#Library and Data Loading

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from scipy import stats
from scipy.stats import randint

# prep
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.datasets import make_classification
from sklearn.preprocessing import binarize, LabelEncoder, MinMaxScaler

# models
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,
ExtraTreesClassifier

# Validation libraries
from sklearn import metrics
from sklearn.metrics import accuracy_score, mean_squared_error,
precision_recall_curve
from sklearn.model_selection import cross_val_score

from sklearn.model_selection import RandomizedSearchCV

#Bagging
from sklearn.ensemble import BaggingClassifier, AdaBoostClassifier
from sklearn.neighbors import KNeighborsClassifier

#Naive bayes
from sklearn.naive_bayes import GaussianNB

train_df = pd.read_csv('survey.csv')
print(train_df.shape)
print(train_df.describe())
print(train_df.info())
```

```
(1259, 27)
                Age
count  1.259000e+03
mean   7.942815e+07
std    2.818299e+09
min   -1.726000e+03
```

```
25%    2.700000e+01
50%    3.100000e+01
75%    3.600000e+01
max    1.000000e+11
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1259 entries, 0 to 1258
Data columns (total 27 columns):
 #   Column                     Non-Null Count  Dtype 
---  ------                     --------------  ----- 
 0   Timestamp                  1259 non-null   object
 1   Age                        1259 non-null   int64 
 2   Gender                     1259 non-null   object
 3   Country                    1259 non-null   object
 4   state                      744 non-null    object
 5   self_employed              1241 non-null   object
 6   family_history             1259 non-null   object
 7   treatment                  1259 non-null   object
 8   work_interfere             995 non-null    object
 9   no_employees               1259 non-null   object
 10  remote_work                1259 non-null   object
 11  tech_company               1259 non-null   object
 12  benefits                   1259 non-null   object
 13  care_options               1259 non-null   object
 14  wellness_program           1259 non-null   object
 15  seek_help                  1259 non-null   object
 16  anonymity                  1259 non-null   object
 17  leave                      1259 non-null   object
 18  mental_health_consequence  1259 non-null   object
 19  phys_health_consequence    1259 non-null   object
 20  coworkers                  1259 non-null   object
 21  supervisor                 1259 non-null   object
 22  mental_health_interview    1259 non-null   object
 23  phys_health_interview      1259 non-null   object
 24  mental_vs_physical         1259 non-null   object
 25  obs_consequence            1259 non-null   object
 26  comments                   164 non-null    object
dtypes: int64(1), object(26)
memory usage: 265.7+ KB
None
```

#Data Cleaning

```
#missing data
total = train_df.isnull().sum().sort_values(ascending=False)
percent = 
(train_df.isnull().sum()/train_df.isnull().count()).sort_values(ascend
ing=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 
'Percent'])
missing_data.head(20)
print(missing_data)
```

```
                            Total   Percent
comments                     1095  0.869738
state                         515  0.409055
work_interfere                264  0.209690
self_employed                  18  0.014297
seek_help                       0  0.000000
obs_consequence                 0  0.000000
mental_vs_physical              0  0.000000
phys_health_interview           0  0.000000
mental_health_interview         0  0.000000
supervisor                      0  0.000000
coworkers                       0  0.000000
phys_health_consequence         0  0.000000
mental_health_consequence       0  0.000000
leave                           0  0.000000
anonymity                       0  0.000000
Timestamp                       0  0.000000
wellness_program                0  0.000000
Age                             0  0.000000
benefits                        0  0.000000
tech_company                    0  0.000000
remote_work                     0  0.000000
no_employees                    0  0.000000
treatment                       0  0.000000
family_history                  0  0.000000
Country                         0  0.000000
Gender                          0  0.000000
care_options                    0  0.000000
```

```
#dealing with missing data
train_df.drop(['comments'], axis= 1, inplace=True)
train_df.drop(['state'], axis= 1, inplace=True)
train_df.drop(['Timestamp'], axis= 1, inplace=True)

train_df.isnull().sum().max() #just checking that there's no missing
data missing...
train_df.head(5)
```

```
   Age  Gender         Country self_employed family_history treatment
\
0   37  Female   United States           NaN             No       Yes

1   44       M   United States           NaN             No        No

2   32    Male          Canada           NaN             No        No

3   31    Male  United Kingdom           NaN            Yes       Yes

4   31    Male   United States           NaN             No        No
```

```
  work_interfere    no_employees remote_work tech_company  ...
anonymity  \
0         Often            6-25          No          Yes  ...
Yes
1        Rarely  More than 1000          No           No  ...  Don't
know
2        Rarely            6-25          No          Yes  ...  Don't
know
3         Often          26-100          No          Yes  ...
No
4         Never         100-500         Yes          Yes  ...  Don't
know

                leave mental_health_consequence
phys_health_consequence  \
0       Somewhat easy                        No
No
1          Don't know                     Maybe
No
2  Somewhat difficult                        No
No
3  Somewhat difficult                       Yes
Yes
4          Don't know                        No
No

      coworkers supervisor mental_health_interview
phys_health_interview  \
0  Some of them        Yes                      No
Maybe
1            No         No                      No
No
2           Yes        Yes                     Yes
Yes
3  Some of them         No                   Maybe
Maybe
4  Some of them        Yes                     Yes
Yes

  mental_vs_physical obs_consequence
0                Yes              No
1         Don't know              No
2                 No              No
3                 No             Yes
4         Don't know              No

[5 rows x 24 columns]
```

Cleaning NaN

```python
# Assign default values for each data type
defaultInt = 0
defaultString = 'NaN'
defaultFloat = 0.0

# Create lists by data tpe
intFeatures = ['Age']
stringFeatures = ['Gender', 'Country', 'self_employed',
'family_history', 'treatment', 'work_interfere',
                 'no_employees', 'remote_work', 'tech_company',
'anonymity', 'leave', 'mental_health_consequence',
                 'phys_health_consequence', 'coworkers', 'supervisor',
'mental_health_interview', 'phys_health_interview',
                 'mental_vs_physical', 'obs_consequence', 'benefits',
'care_options', 'wellness_program',
                 'seek_help']
floatFeatures = []

# Clean the NaN's
for feature in train_df:
    if feature in intFeatures:
        train_df[feature] = train_df[feature].fillna(defaultInt)
    elif feature in stringFeatures:
        train_df[feature] = train_df[feature].fillna(defaultString)
    elif feature in floatFeatures:
        train_df[feature] = train_df[feature].fillna(defaultFloat)
    else:
        print('Error: Feature %s not recognized.' % feature)
train_df.head()
```

```
   Age  Gender         Country self_employed family_history treatment
\
0   37  Female   United States           NaN             No       Yes

1   44       M   United States           NaN             No        No

2   32    Male          Canada           NaN             No        No

3   31    Male  United Kingdom           NaN            Yes       Yes

4   31    Male   United States           NaN             No        No


  work_interfere    no_employees remote_work tech_company  ...
anonymity  \
0          Often            6-25          No          Yes  ...
Yes
1         Rarely  More than 1000          No           No  ...  Don't
know
2         Rarely            6-25          No          Yes  ...  Don't
```

```
know
3          Often          26-100          No          Yes  ...
No
4          Never         100-500         Yes          Yes  ...  Don't
know

                leave mental_health_consequence
phys_health_consequence  \
0       Somewhat easy                        No
No
1          Don't know                     Maybe
No
2  Somewhat difficult                        No
No
3  Somewhat difficult                       Yes
Yes
4          Don't know                        No
No

      coworkers supervisor mental_health_interview
phys_health_interview  \
0  Some of them        Yes                      No
Maybe
1            No         No                      No
No
2           Yes        Yes                     Yes
Yes
3  Some of them         No                   Maybe
Maybe
4  Some of them        Yes                     Yes
Yes

  mental_vs_physical obs_consequence
0                Yes              No
1         Don't know              No
2                 No              No
3                 No             Yes
4         Don't know              No

[5 rows x 24 columns]
```

```python
#Clean 'Gender'
gender = train_df['Gender'].unique()
print(gender)
```

```
['Female' 'M' 'Male' 'male' 'female' 'm' 'Male-ish' 'maile' 'Trans-
female'
 'Cis Female' 'F' 'something kinda male?' 'Cis Male' 'Woman' 'f' 'Mal'
 'Male (CIS)' 'queer/she/they' 'non-binary' 'Femake' 'woman' 'Make'
'Nah'
```

```
 'All' 'Enby' 'fluid' 'Genderqueer' 'Female ' 'Androgyne' 'Agender'
 'cis-female/femme' 'Guy (-ish) ^_^' 'male leaning androgynous' 'Male
'
 'Man' 'Trans woman' 'msle' 'Neuter' 'Female (trans)' 'queer'
 'Female (cis)' 'Mail' 'cis male' 'A little about you' 'Malr' 'p'
'femail'
 'Cis Man' 'ostensibly male, unsure what that really means']
```

```python
#Made gender groups
male_str = ["male", "m", "male-ish", "maile", "mal", "male (cis)",
"make", "male ", "man","msle", "mail", "malr","cis man", "Cis Male",
"cis male"]
trans_str = ["trans-female", "something kinda male?",
"queer/she/they", "non-binary","nah", "all", "enby", "fluid",
"genderqueer", "androgyne", "agender", "male leaning androgynous",
"guy (-ish) ^_^", "trans woman", "neuter", "female (trans)", "queer",
"ostensibly male, unsure what that really means"]
female_str = ["cis female", "f", "female", "woman",  "femake", "female
","cis-female/femme", "female (cis)", "femail"]

for (row, col) in train_df.iterrows():

    if str.lower(col.Gender) in male_str:
        train_df['Gender'].replace(to_replace=col.Gender,
value='male', inplace=True)

    if str.lower(col.Gender) in female_str:
        train_df['Gender'].replace(to_replace=col.Gender,
value='female', inplace=True)

    if str.lower(col.Gender) in trans_str:
        train_df['Gender'].replace(to_replace=col.Gender,
value='trans', inplace=True)

#Get rid of bullshit
stk_list = ['A little about you', 'p']
train_df = train_df[~train_df['Gender'].isin(stk_list)]

print(train_df['Gender'].unique())
```

```
['female' 'male' 'trans']
```

```python
#complete missing age with mean
train_df['Age'].fillna(train_df['Age'].median(), inplace = True)

# Fill with media() values < 18 and > 120
s = pd.Series(train_df['Age'])
s[s<18] = train_df['Age'].median()
train_df['Age'] = s
s = pd.Series(train_df['Age'])
```

```
s[s>120] = train_df['Age'].median()
train_df['Age'] = s

#Ranges of Age
train_df['age_range'] = pd.cut(train_df['Age'], [0,20,30,65,100],
labels=["0-20", "21-30", "31-65", "66-100"], include_lowest=True)

#There are only 0.014% of self employed so let's change NaN to NOT
self_employed
#Replace "NaN" string from defaultString
train_df['self_employed'] =
train_df['self_employed'].replace([defaultString], 'No')
print(train_df['self_employed'].unique())
```

```
['No' 'Yes']
```

```
#There are only 0.20% of self work_interfere so let's change NaN to
"Don't know
#Replace "NaN" string from defaultString

train_df['work_interfere'] =
train_df['work_interfere'].replace([defaultString], 'Don\'t know' )
print(train_df['work_interfere'].unique())
```

```
['Often' 'Rarely' 'Never' 'Sometimes' "Don't know"]
```

#Encoding Data

```
#Encoding data
labelDict = {}
for feature in train_df:
    le = preprocessing.LabelEncoder()
    le.fit(train_df[feature])
    le_name_mapping = dict(zip(le.classes_,
le.transform(le.classes_)))
    train_df[feature] = le.transform(train_df[feature])
    # Get labels
    labelKey = 'label_' + feature
    labelValue = [*le_name_mapping]
    labelDict[labelKey] =labelValue

for key, value in labelDict.items():
    print(key, value)
```

```
label_Age [18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32,
33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49,
50, 51, 53, 54, 55, 56, 57, 58, 60, 61, 62, 65, 72]
label_Gender ['female', 'male', 'trans']
label_Country ['Australia', 'Austria', 'Belgium', 'Bosnia and
Herzegovina', 'Brazil', 'Bulgaria', 'Canada', 'China', 'Colombia',
'Costa Rica', 'Croatia', 'Czech Republic', 'Denmark', 'Finland',
```

```
'France', 'Georgia', 'Germany', 'Greece', 'Hungary', 'India',
'Ireland', 'Israel', 'Italy', 'Japan', 'Latvia', 'Mexico', 'Moldova',
'Netherlands', 'New Zealand', 'Nigeria', 'Norway', 'Philippines',
'Poland', 'Portugal', 'Romania', 'Russia', 'Singapore', 'Slovenia',
'South Africa', 'Spain', 'Sweden', 'Switzerland', 'Thailand', 'United
Kingdom', 'United States', 'Uruguay', 'Zimbabwe']
label_self_employed ['No', 'Yes']
label_family_history ['No', 'Yes']
label_treatment ['No', 'Yes']
label_work_interfere ["Don't know", 'Never', 'Often', 'Rarely',
'Sometimes']
label_no_employees ['1-5', '100-500', '26-100', '500-1000', '6-25',
'More than 1000']
label_remote_work ['No', 'Yes']
label_tech_company ['No', 'Yes']
label_benefits ["Don't know", 'No', 'Yes']
label_care_options ['No', 'Not sure', 'Yes']
label_wellness_program ["Don't know", 'No', 'Yes']
label_seek_help ["Don't know", 'No', 'Yes']
label_anonymity ["Don't know", 'No', 'Yes']
label_leave ["Don't know", 'Somewhat difficult', 'Somewhat easy',
'Very difficult', 'Very easy']
label_mental_health_consequence ['Maybe', 'No', 'Yes']
label_phys_health_consequence ['Maybe', 'No', 'Yes']
label_coworkers ['No', 'Some of them', 'Yes']
label_supervisor ['No', 'Some of them', 'Yes']
label_mental_health_interview ['Maybe', 'No', 'Yes']
label_phys_health_interview ['Maybe', 'No', 'Yes']
label_mental_vs_physical ["Don't know", 'No', 'Yes']
label_obs_consequence ['No', 'Yes']
label_age_range ['0-20', '21-30', '31-65', '66-100']
```

```
#Get rid of 'Country'
train_df = train_df.drop(['Country'], axis= 1)
train_df.head()
```

```
   Age  Gender  self_employed  family_history  treatment
work_interfere  \
0   19       0              0               0          1
2
1   26       1              0               0          0
3
2   14       1              0               0          0
3
3   13       1              0               1          1
2
4   13       1              0               0          0
1

   no_employees  remote_work  tech_company  benefits  ...  leave  \
```

```
0             4            0             1         2  ...      2
1             5            0             0         0  ...      0
2             4            0             1         1  ...      1
3             2            0             1         1  ...      1
4             1            1             1         2  ...      0

   mental_health_consequence  phys_health_consequence  coworkers
supervisor  \
0                          1                        1          1
2
1                          0                        1          0
0
2                          1                        1          2
2
3                          2                        2          1
0
4                          1                        1          1
2

   mental_health_interview  phys_health_interview  mental_vs_physical
\
0                        1                      0                   2

