In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib import pyplot as plt
from sklearn import preprocessing
from sklearn import metrics
from sklearn.preprocessing import MinMaxScaler
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn import svm
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier,E
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import classification_report,f1_score,recall_score ,precisic
from mlxtend.plotting import plot_confusion_matrix
import lightgbm as lgb
import warnings
warnings.filterwarnings("ignore")
```

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

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

Out[3]:

	Education	JoiningYear	City	PaymentTier	Age	Gender	EverBenched	ExperienceInCurren
0	Bachelors	2017	Bangalore	3	34	Male	No	
1	Bachelors	2013	Pune	1	28	Female	No	
2	Bachelors	2014	New Delhi	3	38	Female	No	
3	Masters	2016	Bangalore	3	27	Male	No	
4	Masters	2017	Pune	3	24	Male	Yes	

EDA

In [4]:
```
df.rename(columns={'ExperienceInCurrentDomain': 'ECD'}, inplace=True)
```

In [5]:
```
df.describe()
```

Out[5]:

	JoiningYear	PaymentTier	Age	ECD	LeaveOrNot
count	4653.000000	4653.000000	4653.000000	4653.000000	4653.000000
mean	2015.062970	2.698259	29.393295	2.905652	0.343864
std	1.863377	0.561435	4.826087	1.558240	0.475047
min	2012.000000	1.000000	22.000000	0.000000	0.000000
25%	2013.000000	3.000000	26.000000	2.000000	0.000000
50%	2015.000000	3.000000	28.000000	3.000000	0.000000
75%	2017.000000	3.000000	32.000000	4.000000	1.000000
max	2018.000000	3.000000	41.000000	7.000000	1.000000

In [6]:
```
df.shape
```

Out[6]:
```
(4653, 9)
```

In [7]:
```
df.columns
```

Out[7]:
```
Index(['Education', 'JoiningYear', 'City', 'PaymentTier', 'Age', 'Gender',
       'EverBenched', 'ECD', 'LeaveOrNot'],
      dtype='object')
```

In [8]:
```
df.info()
```

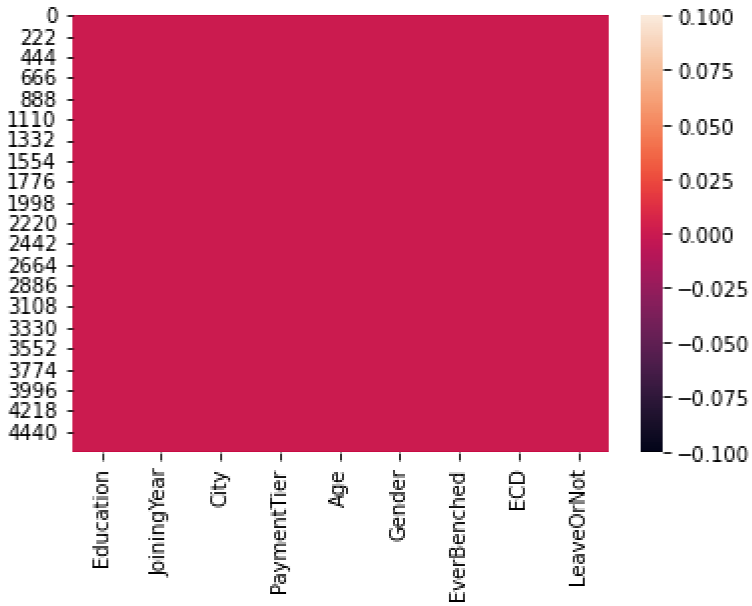
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4653 entries, 0 to 4652
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Education    4653 non-null   object
 1   JoiningYear  4653 non-null   int64 
 2   City         4653 non-null   object
 3   PaymentTier  4653 non-null   int64 
 4   Age          4653 non-null   int64 
 5   Gender       4653 non-null   object
 6   EverBenched  4653 non-null   object
 7   ECD          4653 non-null   int64 
 8   LeaveOrNot   4653 non-null   int64 
dtypes: int64(5), object(4)
memory usage: 327.3+ KB
```

In [9]:
```
df.isnull().sum()
```

Out[9]:
```
Education      0
JoiningYear    0
City           0
PaymentTier    0
Age            0
Gender         0
EverBenched    0
ECD            0
LeaveOrNot     0
dtype: int64
```

In [10]:
```
sns.heatmap(df.isnull())
```

Out[10]:
```
<AxesSubplot:>
```

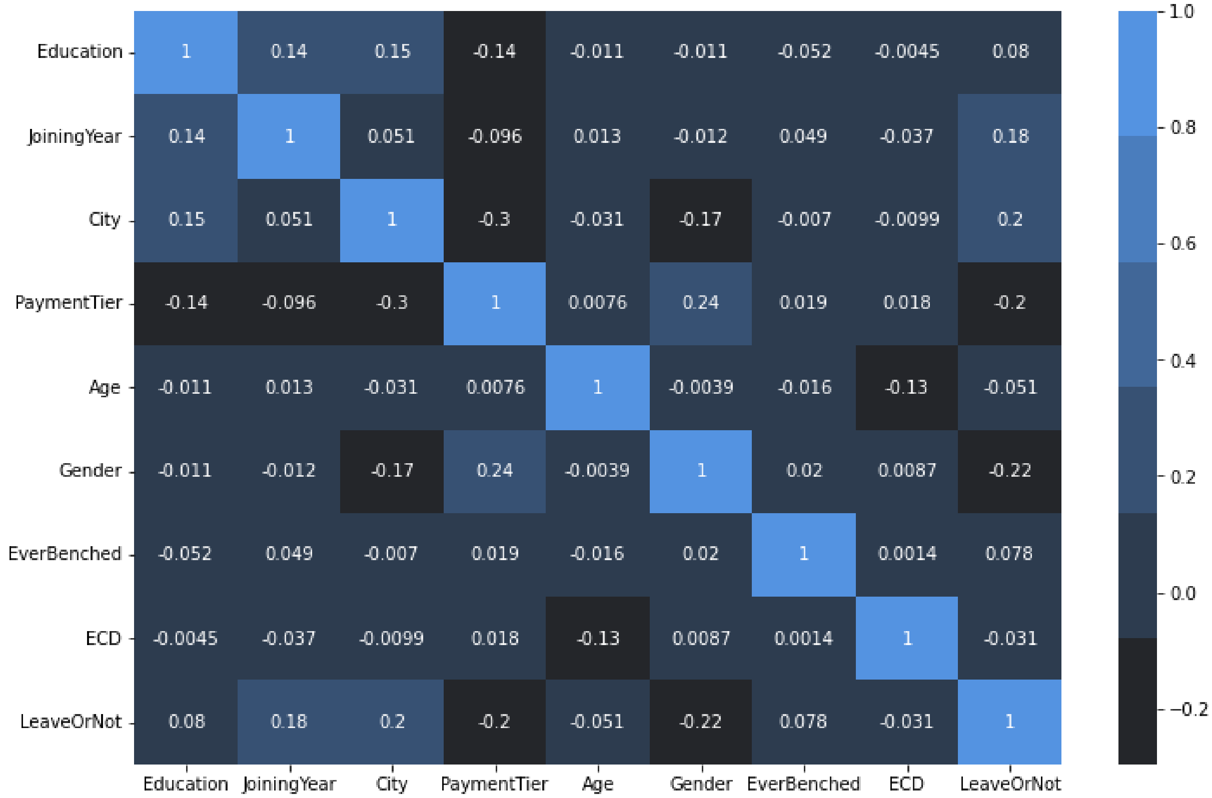


Categorical Features

In [11]:
```
labelencoder = preprocessing.LabelEncoder()
df['Education'] = labelencoder.fit_transform(df['Education'])
df['City'] = labelencoder.fit_transform(df['City'])
df['Gender'] = labelencoder.fit_transform(df['Gender'])
df['EverBenched'] = labelencoder.fit_transform(df['EverBenched'])
```

In [12]:
```python
plt.figure(figsize = (12,8))
sns.heatmap(df.corr() , annot=True,cmap=sns.dark_palette((250, 75, 60), input="hu
```

Out[12]:
```
<AxesSubplot:>
```

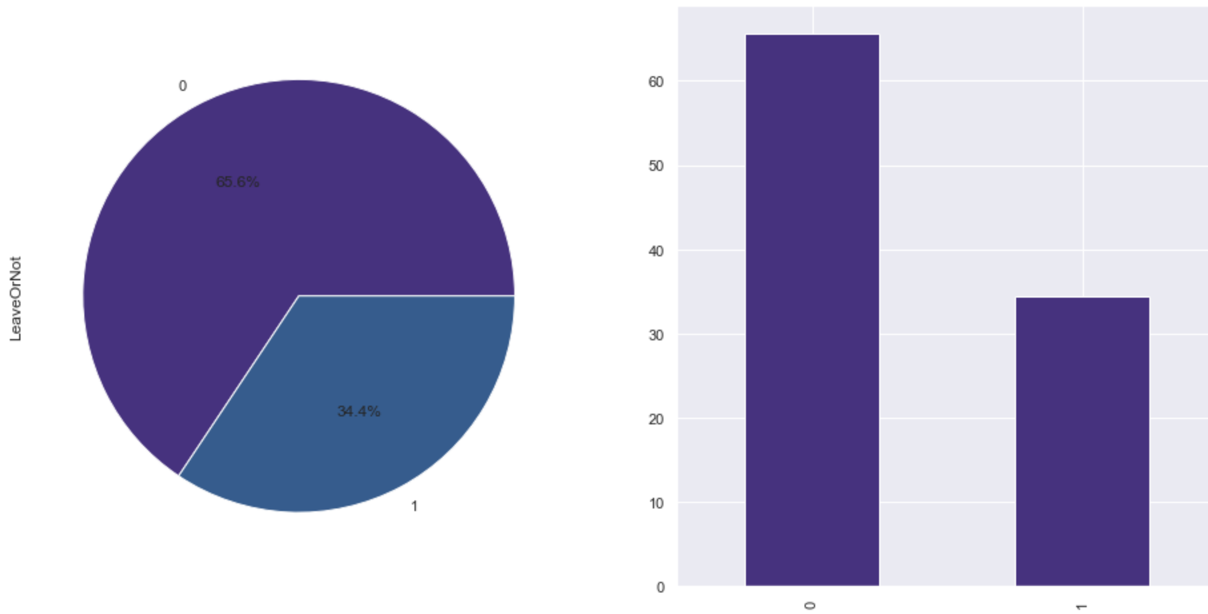


Correlation is very weak between features !!!

