Mental health data prediction with machine learning

Libraries and loading data

In [1]:
```
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

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

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

#Naive bayes
from sklearn.naive_bayes import GaussianNB

#Stacking
from mlxtend.classifier import StackingClassifier


from subprocess import check_output
print(check_output(["ls", "../input"]).decode("utf8"))


#reading in CSV's from a file path
train_df = pd.read_csv('../input/survey.csv')


print(train_df.shape)

print(train_df.describe())

print(train_df.info())
```

```
survey.csv

(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):
Timestamp                    1259 non-null object
Age                          1259 non-null int64
Gender                       1259 non-null object
Country                      1259 non-null object
state                        744 non-null object
self_employed                1241 non-null object
family_history               1259 non-null object
treatment                    1259 non-null object
work_interfere               995 non-null object
no_employees                 1259 non-null object
remote_work                  1259 non-null object
tech_company                 1259 non-null object
benefits                     1259 non-null object
care_options                 1259 non-null object
wellness_program             1259 non-null object
seek_help                    1259 non-null object
anonymity                    1259 non-null object
leave                        1259 non-null object
mental_health_consequence    1259 non-null object
phys_health_consequence      1259 non-null object
coworkers                    1259 non-null object
supervisor                   1259 non-null object
mental_health_interview      1259 non-null object
phys_health_interview        1259 non-null object
mental_vs_physical           1259 non-null object
obs_consequence              1259 non-null object
comments                     164 non-null object
dtypes: int64(1), object(26)
memory usage: 265.6+ KB
None
/opt/conda/lib/python3.6/site-packages/sklearn/cross_validation.py:41: DeprecationWar
ning: This module was deprecated in version 0.18 in favor of the model_selection modu
le into which all the refactored classes and functions are moved. Also note that the
interface of the new CV iterators are different from that of this module. This module
will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/grid_search.py:42: DeprecationWarning:
This module was deprecated in version 0.18 in favor of the model_selection module int
o which all the refactored classes and functions are moved. This module will be remov
ed in 0.20.
  DeprecationWarning)
```

Data cleaning

Look at the missing data

In [2]:
```
total = train_df.isnull().sum().sort_values(ascending=False)
percent = (train_df.isnull().sum()/train_df.isnull().count()).sort_values(ascending=Fa
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
benefits                       0  0.000000
Age                            0  0.000000
Gender                         0  0.000000
Country                        0  0.000000
family_history                 0  0.000000
treatment                      0  0.000000
no_employees                   0  0.000000
remote_work                    0  0.000000
tech_company                   0  0.000000
care_options                   0  0.000000
obs_consequence                0  0.000000
wellness_program               0  0.000000
seek_help                      0  0.000000
anonymity                      0  0.000000
leave                          0  0.000000
mental_health_consequence      0  0.000000
phys_health_consequence        0  0.000000
coworkers                      0  0.000000
supervisor                     0  0.000000
mental_health_interview        0  0.000000
phys_health_interview          0  0.000000
mental_vs_physical             0  0.000000
Timestamp                      0  0.000000
```

Handing the missing data

In [3]:
```
train_df = train_df.drop(['comments'], axis= 1)
train_df = train_df.drop(['state'], axis= 1)
train_df = train_df.drop(['Timestamp'], axis= 1)

train_df.isnull().sum().max()
train_df.head(5)
```

Out[3]:

	Age	Gender	Country	self_employed	family_history	treatment	work_interfere	no_employees	r
0	37	Female	United States	NaN	No	Yes	Often	6-25	
1	44	M	United States	NaN	No	No	Rarely	More than 1000	
2	32	Male	Canada	NaN	No	No	Rarely	6-25	
3	31	Male	United Kingdom	NaN	Yes	Yes	Often	26-100	
4	31	Male	United States	NaN	No	No	Never	100-500	

Cleaning the NaN data

In [4]:

```
# 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',
                  'no_employees', 'remote_work', 'tech_company', 'anonymity', 'leave',
                  'phys_health_consequence', 'coworkers', 'supervisor', 'mental_health_
                  'mental_vs_physical', 'obs_consequence', 'benefits', 'care_options',
                  'seek_help']
floatFeatures = []

# Clean the NaN's data
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(5)
```

Out[4]:

	Age	Gender	Country	self_employed	family_history	treatment	work_interfere	no_employees	r
0	37	Female	United States	NaN	No	Yes	Often	6-25	
1	44	M	United States	NaN	No	No	Rarely	More than 1000	
2	32	Male	Canada	NaN	No	No	Rarely	6-25	
3	31	Male	United Kingdom	NaN	Yes	Yes	Often	26-100	
4	31	Male	United States	NaN	No	No	Never	100-500	

In [5]:

```
#Clean 'Gender'
#Slower case all columm's elements
gender = train_df['Gender'].str.lower()
#print(gender)

#Select unique elements
gender = train_df['Gender'].unique()

#Made gender groups
male_str = ["male", "m", "male-ish", "maile", "mal", "male (cis)", "make", "male ", "m
trans_str = ["trans-female", "something kinda male?", "queer/she/they", "non-binary","
female_str = ["cis female", "f", "female", "woman",  "femake", "female ","cis-female/f

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']
```

In [6]:

```
#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-
```

In [7]:
```
#There are only 0.014% of self employed so let's change NaN to NOT self_employed
#Replace "NaN" string from default String
train_df['self_employed'] = train_df['self_employed'].replace([defaultString], 'No')
print(train_df['self_employed'].unique())
```

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

In [8]:
```
#There are only 0.20% of self work_interfere so let's change NaN to "Don't know
#Replace "NaN" string from default String

train_df['work_interfere'] = train_df['work_interfere'].replace([defaultString], 'Don'
print(train_df['work_interfere'].unique())
```

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

Encoding the data

In [9]:
```
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)

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