1                        1                      1                   0

2                        2                      2                   1

3                        0                      0                   1

4                        2                      2                   0


   obs_consequence  age_range
0                0          2
1                0          2
2                0          2
3                1          2
4                0          2

[5 rows x 24 columns]
```

Testing there aren't any missing data

```
#missing data
total = train_df.isnull().sum().sort_values(ascending=False)
percent =
(train_df.isnull().sum()/train_df.isnull().count()).sort_values(ascend
ing=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total',
'Percent'])
```

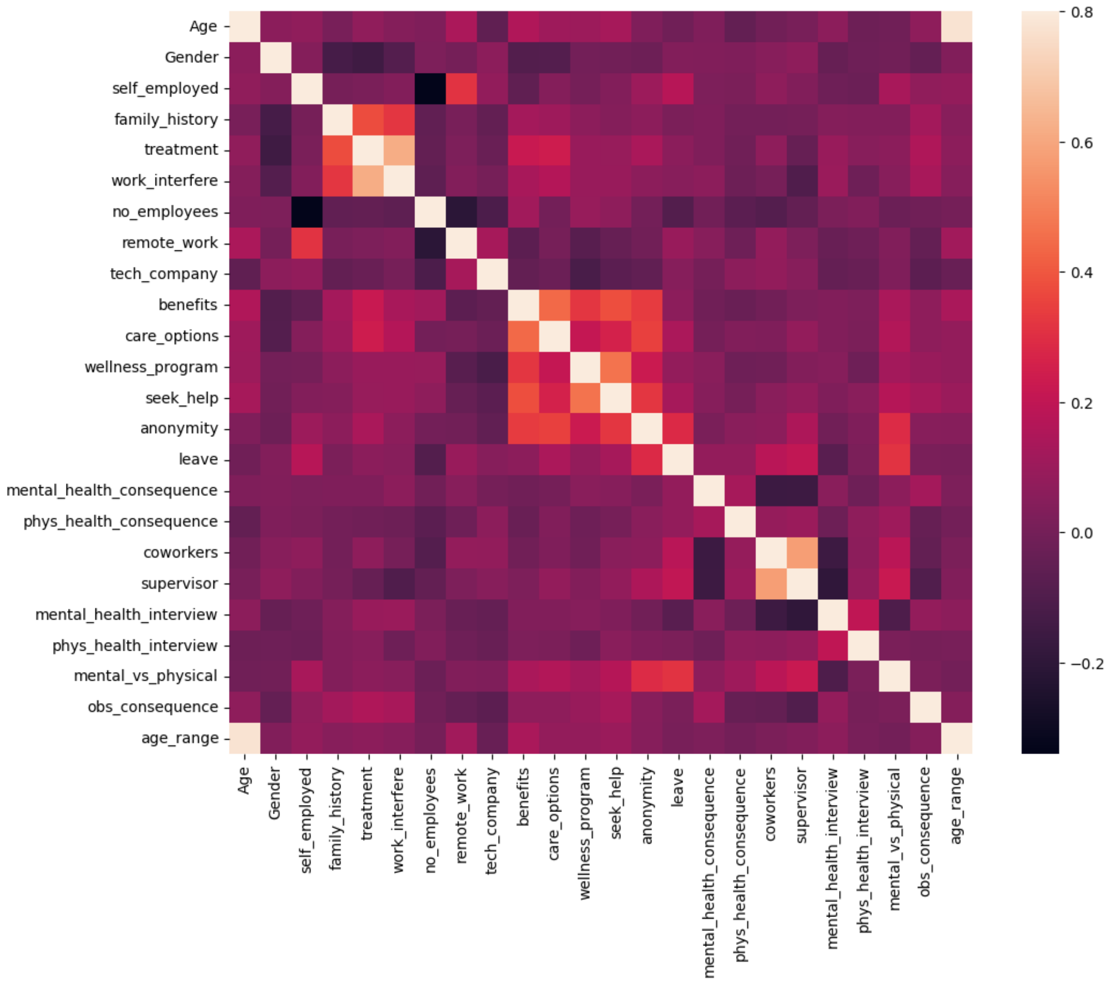
```
missing_data.head(20)
print(missing_data)
```

```
                            Total  Percent
Age                             0      0.0
Gender                          0      0.0
obs_consequence                 0      0.0
mental_vs_physical              0      0.0
phys_health_interview           0      0.0
mental_health_interview         0      0.0
supervisor                      0      0.0
coworkers                       0      0.0
phys_health_consequence         0      0.0
mental_health_consequence       0      0.0
leave                           0      0.0
anonymity                       0      0.0
seek_help                       0      0.0
wellness_program                0      0.0
care_options                    0      0.0
benefits                        0      0.0
tech_company                    0      0.0
remote_work                     0      0.0
no_employees                    0      0.0
work_interfere                  0      0.0
treatment                       0      0.0
family_history                  0      0.0
self_employed                   0      0.0
age_range                       0      0.0
```

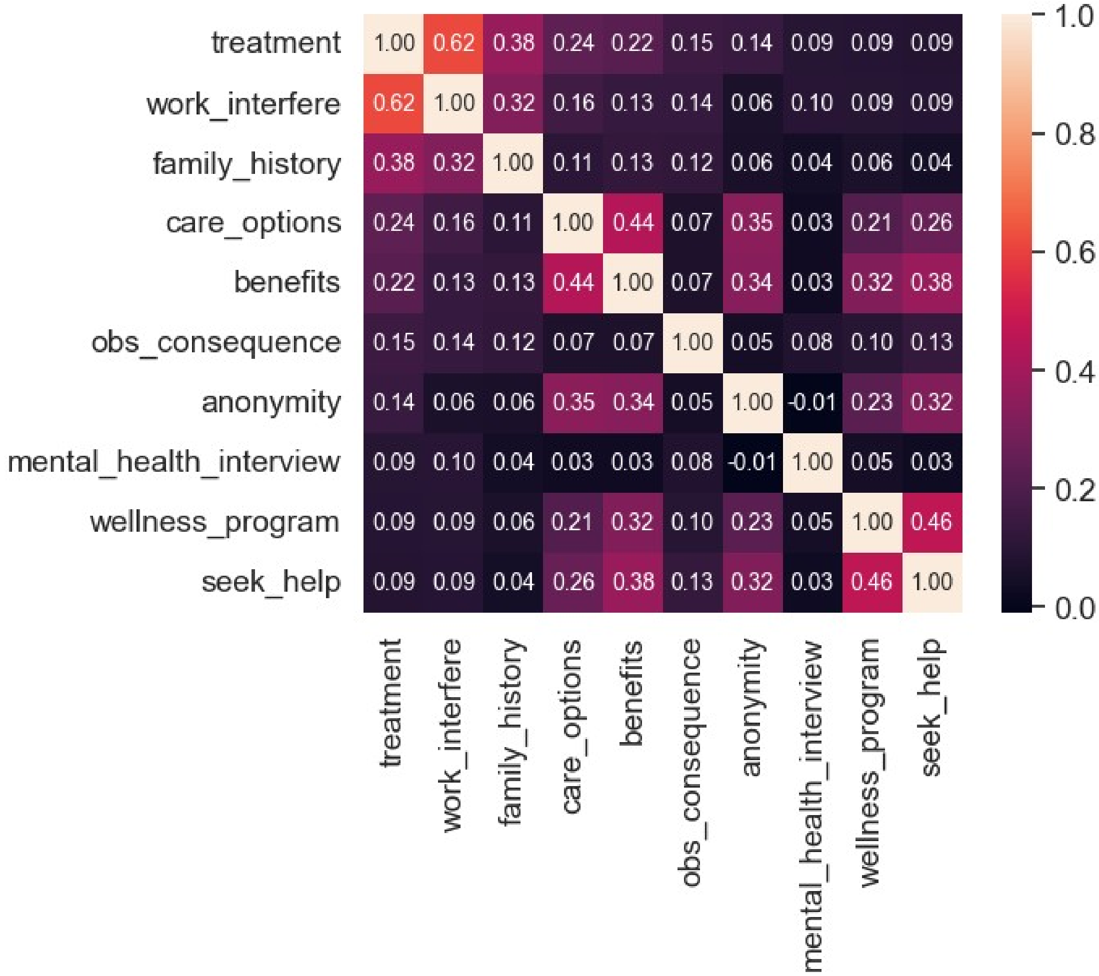
Features Scaling: We're going to scale age, because it is extremely different from the other ones.

#Covariance Matrix. Variability comparison between categories of variables

```
#correlation matrix
corrmat = train_df.corr()
f, ax = plt.subplots(figsize=(12, 9))
sns.heatmap(corrmat, vmax=.8, square=True);
plt.show()
```




```
#treatment correlation matrix
k = 10 #number of variables for heatmap
cols = corrmat.nlargest(k, 'treatment')['treatment'].index
cm = np.corrcoef(train_df[cols].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f',
annot_kws={'size': 10}, yticklabels=cols.values,
xticklabels=cols.values)
plt.show()
```



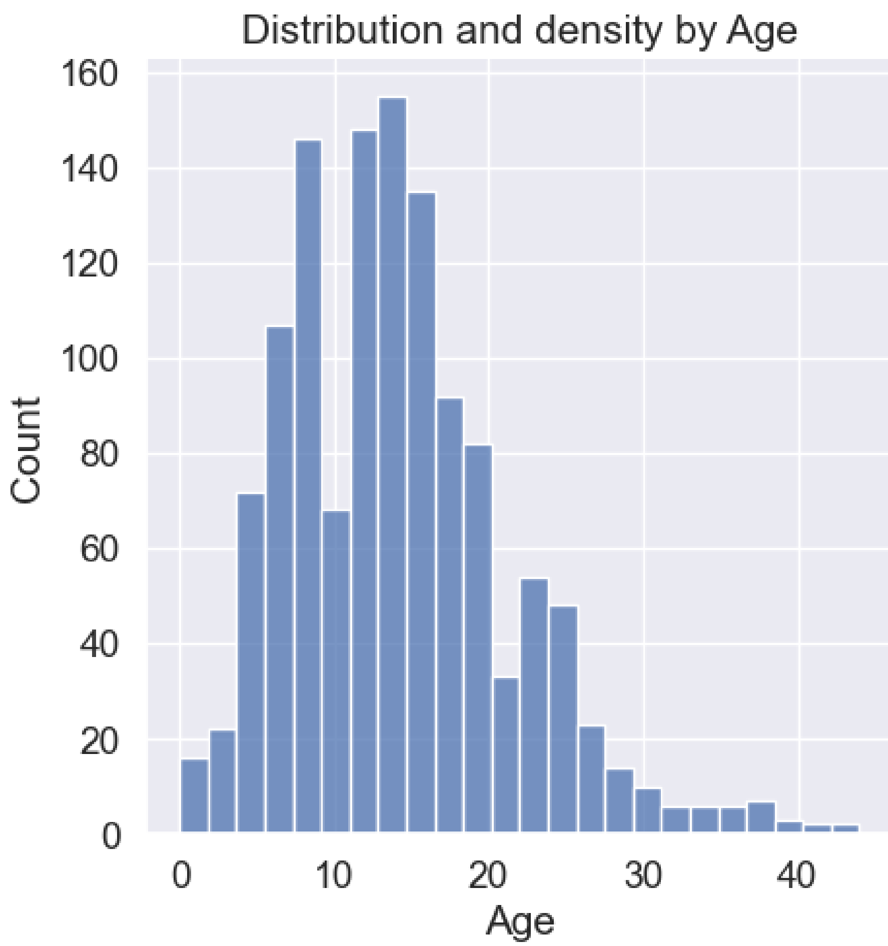
#Some charts to see data relationship

Distribution and density by Age

```
# Distribution and density by Age
plt.figure(figsize=(12,8))
sns.displot(train_df["Age"], bins=24)
plt.title("Distribution and density by Age")
plt.xlabel("Age")
```

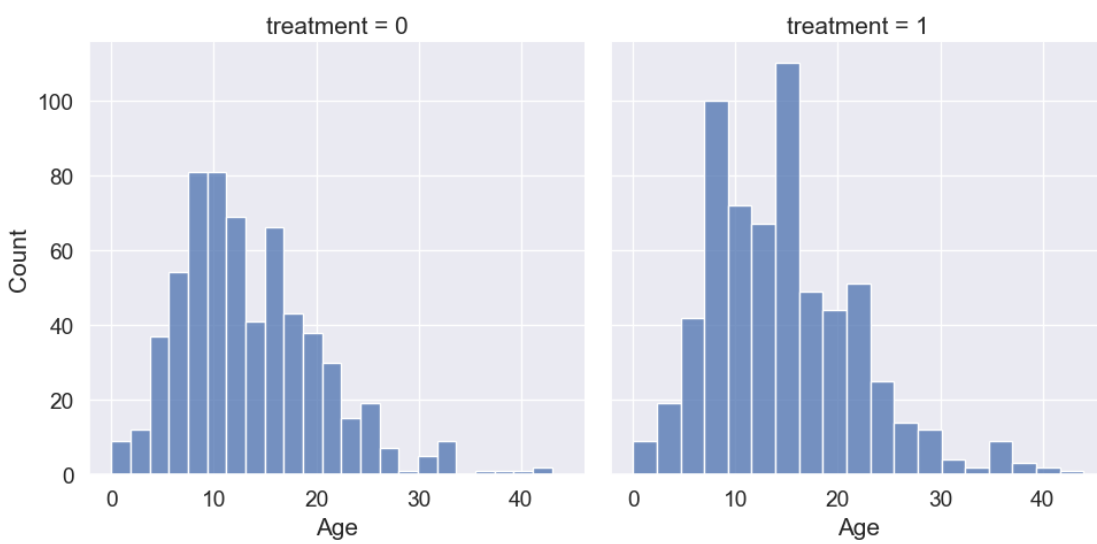
```
Text(0.5, 16.944444444444436, 'Age')
```

```
<Figure size 1200x800 with 0 Axes>
```



Separate by treatment

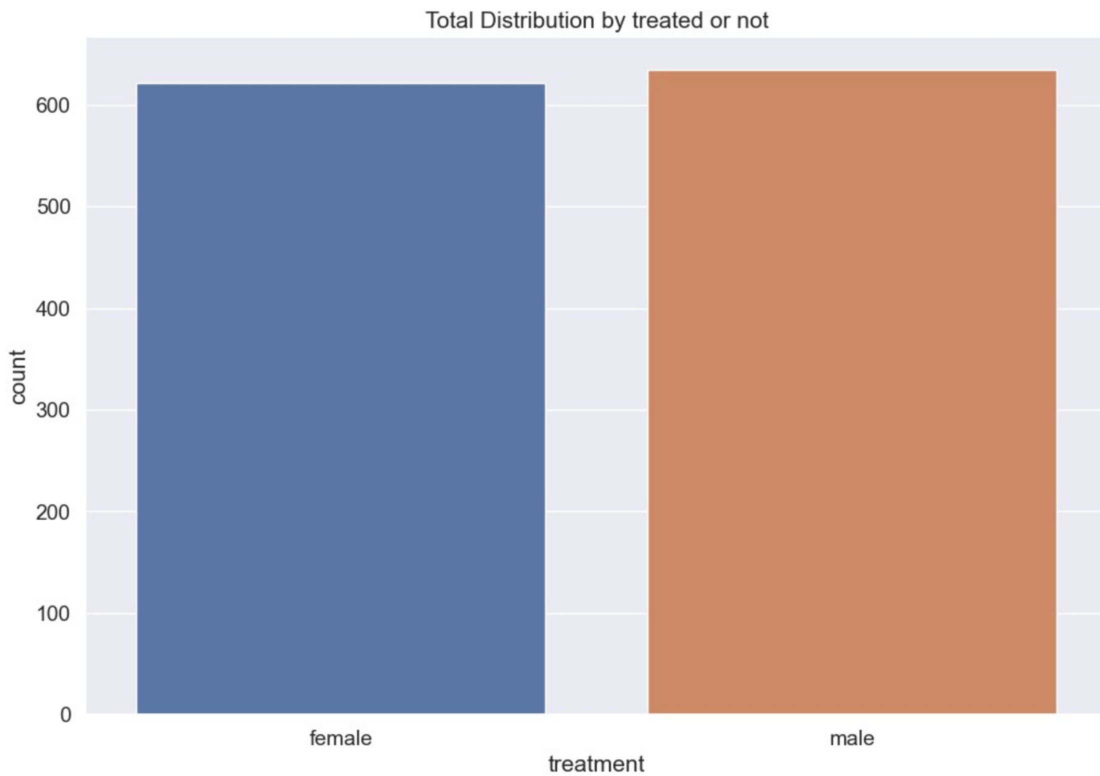
```
g = sns.FacetGrid(train_df, col='treatment', height=5)
g = g.map(sns.histplot, "Age")
```



How many people has been treated?

