right:0.0
                                right:0.0
                right:X_0 <= 0.0 ? 0.07605263157894751
                                left:1.0
                                right:X_5 <= 0.7964441031675534 ?
0.08895044629116648
                                                                left:1.0
                                                                right:0.0
        right:X_3 <= 0.4666666666666667 ? 0.2400000000000001
                left:X_5 <= 0.0801045939366328 ? 0.08526315789473664
                                left:1.0
                                right:X_5 <= 0.9790540099529582 ?
0.09972299168975085
                                                                left:0.0
                                                                right:1.0
                right:X_7 <= 0.29 ? 0.31999999999999984
                                left:0.0
                                right:1.0
    right:X_3 <= 0.4 ? 0.19839106523237326
        left:X_6 <= 0.71 ? 0.07772268135904487
                left:X_5 <= 0.011299260249263768 ? 0.03679999999999998
                                left:0.0
                                right:0.0
                right:X_7 <= 0.24 ? 0.5
                                left:0.0
                                right:1.0
        right:X_7 <= 0.47 ? 0.11071983141082514
                left:X_6 <= 0.52 ? 0.499054820415879
                                left:0.0
                                right:1.0
```

```
right:1.0
```

```
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report
prediction= classifier.predict(X_test_dt)
accuracy = accuracy_score(Y_test_dt, prediction)
conf_matrix = confusion_matrix(Y_test_dt, prediction)
class_report = classification_report(Y_test_dt,prediction)
print("Accuracy: ", accuracy)
print("Confusion Matrix:\n", conf_matrix)
print("Classification Report:\n", class_report)
```

```
Accuracy:  0.8966666666666666
Confusion Matrix:
 [[192  16]
 [ 15  77]]
Classification Report:
               precision    recall  f1-score   support

         0.0       0.93      0.92      0.93       208
         1.0       0.83      0.84      0.83        92

    accuracy                           0.90       300
   macro avg       0.88      0.88      0.88       300
weighted avg       0.90      0.90      0.90       300
```

1 Naive Bayes

```
NUM_FEATURES = 10
NUM_CLASSES = 2
NUM_POINTS = 1500
METRIC = "gaussian"
```

```
def plotDists(y) :
    return sns.countplot(x=y)

def acc(true, pred) :
    assert len(true)==len(pred), "Truth and Pred Lengths not same"
    true = np.array(true)
    pred = np.array(pred).astype(np.int32)
    return np.sum(true==pred)/len(true)
```