```
label_Age [18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 3
6, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 53, 54, 55, 56, 57, 5
8, 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']
```

Out[9]:

	Age	Gender	self_employed	family_history	treatment	work_interfere	no_employees	remote_wor
0	19	0	0	0	1	2	4	
1	26	1	0	0	0	3	5	
2	14	1	0	0	0	3	4	
3	13	1	0	1	1	2	2	
4	13	1	0	0	0	1	1	

Check there has any missing data

In [10]:

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

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

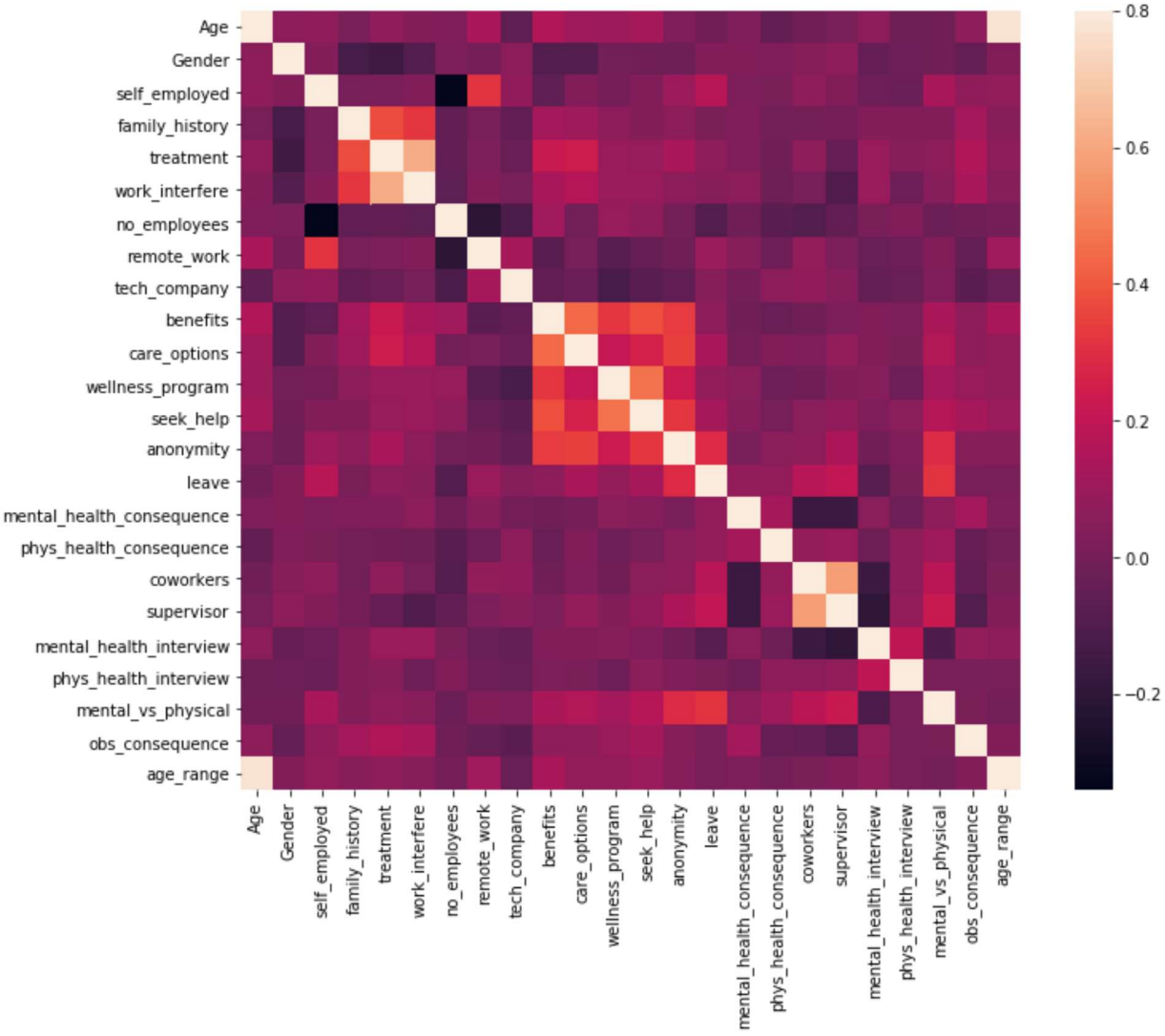
Features Scaling

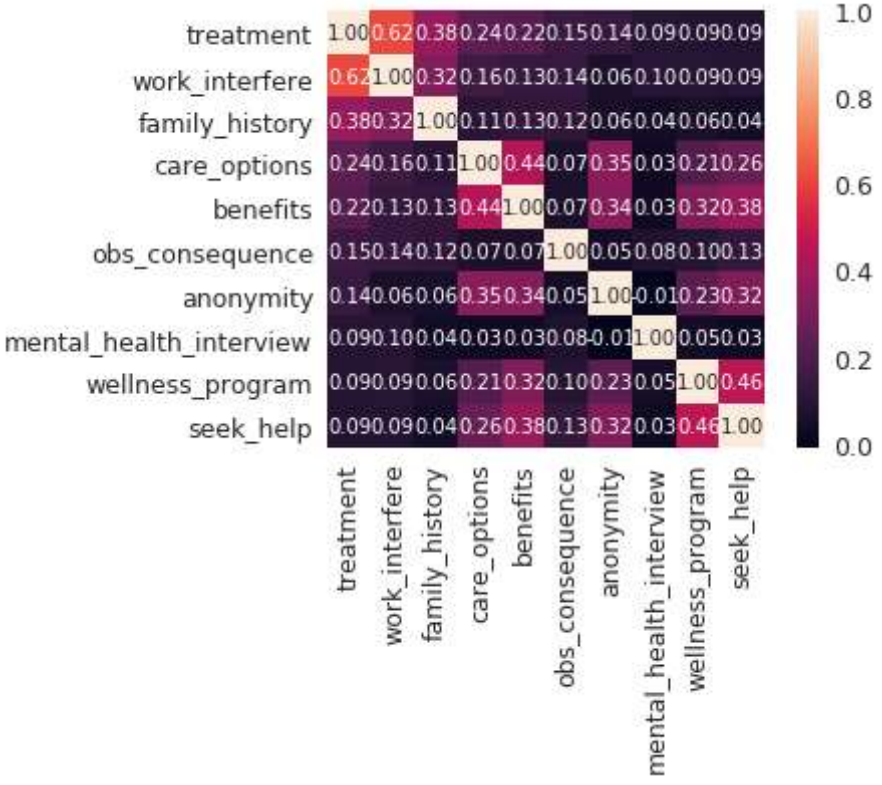
We need to scale 'age', because this feature is extremely different from the othere ones.

Covariance Matrix.

Variability comparison between categories of variables

In [11]:
```
#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':
plt.show()
```


Age
Gender
self_employed
family_history
treatment
work_interfere
no_employees
remote_work
tech_company
benefits
care_options
wellness_program
seek_help
anonymity
leave
mental_health_consequence
phys_health_consequence
coworkers
supervisor
mental_health_interview
phys_health_interview
mental_vs_physical
obs_consequence
age_range
0.8
0.6
0.4
0.2
0.0
−0.2

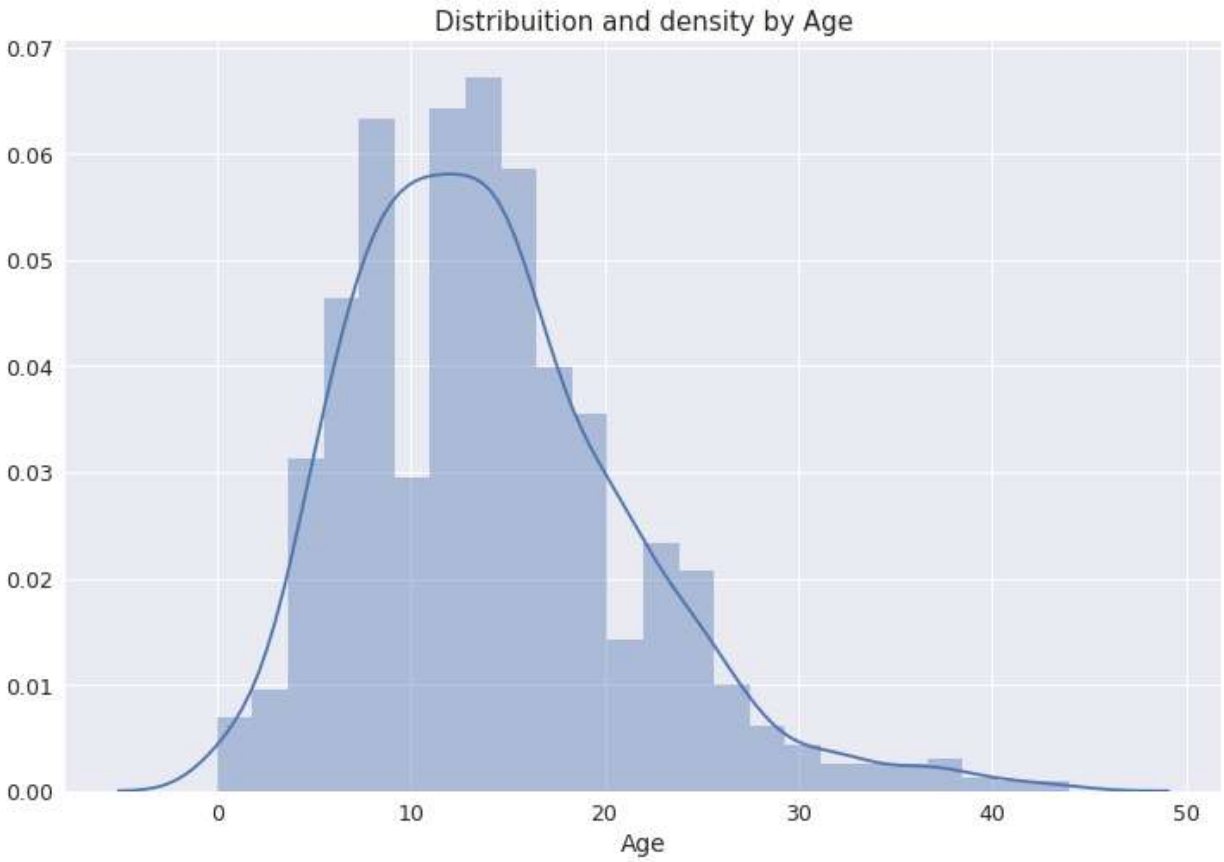

treatment 1.00 0.62 0.38 0.24 0.22 0.15 0.14 0.09 0.09 0.09
work_interfere 0.62 1.00 0.32 0.16 0.13 0.14 0.06 0.10 0.09 0.09
family_history 0.38 0.32 1.00 0.11 0.13 0.12 0.06 0.04 0.06 0.04
care_options 0.24 0.16 0.11 1.00 0.44 0.07 0.35 0.03 0.21 0.26
benefits 0.22 0.13 0.13 0.44 1.00 0.07 0.34 0.03 0.32 0.38
obs_consequence 0.15 0.14 0.12 0.07 0.07 1.00 0.05 0.08 0.10 0.13
anonymity 0.14 0.06 0.06 0.35 0.34 0.05 1.00 -0.01 0.23 0.32
mental_health_interview 0.09 0.10 0.04 0.03 0.03 0.08 -0.01 1.00 0.05 0.03
wellness_program 0.09 0.09 0.06 0.21 0.32 0.10 0.23 0.05 1.00 0.46
seek_help 0.09 0.09 0.04 0.26 0.38 0.13 0.32 0.03 0.46 1.00
treatment
work_interfere
family_history
care_options
benefits
obs_consequence
anonymity
mental_health_interview
wellness_program
seek_help
1.0
0.8
0.6
0.4
0.2
0.0

EDA to see data relationships

The distribiution and density by 'Age'.

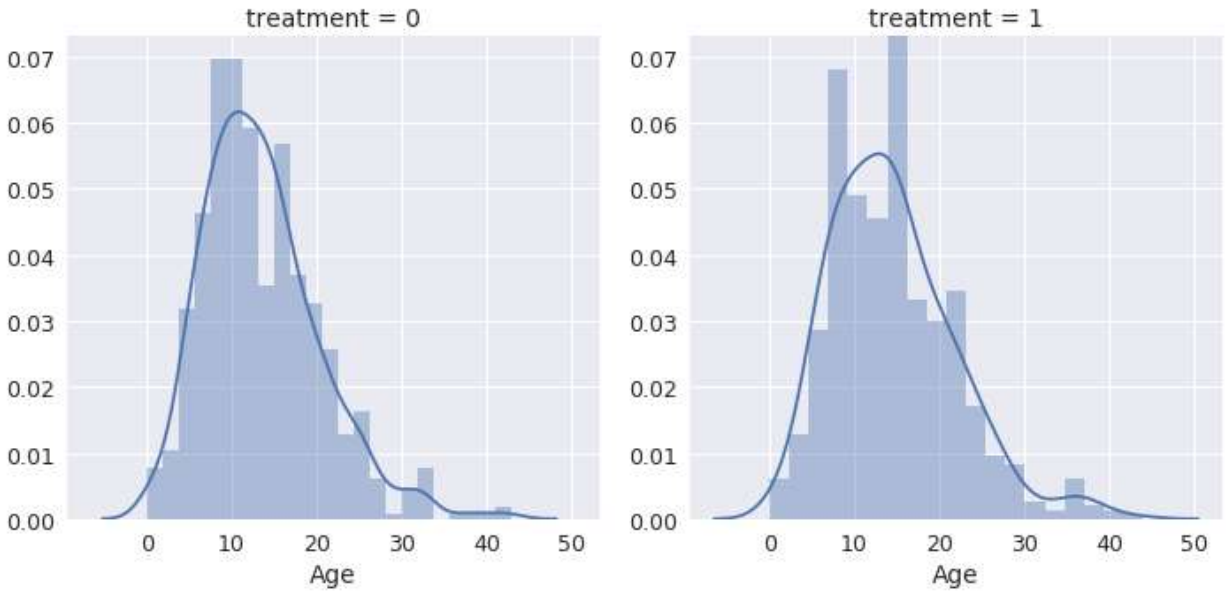
In [12]:
```
plt.figure(figsize=(12,8))
sns.distplot(train_df["Age"], bins=24)
plt.title("Distribuition and density by Age")
plt.xlabel("Age")
```

Out[12]:
```
Text(0.5,0,'Age')
```



Separate by treatment

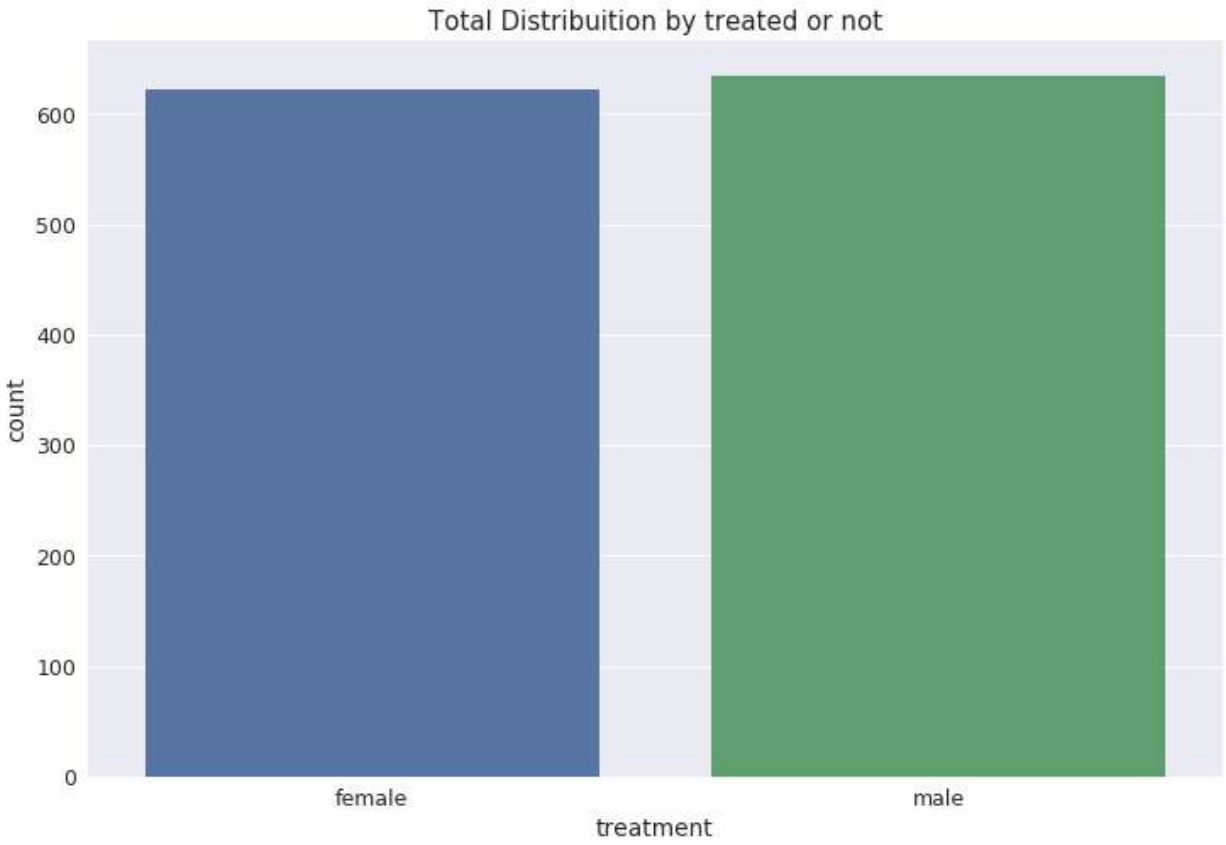
In [13]:
```
g = sns.FacetGrid(train_df, col='treatment', size=5)
g = g.map(sns.distplot, "Age")
```



Check how many people has been treated

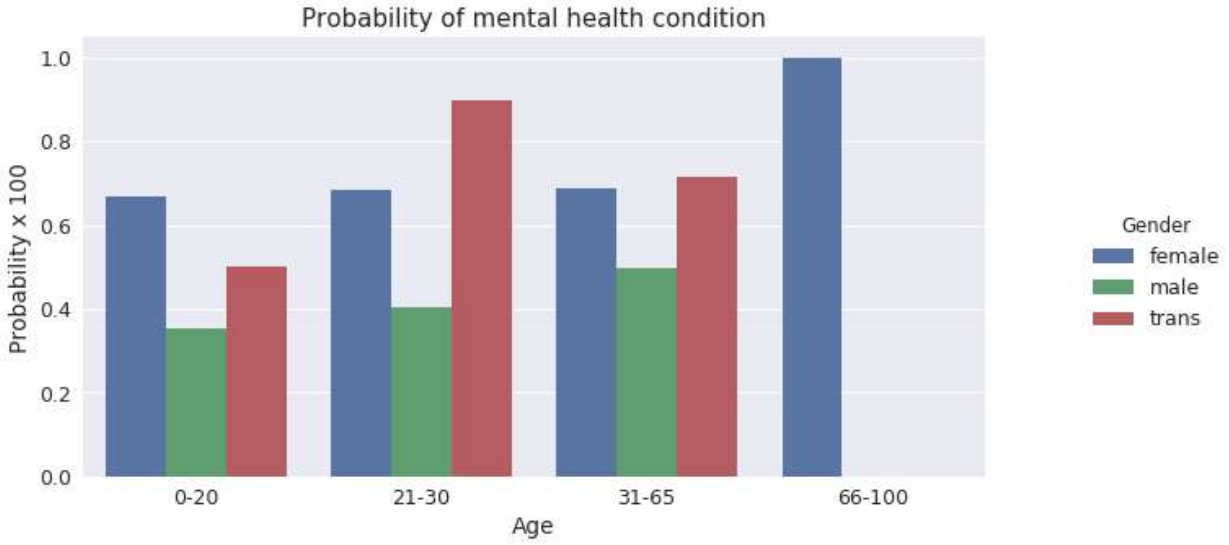
In [14]:
```
plt.figure(figsize=(12,8))
labels = labelDict['label_Gender']
g = sns.countplot(x="treatment", data=train_df)
g.set_xticklabels(labels)