```
plt.figure(figsize=(12,8))
labels = labelDict['label_Gender']
g = sns.countplot(x="treatment", data=train_df)
g.set_xticklabels(labels[:len(g.get_xticks())])

plt.title('Total Distribution by treated or not')
```

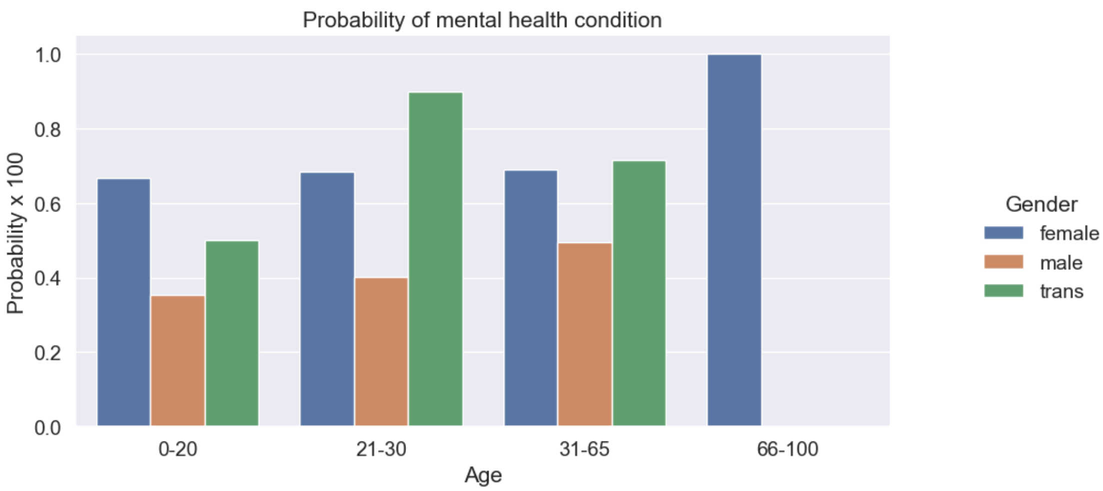
```
Text(0.5, 1.0, 'Total Distribution by treated or not')
```



Nested barplot to show probabilities for class and sex

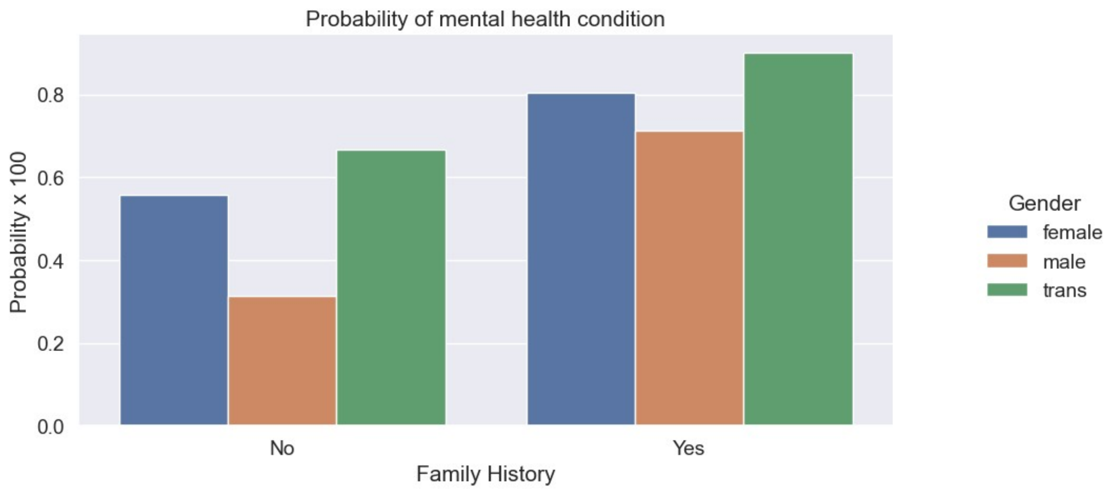
```
o = labelDict['label_age_range']

g = sns.catplot(x="age_range", y="treatment", hue="Gender",
data=train_df, kind="bar",  errorbar=None, height=5, aspect=2,
legend_out = True)
g.set_xticklabels(o)

plt.title('Probability of mental health condition')
plt.ylabel('Probability x 100')
plt.xlabel('Age')
# replace legend labels

new_labels = labelDict['label_Gender']
for t, l in zip(g._legend.texts, new_labels): t.set_text(l)
```

```
# Positioning the legend
g.fig.subplots_adjust(top=0.9,right=0.8)

plt.show()
```



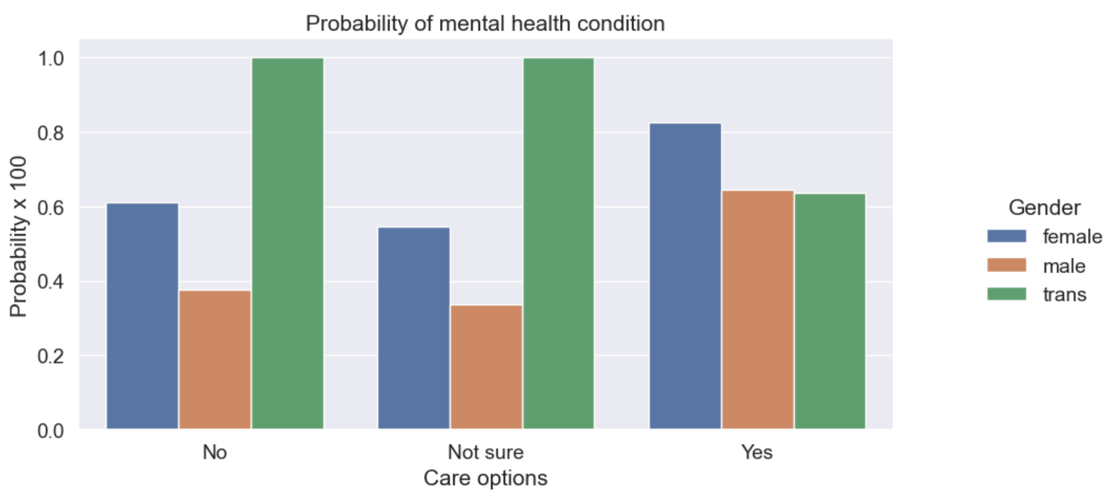
Barplot to show probabilities for family history

```
o = labelDict['label_family_history']
g = sns.catplot(x="family_history", y="treatment", hue="Gender",
data=train_df, kind="bar", errorbar=None, height=5, aspect=2,
legend_out = True)
g.set_xticklabels(o)
plt.title('Probability of mental health condition')
plt.ylabel('Probability x 100')
plt.xlabel('Family History')

# replace legend labels
new_labels = labelDict['label_Gender']
for t, l in zip(g._legend.texts, new_labels): t.set_text(l)

# Positioning the legend
g.fig.subplots_adjust(top=0.9,right=0.8)

plt.show()
```



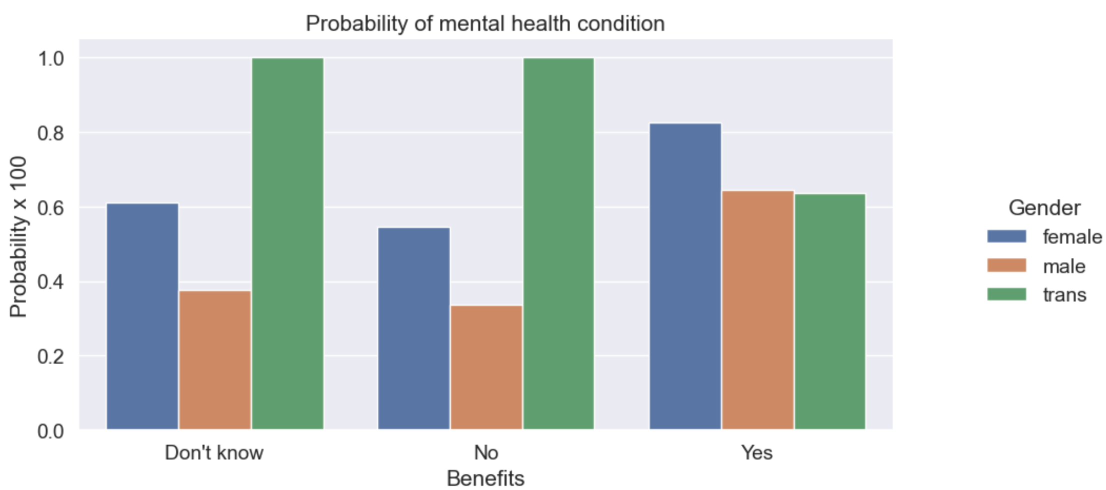
Barplot to show probabilities for care options

```
o = labelDict['label_care_options']
g = sns.catplot(x="care_options", y="treatment", hue="Gender",
data=train_df, kind="bar", errorbar=None, height=5, aspect=2,
legend_out = True)
g.set_xticklabels(o)
plt.title('Probability of mental health condition')
plt.ylabel('Probability x 100')
plt.xlabel('Care options')

# replace legend labels
new_labels = labelDict['label_Gender']
for t, l in zip(g._legend.texts, new_labels): t.set_text(l)

# Positioning the legend
g.fig.subplots_adjust(top=0.9,right=0.8)
plt.show()
```



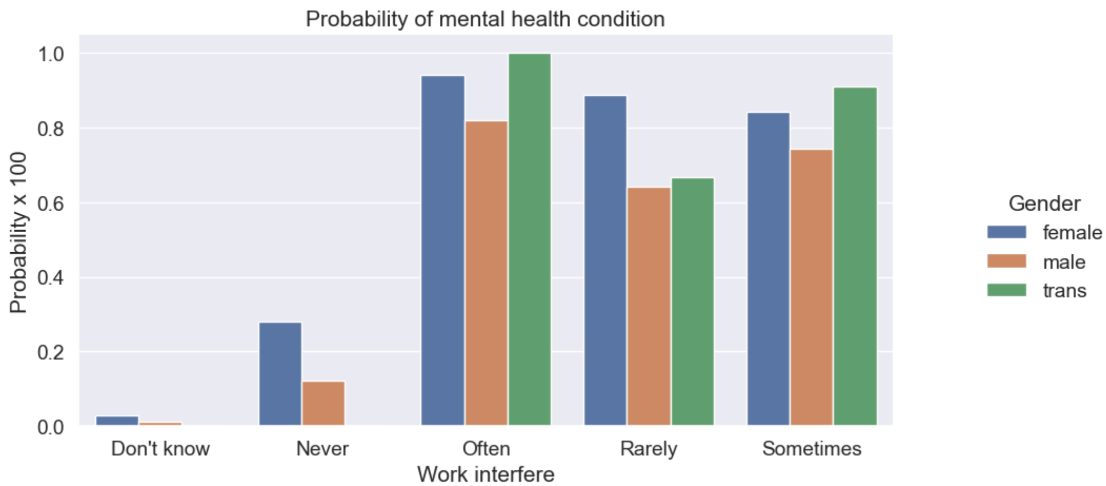
Barplot to show probabilities for benefits

```
o = labelDict['label_benefits']
g = sns.catplot(x="care_options", y="treatment", hue="Gender",
data=train_df, kind="bar", errorbar=None, height=5, aspect=2,
legend_out = True)
g.set_xticklabels(o)
plt.title('Probability of mental health condition')
plt.ylabel('Probability x 100')
plt.xlabel('Benefits')

# replace legend labels
new_labels = labelDict['label_Gender']
for t, l in zip(g._legend.texts, new_labels): t.set_text(l)

# Positioning the legend
g.fig.subplots_adjust(top=0.9,right=0.8)
plt.show()
```



Barplot to show probabilities for work interfere

```
o = labelDict['label_work_interfere']
g = sns.catplot(x="work_interfere", y="treatment", hue="Gender",
data=train_df, kind="bar", errorbar=None, height=5, aspect=2,
legend_out = True)
g.set_xticklabels(o)
plt.title('Probability of mental health condition')
plt.ylabel('Probability x 100')
plt.xlabel('Work interfere')

# replace legend labels
new_labels = labelDict['label_Gender']
for t, l in zip(g._legend.texts, new_labels): t.set_text(l)

# Positioning the legend
g.fig.subplots_adjust(top=0.9,right=0.8)
plt.show()
```



#Scaling and Fitting

Features Scaling We're going to scale age, because is extremely different from the othere ones.