Data visualization

In [13]:
```
sns.set_theme(palette="viridis")
fig, axs = plt.subplots(ncols=2,figsize=(16, 8))
(df['LeaveOrNot'].value_counts(normalize=True)*100).plot.pie(autopct='%1.1f%%', a
(df['LeaveOrNot'].value_counts(normalize=True)*100).plot.bar(ax=axs[1])
```

Out[13]: <AxesSubplot:>



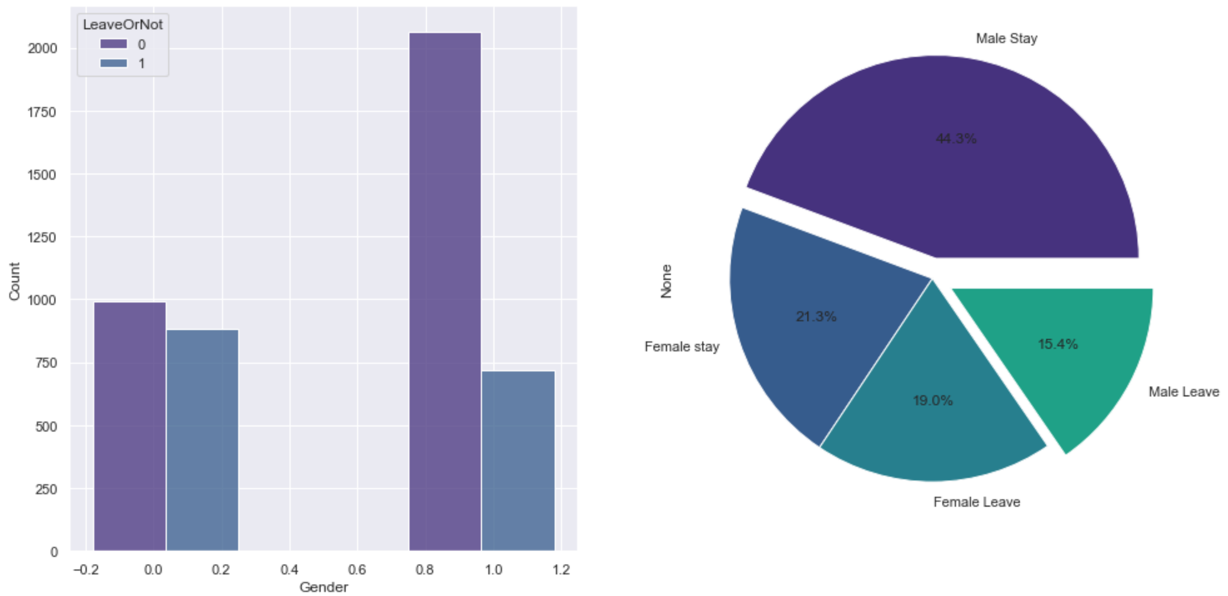
0 >>> 65% staying

1 >>> 34% leaving

imbalnceing in the target

In [14]:
```
fig, axs = plt.subplots(ncols=2,figsize=(16, 8))
explode = [0.1,0.0,0.0,0.1]
labels = ["Male Stay", "Female stay", "Female Leave", "Male Leave"]
sns.histplot(data=df, x="Gender", hue="LeaveOrNot", multiple="dodge", shrink=6, a
(df[['Gender','LeaveOrNot']].value_counts(normalize=True)*100).plot.pie(autopct='
```

Out[14]: <AxesSubplot:ylabel='None'>

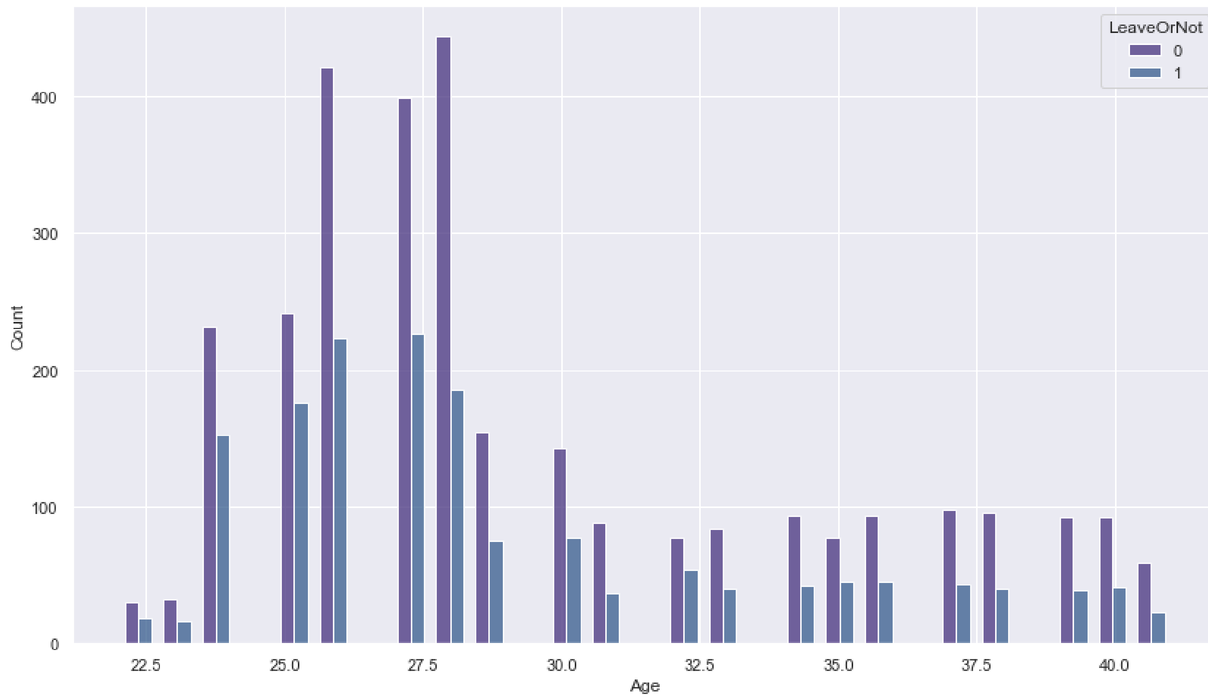


Male >>> 44% staying, 15% leaving

Female >>> 21% staying, 19% leaving

In [15]:
```
fig, axs= plt.subplots(figsize=(14, 8))
sns.histplot(data=df, x="Age", hue="LeaveOrNot", multiple="dodge", shrink=.7)
```

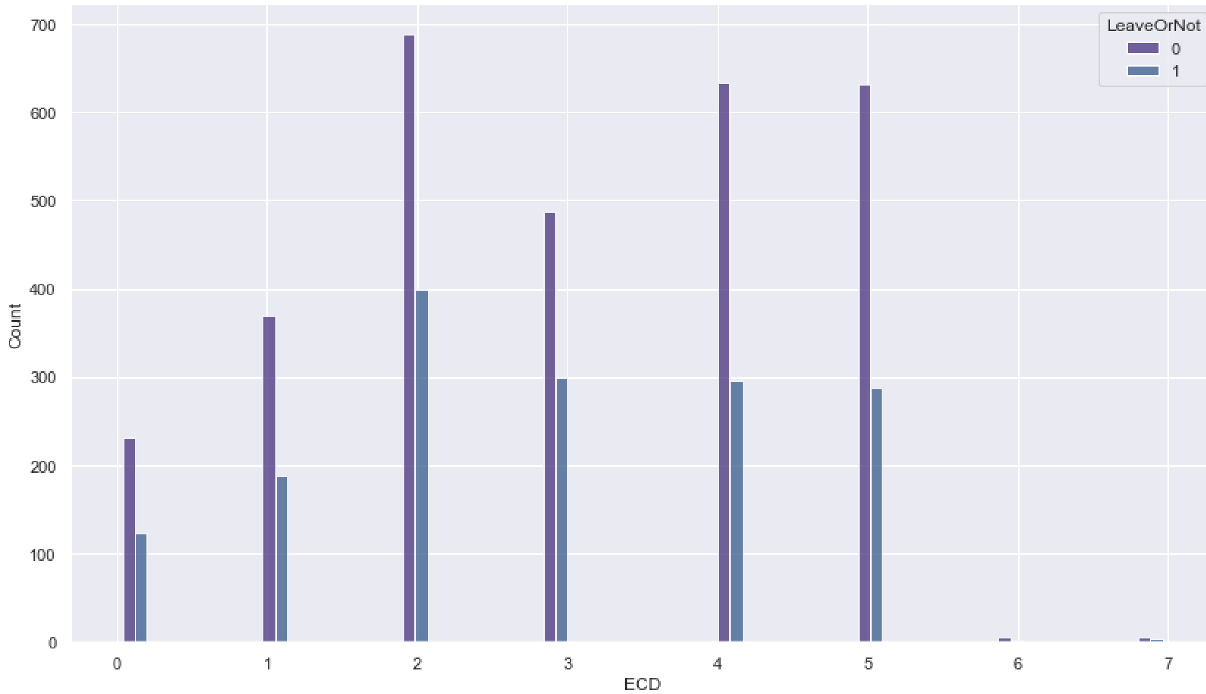
Out[15]:
```
<AxesSubplot:xlabel='Age', ylabel='Count'>
```



28 years is the highest and lowest in leaving and staying

In [16]:
```
fig, axs= plt.subplots(figsize=(14, 8))
sns.histplot(data=df, x="ECD", hue="LeaveOrNot", multiple="dodge", shrink=0.7)
```

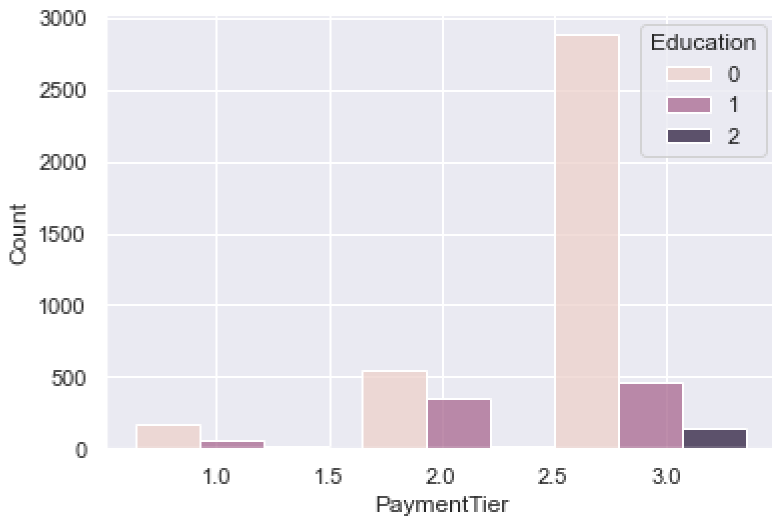
Out[16]: <AxesSubplot:xlabel='ECD', ylabel='Count'>