```
class NaiveBayes :
    def __init__(self, x, y, metric="gaussian", use_log=False) :
        self.x = np.array(x)
        self.y = np.array(y)
```

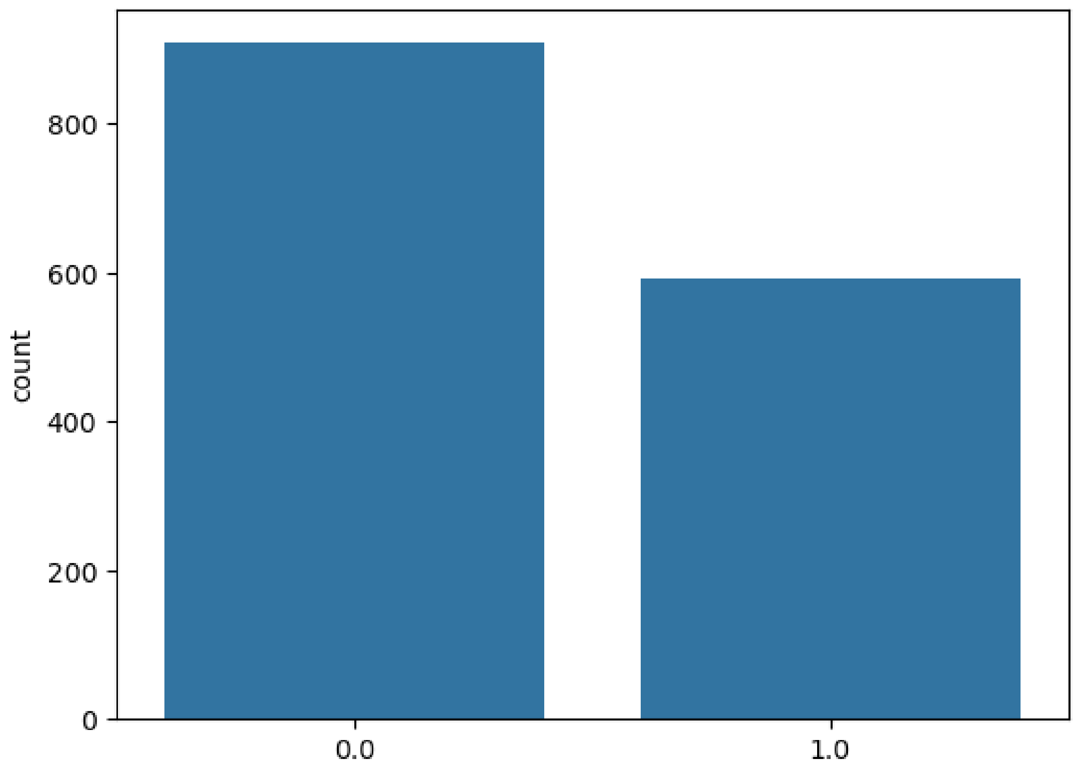
```
        self.data = np.concatenate((self.x, self.y.reshape(-1, 1)), axis=1)
        self.n_features = self.x.shape[1]
        self.classes = set(y)
        self.n_classes = len(self.classes)
        assert metric in ["gaussian"], "Invalid metric"
        self.metric = metric
        self.use_log = use_log

    def fit(self) :
        self.summary = {}
        for i in self.classes :
            d = self.data[self.data[:,-1]==i]
            mean = np.mean(d, axis=0)[:-1]
            std = np.std(d, axis=0)[:-1]
            l = len(d)
            self.summary[i] = {
                "mean" : mean,
                "std" : std,
                "len" : l
            }

    def get_probability(self, inp, mean, std) :
        if self.metric=="gaussian" :
            exponent = np.exp(-(((inp-mean)**2)/(2*(std**2))))
            res = (1 / (np.sqrt(2 * np.pi) * std)) * exponent
            if self.use_log :
                return np.log(1+res)
            return res

    def predict(self, x) :
        assert self.summary, "Classifier not fit yet"
        results = []
        # Convert x to numerical type if it's a DataFrame
        if isinstance(x, pd.DataFrame):
            x = x.values.astype(np.float64)
        for inp in x :
            pred_class = -1
            pred_prob = 0
            for i in self.classes :
                probs = self.get_probability(inp, self.summary[i]["mean"], self.
↪summary[i]["std"])
                class_prob = np.prod(probs)
                if class_prob > pred_prob :
                    pred_class = i
                    pred_prob = class_prob
            results.append(pred_class)
        return results
```

[ ]:
```
x = df_min_max.drop("HiringDecision",axis=1)
y = df_min_max["HiringDecision"]
df_min_max.head()
```

[ ]:
```
        Age  Gender  EducationLevel  ExperienceYears  PreviousCompanies  \
0  0.200000     1.0        0.333333         0.000000               0.50
1  0.633333     1.0        1.000000         0.800000               0.50
2  0.933333     0.0        0.333333         0.200000               0.25
3  0.466667     1.0        0.333333         0.333333               0.25
4  0.333333     0.0        0.000000         0.400000               0.00

   DistanceFromCompany  InterviewScore  SkillScore  PersonalityScore  \
0             0.515450            0.48        0.78              0.91
1             0.497013            0.35        0.68              0.80
2             0.177927            0.20        0.67              0.13
3             0.107611            0.36        0.27              0.70
4             0.842135            0.23        0.52              0.85