```
# Scaling Age
scaler = MinMaxScaler()
train_df['Age'] = scaler.fit_transform(train_df[['Age']])
train_df.head()
```

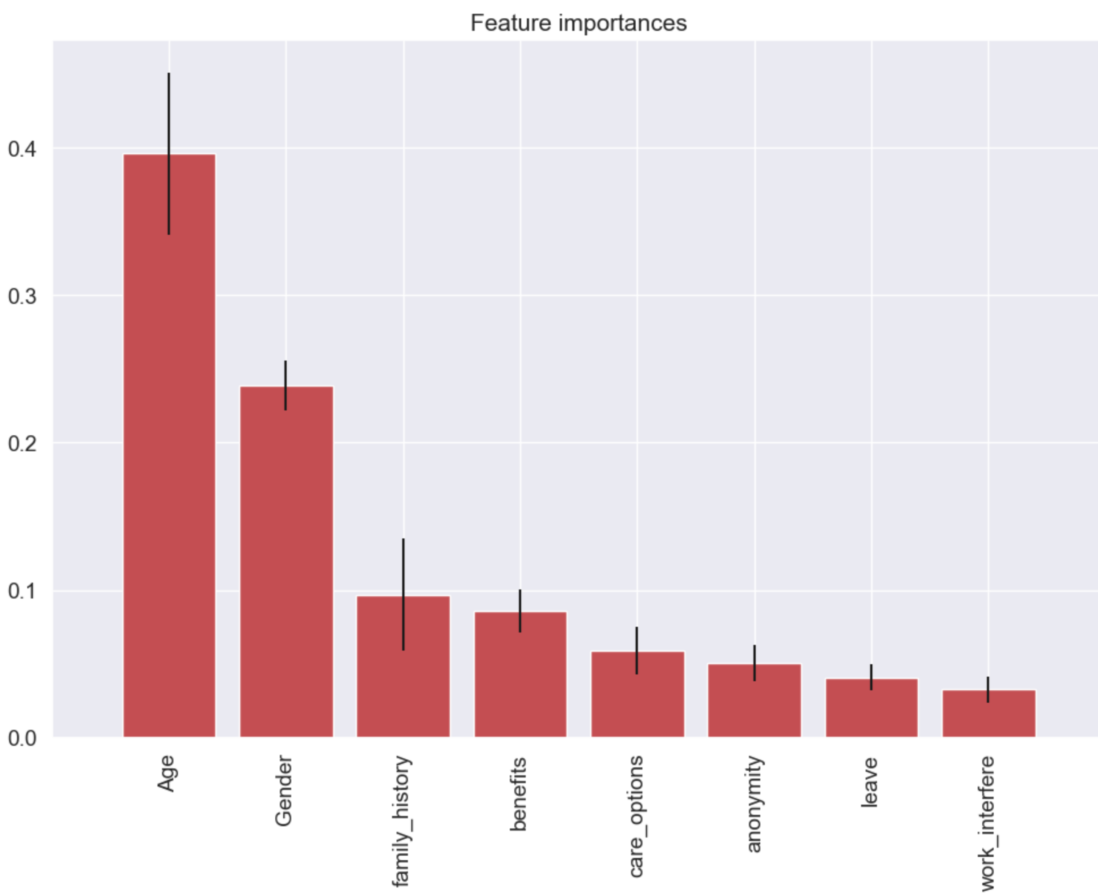
```
        Age  Gender  self_employed  family_history  treatment
work_interfere  \
0  0.431818       0              0               0          1
2
1  0.590909       1              0               0          0
3
2  0.318182       1              0               0          0
3
3  0.295455       1              0               1          1
2
4  0.295455       1              0               0          0
1

   no_employees  remote_work  tech_company  benefits  ...  leave  \
0             4            0             1         2  ...      2
1             5            0             0         0  ...      0
2             4            0             1         1  ...      1
3             2            0             1         1  ...      1
4             1            1             1         2  ...      0

   mental_health_consequence  phys_health_consequence  coworkers
supervisor  \
0                          1                        1          1
2
1                          0                        1          0
```

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

   mental_health_interview  phys_health_interview  mental_vs_physical
\
0                        1                      0                   2

1                        1                      1                   0

2                        2                      2                   1

3                        0                      0                   1

4                        2                      2                   0


   obs_consequence  age_range
0                0          2
1                0          2
2                0          2
3                1          2
4                0          2

[5 rows x 24 columns]
```

Spilitting Dataset

```
# define X and y
feature_cols = ['Age', 'Gender', 'family_history', 'benefits',
'care_options', 'anonymity', 'leave', 'work_interfere']
X = train_df[feature_cols]
y = train_df.treatment

# split X and y into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.30, random_state=0)

# Create dictionaries for final graph
methodDict = {}
rmseDict = ()

# Build a forest and compute the feature importances
forest = ExtraTreesClassifier(n_estimators=250,
                              random_state=0)
```

```
forest.fit(X, y)
importances = forest.feature_importances_
std = np.std([tree.feature_importances_ for tree in
forest.estimators_],
             axis=0)
indices = np.argsort(importances)[::-1]

labels = []
for f in range(X.shape[1]):
    labels.append(feature_cols[f])

# Plot the feature importances of the forest
plt.figure(figsize=(12,8))
plt.title("Feature importances")
plt.bar(range(X.shape[1]), importances[indices],
       color="r", yerr=std[indices], align="center")
plt.xticks(range(X.shape[1]), labels, rotation='vertical')
plt.xlim([-1, X.shape[1]])
plt.show()
```



#Tuning

```
def evalClassModel(model, y_test, y_pred_class, plot=False):
    #Classification accuracy: percentage of correct predictions
    # calculate accuracy
    print('Accuracy:', metrics.accuracy_score(y_test, y_pred_class))

    #Null accuracy: accuracy that could be achieved by always
predicting the most frequent class
    # examine the class distribution of the testing set (using a
Pandas Series method)
    print('Null accuracy:\n', y_test.value_counts())

    # calculate the percentage of ones
    print('Percentage of ones:', y_test.mean())

    # calculate the percentage of zeros
    print('Percentage of zeros:',1 - y_test.mean())

    #Comparing the true and predicted response values
    print('True:', y_test.values[0:25])
    print('Pred:', y_pred_class[0:25])

    #Confusion matrix
    # save confusion matrix and slice into four pieces
    confusion = metrics.confusion_matrix(y_test, y_pred_class)
    #[row, column]
    TP = confusion[1, 1]
    TN = confusion[0, 0]
    FP = confusion[0, 1]
    FN = confusion[1, 0]

    # visualize Confusion Matrix
    sns.heatmap(confusion,annot=True,fmt="d")
    plt.title('Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

    #Metrics computed from a confusion matrix
    #Classification Accuracy: Overall, how often is the classifier
correct?
    accuracy = metrics.accuracy_score(y_test, y_pred_class)
    print('Classification Accuracy:', accuracy)

    #Classification Error: Overall, how often is the classifier
incorrect?
    print('Classification Error:', 1 - metrics.accuracy_score(y_test,
y_pred_class))

    #False Positive Rate: When the actual value is negative, how often
is the prediction incorrect?
```

```
    false_positive_rate = FP / float(TN + FP)
    print('False Positive Rate:', false_positive_rate)

    #Precision: When a positive value is predicted, how often is the
prediction correct?
    print('Precision:', metrics.precision_score(y_test, y_pred_class))


    # IMPORTANT: first argument is true values, second argument is
predicted probabilities
    print('AUC Score:', metrics.roc_auc_score(y_test, y_pred_class))

    # calculate cross-validated AUC
    print('Cross-validated AUC:', cross_val_score(model, X, y, cv=10,
scoring='roc_auc').mean())

    ##########################################
    #Adjusting the classification threshold
    ##########################################
    # print the first 10 predicted responses
    print('First 10 predicted responses:\n', model.predict(X_test)
[0:10])

    # print the first 10 predicted probabilities of class membership
    print('First 10 predicted probabilities of class members:\n',
model.predict_proba(X_test)[0:10])

    # print the first 10 predicted probabilities for class 1
    model.predict_proba(X_test)[0:10, 1]

    # store the predicted probabilities for class 1
    y_pred_prob = model.predict_proba(X_test)[:, 1]

    if plot == True:
        # histogram of predicted probabilities
        plt.rcParams['font.size'] = 12
        plt.hist(y_pred_prob, bins=8)

        # x-axis limit from 0 to 1
        plt.xlim(0,1)
        plt.title('Histogram of predicted probabilities')
        plt.xlabel('Predicted probability of treatment')
        plt.ylabel('Frequency')


    # predict treatment if the predicted probability is greater than
0.3
    # it will return 1 for all values above 0.3 and 0 otherwise
    # results are 2D so we slice out the first column
    # y_pred_prob = y_pred_prob.reshape(-1,1)
```

```
    # y_pred_class = binarize(y_pred_prob, 0.3)[0]
    y_pred_prob = y_pred_prob.reshape(-1,1)
    y_pred_class = binarize(y_pred_prob, threshold=0.3)[:,0]


    # print the first 10 predicted probabilities
    print('First 10 predicted probabilities:\n', y_pred_prob[0:10])

    ##########################################
    #ROC Curves and Area Under the Curve (AUC)
    ##########################################

    #AUC is the percentage of the ROC plot that is underneath the
curve
    #Higher value = better classifier
    roc_auc = metrics.roc_auc_score(y_test, y_pred_prob)



    # IMPORTANT: first argument is true values, second argument is
predicted probabilities
    # roc_curve returns 3 objects fpr, tpr, thresholds
    # fpr: false positive rate
    # tpr: true positive rate
    fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_prob)
    if plot == True:
        plt.figure()

        plt.plot(fpr, tpr, color='darkorange', label='ROC curve (area
= %0.2f)' % roc_auc)
        plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
        plt.xlim([0.0, 1.0])
        plt.ylim([0.0, 1.0])
        plt.rcParams['font.size'] = 12
        plt.title('ROC curve for treatment classifier')
        plt.xlabel('False Positive Rate (1 - Specificity)')
        plt.ylabel('True Positive Rate (Sensitivity)')
        plt.legend(loc="lower right")
        plt.show()

    # define a function that accepts a threshold and prints
sensitivity and specificity
    def evaluate_threshold(threshold):
        #Sensitivity: When the actual value is positive, how often is
the prediction correct?
        #Specificity: When the actual value is negative, how often is
the prediction correct?print('Sensitivity for ' + str(threshold) +
' :', tpr[thresholds > threshold][-1])
        print('Specificity for ' + str(threshold) + ' :', 1 -
fpr[thresholds > threshold][-1])
```

```
    # One way of setting threshold
    predict_mine = np.where(y_pred_prob > 0.50, 1, 0)
    confusion = metrics.confusion_matrix(y_test, predict_mine)
    print(confusion)



    return accuracy
```

Tuning with cross validation score

```
def tuningCV(knn):

    # search for an optimal value of K for KNN
    k_range = list(range(1, 31))
    k_scores = []
    for k in k_range:
        knn = KNeighborsClassifier(n_neighbors=k)
        scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
        k_scores.append(scores.mean())
    print(k_scores)
    # plot the value of K for KNN (x-axis) versus the cross-validated
accuracy (y-axis)
    plt.plot(k_range, k_scores)
    plt.xlabel('Value of K for KNN')
    plt.ylabel('Cross-Validated Accuracy')
    plt.show()
```

Tuning with GridSearchCV

```
from sklearn.model_selection import GridSearchCV

def tuningGridSerach(knn):
    #More efficient parameter tuning using GridSearchCV
    k_range = list(range(1, 31))
    print(k_range)

    # create a parameter grid: map the parameter names to the values
that should be searched
    param_grid = dict(n_neighbors=k_range)
    print(param_grid)

    # instantiate the grid
    grid = GridSearchCV(knn, param_grid, cv=10, scoring='accuracy')

    # fit the grid with data
    grid.fit(X, y)

    # view the complete results (list of named tuples)
    grid.grid_scores_
```

```
    # examine the first tuple
    print(grid.grid_scores_[0].parameters)
    print(grid.grid_scores_[0].cv_validation_scores)
    print(grid.grid_scores_[0].mean_validation_score)

    # create a list of the mean scores only
    grid_mean_scores = [result.mean_validation_score for result in
grid.grid_scores_]
    print(grid_mean_scores)

    # plot the results
    plt.plot(k_range, grid_mean_scores)
    plt.xlabel('Value of K for KNN')
    plt.ylabel('Cross-Validated Accuracy')
    plt.show()

    # examine the best model
    print('GridSearch best score', grid.best_score_)
    print('GridSearch best params', grid.best_params_)
    print('GridSearch best estimator', grid.best_estimator_)
```

Tuning with RandomizedSearchCV

```
def tuningRandomizedSearchCV(model, param_dist):
    #Searching multiple parameters simultaneously
    # n_iter controls the number of searches
    rand = RandomizedSearchCV(model, param_dist, cv=10,
scoring='accuracy', n_iter=10, random_state=5)
    rand.fit(X, y)
    rand.cv_results_

    # examine the best model
    print('Rand. Best Score: ', rand.best_score_)
    print('Rand. Best Params: ', rand.best_params_)

    # run RandomizedSearchCV 20 times (with n_iter=10) and record the
best score
    best_scores = []
    for _ in range(20):
        rand = RandomizedSearchCV(model, param_dist, cv=10,
scoring='accuracy', n_iter=10)
        rand.fit(X, y)
        best_scores.append(round(rand.best_score_, 3))
    print(best_scores)
```

Tuning with searching multiple parameters simultaneously

```
def tuningMultParam(knn):

    #Searching multiple parameters simultaneously
```

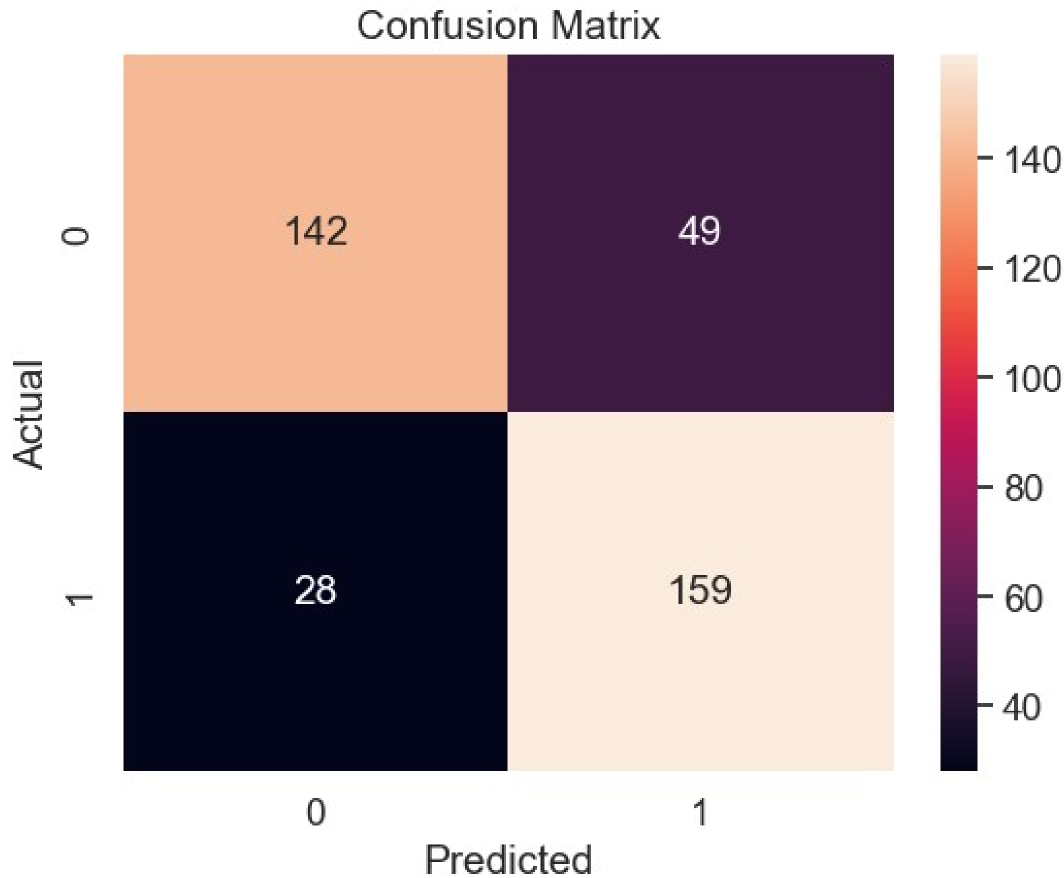
```
    # define the parameter values that should be searched
    k_range = list(range(1, 31))
    weight_options = ['uniform', 'distance']

    # create a parameter grid: map the parameter names to the values
that should be searched
    param_grid = dict(n_neighbors=k_range, weights=weight_options)
    print(param_grid)

    # instantiate and fit the grid
    grid = GridSearchCV(knn, param_grid, cv=10, scoring='accuracy')
    grid.fit(X, y)

    # view the complete results
    print(grid.grid_scores_)

    # examine the best model
    print('Multiparam. Best Score: ', grid.best_score_)
    print('Multiparam. Best Params: ', grid.best_params_)
```