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

Out[14]:
```
Text(0.5,1,'Total Distribuition by treated or not')
```



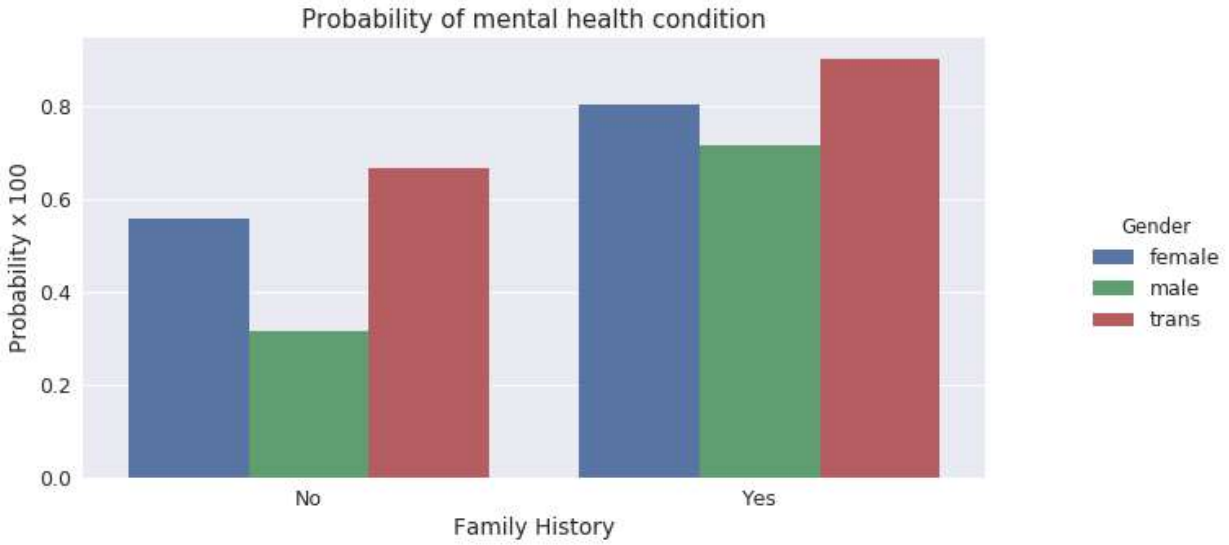
Draw a nested barplot to show probabilities for class and sex

In [15]:
```
o = labelDict['label_age_range']

g = sns.factorplot(x="age_range", y="treatment", hue="Gender", data=train_df, kind="ba
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()
```



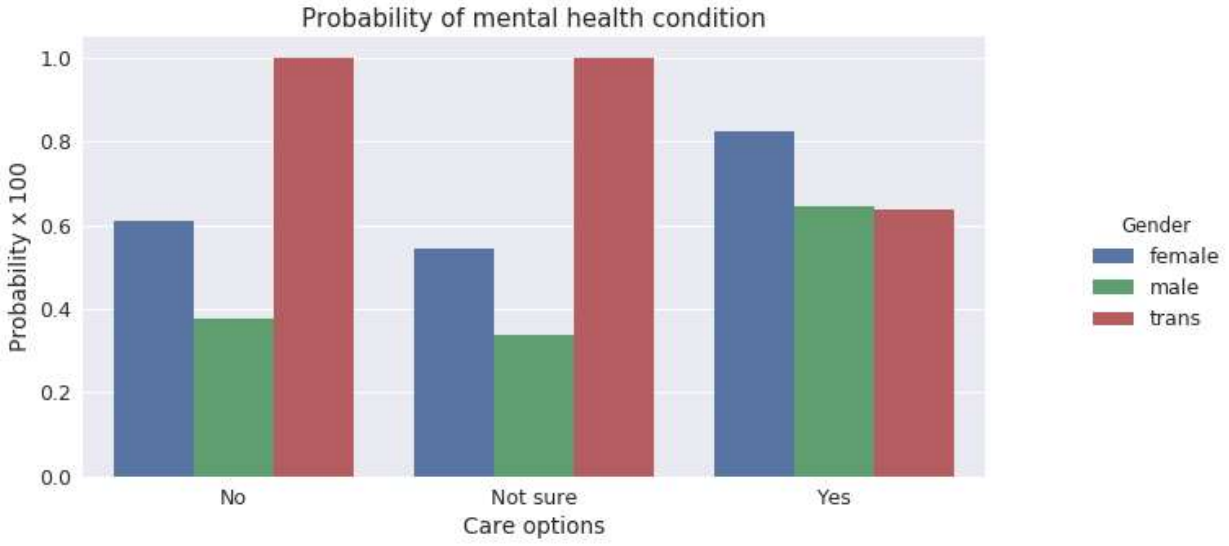
Barplot to show probabilities for 'family history'

In [16]:
```
o = labelDict['label_family_history']
g = sns.factorplot(x="family_history", y="treatment", hue="Gender", data=train_df, kin
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'

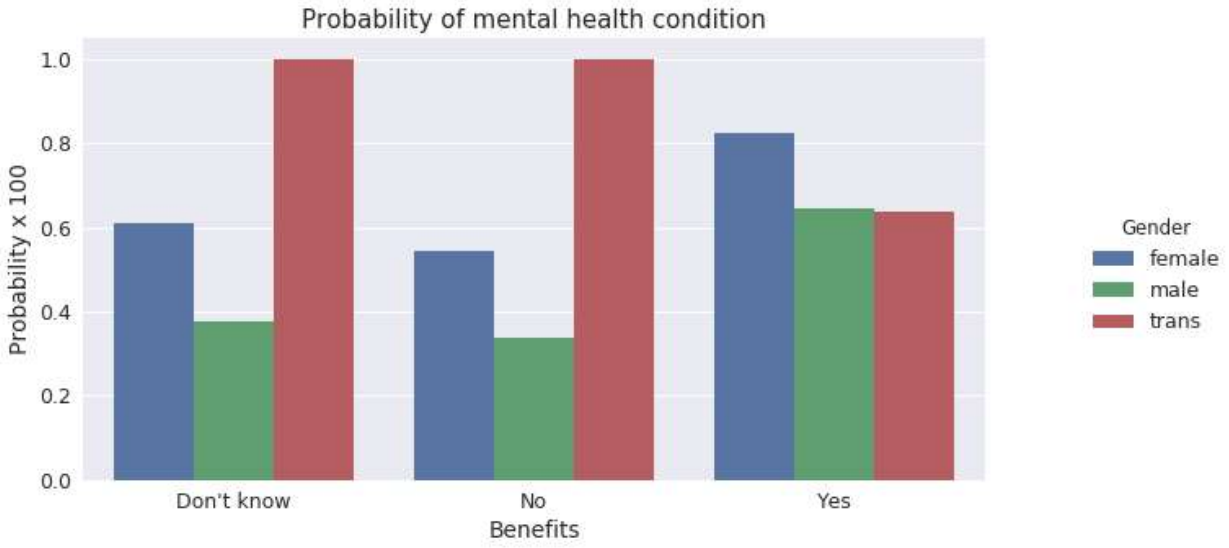
In [17]:
```
o = labelDict['label_care_options']
g = sns.factorplot(x="care_options", y="treatment", hue="Gender", data=train_df, kind=
g.set_xticklabels(o)
plt.title('Probability of mental health condition')
plt.ylabel('Probability x 100')
plt.xlabel('Care options')

# 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'

In [18]:
```
o = labelDict['label_benefits']
g = sns.factorplot(x="care_options", y="treatment", hue="Gender", data=train_df, kind=
g.set_xticklabels(o)
plt.title('Probability of mental health condition')
plt.ylabel('Probability x 100')
```