2years exp. >>> highest in staying and leaving

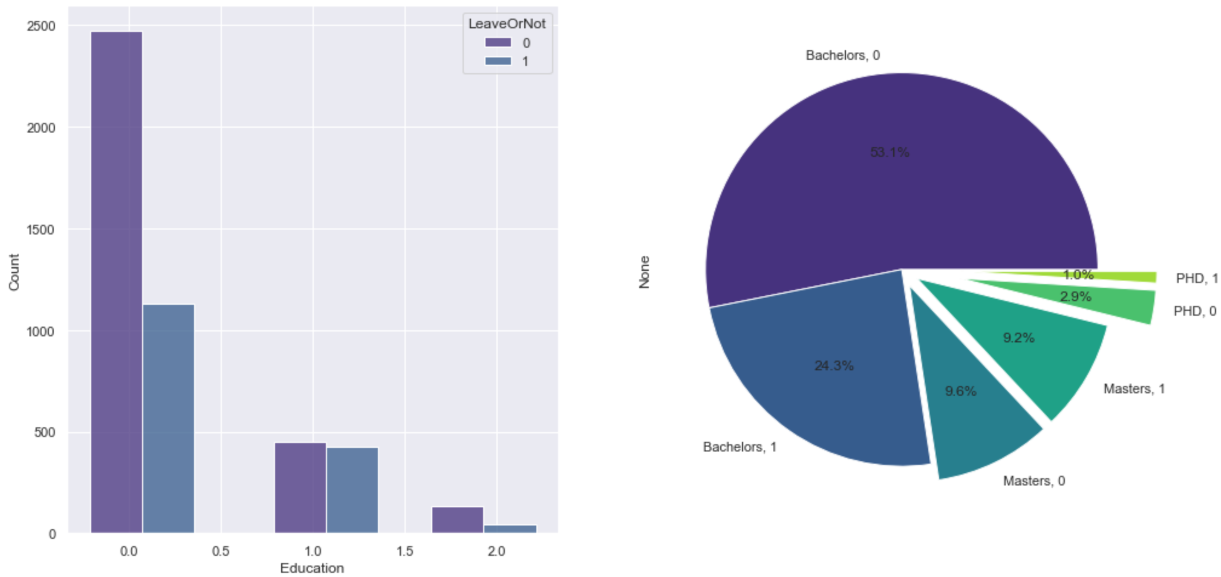
In [17]:
```
sns.histplot(data=df, x="PaymentTier", hue="Education", multiple="dodge", shrink=
```

Out[17]: <AxesSubplot:xlabel='PaymentTier', ylabel='Count'>



In [18]:
```
fig, axs = plt.subplots(ncols=2,figsize=(16, 8))
explode = [0.0,0.0,0.09,0.09,0.3,0.3]
labels = ["Bachelors, 0", "Bachelors, 1", "Masters, 0", "Masters, 1" , "PHD, 0" ,
sns.histplot(data=df, x="Education", hue="LeaveOrNot", multiple="dodge", shrink=4
(df[['Education','LeaveOrNot']].value_counts(normalize=True)*100).plot.pie(autopc
```

Out[18]: <AxesSubplot:ylabel='None'>

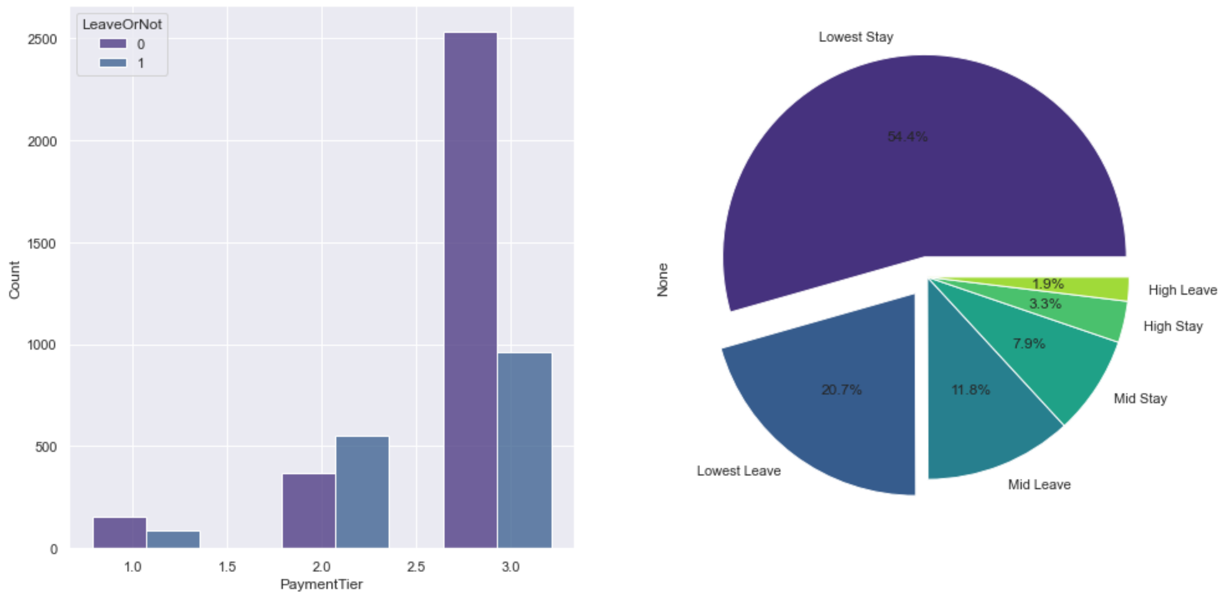


Bachelors >>> 53% Staying , 24% leaving

Master >>> 9.2% leaving, 9.2% staying

In [19]:
```
fig, axs = plt.subplots(ncols=2,figsize=(16, 8))
explode = [0.1,0.1,0.0,0.0,0.0,0.0]
labels = ["Lowest Stay", "Lowest Leave", "Mid Leave", "Mid Stay" , "High Stay" ,
sns.histplot(data=df, x="PaymentTier", hue="LeaveOrNot", multiple="dodge", shrink
(df[['PaymentTier','LeaveOrNot']].value_counts(normalize=True)*100).plot.pie(autc
```

Out[19]:
```
<AxesSubplot:ylabel='None'>
```



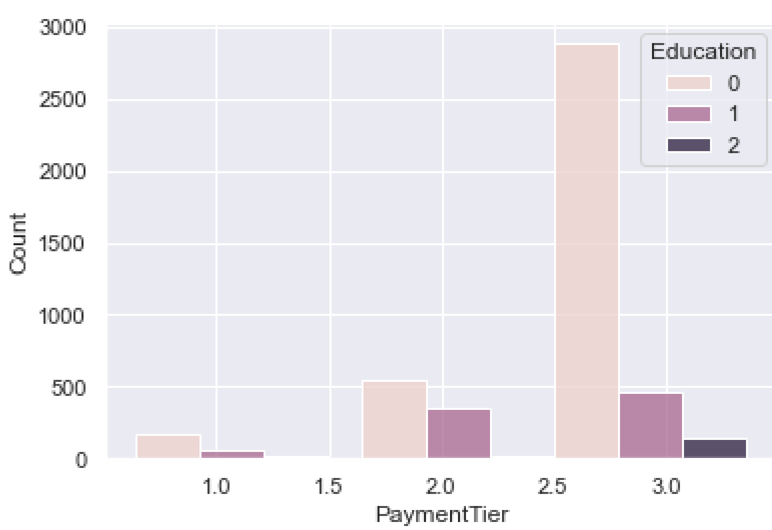
The type of payment tier

-1: HIGHEST -2: MID LEVEL -3:LOWEST

tier payment >>> the lowest 54% staying ,20% leaving

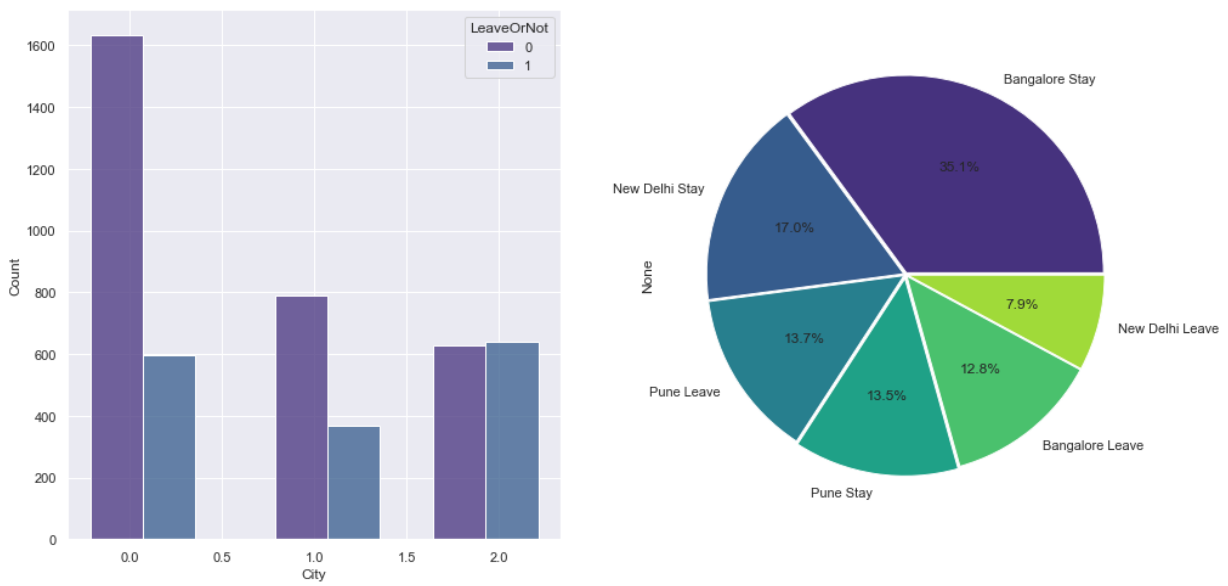
In [20]:
```
sns.histplot(data=df, x="PaymentTier", hue="Education", multiple="dodge", shrink=
```