#Evaluating models

Logistic Regression

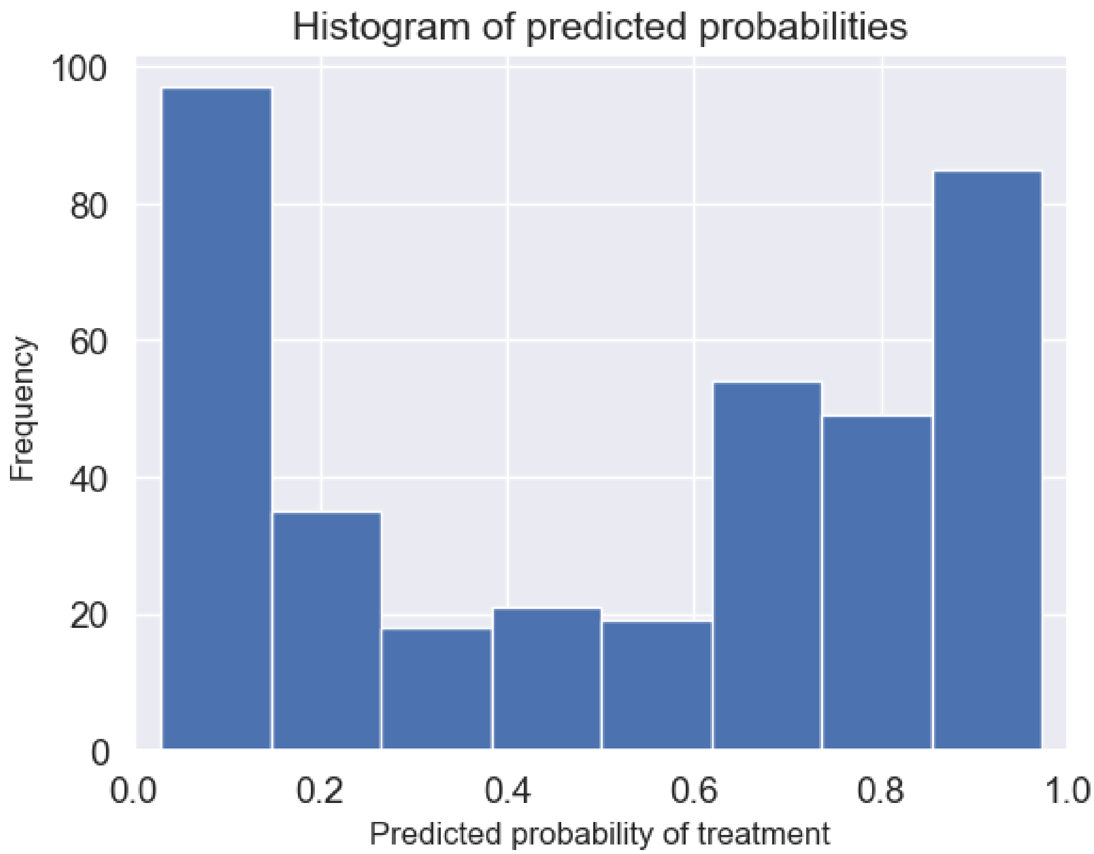
```
def logisticRegression():
    # train a logistic regression model on the training set
    logreg = LogisticRegression()
    logreg.fit(X_train, y_train)

    # make class predictions for the testing set
    y_pred_class = logreg.predict(X_test)

    accuracy_score = evalClassModel(logreg, y_test,
y_pred_class,plot=True)

    #Data for final graph
    methodDict['Log. Regression'] = accuracy_score * 100

logisticRegression()
```

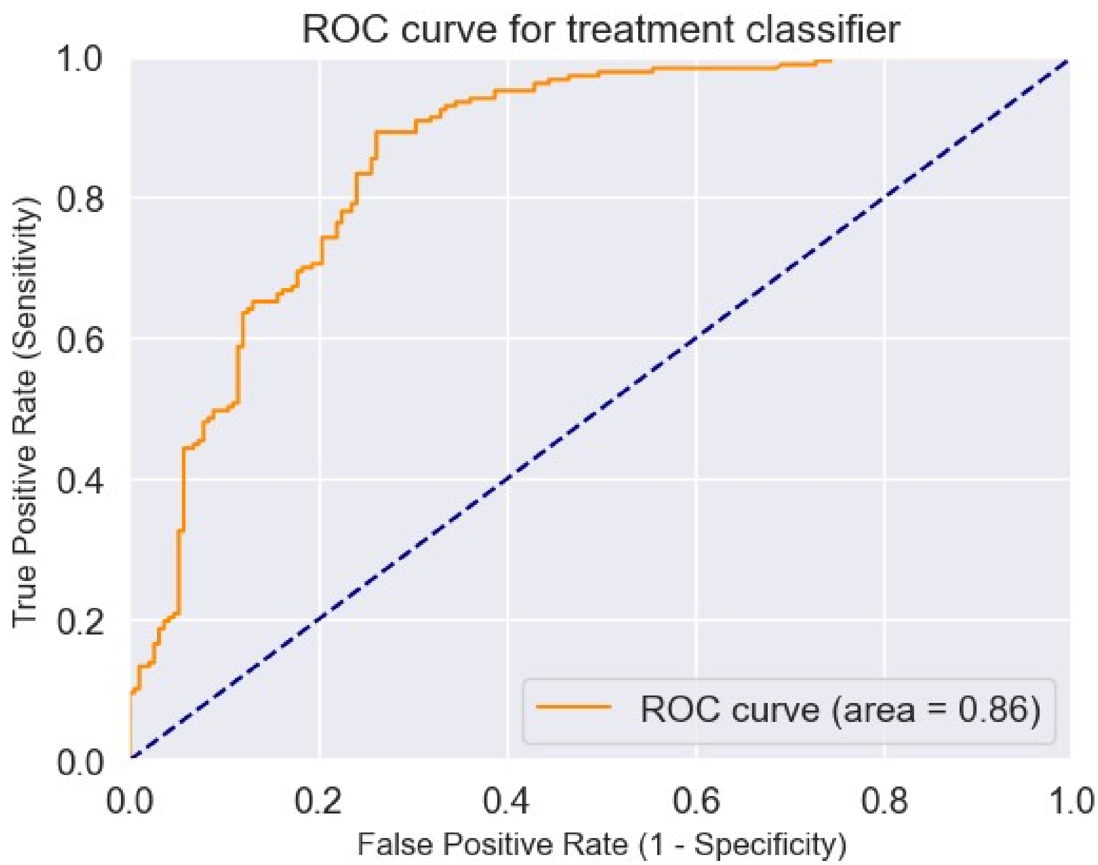
```
Accuracy: 0.7962962962962963
Null accuracy:
 0    191
1    187
Name: treatment, dtype: int64
Percentage of ones: 0.4947089947089947
Percentage of zeros: 0.5052910052910053
True: [0 0 0 0 0 0 0 0 1 1 0 1 1 0 1 1 0 1 0 0 0 1 1 0 0]
Pred: [1 0 0 0 1 1 0 1 0 1 0 1 1 0 1 1 1 1 0 0 0 0 1 0 0]
```




```
Classification Accuracy: 0.7962962962962963
Classification Error: 0.20370370370370372
False Positive Rate: 0.25654450261780104
Precision: 0.7644230769230769
AUC Score: 0.7968614385306716
Cross-validated AUC: 0.8753623882722146
First 10 predicted responses:
 [1 0 0 0 1 1 0 1 0 1]
First 10 predicted probabilities of class members:
 [[0.09193053 0.90806947]
 [0.95991564 0.04008436]
 [0.96547467 0.03452533]
 [0.78757121 0.21242879]
 [0.38959922 0.61040078]
 [0.05264207 0.94735793]
 [0.75035574 0.24964426]
 [0.19065116 0.80934884]
 [0.61612081 0.38387919]
 [0.47699963 0.52300037]]
First 10 predicted probabilities:
 [[0.90806947]
 [0.04008436]
 [0.03452533]
```

```
[0.21242879]
[0.61040078]
[0.94735793]
[0.24964426]
[0.80934884]
[0.38387919]
[0.52300037]]
```





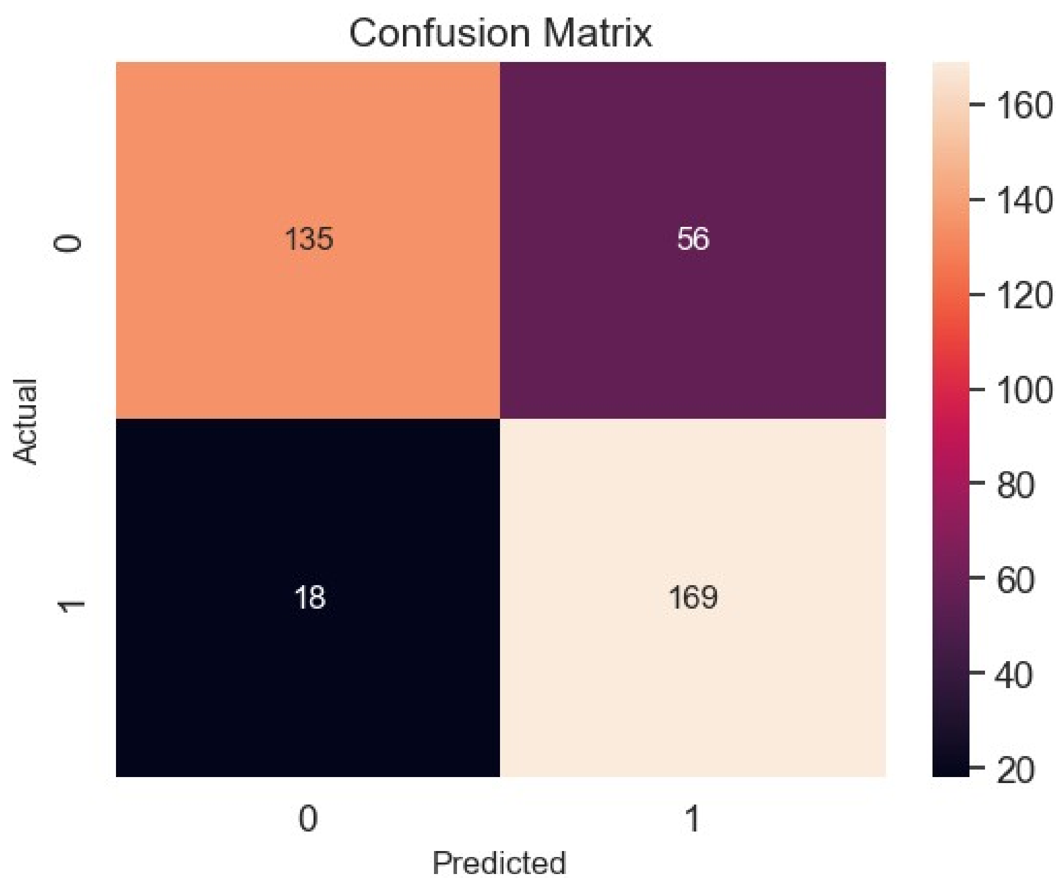

```
[[142  49]
 [ 28 159]]
```

KNeighbors Classifier

```
def Knn():
    # Calculating the best parameters
    knn = KNeighborsClassifier(n_neighbors=5)

    # define the parameter values that should be searched
    k_range = list(range(1, 31))
    weight_options = ['uniform', 'distance']

    # specify "parameter distributions" rather than a "parameter grid"
    param_dist = dict(n_neighbors=k_range, weights=weight_options)
    tuningRandomizedSearchCV(knn, param_dist)

    # train a KNeighborsClassifier model on the training set
    knn = KNeighborsClassifier(n_neighbors=27, weights='uniform')
    knn.fit(X_train, y_train)

    # make class predictions for the testing set
    y_pred_class = knn.predict(X_test)
```

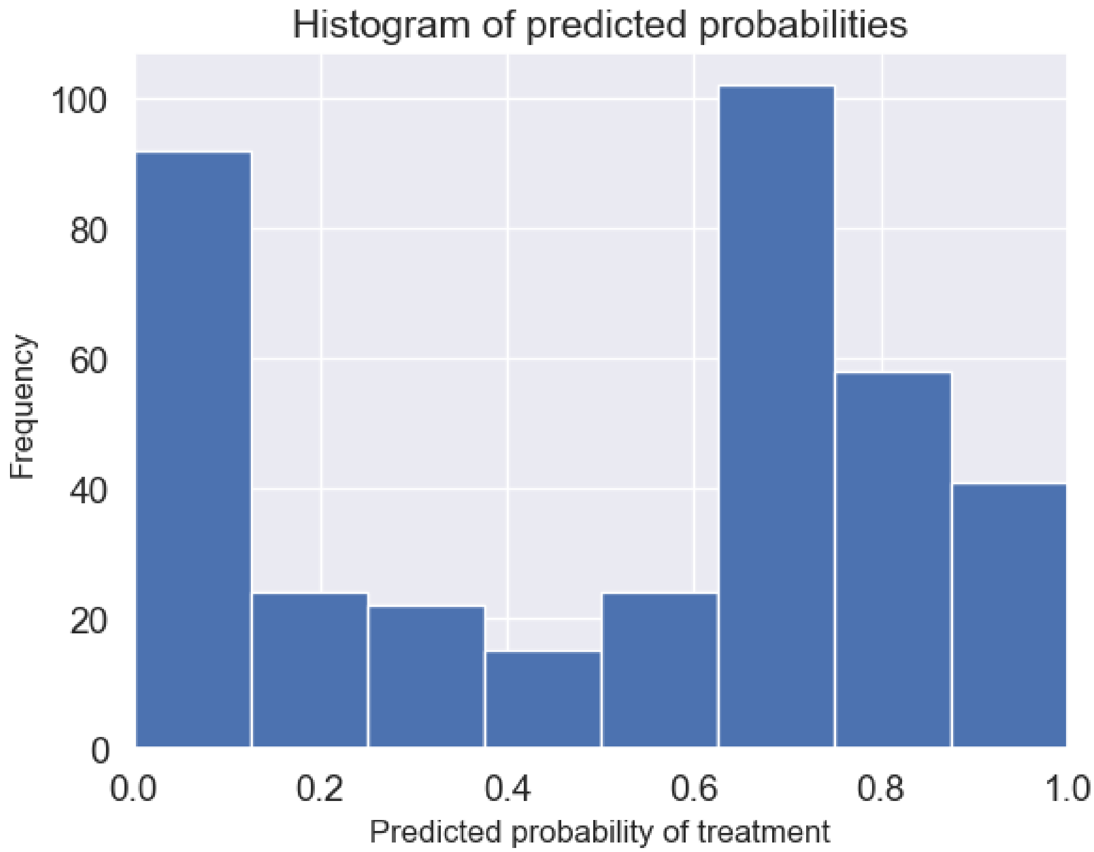
```
    accuracy_score = evalClassModel(knn, y_test, y_pred_class, True)

    #Data for final graph
    methodDict['K-Neighbors'] = accuracy_score * 100
```