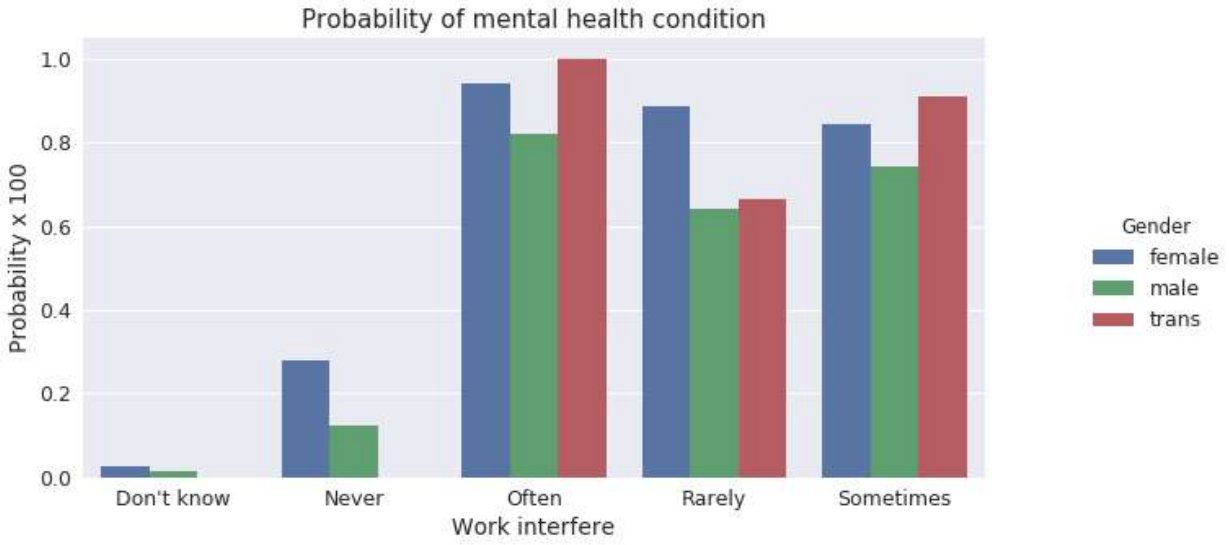
```
plt.xlabel('Benefits')

# 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'

In [19]:

```
o = labelDict['label_work_interfere']
g = sns.factorplot(x="work_interfere", y="treatment", hue="Gender", data=train_df, kir
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 'age'

In [20]:
```
scaler = MinMaxScaler()
train_df['Age'] = scaler.fit_transform(train_df[['Age']])
train_df.head()
```

Out[20]:

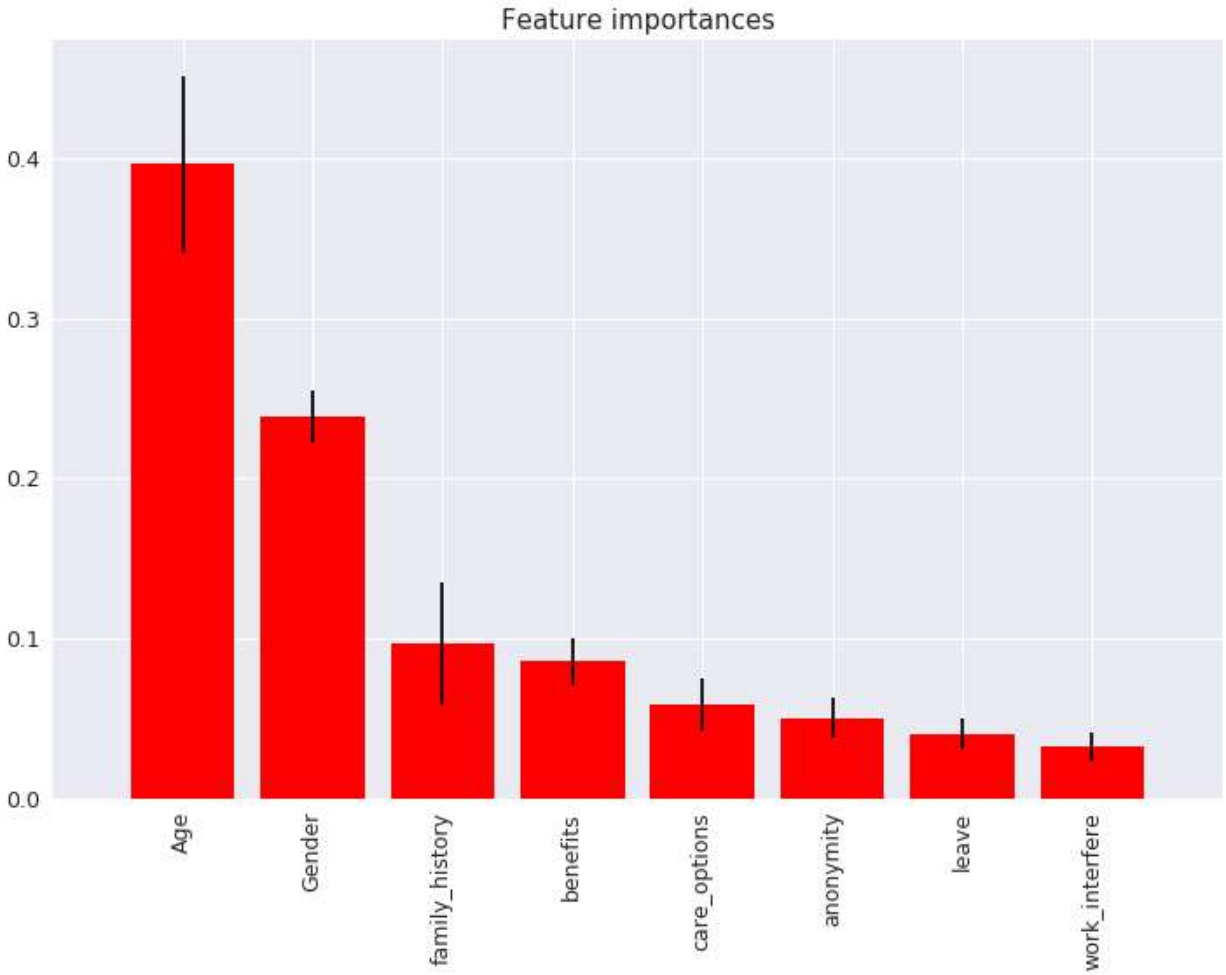
	Age	Gender	self_employed	family_history	treatment	work_interfere	no_employees	remote
0	0.431818	0	0	0	1	2	4	
1	0.590909	1	0	0	0	3	5	
2	0.318182	1	0	0	0	3	4	
3	0.295455	1	0	1	1	2	2	
4	0.295455	1	0	0	0	1	1	

Splilt the dataset

In [21]:
```
# define X and y
feature_cols = ['Age', 'Gender', 'family_history', 'benefits', 'care_options', 'anonym
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

# Create dictionaries for final graph
# Use: methodDict['Stacking'] = accuracy_score
methodDict = {}
rmseDict = ()
```

In [22]:
```
# 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()
```



Model Tuning

In [23]:
```
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 freq
    # 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 predicti
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 correc
print('Precision:', metrics.precision_score(y_test, y_pred_class))


# IMPORTANT: first argument is true values, second argument is predicted probabili
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


#Adjusting the classification threshold
# print the first 10 predicted responses
# 1D array (vector) of binary values (0, 1)
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(

# 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
        # adjust the font size
        plt.rcParams['font.size'] = 12
        # 8 bins
        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]

    # 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)

    #Question: Wouldn't it be nice if we could see how sensitivity and specificity are
    #Answer: Plot the ROC curve!


    #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 probabili
    # we pass y_test and y_pred_prob
    # we do not use y_pred_class, because it will give incorrect results without gener
    # 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_
        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 specificit
```

```
    def evaluate_threshold(threshold):
        #Sensitivity: When the actual value is positive, how often is the prediction c
        #Specificity: When the actual value is negative, how often is the prediction c
        print('Specificity for ' + str(threshold) + ' :', 1 - fpr[thresholds > thresho

    # 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

In [24]:
```
# 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

In [25]:
```
def tuningGridSerach(knn):
    #More efficient parameter tuning using GridSearchCV
    # define the parameter values that should be searched
    k_range = list(range(1, 31))
    print(k_range)

    # create a parameter grid: map the parameter names to the values that should be se
    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

In [26]:
```
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,
    rand.fit(X, y)
    rand.grid_scores_

    # 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
        rand.fit(X, y)
        best_scores.append(round(rand.best_score_, 3))
    print(best_scores)
```

Tuning with searching multiple parameters simultaneously

In [27]:
```
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 se
    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_)
```

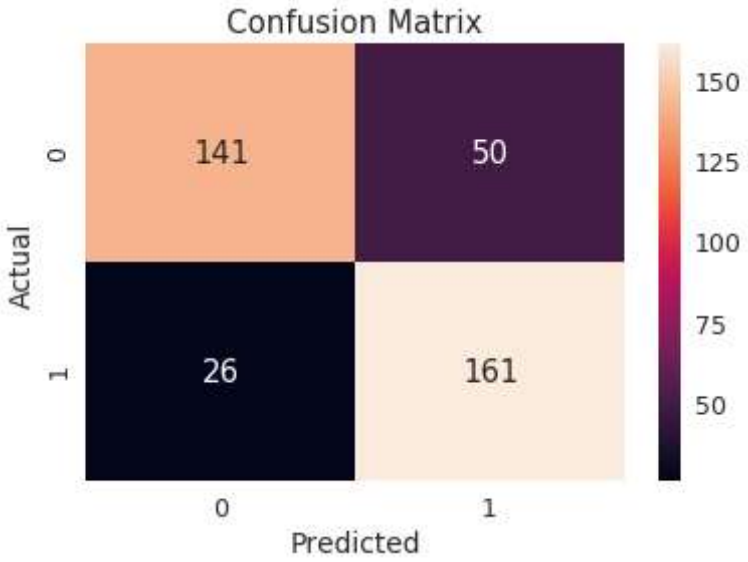
Evaluating models

Logistic Regression

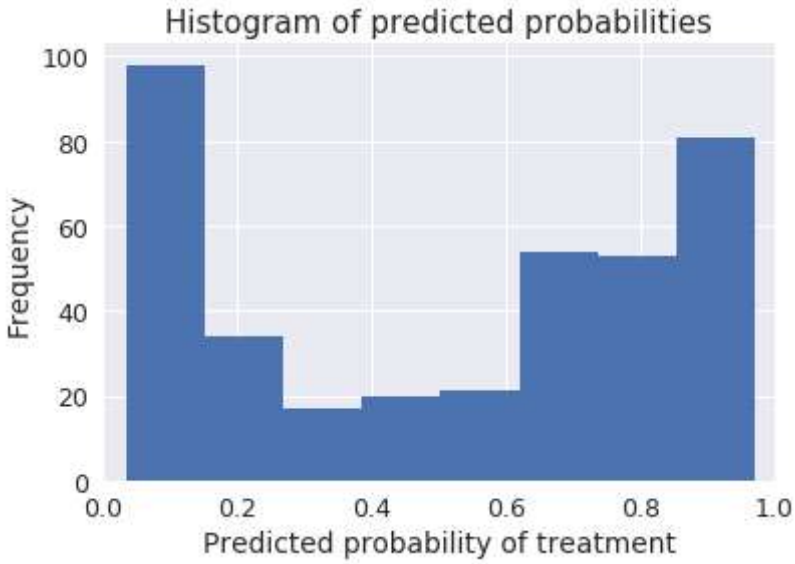
In [28]:
```
def logisticRegression():
    # train a logistic regression model on the training set
    logreg = LogisticRegression()
    logreg.fit(X_train, y_train)

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

    print('########### Logistic Regression ###############')