Out[20]:
```
<AxesSubplot:xlabel='PaymentTier', ylabel='Count'>
```



In [21]:
```
fig, axs = plt.subplots(ncols=2,figsize=(16, 8))
explode = [0.01,0.01,0.01,0.02,0.01,0.01]
labels = ["Bangalore Stay", "New Delhi Stay", "Pune Leave", "Pune Stay" , "Bangal
sns.histplot(data=df, x="City", hue="LeaveOrNot", multiple="dodge", shrink=4, ax=
(df[['City','LeaveOrNot']].value_counts(normalize=True)*100).plot.pie(autopct='%1
```

Out[21]: `<AxesSubplot:ylabel='None'>`



Bangalore >>> 12.8% leaving

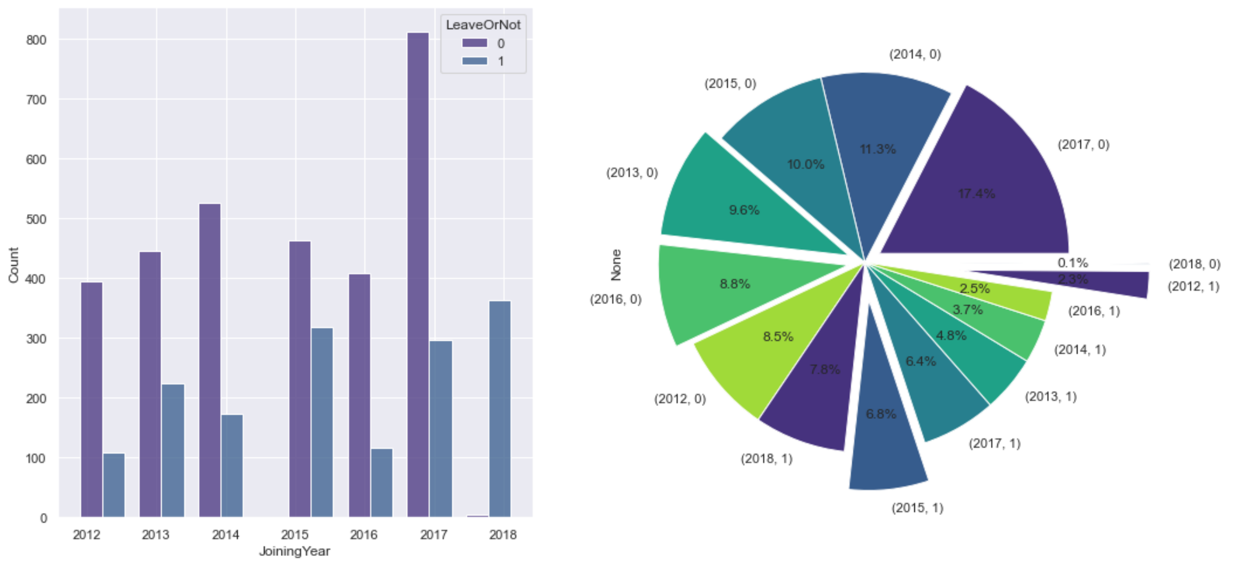
New Delhi >>> 8% leaving

In [22]:
```
sns.histplot(data=df, x="PaymentTier", hue="City", multiple="dodge", shrink=4)
```

Out[22]: `<AxesSubplot:xlabel='PaymentTier', ylabel='Count'>`

In [23]:
```
fig, axs = plt.subplots(ncols=2,figsize=(16, 8))
explode = [0.09,0.0,0.0,0.09,0.09,0.0,0.0,0.2,0.0,0.0,0.0,0.0,0.5,.5]
sns.histplot(data=df, x="JoiningYear", hue="LeaveOrNot", multiple="dodge", shrink
(df[['JoiningYear','LeaveOrNot']].value_counts(normalize=True)*100).plot.pie(autc
```

Out[23]: <AxesSubplot:ylabel='None'>

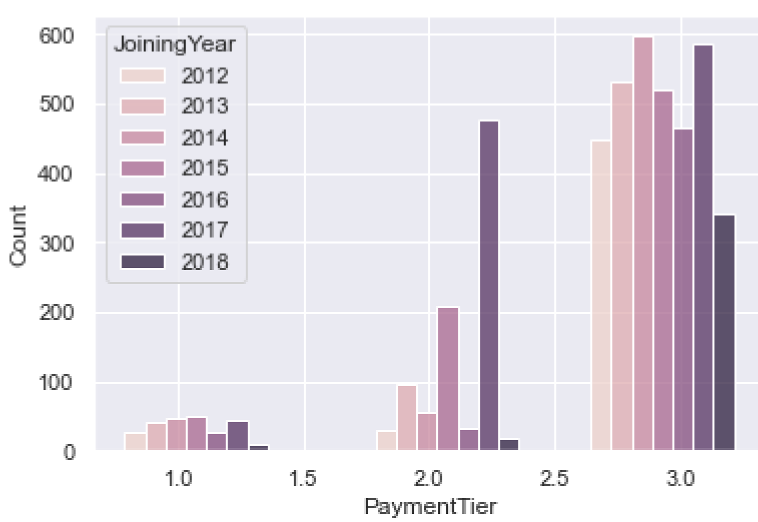


2018 >>> all in 2017 leaving

2012, 2016 is the lowest year

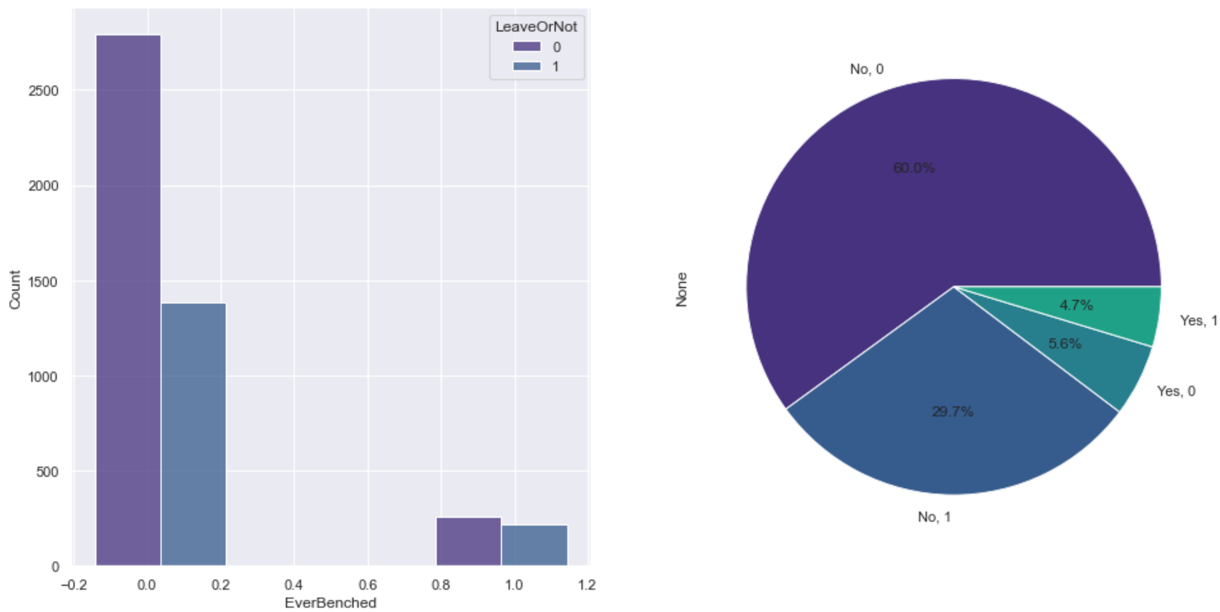
In [24]:
```
sns.histplot(data=df, x="PaymentTier", hue="JoiningYear", multiple="dodge", shrir
```

Out[24]: <AxesSubplot:xlabel='PaymentTier', ylabel='Count'>



In [25]:
```
fig, axs = plt.subplots(ncols=2,figsize=(16, 8))
labels = ["No, 0", "No, 1", "Yes, 0", "Yes, 1"]
sns.histplot(data=df, x="EverBenched", hue="LeaveOrNot", multiple="dodge", shrink
(df[['EverBenched','LeaveOrNot']].value_counts(normalize=True)*100).plot.pie(auto
```

Out[25]:
```
<AxesSubplot:ylabel='None'>
```



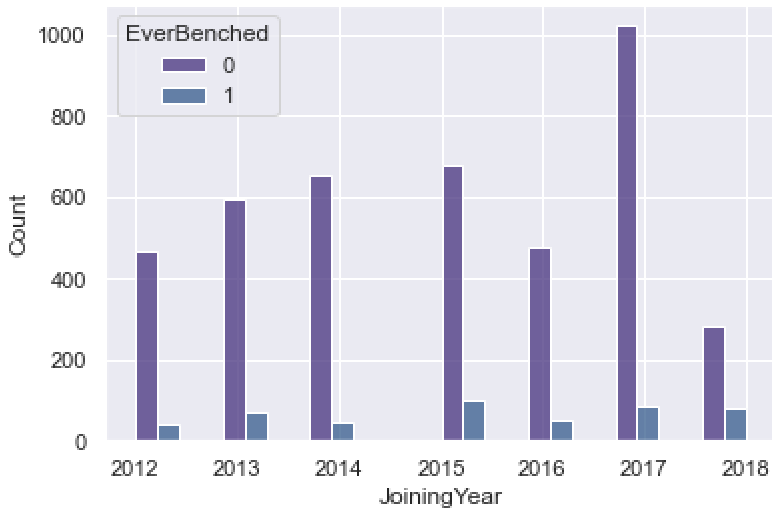
it means ever kept out of the projects for 1 month or more

30% from not behanced leaving

5.6% behanced and not leaving

In [26]:
```
sns.histplot(data=df, x="JoiningYear", hue="EverBenched", multiple="dodge", shrir
```

Out[26]: <AxesSubplot:xlabel='JoiningYear', ylabel='Count'>



Normalization, Over sampling, and Train-Test-split

In [27]:
```
sc= MinMaxScaler()
X =pd.DataFrame(sc.fit_transform(df.drop(["LeaveOrNot"],axis = 1)))
Y = df['LeaveOrNot'].values
```

In [28]:
```
sm = SMOTE(random_state=42)
X,Y=sm.fit_resample(X, Y)
X_train,X_test,Y_train,Y_test = train_test_split(X,Y, test_size=0.2 , random_stat
```