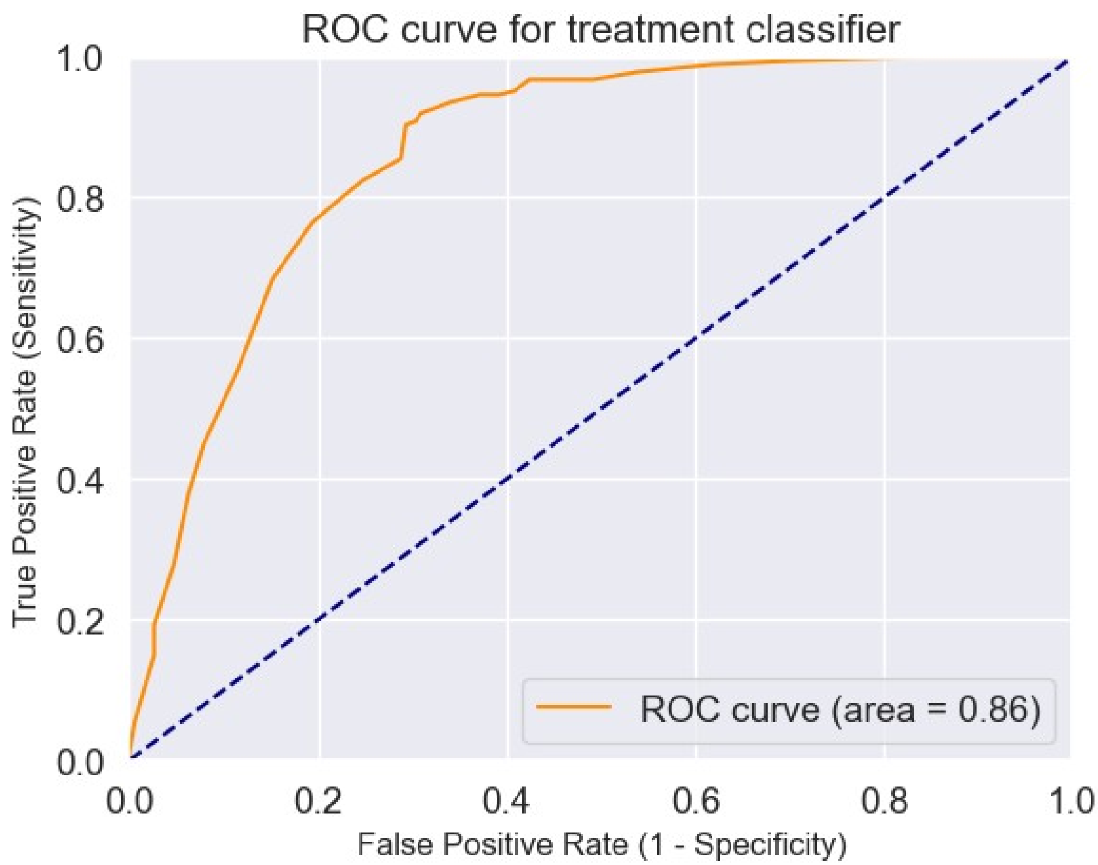
```
Knn()

Rand. Best Score:  0.8217650793650794
Rand. Best Params:  {'weights': 'uniform', 'n_neighbors': 27}
[0.822, 0.822, 0.822, 0.822, 0.819, 0.813, 0.815, 0.819, 0.803, 0.819,
0.822, 0.817, 0.814, 0.814, 0.819, 0.822, 0.819, 0.819, 0.812, 0.81]
Accuracy: 0.8042328042328042
Null accuracy:
 0    191
1    187
Name: treatment, dtype: int64
Percentage of ones: 0.4947089947089947
Percentage of zeros: 0.5052910052910053
True: [0 0 0 0 0 0 0 0 1 1 0 1 1 0 1 1 0 1 0 0 0 1 1 0 0]
Pred: [1 0 0 0 1 1 0 1 1 1 0 1 1 0 1 1 1 1 0 0 0 0 1 0 0]
```




```
Classification Accuracy: 0.8042328042328042
Classification Error: 0.1957671957671958
False Positive Rate: 0.2931937172774869
```

```
Precision: 0.7511111111111111
AUC Score: 0.8052747991152673
Cross-validated AUC: 0.8784644661702792
First 10 predicted responses:
 [1 0 0 0 1 1 0 1 1 1]
First 10 predicted probabilities of class members:
 [[0.33333333 0.66666667]
 [1.         0.        ]
 [1.         0.        ]
 [0.66666667 0.33333333]
 [0.37037037 0.62962963]
 [0.03703704 0.96296296]
 [0.59259259 0.40740741]
 [0.37037037 0.62962963]
 [0.33333333 0.66666667]
 [0.33333333 0.66666667]]
First 10 predicted probabilities:
 [[0.66666667]
 [0.        ]
 [0.        ]
 [0.33333333]
 [0.62962963]
 [0.96296296]
 [0.40740741]
 [0.62962963]
 [0.66666667]
 [0.66666667]]
```


Histogram of predicted probabilities
Frequency
0
20
40
60
80
100
0.0
0.2
0.4
0.6
0.8
1.0
Predicted probability of treatment

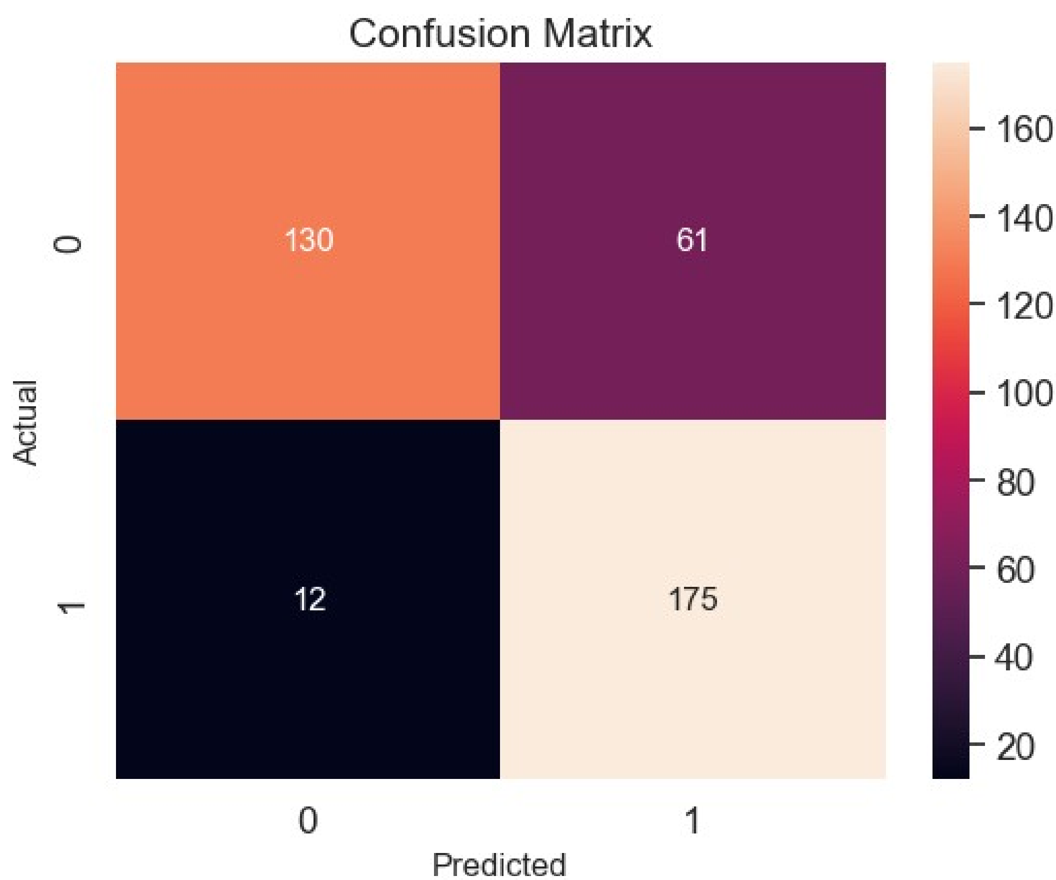



```
[[135  56]
 [ 18 169]]
```

Decision Tree classifier

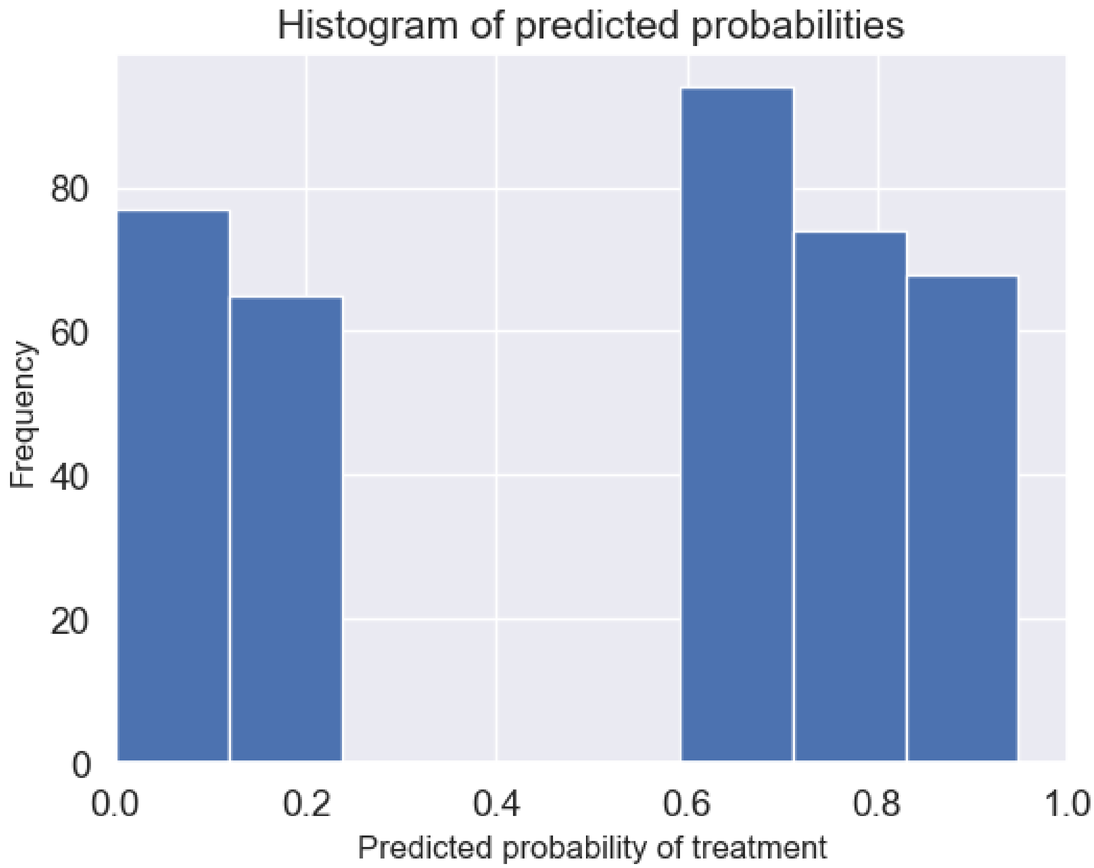
```python
def treeClassifier():
    # Calculating the best parameters
    tree = DecisionTreeClassifier()
    featuresSize = feature_cols.__len__()
    param_dist = {"max_depth": [3, None],
              "max_features": randint(1, featuresSize),
              "min_samples_split": randint(2, 9),
              "min_samples_leaf": randint(1, 9),
              "criterion": ["gini", "entropy"]}
    tuningRandomizedSearchCV(tree, param_dist)

    # train a decision tree model on the training set
    tree = DecisionTreeClassifier(max_depth=3, min_samples_split=8, 
max_features=6, criterion='entropy', min_samples_leaf=7)
    tree.fit(X_train, y_train)

    # make class predictions for the testing set
    y_pred_class = tree.predict(X_test)
```

```
    accuracy_score = evalClassModel(tree, y_test, y_pred_class, True)

    #Data for final graph
    methodDict['Decision Tree Classifier'] = accuracy_score * 100

treeClassifier()

Rand. Best Score:  0.8305206349206349
Rand. Best Params:  {'criterion': 'entropy', 'max_depth': 3,
'max_features': 7, 'min_samples_leaf': 6, 'min_samples_split': 4}
[0.831, 0.831, 0.831, 0.831, 0.822, 0.831, 0.828, 0.822, 0.823, 0.831,
0.815, 0.829, 0.831, 0.829, 0.831, 0.83, 0.831, 0.804, 0.831, 0.827]
Accuracy: 0.8068783068783069
Null accuracy:
 0    191
1    187
Name: treatment, dtype: int64
Percentage of ones: 0.4947089947089947
Percentage of zeros: 0.5052910052910053
True: [0 0 0 0 0 0 0 0 1 1 0 1 1 0 1 1 0 1 0 0 0 1 1 0 0]
Pred: [1 0 0 0 1 1 0 1 1 1 0 1 1 0 1 1 1 1 0 0 0 0 1 0 0]
```