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

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

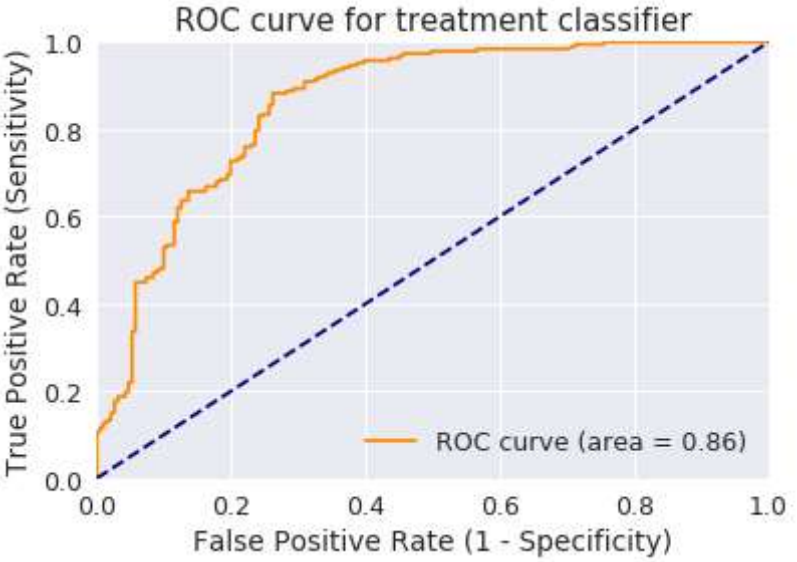
In [29]:
```
logisticRegression()
```

```
########### Logistic Regression ###############
Accuracy: 0.798941798942
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: 0.798941798942
Classification Error: 0.201058201058
False Positive Rate: 0.261780104712
Precision: 0.763033175355
AUC Score: 0.799591231066
Cross-validated AUC: 0.875357422875
First 10 predicted responses:
 [1 0 0 0 1 1 0 1 0 1]
First 10 predicted probabilities of class members:
 [[ 0.09763161  0.90236839]
 [ 0.95330977  0.04669023]
 [ 0.96013985  0.03986015]
 [ 0.78441354  0.21558646]
 [ 0.37834349  0.62165651]
 [ 0.06235819  0.93764181]
 [ 0.74803691  0.25196309]
 [ 0.1743978   0.8256022 ]
 [ 0.61145489  0.38854511]
 [ 0.49232517  0.50767483]]
First 10 predicted probabilities:
 [[ 0.90236839]
 [ 0.04669023]
 [ 0.03986015]
 [ 0.21558646]
 [ 0.62165651]
 [ 0.93764181]
 [ 0.25196309]
 [ 0.8256022 ]
 [ 0.38854511]
 [ 0.50767483]]
```






```
[[141  50]
 [ 26 161]]
```

KNeighbors Classifier

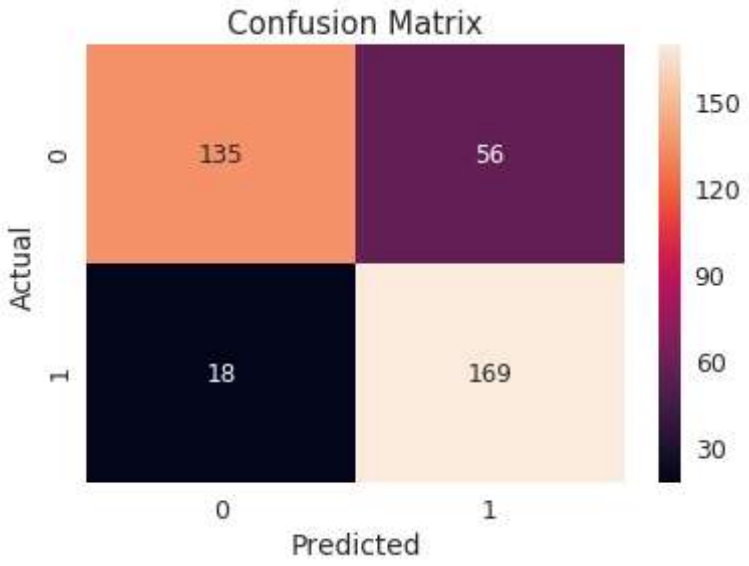
In [30]:

```python
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)
```

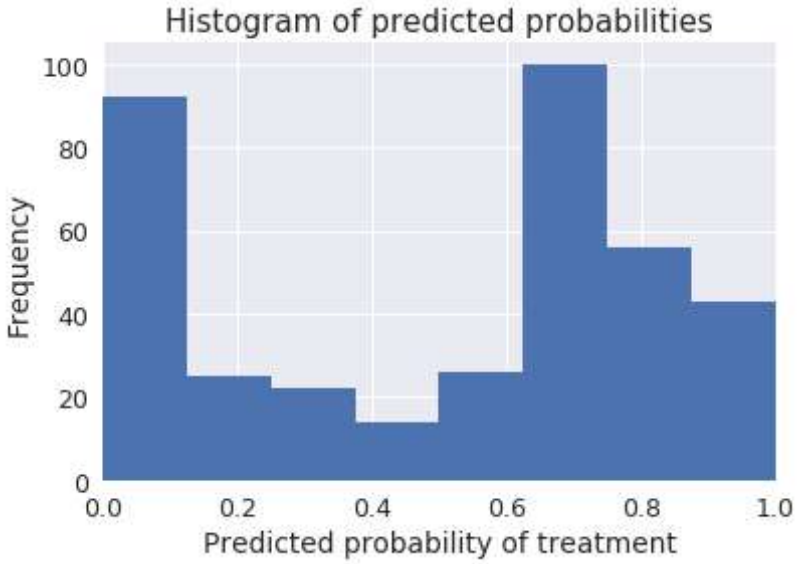
```
    print('########### KNeighborsClassifier ###############')

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

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

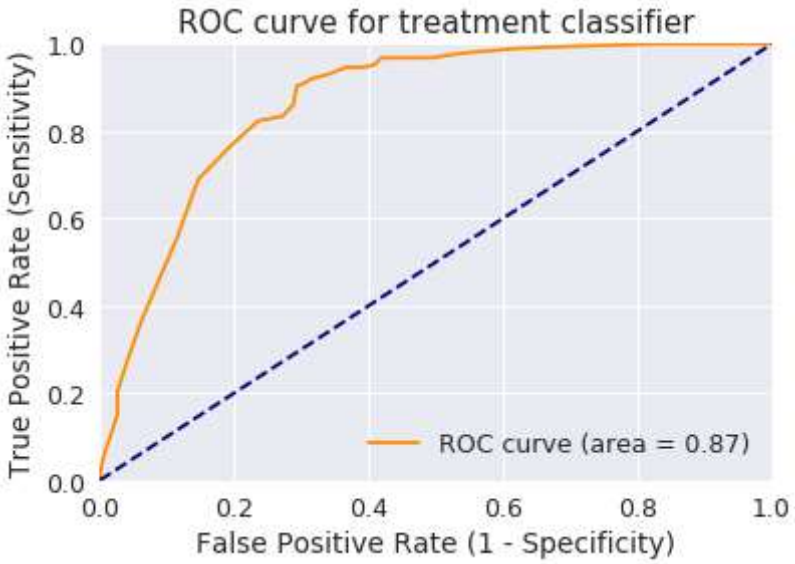
In [31]:
```
Knn()
```

```
Rand. Best Score:  0.8194112967382657
Rand. Best Params:  {'weights': 'uniform', 'n_neighbors': 15}
[0.814, 0.819, 0.819, 0.82, 0.819, 0.815, 0.814, 0.819, 0.819, 0.82, 0.815, 0.815, 0.
82, 0.814, 0.806, 0.812, 0.815, 0.819, 0.818, 0.818]
########### KNeighborsClassifier ###############
Accuracy: 0.804232804233
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: 0.804232804233
Classification Error: 0.195767195767
False Positive Rate: 0.293193717277
Precision: 0.751111111111
AUC Score: 0.805274799115
Cross-validated AUC: 0.878801643305
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]]
```





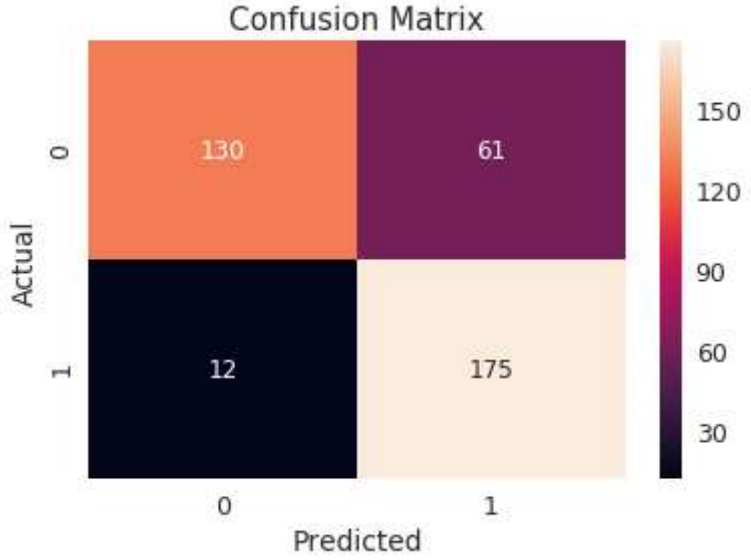

```
[[135  56]
 [ 18 169]]
```

Decision Tree classifier

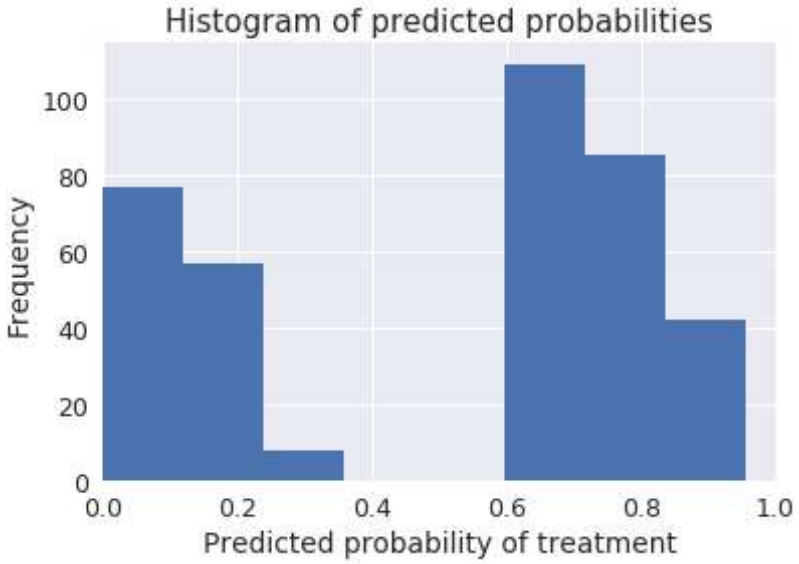
In [32]:
```
def treeClassifier():
    # Calculating the best parameters
    tree = DecisionTreeClassifier()
    featuresSize = feature_cols.__len__()
    param_dist = {"max_depth": [3, None],
              "max_features": randint(1, featuresSize),
              "min_samples_split": randint(2, 9),
              "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, cr
    tree.fit(X_train, y_train)

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

    print('########### Tree classifier ################')

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

    #Data for final graph
    methodDict['Tree clas.'] = accuracy_score * 100
```

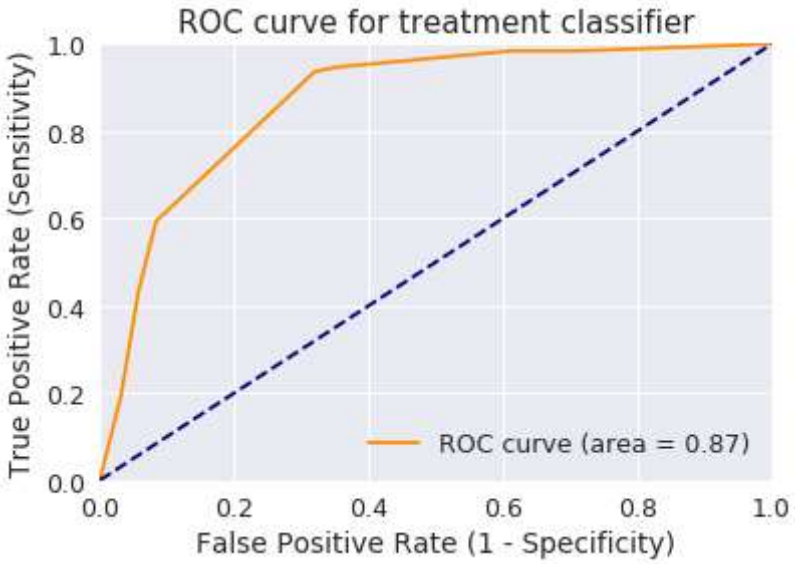
In [33]:
```
treeClassifier()
```