Modeling

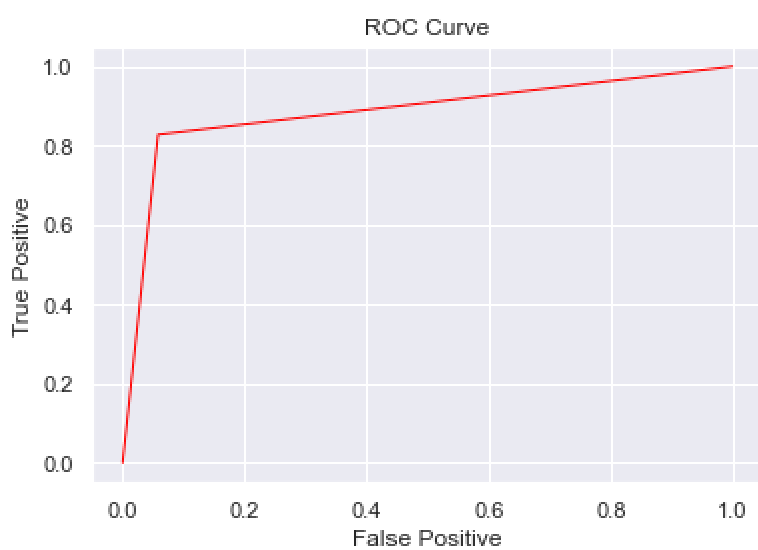
1-LGBMClassifier

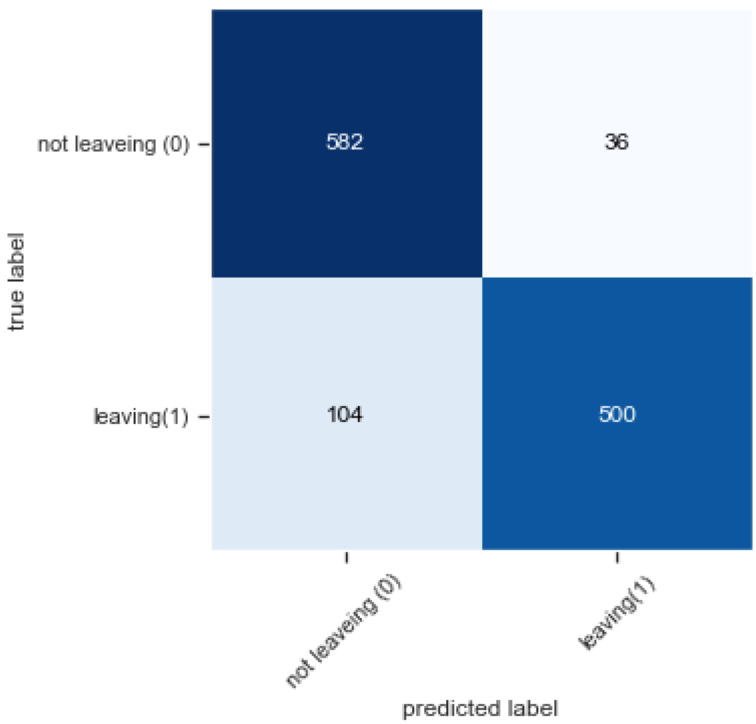
In [29]:
```
clf = lgb.LGBMClassifier()
clf.fit(X_train, Y_train)
Y_pred_test = clf.predict(X_test)
print("F1-Score:",metrics.f1_score(Y_test, Y_pred_test))
print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred_test))
print("Precision:",metrics.precision_score(Y_test, Y_pred_test))
print("Recall:",metrics.recall_score(Y_test, Y_pred_test))
print("AUC:",metrics.roc_auc_score(Y_test, Y_pred_test))
print(classification_report(Y_test, Y_pred_test))
cutoff_grid = np.linspace(0.0,1.0,100)
TPR = []
FPR = []
cutoff_grid
FPR, TPR, cutoffs = metrics.roc_curve(Y_test, Y_pred_test,pos_label=1)
confusion_matrix=confusion_matrix(Y_test,Y_pred_test)
plt.plot(FPR,TPR,c='red',linewidth=1.0)
plt.xlabel('False Positive')
plt.ylabel('True Positive')
plt.title('ROC Curve')
plot_confusion_matrix(confusion_matrix,class_names=["not leaveing (0)","leaving(1
plt.show()
```

```
F1-Score: 0.8771929824561403
Accuracy: 0.8854337152209493
Precision: 0.9328358208955224
Recall: 0.8278145695364238
AUC: 0.8847810711759789
              precision    recall  f1-score   support

           0       0.85      0.94      0.89       618
           1       0.93      0.83      0.88       604

    accuracy                           0.89      1222
   macro avg       0.89      0.88      0.88      1222
weighted avg       0.89      0.89      0.89      1222
```



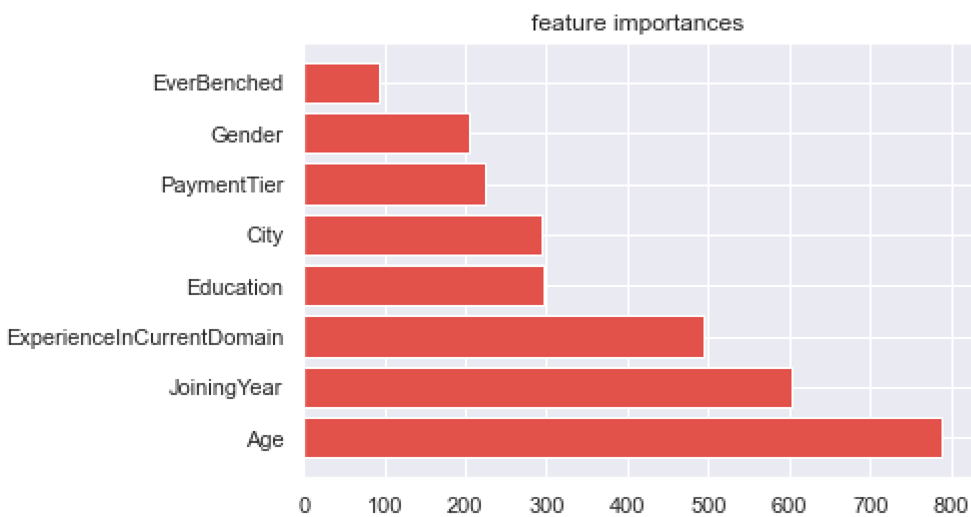

not leaveing (0)
leaving(1)
true label
582
36
104
500
not leaveing (0)
leaving(1)
predicted label

In [30]:
```
def f_importances(coef, names, top=-1):
    imp = coef
    imp, names = zip(*sorted(list(zip(imp, names))))

    # Show all features
    if top == -1:
        top = len(names)

    plt.barh(range(top), imp[::-1][0:top], align='center')
    plt.yticks(range(top), names[::-1][0:top])
    plt.title('feature importances')
    plt.show()

features_names = ['Education', 'JoiningYear', 'City', 'PaymentTier', 'Age', 'Genc
        'EverBenched', 'ExperienceInCurrentDomain']
sns.set_theme(palette="Spectral")
f_importances(abs(clf.feature_importances_), features_names, top=8)
```



in LGBMClassifier the best features for prediction is:

1- Age

2- Joining Year

3- Experience

4- City

5- Education

6- Payment Tier

7- Gender

8- Benching

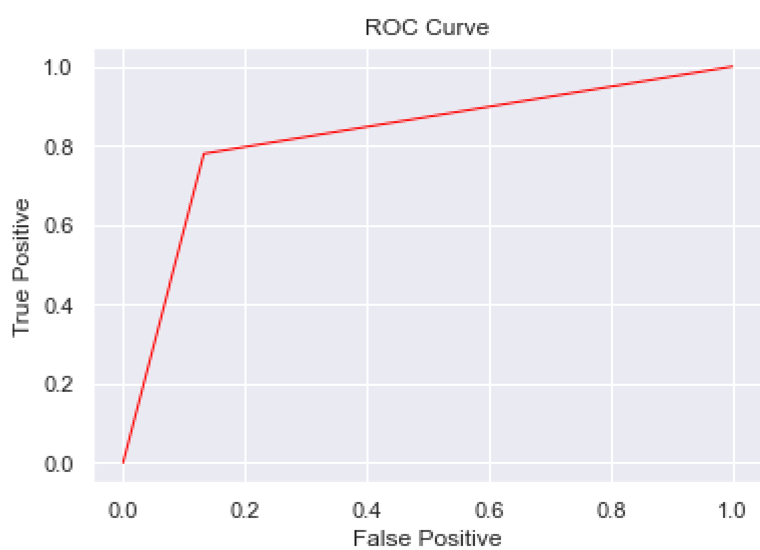
2-KNeighborsClassifier

In [31]:
```
K=KNeighborsClassifier(n_neighbors=10)
K.fit(X_train, Y_train)
Y_pred_k = K.predict(X_test)
print("F1-Score:",metrics.f1_score(Y_test, Y_pred_k))
print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred_k))
print("Precision:",metrics.precision_score(Y_test, Y_pred_k))
print("Recall:",metrics.recall_score(Y_test, Y_pred_k))
print("AUC:",metrics.roc_auc_score(Y_test, Y_pred_k))
print(classification_report(Y_test, Y_pred_k))
cutoff_grid = np.linspace(0.0,1.0,100)
TPR = []
FPR = []
cutoff_grid
FPR, TPR, cutoffs = metrics.roc_curve(Y_test, Y_pred_k,pos_label=1)
plt.plot(FPR,TPR,c='red',linewidth=1.0)
plt.xlabel('False Positive')
plt.ylabel('True Positive')
plt.title('ROC Curve')
plt.show()
```

```
F1-Score: 0.8141745894554884
Accuracy: 0.8240589198036007
Precision: 0.8517179023508138
Recall: 0.7798013245033113
AUC: 0.8235576201804583
              precision    recall  f1-score   support

           0       0.80      0.87      0.83       618
           1       0.85      0.78      0.81       604

    accuracy                           0.82      1222
   macro avg       0.83      0.82      0.82      1222
weighted avg       0.83      0.82      0.82      1222
```