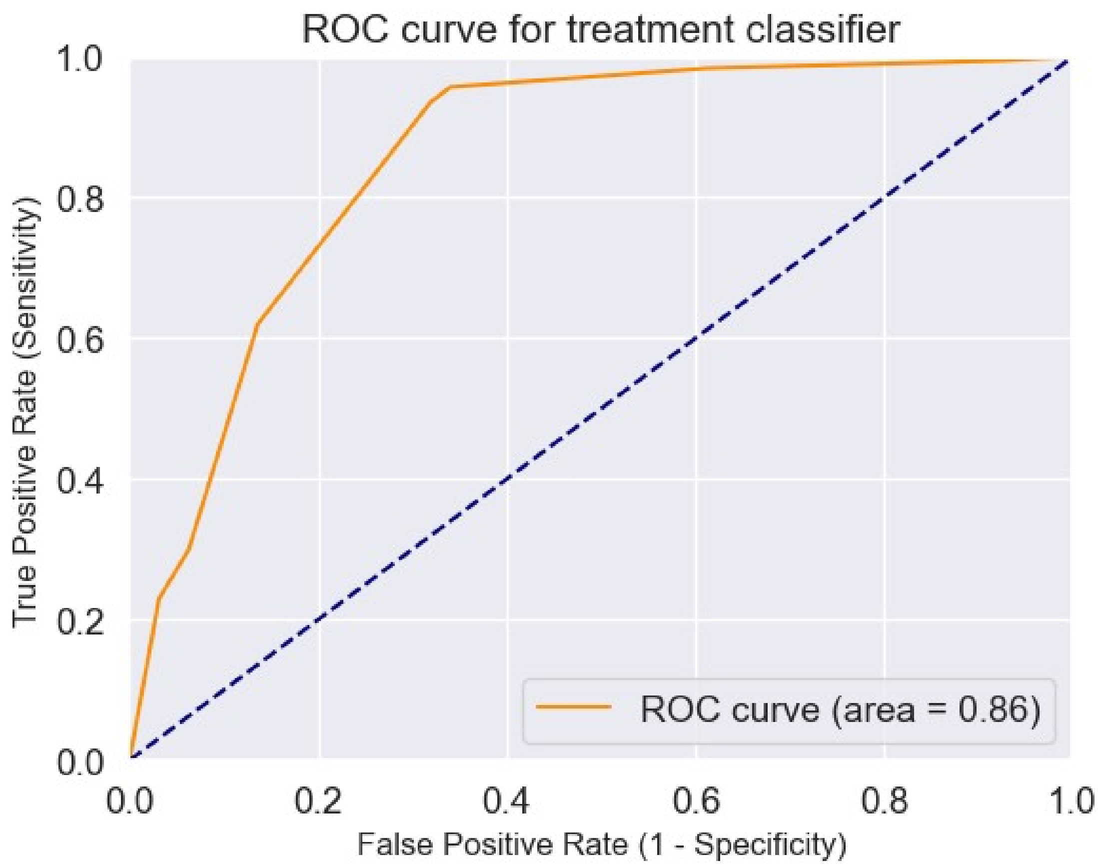



```
Classification Accuracy: 0.8068783068783069
Classification Error: 0.19312169312169314
```

```
False Positive Rate: 0.3193717277486911
Precision: 0.7415254237288136
AUC Score: 0.8082285746283282
Cross-validated AUC: 0.8768782313179155
First 10 predicted responses:
 [1 0 0 0 1 1 0 1 1 1]
First 10 predicted probabilities of class members:
 [[0.18823529 0.81176471]
 [0.99375    0.00625   ]
 [0.99375    0.00625   ]
 [0.88135593 0.11864407]
 [0.36097561 0.63902439]
 [0.05172414 0.94827586]
 [0.88135593 0.11864407]
 [0.11320755 0.88679245]
 [0.36097561 0.63902439]
 [0.36097561 0.63902439]]
First 10 predicted probabilities:
 [[0.81176471]
 [0.00625   ]
 [0.00625   ]
 [0.11864407]
 [0.63902439]
 [0.94827586]
 [0.11864407]
 [0.88679245]
 [0.63902439]
 [0.63902439]]
```



Histogram of predicted probabilities
Frequency
0
20
40
60
80
0.0
0.2
0.4
0.6
0.8
1.0
Predicted probability of treatment



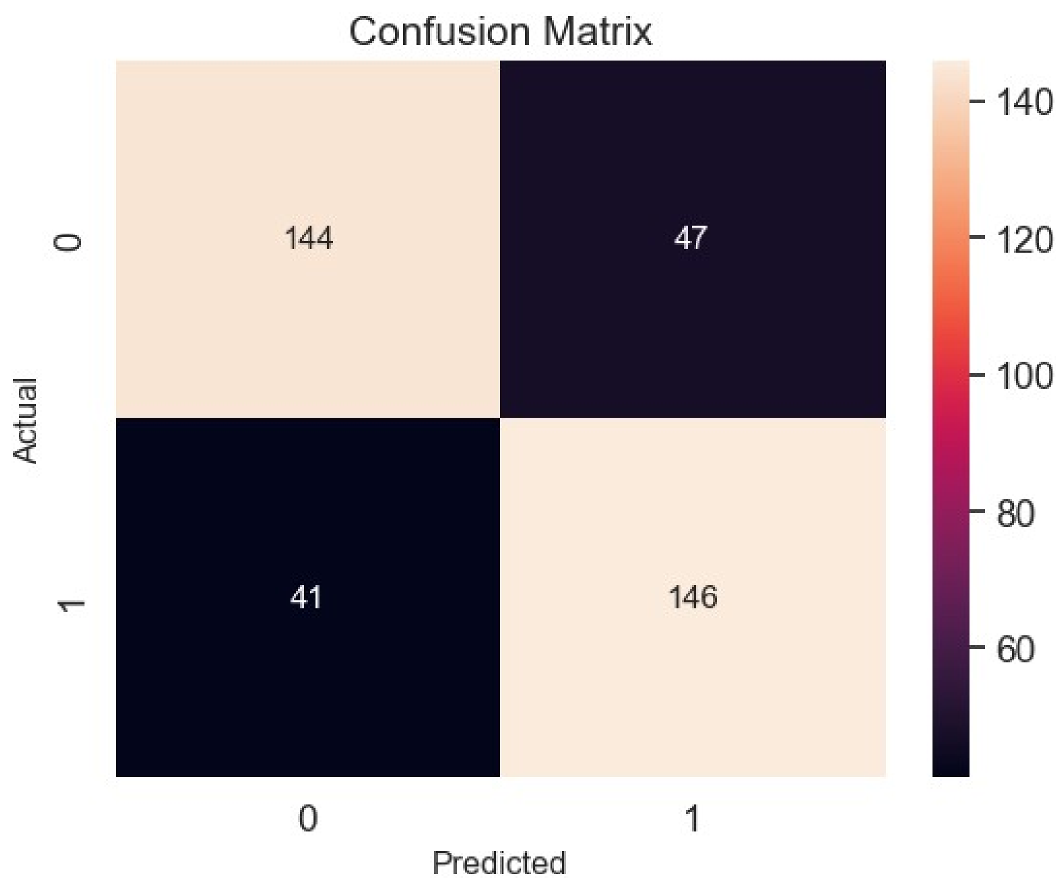

```
[[130  61]
 [ 12 175]]
```

Bagging

```
def bagging():
    # Building and fitting
    bag = BaggingClassifier(DecisionTreeClassifier(), max_samples=1.0,
max_features=1.0, bootstrap_features=False)
    bag.fit(X_train, y_train)

    # make class predictions for the testing set
    y_pred_class = bag.predict(X_test)

    accuracy_score = evalClassModel(bag, y_test, y_pred_class, True)

    #Data for final graph
    methodDict['Bagging'] = accuracy_score * 100

bagging()
```

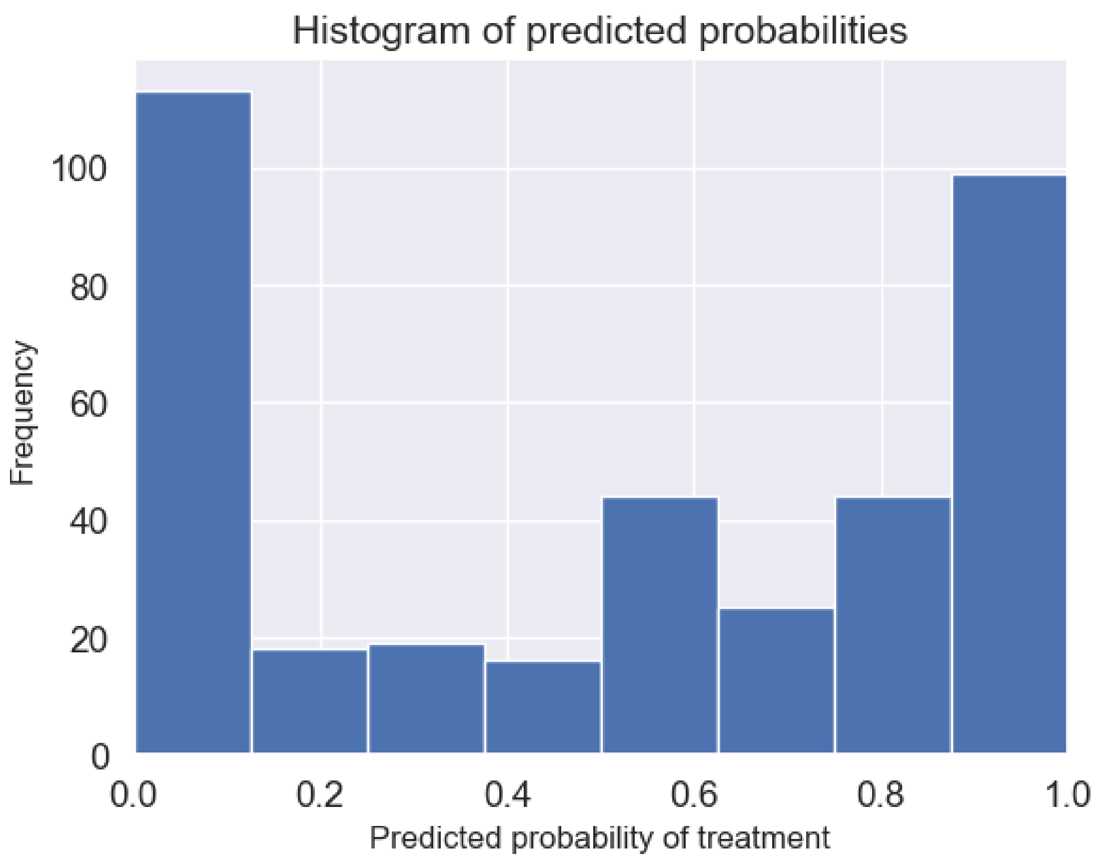
```
Accuracy: 0.7671957671957672
Null accuracy:
 0    191
```

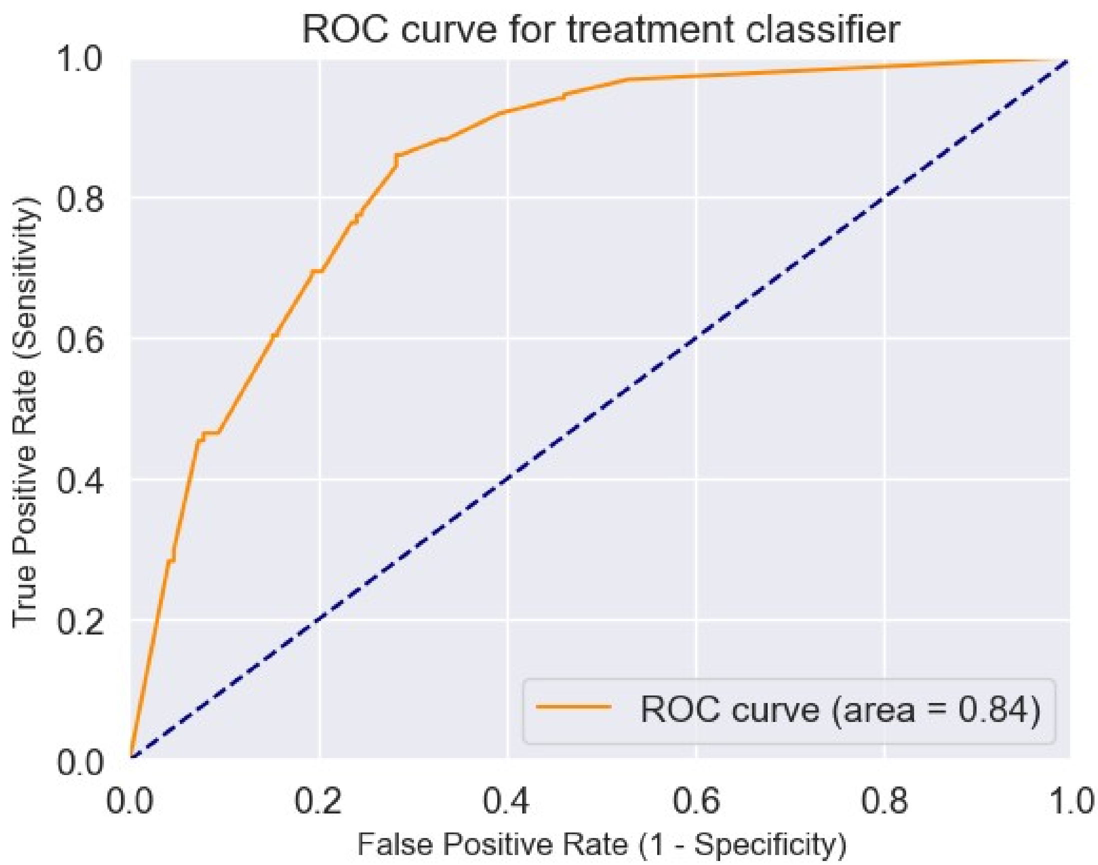
```
1    187
Name: treatment, dtype: int64
Percentage of ones: 0.4947089947089947
Percentage of zeros: 0.5052910052910053
True: [0 0 0 0 0 0 0 0 1 1 0 1 1 0 1 1 0 1 0 0 0 1 1 0 0]
Pred: [1 0 0 0 0 1 0 0 1 1 0 0 1 1 1 1 0 1 0 0 0 0 1 0 0]
```




```
Classification Accuracy: 0.7671957671957672
Classification Error: 0.2328042328042328
False Positive Rate: 0.24607329842931938
Precision: 0.7564766839378239
AUC Score: 0.7673376823361424
Cross-validated AUC: 0.8385892697132616
First 10 predicted responses:
 [1 0 0 0 0 1 0 0 1 1]
First 10 predicted probabilities of class members:
 [[0.41 0.59]
 [1.   0.  ]
 [1.   0.  ]
 [0.6  0.4 ]
 [0.8  0.2 ]
 [0.25 0.75]
 [1.   0.  ]
```

```
 [0.7  0.3 ]
 [0.   1.  ]
 [0.3  0.7 ]]
First 10 predicted probabilities:
 [[0.59]
 [0.  ]
 [0.  ]
 [0.4 ]
 [0.2 ]
 [0.75]
 [0.  ]
 [0.3 ]
 [1.  ]
 [0.7 ]]
```