   RecruitmentStrategy  HiringDecision
0                  0.0             1.0
1                  0.5             1.0
2                  0.5             0.0
3                  1.0             0.0
4                  0.5             0.0
```

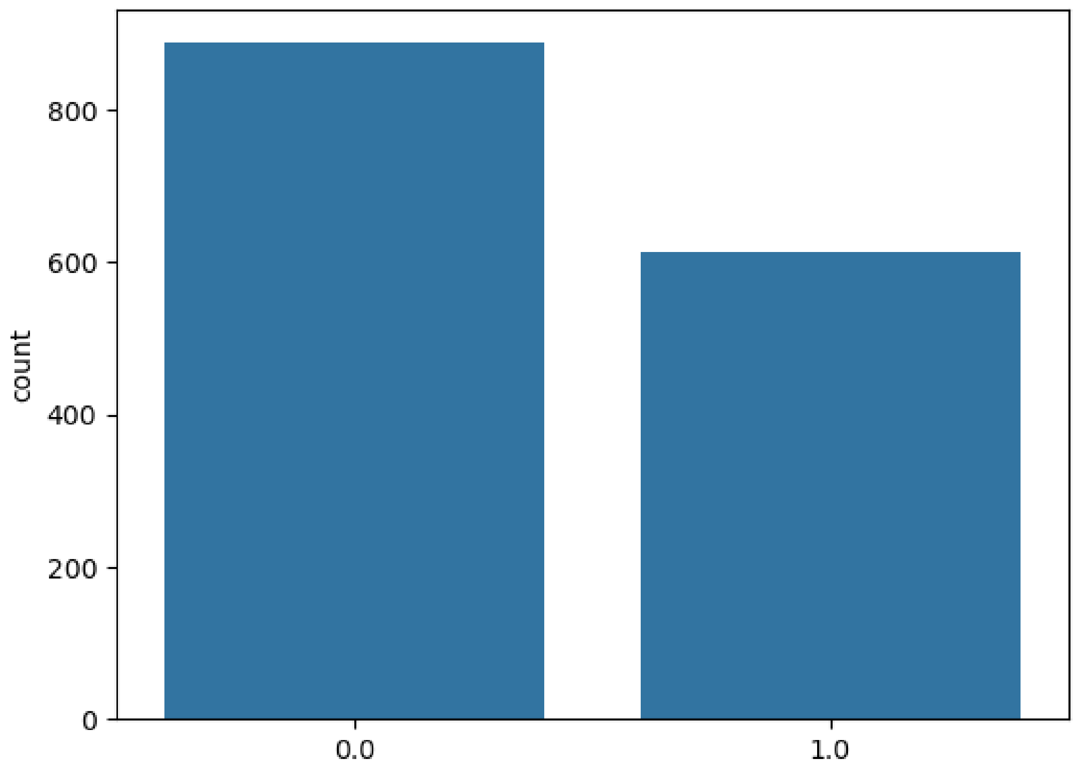
[ ]:
```
nbg = NaiveBayes(x, y, METRIC)
nbg.fit()
acc(y, nbg.predict(x.values))
plotDists(nbg.predict(x))
```

[ ]:
```
<Axes: ylabel='count'>
```



[ ]:
```
nbgl = NaiveBayes(x, y, METRIC, use_log=True)
nbgl.fit()
acc(y, nbgl.predict(x))
plotDists(nbgl.predict(x))
```

[ ]: <Axes: ylabel='count'>



[ ]:
```
from sklearn.metrics import confusion_matrix

# Assuming 'y' contains the true labels and 'nbg.predict(x)' contains the␣
↪predicted labels
y_pred = nbg.predict(x)
cm = confusion_matrix(y, y_pred)

print("Confusion Matrix:")
print(cm)

#Confusion Matrix
print("\nExplanation of the Confusion Matrix:")
print("True Positive (TP):", cm[1, 1], " - The model correctly predicted the␣
↪positive class (HiringDecision = 1).")
print("True Negative (TN):", cm[0, 0], " - The model correctly predicted the␣
↪negative class (HiringDecision = 0).")
print("False Positive (FP):", cm[0, 1], " - The model incorrectly predicted the␣
↪positive class (HiringDecision = 1) when it was actually negative␣
↪(HiringDecision = 0).")
```

```
print("False Negative (FN):", cm[1, 0], " - The model incorrectly predicted the␣
↪negative class (HiringDecision = 0) when it was actually positive␣
↪(HiringDecision = 1).")