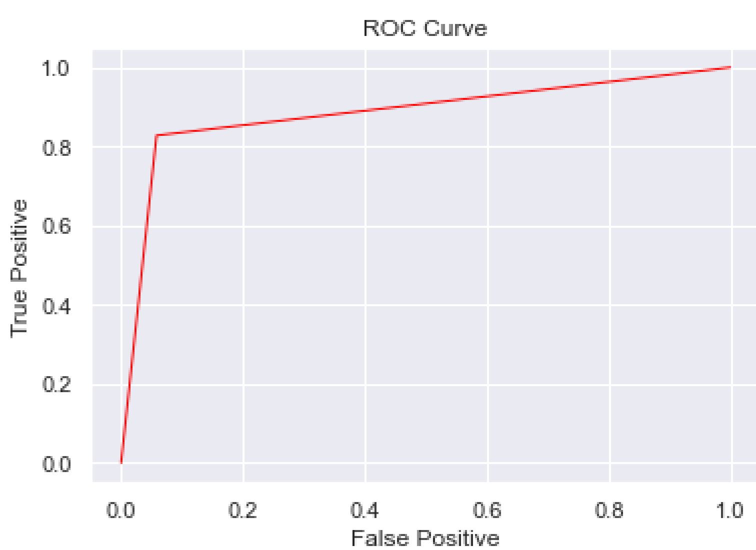
3-DecisionTreeClassifier

In [32]:
```
D=DecisionTreeClassifier(max_depth=8,max_features=8,random_state=42)
D.fit(X_train, Y_train)
Y_pred_d = D.predict(X_test)
print("F1-Score:",metrics.f1_score(Y_test, Y_pred_d))
print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred_d))
print("Precision:",metrics.precision_score(Y_test, Y_pred_d))
print("Recall:",metrics.recall_score(Y_test, Y_pred_d))
print("AUC:",metrics.roc_auc_score(Y_test, Y_pred_d))
print(classification_report(Y_test, Y_pred_d))
cutoff_grid = np.linspace(0.0,1.0,100)
TPR = []
FPR = []
cutoff_grid
FPR, TPR, cutoffs = metrics.roc_curve(Y_test, Y_pred_test,pos_label=1)
plt.plot(FPR,TPR,c='red',linewidth=1.0)
plt.xlabel('False Positive')
plt.ylabel('True Positive')
plt.title('ROC Curve')
plt.show()
```

```
F1-Score: 0.8313796212804329
Accuracy: 0.8469721767594108
Precision: 0.9128712871287129
Recall: 0.7632450331125827
AUC: 0.8460238110546733
              precision    recall  f1-score   support

           0       0.80      0.93      0.86       618
           1       0.91      0.76      0.83       604

    accuracy                           0.85      1222
   macro avg       0.86      0.85      0.85      1222
weighted avg       0.86      0.85      0.85      1222
```

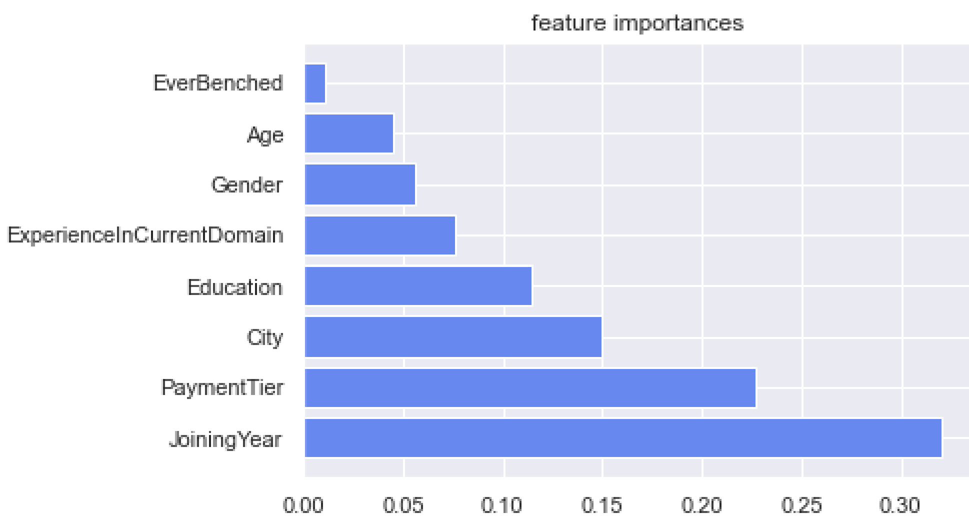


In [33]:
```
def f_importances(coef, names, top=-1):
    imp = coef
    imp, names = zip(*sorted(list(zip(imp, names))))

    # Show all features
    if top == -1:
        top = len(names)

    plt.barh(range(top), imp[::-1][0:top], align='center')
    plt.yticks(range(top), names[::-1][0:top])
    plt.title('feature importances')
    plt.show()

features_names = ['Education', 'JoiningYear', 'City', 'PaymentTier', 'Age', 'Genc
       'EverBenched', 'ExperienceInCurrentDomain']
sns.set_theme(palette="coolwarm")
f_importances(abs(D.feature_importances_), features_names, top=8)
```



in DecisionTreeClassifier the best features for prediction is:

1- Joining Year

2- Payment Tier

3- City

4- Education

5- Gender

6- Age

7- Experience

8- Benching

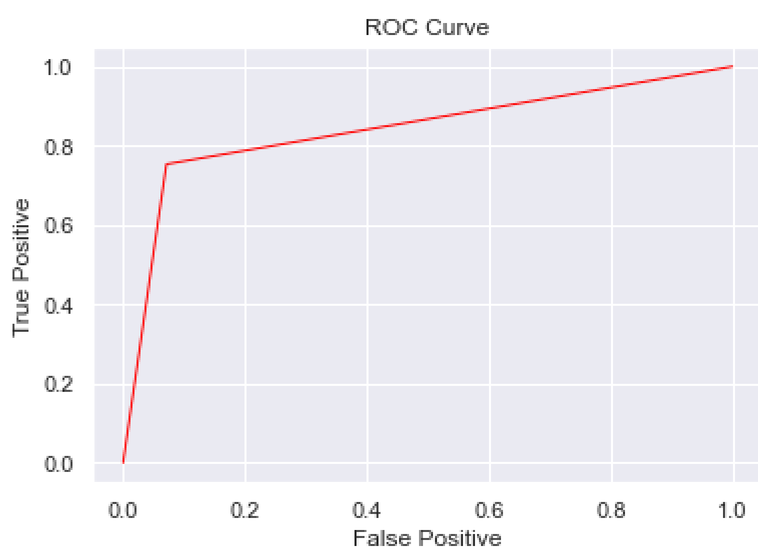
4-RandomForestClassifier

In [34]:
```
R=RandomForestClassifier(n_estimators=5,max_depth=8,max_features=8,random_state=4
R.fit(X_train, Y_train)
Y_pred_r = R.predict(X_test)
print("F1-Score:",metrics.f1_score(Y_test, Y_pred_r))
print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred_r))
print("Precision:",metrics.precision_score(Y_test, Y_pred_r))
print("Recall:",metrics.recall_score(Y_test, Y_pred_r))
print("AUC:",metrics.roc_auc_score(Y_test, Y_pred_r))
print(classification_report(Y_test, Y_pred_r))
cutoff_grid = np.linspace(0.0,1.0,100)
TPR = []
FPR = []
cutoff_grid
FPR, TPR, cutoffs = metrics.roc_curve(Y_test, Y_pred_r,pos_label=1)
plt.plot(FPR,TPR,c='red',linewidth=1.0)
plt.xlabel('False Positive')
plt.ylabel('True Positive')
plt.title('ROC Curve')
plt.show()
```

```
F1-Score: 0.8250226654578423
Accuracy: 0.8420621931260229
Precision: 0.9118236472945892
Recall: 0.7533112582781457
AUC: 0.8410569236374547
              precision    recall  f1-score   support

           0       0.79      0.93      0.86       618
           1       0.91      0.75      0.83       604

    accuracy                           0.84      1222
   macro avg       0.85      0.84      0.84      1222
weighted avg       0.85      0.84      0.84      1222
```

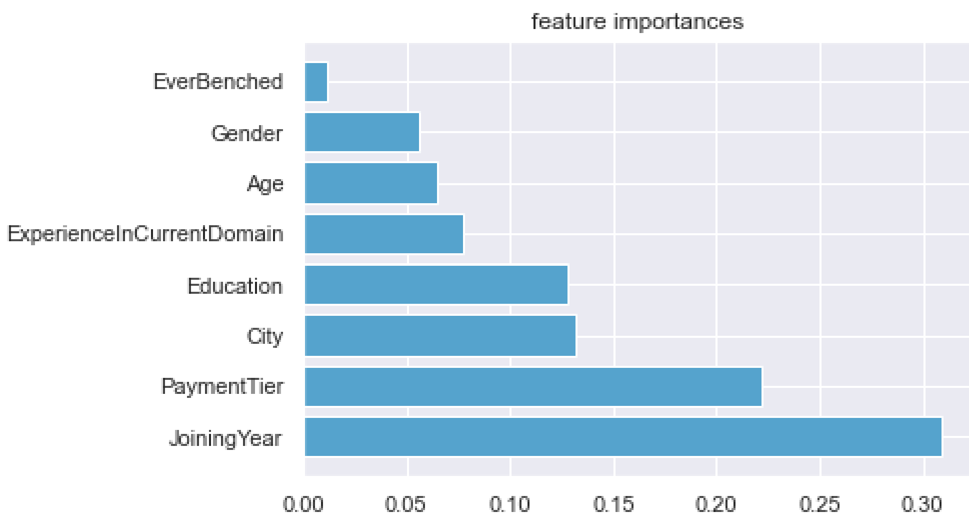


In [35]:
```
def f_importances(coef, names, top=-1):
    imp = coef
    imp, names = zip(*sorted(list(zip(imp, names))))

    # Show all features
    if top == -1:
        top = len(names)

    plt.barh(range(top), imp[::-1][0:top], align='center')
    plt.yticks(range(top), names[::-1][0:top])
    plt.title('feature importances')
    plt.show()

features_names = ['Education', 'JoiningYear', 'City', 'PaymentTier', 'Age', 'Gend
       'EverBenched', 'ExperienceInCurrentDomain']
sns.set_theme(palette="icefire")
f_importances(abs(R.feature_importances_), features_names, top=8)
```



in RandomForestClassifier the best features for prediction is:

1- Joining Year

2- Payment Tier

3- City

4- Education

5- Age

6- Gender

7- Experience

8- Benching

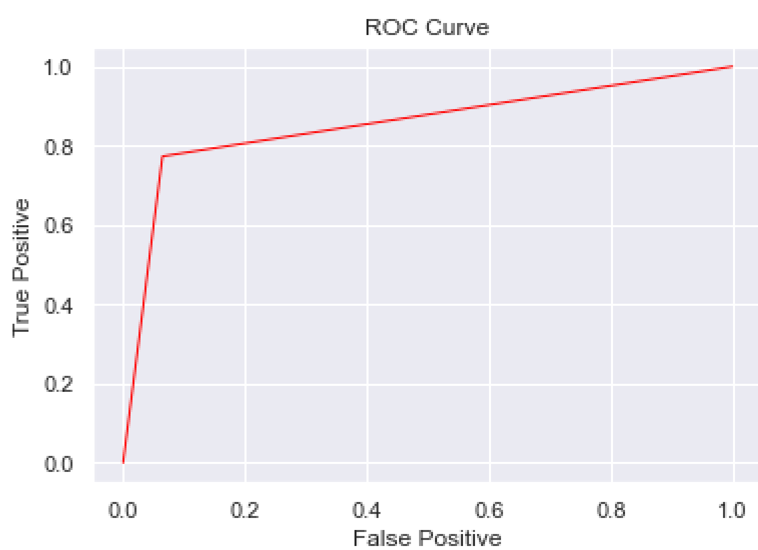
5-GradientBoostingClassifier

In [36]:
```
G=GradientBoostingClassifier(n_estimators =5, max_depth =7, learning_rate = 0.3,
G.fit(X_train, Y_train)
Y_pred_g = G.predict(X_test)
print("F1-Score:",metrics.f1_score(Y_test, Y_pred_g))
print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred_g))
print("Precision:",metrics.precision_score(Y_test, Y_pred_g))
print("Recall:",metrics.recall_score(Y_test, Y_pred_g))
print("AUC:",metrics.roc_auc_score(Y_test, Y_pred_g))
print(classification_report(Y_test, Y_pred_g))
cutoff_grid = np.linspace(0.0,1.0,100)
TPR = []
FPR = []
cutoff_grid
FPR, TPR, cutoffs = metrics.roc_curve(Y_test, Y_pred_g,pos_label=1)
plt.plot(FPR,TPR,c='red',linewidth=1.0)
plt.xlabel('False Positive')
plt.ylabel('True Positive')
plt.title('ROC Curve')
plt.show()
```

```
F1-Score: 0.8406840684068407
Accuracy: 0.8551554828150573
Precision: 0.9211045364891519
Recall: 0.7731788079470199
AUC: 0.8542269444265843
              precision    recall  f1-score   support

           0       0.81      0.94      0.87       618
           1       0.92      0.77      0.84       604

    accuracy                           0.86      1222
   macro avg       0.86      0.85      0.85      1222
weighted avg       0.86      0.86      0.85      1222
```

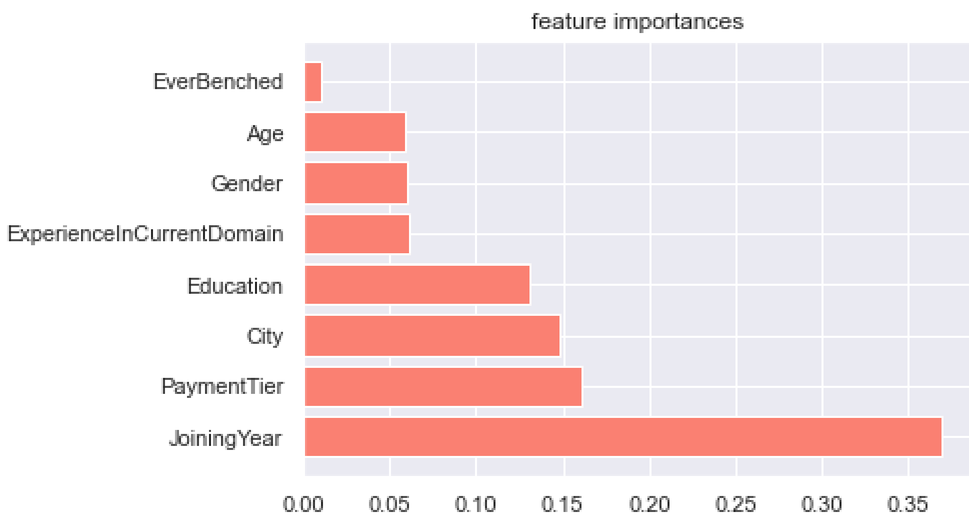


In [37]:
```
def f_importances(coef, names, top=-1):
    imp = coef
    imp, names = zip(*sorted(list(zip(imp, names))))

    # Show all features
    if top == -1:
        top = len(names)

    plt.barh(range(top), imp[::-1][0:top], align='center')
    plt.yticks(range(top), names[::-1][0:top])
    plt.title('feature importances')
    plt.show()

features_names = ['Education', 'JoiningYear', 'City', 'PaymentTier', 'Age', 'Genc
       'EverBenched', 'ExperienceInCurrentDomain']
sns.set_theme(palette="dark:salmon_r")
f_importances(abs(G.feature_importances_), features_names, top=8)
```



in GradientBoostingClassifier the best features for prediction is:

1- Joining Year

2- City

3- Payment Tier

4- Education

5- Gender

6- Age

7- Experience

8- Benching

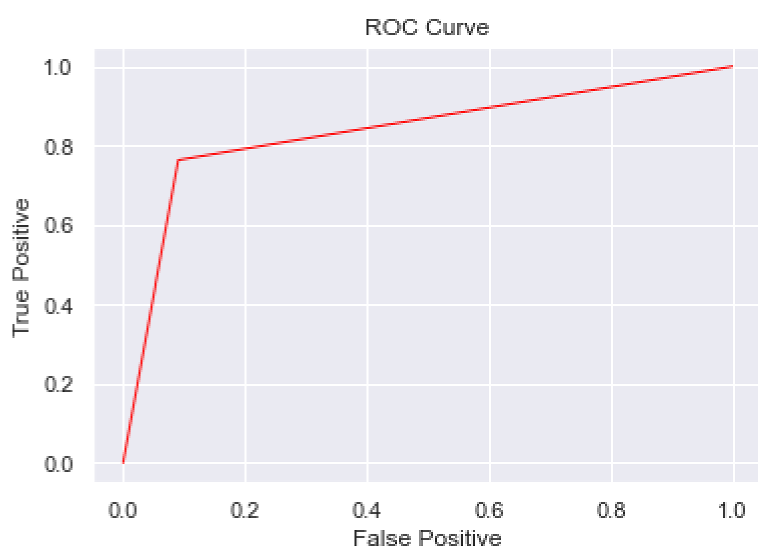
6-Support Vector Machine

In [38]:
```
rbf = svm.SVC(kernel='rbf', gamma=4,C=2).fit(X_train,Y_train)
rbf.fit(X_train, Y_train)
Y_pred_rbf = rbf.predict(X_test)
print("F1-Score:",metrics.f1_score(Y_test, Y_pred_rbf))
print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred_rbf))
print("Precision:",metrics.precision_score(Y_test, Y_pred_rbf))
print("Recall:",metrics.recall_score(Y_test, Y_pred_rbf))
print("AUC:",metrics.roc_auc_score(Y_test, Y_pred_rbf))
print(classification_report(Y_test, Y_pred_rbf))
cutoff_grid = np.linspace(0.0,1.0,100)
TPR = []
FPR = []
cutoff_grid
FPR, TPR, cutoffs = metrics.roc_curve(Y_test, Y_pred_rbf,pos_label=1)
plt.plot(FPR,TPR,c='red',linewidth=1.0)
plt.xlabel('False Positive')
plt.ylabel('True Positive')
plt.title('ROC Curve')
plt.show()
```

```
F1-Score: 0.8224799286351473
Accuracy: 0.837152209492635
Precision: 0.8916827852998066
Recall: 0.7632450331125827
AUC: 0.8363150731905956
              precision    recall  f1-score   support

           0       0.80      0.91      0.85       618
           1       0.89      0.76      0.82       604

    accuracy                           0.84      1222
   macro avg       0.84      0.84      0.84      1222
weighted avg       0.84      0.84      0.84      1222
```



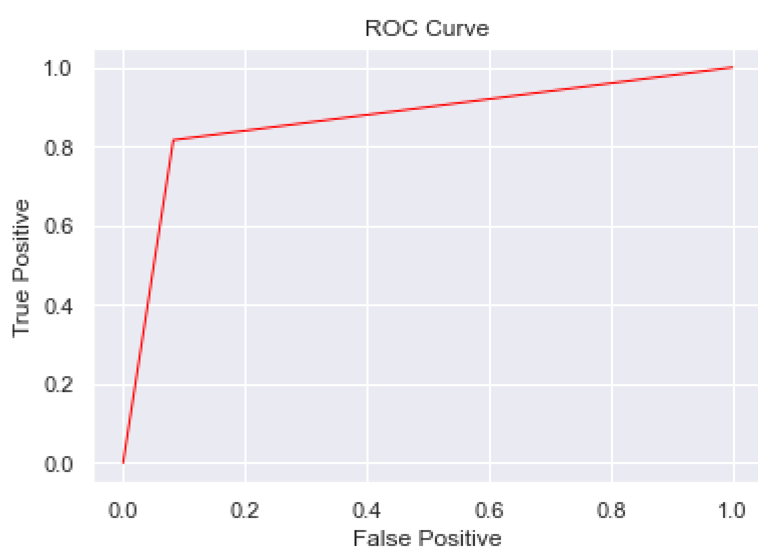
7-ExtraTreesClassifier

In [39]:
```
E = ExtraTreesClassifier(n_estimators=6,min_samples_split=10, random_state=0)
E.fit(X_train, Y_train)
Y_pred_e = E.predict(X_test)
print("F1-Score:",metrics.f1_score(Y_test, Y_pred_e))
print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred_e))
print("Precision:",metrics.precision_score(Y_test, Y_pred_e))
print("Recall:",metrics.recall_score(Y_test, Y_pred_e))
print("AUC:",metrics.roc_auc_score(Y_test, Y_pred_e))
print(classification_report(Y_test, Y_pred_e))
cutoff_grid = np.linspace(0.0,1.0,100)
TPR = []
FPR = []
cutoff_grid
FPR, TPR, cutoffs = metrics.roc_curve(Y_test, Y_pred_e,pos_label=1)
plt.plot(FPR,TPR,c='red',linewidth=1.0)
plt.xlabel('False Positive')
plt.ylabel('True Positive')
plt.title('ROC Curve')
plt.show()
```

```
F1-Score: 0.8588850174216028
Accuracy: 0.867430441898527
Precision: 0.90625
Recall: 0.8162251655629139
AUC: 0.8668504468591268
              precision    recall  f1-score   support

           0       0.84      0.92      0.88       618
           1       0.91      0.82      0.86       604

    accuracy                           0.87      1222
   macro avg       0.87      0.87      0.87      1222
weighted avg       0.87      0.87      0.87      1222
```