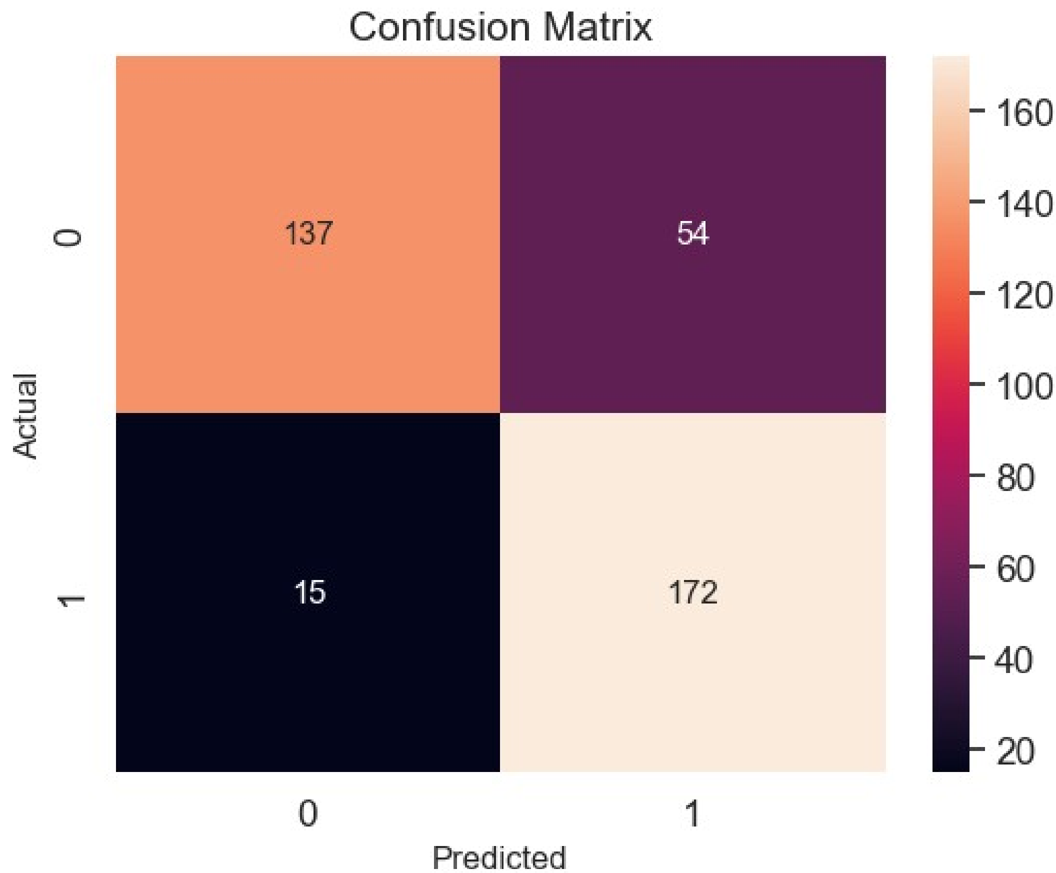

```
[[144  47]
 [ 41 146]]
```

Boosting

```python
def boosting():
    # Building and fitting
    clf = DecisionTreeClassifier(criterion='entropy', max_depth=1)
    boost = AdaBoostClassifier(estimator=clf, n_estimators=500)
    boost.fit(X_train, y_train)

    # make class predictions for the testing set
    y_pred_class = boost.predict(X_test)

    accuracy_score = evalClassModel(boost, y_test, y_pred_class, True)

    #Data for final graph
    methodDict['Boosting'] = accuracy_score * 100

boosting()
```

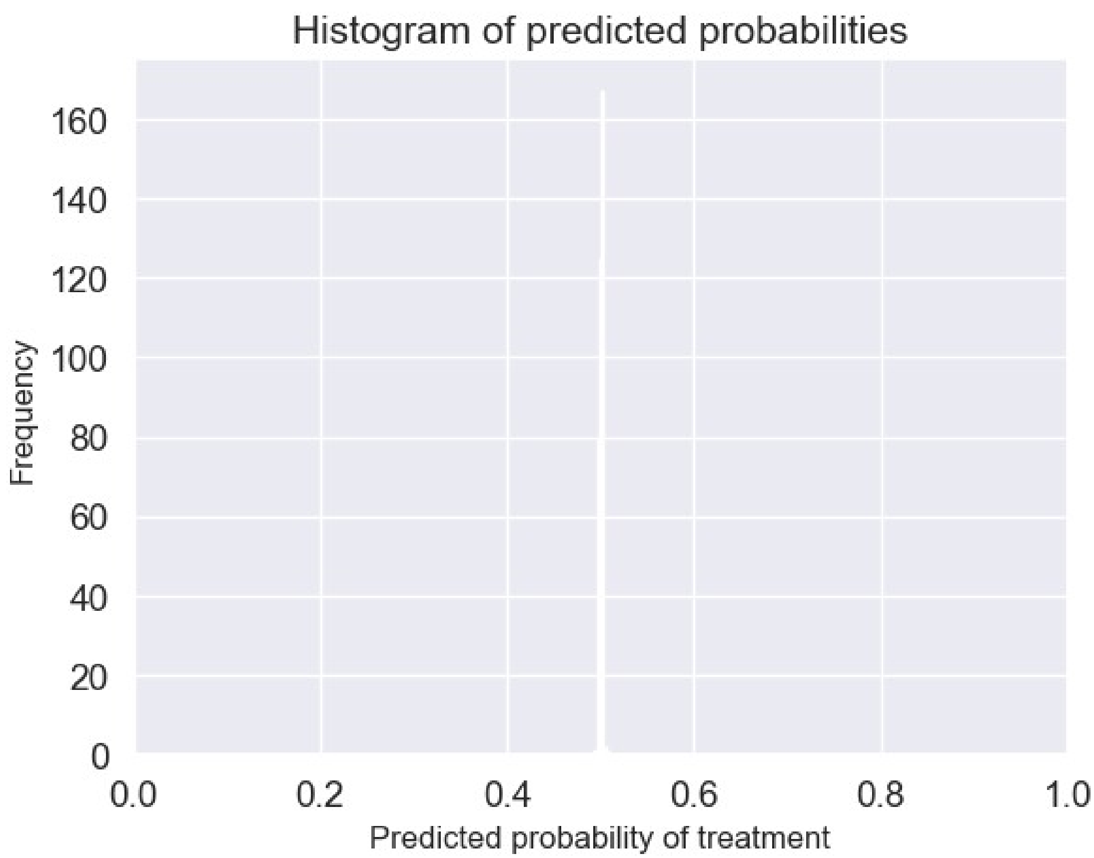
```
Accuracy: 0.8174603174603174
Null accuracy:
 0    191
```

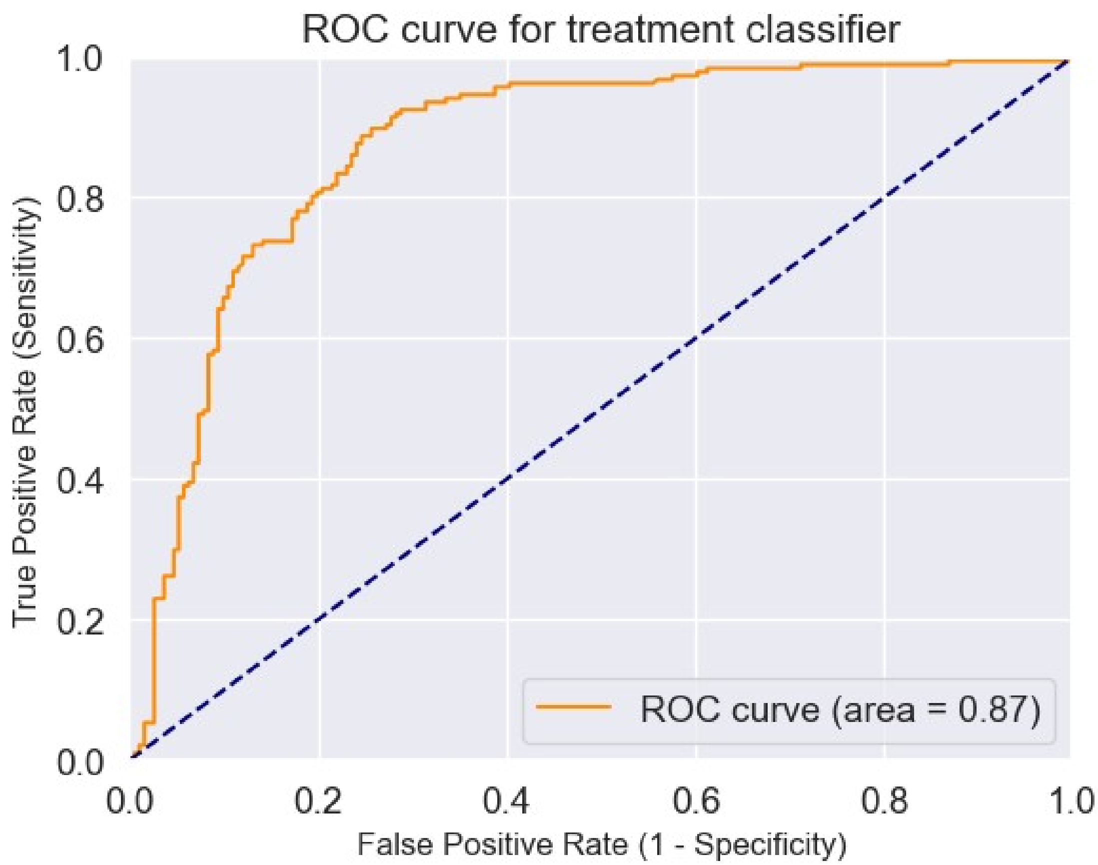
```
1    187
Name: treatment, dtype: int64
Percentage of ones: 0.4947089947089947
Percentage of zeros: 0.5052910052910053
True: [0 0 0 0 0 0 0 0 1 1 0 1 1 0 1 1 0 1 0 0 0 1 1 0 0]
Pred: [1 0 0 0 0 1 0 1 1 1 0 1 1 0 1 1 1 1 0 0 0 0 1 0 0]
```




```
Classification Accuracy: 0.8174603174603174
Classification Error: 0.18253968253968256
False Positive Rate: 0.28272251308900526
Precision: 0.7610619469026548
AUC Score: 0.8185317915838397
Cross-validated AUC: 0.8746279095195426
First 10 predicted responses:
 [1 0 0 0 0 1 0 1 1 1]
First 10 predicted probabilities of class members:
 [[0.49924555 0.50075445]
 [0.50285507 0.49714493]
 [0.50291786 0.49708214]
 [0.50127788 0.49872212]
 [0.50013552 0.49986448]
 [0.49796157 0.50203843]
 [0.50046371 0.49953629]
```

```
 [0.49939483 0.50060517]
 [0.49921757 0.50078243]
 [0.49897133 0.50102867]]
First 10 predicted probabilities:
 [[0.50075445]
 [0.49714493]
 [0.49708214]
 [0.49872212]
 [0.49986448]
 [0.50203843]
 [0.49953629]
 [0.50060517]
 [0.50078243]
 [0.50102867]]
```

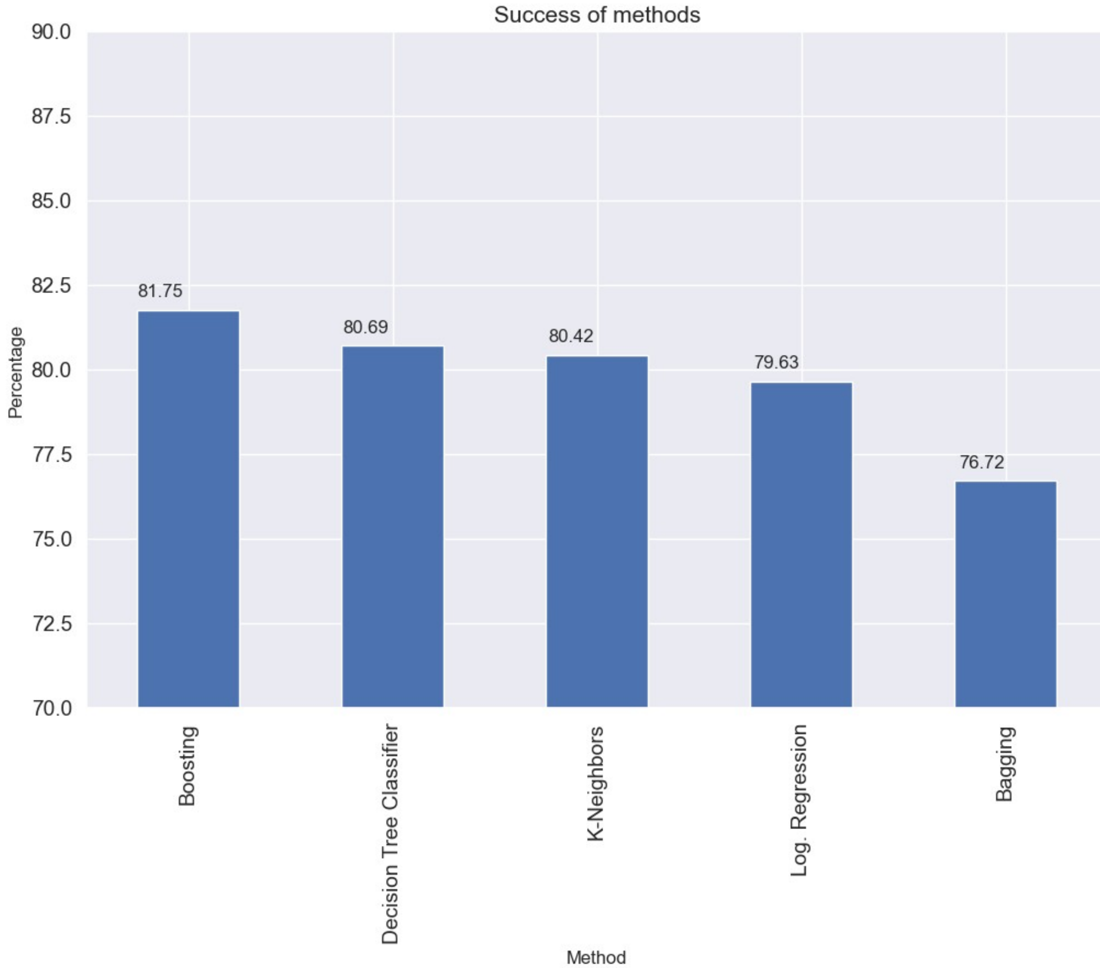





```
[[137  54]
 [ 15 172]]
```

#Success method plot

```
def plotSuccess():
    s = pd.Series(methodDict)
    s = s.sort_values(ascending=False)
    plt.figure(figsize=(12,8))
    #Colors
    ax = s.plot(kind='bar')
    for p in ax.patches:
        ax.annotate(str(round(p.get_height(),2)), (p.get_x() * 1.005,
p.get_height() * 1.005))
    plt.ylim([70.0, 90.0])
    plt.xlabel('Method')
    plt.ylabel('Percentage')
    plt.title('Success of methods')

    plt.show()

plotSuccess()
```



#Creating predictions on test set

```
# Generate predictions with the best method
clf = AdaBoostClassifier()
clf.fit(X, y)
dfTestPredictions = clf.predict(X_test)

# Write predictions to csv file
# We don't have any significative field so we save the index
results = pd.DataFrame({'Index': X_test.index, 'Treatment':
dfTestPredictions})
# Save to file
# This file will be visible after publishing in the output section
results.to_csv('results.csv', index=False)
results.head()
```

	Index	Treatment
0	5	1
1	494	0
2	52	0

```
3    984          0
4    186          0
```

#Submission

```
results = pd.DataFrame({'Index': X_test.index, 'Treatment':
dfTestPredictions})
results
```

```
     Index  Treatment
0        5          1
1      494          0
2       52          0
3      984          0
4      186          0
..     ...        ...
373   1084          1
374    506          0
375   1142          0
376   1124          0
377    689          1

[378 rows x 2 columns]
```