```
Rand. Best Score:  0.8305489260143198
Rand. Best Params:  {'criterion': 'entropy', 'max_depth': 3, 'max_features': 7, 'min_
samples_leaf': 7, 'min_samples_split': 8}
[0.831, 0.831, 0.831, 0.83, 0.831, 0.82, 0.831, 0.831, 0.831, 0.831, 0.831, 0.828, 0.
83, 0.829, 0.831, 0.831, 0.831, 0.829, 0.831, 0.831]
############ Tree classifier ################
Accuracy: 0.806878306878
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: 0.806878306878
Classification Error: 0.193121693122
False Positive Rate: 0.319371727749
Precision: 0.741525423729
AUC Score: 0.808228574628
Cross-validated AUC: 0.888575868856
First 10 predicted responses:
 [1 0 0 0 1 1 0 1 1 1]
First 10 predicted probabilities of class members:
 [[ 0.17355372  0.82644628]
 [ 0.97959184  0.02040816]
 [ 1.          0.        ]
 [ 0.8778626   0.1221374 ]
 [ 0.304       0.696     ]
 [ 0.04301075  0.95698925]
 [ 0.8778626   0.1221374 ]
 [ 0.304       0.696     ]
 [ 0.17355372  0.82644628]
 [ 0.2125      0.7875    ]]
First 10 predicted probabilities:
 [[ 0.82644628]
 [ 0.02040816]
 [ 0.        ]
 [ 0.1221374 ]
 [ 0.696     ]
 [ 0.95698925]
 [ 0.1221374 ]
 [ 0.696     ]
 [ 0.82644628]
 [ 0.7875    ]]
```





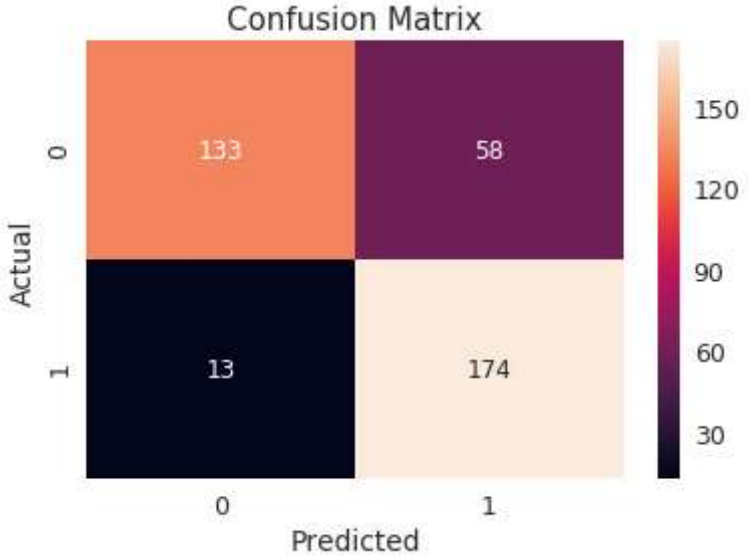

```
[[130  61]
 [ 12 175]]
```

Random Forests

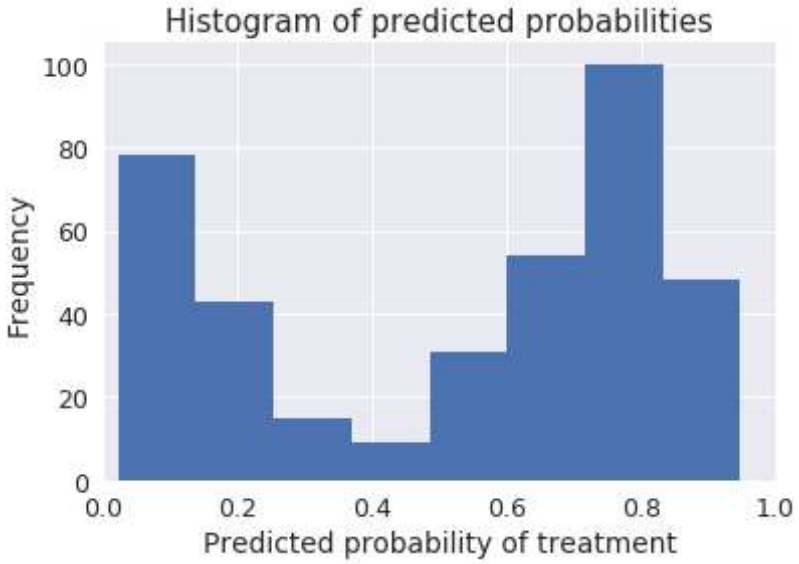
In [34]:
```
def randomForest():
    # Calculating the best parameters
    forest = RandomForestClassifier(n_estimators = 20)

    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(forest, param_dist)

    # Building and fitting my_forest
    forest = RandomForestClassifier(max_depth = None, min_samples_leaf=8, min_samples_
    my_forest = forest.fit(X_train, y_train)

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

    print('########### Random Forests ###############')

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

    #Data for final graph
    methodDict['R. Forest'] = accuracy_score * 100
```

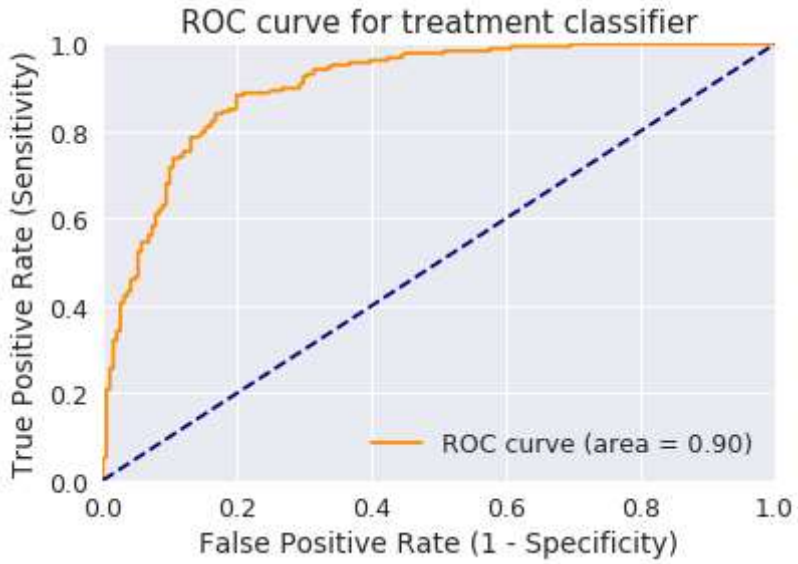
In [35]:
```
randomForest()
```

```
Rand. Best Score:  0.8305489260143198
Rand. Best Params:  {'criterion': 'gini', 'max_depth': 3, 'max_features': 6, 'min_sam
ples_leaf': 5, 'min_samples_split': 4}
[0.832, 0.832, 0.831, 0.83, 0.831, 0.831, 0.832, 0.831, 0.831, 0.839, 0.831, 0.831,
0.831, 0.831, 0.831, 0.831, 0.831, 0.831, 0.831, 0.831, 0.831]
############ Random Forests ###############
Accuracy: 0.812169312169
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: 0.812169312169
Classification Error: 0.187830687831
False Positive Rate: 0.303664921466
Precision: 0.75
AUC Score: 0.813408180978
Cross-validated AUC: 0.893237767217
First 10 predicted responses:
 [1 0 0 0 1 1 0 1 1 1]
First 10 predicted probabilities of class members:
 [[ 0.2555794   0.7444206 ]
 [ 0.95069083  0.04930917]
 [ 0.93851009  0.06148991]
 [ 0.87096597  0.12903403]
 [ 0.40653554  0.59346446]
 [ 0.17282958  0.82717042]
 [ 0.89450448  0.10549552]
 [ 0.4065912   0.5934088 ]
 [ 0.20540631  0.79459369]
 [ 0.19337644  0.80662356]]
First 10 predicted probabilities:
 [[ 0.7444206 ]
 [ 0.04930917]
 [ 0.06148991]
 [ 0.12903403]
 [ 0.59346446]
 [ 0.82717042]
 [ 0.10549552]
 [ 0.5934088 ]
 [ 0.79459369]
 [ 0.80662356]]
```





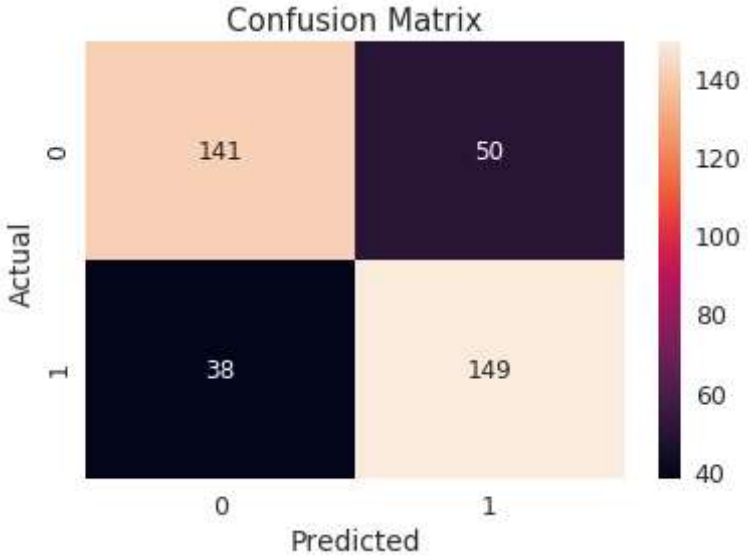

```
[[133  58]
 [ 13 174]]
```

Bagging

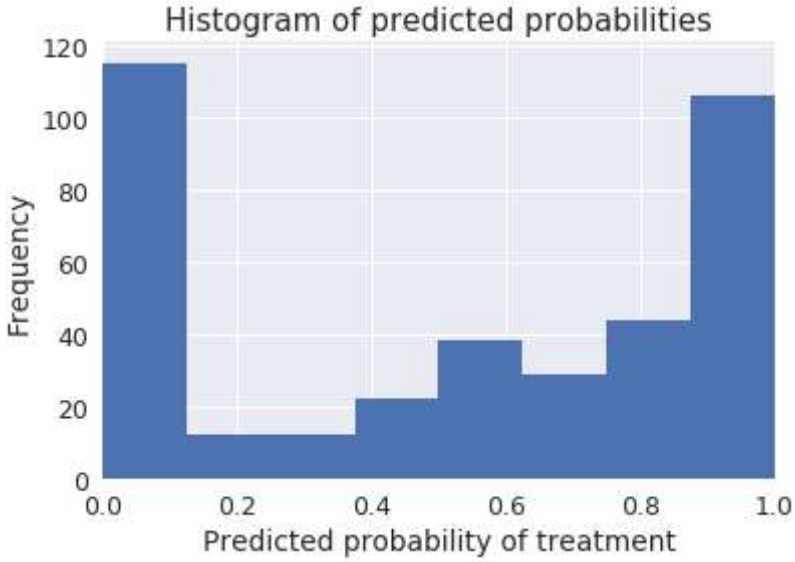
In [36]:
```
def bagging():
    # Building and fitting
    bag = BaggingClassifier(DecisionTreeClassifier(), max_samples=1.0, max_features=1.
    bag.fit(X_train, y_train)