# Additional analysis (optional)
accuracy = (cm[0, 0] + cm[1, 1]) / np.sum(cm)
precision = cm[1, 1] / (cm[1, 1] + cm[0, 1])
recall = cm[1, 1] / (cm[1, 1] + cm[1, 0])
f1_score = 2 * (precision * recall) / (precision + recall)

print("\nAccuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-Score:", f1_score)
```

```
Confusion Matrix:
[[839 196]
 [ 69 396]]

Explanation of the Confusion Matrix:
True Positive (TP): 396  - The model correctly predicted the positive class
(HiringDecision = 1).
True Negative (TN): 839  - The model correctly predicted the negative class
(HiringDecision = 0).
False Positive (FP): 196  - The model incorrectly predicted the positive class
(HiringDecision = 1) when it was actually negative (HiringDecision = 0).
False Negative (FN): 69  - The model incorrectly predicted the negative class
(HiringDecision = 0) when it was actually positive (HiringDecision = 1).

Accuracy: 0.8233333333333334
Precision: 0.668918918918919
Recall: 0.8516129032258064
F1-Score: 0.7492904446546831
```

[ ]:
```
from sklearn.metrics import confusion_matrix

# Assuming 'y' contains the true labels and 'nbg.predict(x)' contains the␣
↪predicted labels
y_pred = nbg.predict(x)
cm = confusion_matrix(y, y_pred)

print("Confusion Matrix:")
print(cm)

#Confusion Matrix
print("\nExplanation of the Confusion Matrix:")
```

```
print("True Positive (TP):", cm[1, 1], " - The model correctly predicted the␣
↪positive class (HiringDecision = 1).")
print("True Negative (TN):", cm[0, 0], " - The model correctly predicted the␣
↪negative class (HiringDecision = 0).")
print("False Positive (FP):", cm[0, 1], " - The model incorrectly predicted the␣
↪positive class (HiringDecision = 1) when it was actually negative␣
↪(HiringDecision = 0).")
print("False Negative (FN):", cm[1, 0], " - The model incorrectly predicted the␣
↪negative class (HiringDecision = 0) when it was actually positive␣
↪(HiringDecision = 1).")

# Additional analysis (optional)
accuracy = (cm[0, 0] + cm[1, 1]) / np.sum(cm)
precision = cm[1, 1] / (cm[1, 1] + cm[0, 1])
recall = cm[1, 1] / (cm[1, 1] + cm[1, 0])
f1_score = 2 * (precision * recall) / (precision + recall)

print("\nAccuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-Score:", f1_score)
```

```
Confusion Matrix:
[[839 196]
 [ 69 396]]

Explanation of the Confusion Matrix:
True Positive (TP): 396  - The model correctly predicted the positive class
(HiringDecision = 1).
True Negative (TN): 839  - The model correctly predicted the negative class
(HiringDecision = 0).
False Positive (FP): 196  - The model incorrectly predicted the positive class
(HiringDecision = 1) when it was actually negative (HiringDecision = 0).
False Negative (FN): 69  - The model incorrectly predicted the negative class
(HiringDecision = 0) when it was actually positive (HiringDecision = 1).

Accuracy: 0.8233333333333334
Precision: 0.668918918918919
Recall: 0.8516129032258064
F1-Score: 0.7492904446546831
```

[11]:
```
# CONCLUSION:

# Comparative analysis of Logistic Regression, Decision Tree, and Naive Bayes␣
↪for hiring prediction reveals that Decision Tree consistently
# outperforms the other models.
```

```
# Decision Tree achieved a notable accuracy of 89.6% compared to Logistic␣
↪Regression's 86.7% and Naive Bayes' 82.3%.
# These findings strongly suggest that Decision Tree is the optimal choice for␣
↪predicting hiring outcomes in this specific dataset
```