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

    print('############ Bagging ################')

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

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

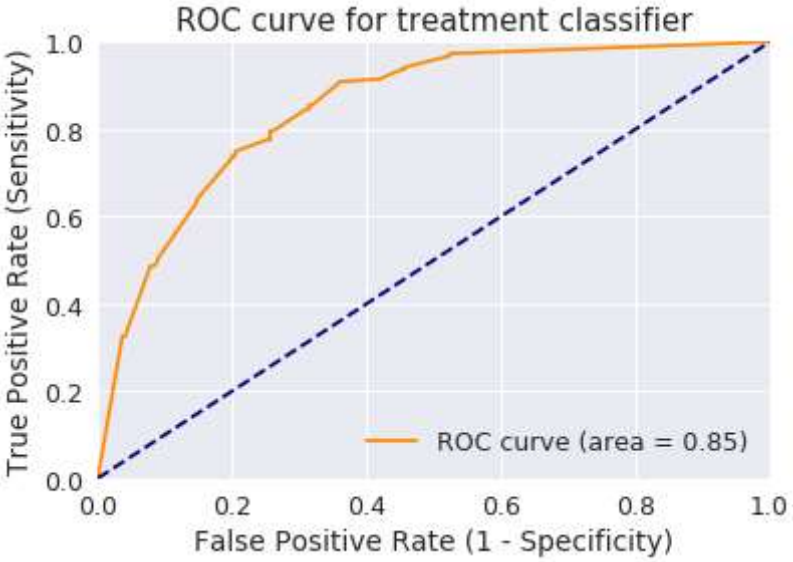
In [37]:
```
bagging()
```

```
############ Bagging ################
Accuracy: 0.767195767196
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 1 1 1 1 0 1 1 0 0 0 0 1 0 0]
```




```
Classification Accuracy: 0.767195767196
Classification Error: 0.232804232804
False Positive Rate: 0.261780104712
Precision: 0.748743718593
AUC Score: 0.767505669569
Cross-validated AUC: 0.845342301907
First 10 predicted responses:
 [1 0 0 0 0 1 0 0 1 1]
First 10 predicted probabilities of class members:
 [[ 0.13333333  0.86666667]
 [ 1.          0.        ]
 [ 1.          0.        ]
 [ 0.9         0.1       ]
 [ 0.7         0.3       ]
 [ 0.25        0.75      ]
 [ 1.          0.        ]
 [ 0.7         0.3       ]
 [ 0.1         0.9       ]
 [ 0.1         0.9       ]]
First 10 predicted probabilities:
 [[ 0.86666667]
 [ 0.        ]
 [ 0.        ]
 [ 0.1       ]
 [ 0.3       ]
 [ 0.75      ]
 [ 0.        ]
 [ 0.3       ]
 [ 0.9       ]
 [ 0.9       ]]
```





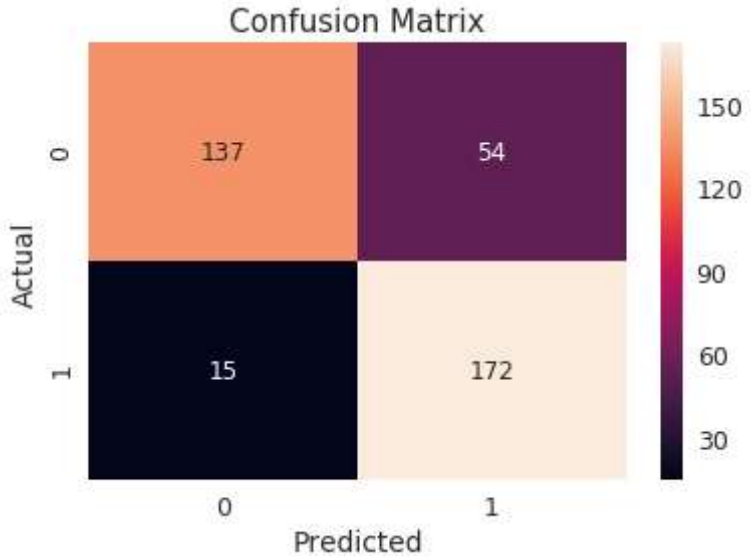

```
[[141  50]
 [ 38 149]]
```

Boosting

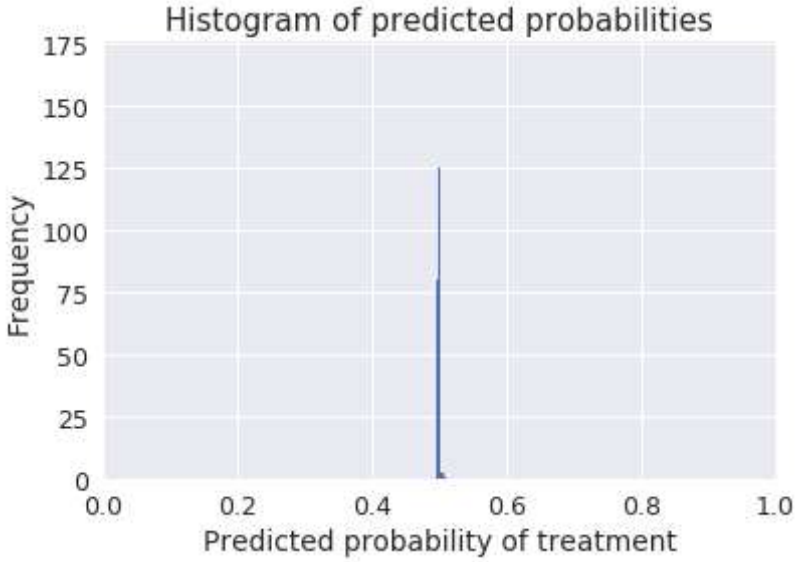
In [38]:
```python
def boosting():
    # Building and fitting
    clf = DecisionTreeClassifier(criterion='entropy', max_depth=1)
    boost = AdaBoostClassifier(base_estimator=clf, n_estimators=500)
    boost.fit(X_train, y_train)

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

    print('########### Boosting ###############')

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

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

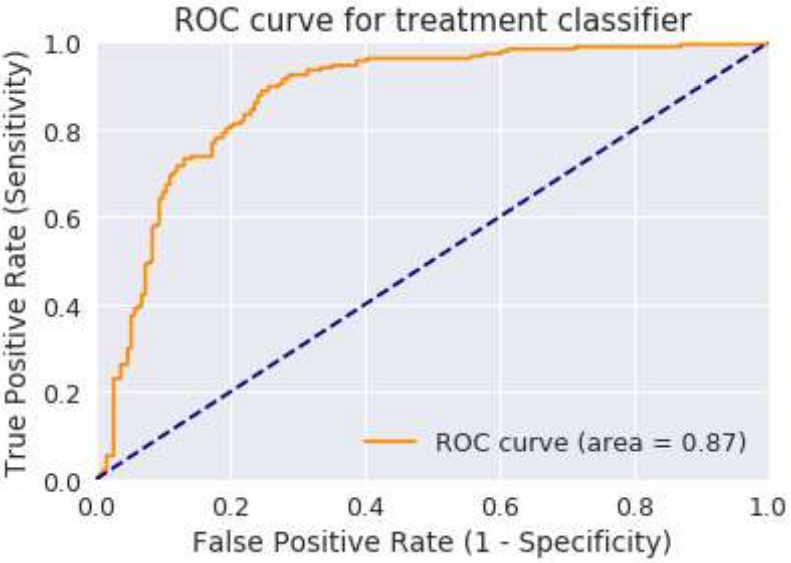
In [39]:
```python
boosting()
```

```
########### Boosting ###############
Accuracy: 0.81746031746
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: 0.81746031746
Classification Error: 0.18253968254
False Positive Rate: 0.282722513089
Precision: 0.761061946903
AUC Score: 0.818531791584
Cross-validated AUC: 0.874085341462
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]]
```





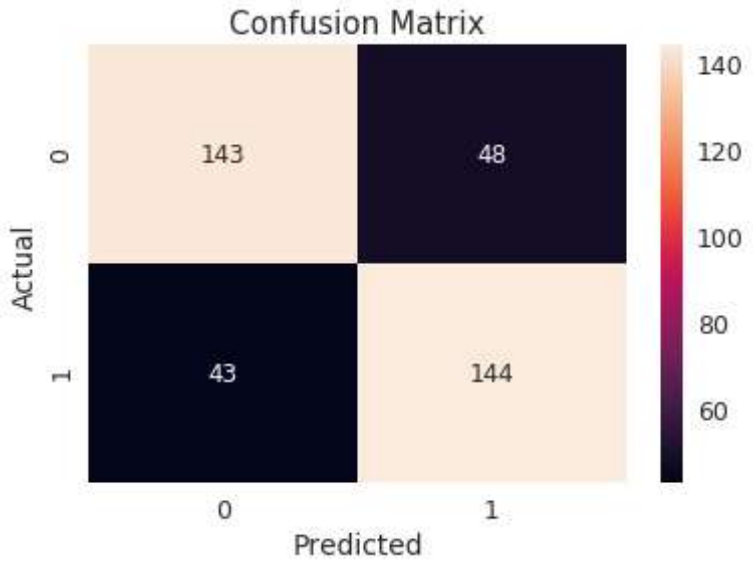

```
[[137  54]
 [ 15 172]]
```

Stacking

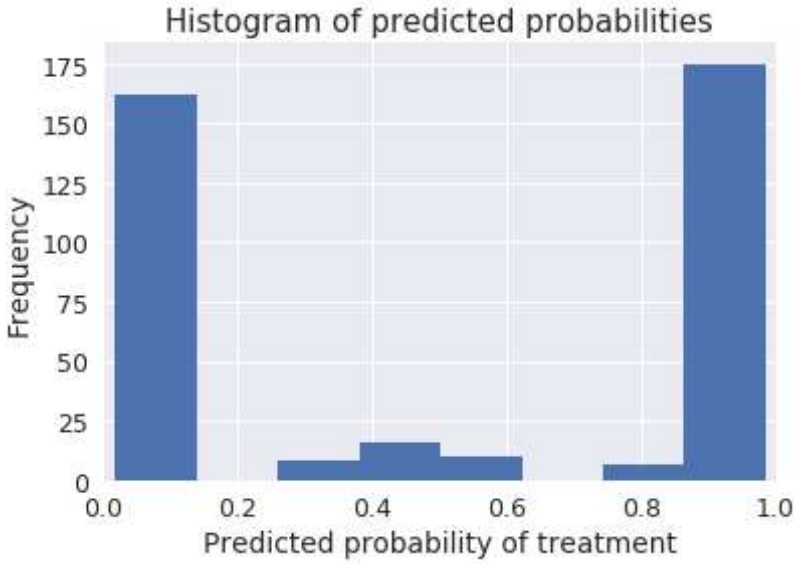
In [40]:
```
def stacking():
    # Building and fitting
    clf1 = KNeighborsClassifier(n_neighbors=1)
    clf2 = RandomForestClassifier(random_state=1)
    clf3 = GaussianNB()
    lr = LogisticRegression()
    stack = StackingClassifier(classifiers=[clf1, clf2, clf3], meta_classifier=lr)
    stack.fit(X_train, y_train)

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

    print('############ Stacking ################')

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

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

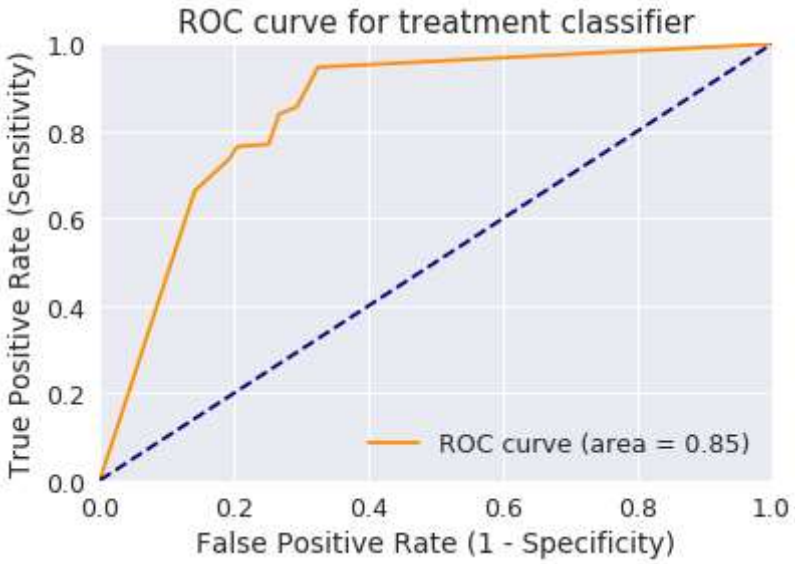
In [41]:
```
stacking()
```

```
############ Stacking ################
Accuracy: 0.759259259259
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 1 1 1 1 1 0 1 0 0 0 0 1 0 0]
```



```
Classification Accuracy: 0.759259259259
Classification Error: 0.240740740741
False Positive Rate: 0.251308900524
Precision: 0.75
AUC Score: 0.759372287706
Cross-validated AUC: 0.840591797875
First 10 predicted responses:
 [1 0 0 0 0 1 0 0 1 1]
First 10 predicted probabilities of class members:
 [[ 0.01481486  0.98518514]
 [ 0.98086439  0.01913561]
 [ 0.98086439  0.01913561]
 [ 0.98086439  0.01913561]
 [ 0.98086439  0.01913561]
 [ 0.01481486  0.98518514]
 [ 0.98086439  0.01913561]
 [ 0.9602071   0.0397929 ]
 [ 0.030955    0.969045  ]
 [ 0.01481486  0.98518514]]
First 10 predicted probabilities:
 [[ 0.98518514]
 [ 0.01913561]
 [ 0.01913561]
 [ 0.01913561]
 [ 0.01913561]
 [ 0.98518514]
 [ 0.01913561]
 [ 0.0397929 ]
 [ 0.969045  ]
 [ 0.98518514]]
```






```
[[143  48]
 [ 43 144]]
```

Predicting with Neural Network

In [42]:

```
import tensorflow as tf
import argparse


batch_size = 100
train_steps = 1000

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state

def train_input_fn(features, labels, batch_size):
    """An input function for training"""
    # Convert the inputs to a Dataset.
    dataset = tf.data.Dataset.from_tensor_slices((dict(features), labels))

    # Shuffle, repeat, and batch the examples.
    return dataset.shuffle(1000).repeat().batch(batch_size)

def eval_input_fn(features, labels, batch_size):
    """An input function for evaluation or prediction"""
    features=dict(features)
    if labels is None:
        # No labels, use only features.
        inputs = features
    else:
        inputs = (features, labels)

    # Convert the inputs to a Dataset.
    dataset = tf.data.Dataset.from_tensor_slices(inputs)

    # Batch the examples
    assert batch_size is not None, "batch_size must not be None"
    dataset = dataset.batch(batch_size)

    # Return the dataset.
    return dataset
```

A feature column is an object that describes how the model should use raw input data from the features dictionary. When building an Estimator model, you pass it a list of feature columns that describe the features you want the model to use.

In [43]:
```
# Define Tensorflow feature columns
age = tf.feature_column.numeric_column("Age")
gender = tf.feature_column.numeric_column("Gender")
family_history = tf.feature_column.numeric_column("family_history")
benefits = tf.feature_column.numeric_column("benefits")
care_options = tf.feature_column.numeric_column("care_options")
anonymity = tf.feature_column.numeric_column("anonymity")
leave = tf.feature_column.numeric_column("leave")
work_interfere = tf.feature_column.numeric_column("work_interfere")
feature_columns = [age, gender, family_history, benefits, care_options, anonymity, lea
```

Instantiate an Estimator

Our problem is a classic binary classification task where we predict whether a patient needs treatment or not. To accomplish this, we will use the tf.estimator.DNNClassifier for deep multi-class classification models.

In [44]:
```
# Build a DNN with 2 hidden layers and 10 nodes in each hidden layer.
model = tf.estimator.DNNClassifier(feature_columns=feature_columns,
                                   hidden_units=[10, 10],
                                   optimizer=tf.train.ProximalAdagradOptimizer(
                                     learning_rate=0.1,
                                     l1_regularization_strength=0.001
                                   ))
```

Train, Evaluate, and Predict

Now that we have an Estimator object, we can call methods to do the following:

- Train the model.
- Evaluate the trained model.
- Use the trained model to make predictions.

Train the model

The steps argument tells the method to stop training after a number of training steps.

In [45]:
```
model.train(input_fn=lambda:train_input_fn(X_train, y_train, batch_size), steps=train_
```

Out[45]:
```
<tensorflow.python.estimator.canned.dnn.DNNClassifier at 0x7f1bba5cfbe0>
```

Evaluate the trained model

Now that the model has been trained, we can get some statistics on its performance. The following code block evaluates the accuracy of the trained model on the test data.

In [46]:
```
# Evaluate the model.
eval_result = model.evaluate(
    input_fn=lambda:eval_input_fn(X_test, y_test, batch_size))

print('\nTest set accuracy: {accuracy:0.2f}\n'.format(**eval_result))
```

```
#Data for final graph
accuracy = eval_result['accuracy'] * 100
methodDict['NN DNNClasif.'] = accuracy
```

```
Test set accuracy: 0.80
```

Making predictions from the trained model

We now have a trained model that produces good evaluation results. We can now use the trained model to predict whether a patient needs treatment or not.

In [47]:
```
predictions = list(model.predict(input_fn=lambda:eval_input_fn(X_train, y_train, batch
```

In [48]:
```
# Generate predictions from the model
template = ('\nIndex: "{}", Prediction is "{}" ({:.1f}%), expected "{}"')

# Dictionary for predictions
col1 = []
col2 = []
col3 = []


for idx, input, p in zip(X_train.index, y_train, predictions):
    v  = p["class_ids"][0]
    class_id = p['class_ids'][0]
    probability = p['probabilities'][class_id] # Probability

    # Adding to dataframe
    col1.append(idx) # Index
    col2.append(v) # Prediction
    col3.append(input) # Expecter


    #print(template.format(idx, v, 100 * probability, input))


results = pd.DataFrame({'index':col1, 'prediction':col2, 'expected':col3})
results.head()
```

Out[48]:

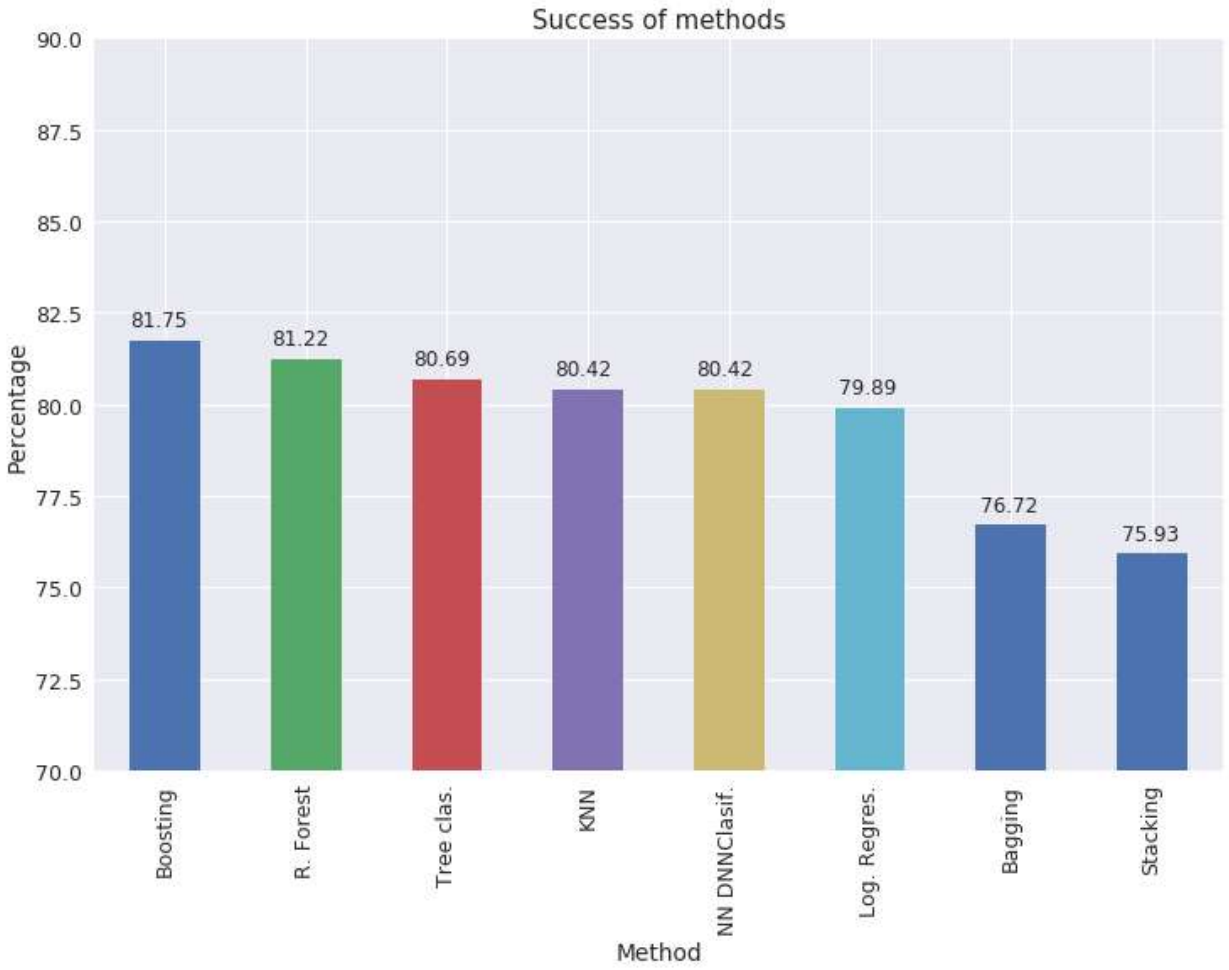
	index	prediction	expected
0	929	0	0
1	901	1	1
2	579	1	1
3	367	1	1
4	615	1	1

Success method plot

In [49]:
```
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() *
    plt.ylim([70.0, 90.0])
    plt.xlabel('Method')
    plt.ylabel('Percentage')
    plt.title('Success of methods')

    plt.show()
```

In [50]:
```
plotSuccess()
```



Creating predictions on test set

In [51]:
```
# Generate predictions with the best method
clf = AdaBoostClassifier()
clf.fit(X, y)
dfTestPredictions = clf.predict(X_test)


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

Out[51]:

	Index	Treatment
0	5	1
1	494	0
2	52	0
3	984	0
4	186	0