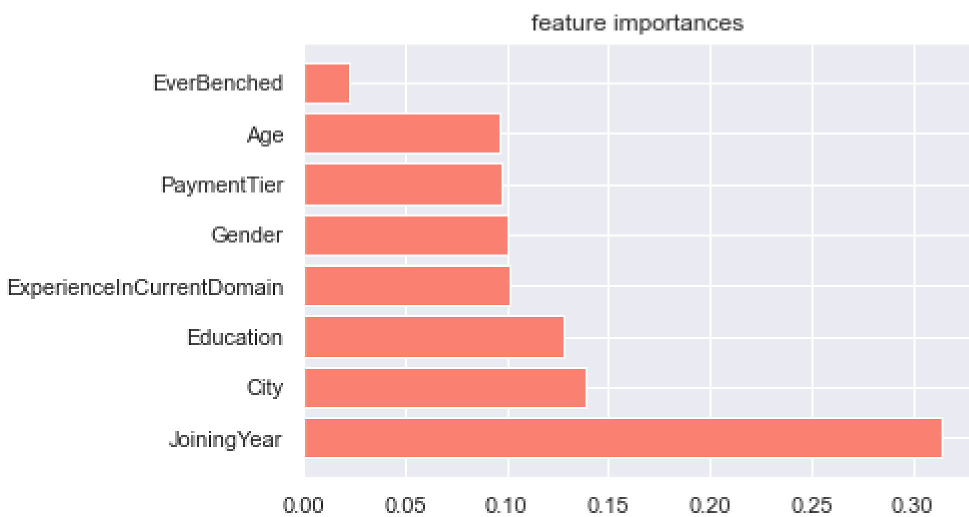
In [40]:
```
def f_importances(coef, names, top=-1):
    imp = coef
    imp, names = zip(*sorted(list(zip(imp, names))))

    # Show all features
    if top == -1:
        top = len(names)

    plt.barh(range(top), imp[::-1][0:top], align='center')
    plt.yticks(range(top), names[::-1][0:top])
    plt.title('feature importances')
    plt.show()

features_names = ['Education', 'JoiningYear', 'City', 'PaymentTier', 'Age', 'Genc
       'EverBenched', 'ExperienceInCurrentDomain']

f_importances(abs(E.feature_importances_), features_names, top=8)
```



in ExtraTreesClassifier the best features for prediction is:

1- Joining Year

2- City

3- Payment Tier

4- Education

5- Gender

6- Age

7- Experience

8- Benching

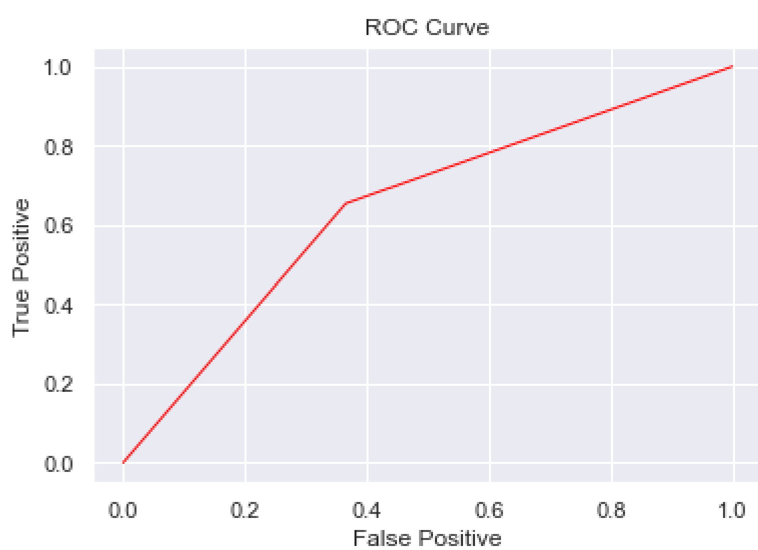
8-LogisticRegression

In [41]:
```
L=LogisticRegression()
L.fit(X_train, Y_train)
Y_pred_l = L.predict(X_test)
print("F1-Score:",metrics.f1_score(Y_test, Y_pred_l))
print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred_l))
print("Precision:",metrics.precision_score(Y_test, Y_pred_l))
print("Recall:",metrics.recall_score(Y_test, Y_pred_l))
print("AUC:",metrics.roc_auc_score(Y_test, Y_pred_l))
print(classification_report(Y_test, Y_pred_l))
cutoff_grid = np.linspace(0.0,1.0,100)
TPR = []
FPR = []
cutoff_grid
FPR, TPR, cutoffs = metrics.roc_curve(Y_test, Y_pred_l,pos_label=1)
plt.plot(FPR,TPR,c='red',linewidth=1.0)
plt.xlabel('False Positive')
plt.ylabel('True Positive')
plt.title('ROC Curve')
plt.show()
```

```
F1-Score: 0.6448979591836734
Accuracy: 0.644026186579378
Precision: 0.6360708534621579
Recall: 0.6539735099337748
AUC: 0.644138858526758
              precision    recall  f1-score   support

           0       0.65      0.63      0.64       618
           1       0.64      0.65      0.64       604

    accuracy                           0.64      1222
   macro avg       0.64      0.64      0.64      1222
weighted avg       0.64      0.64      0.64      1222
```



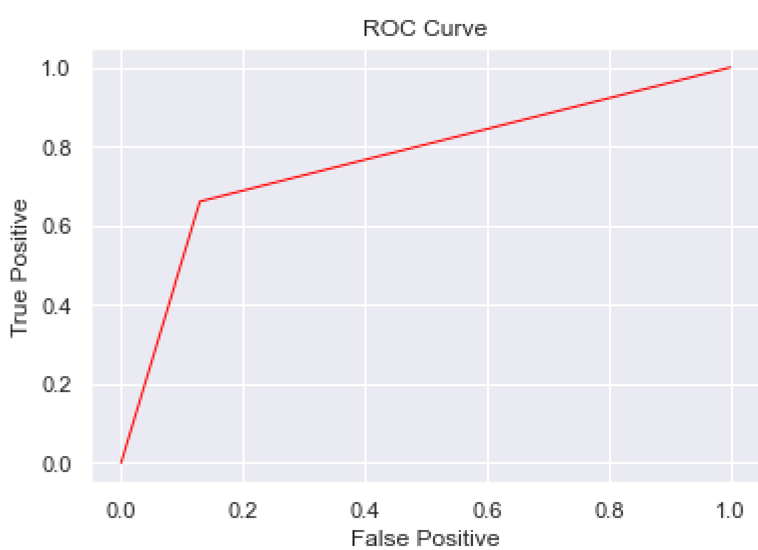
9-AdaBoostClassifier

In [42]:
```
A=AdaBoostClassifier(n_estimators=5,learning_rate=.5)
A.fit(X_train, Y_train)
Y_pred_a = A.predict(X_test)
print("F1-Score:",metrics.f1_score(Y_test, Y_pred_a))
print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred_a))
print("Precision:",metrics.precision_score(Y_test, Y_pred_a))
print("Recall:",metrics.recall_score(Y_test, Y_pred_a))
print("AUC:",metrics.roc_auc_score(Y_test, Y_pred_a))
print(classification_report(Y_test, Y_pred_a))
cutoff_grid = np.linspace(0.0,1.0,100)
TPR = []
FPR = []
cutoff_grid
FPR, TPR, cutoffs = metrics.roc_curve(Y_test, Y_pred_a,pos_label=1)
plt.plot(FPR,TPR,c='red',linewidth=1.0)
plt.xlabel('False Positive')
plt.ylabel('True Positive')
plt.title('ROC Curve')
plt.show()
```

```
F1-Score: 0.7368421052631579
Accuracy: 0.7667757774140753
Precision: 0.8329853862212944
Recall: 0.6605960264900662
AUC: 0.7655730941511819
              precision    recall  f1-score   support

           0       0.72      0.87      0.79       618
           1       0.83      0.66      0.74       604

    accuracy                           0.77      1222
   macro avg       0.78      0.77      0.76      1222
weighted avg       0.78      0.77      0.76      1222
```

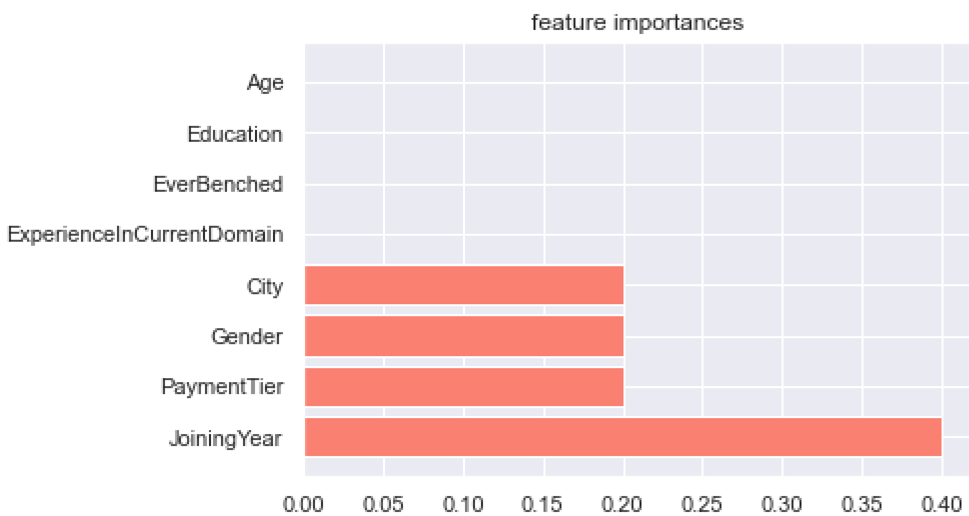


In [43]:
```
def f_importances(coef, names, top=-1):
    imp = coef
    imp, names = zip(*sorted(list(zip(imp, names))))

    # Show all features
    if top == -1:
        top = len(names)

    plt.barh(range(top), imp[::-1][0:top], align='center')
    plt.yticks(range(top), names[::-1][0:top])
    plt.title('feature importances')
    plt.show()
features_names = ['Education', 'JoiningYear', 'City', 'PaymentTier', 'Age', 'Genc

                  'EverBenched', 'ExperienceInCurrentDomain']
f_importances(abs(A.feature_importances_), features_names, top=8)
```



in AdaBoostClassifier the best features for prediction is:

1- Joining Year

2- Payment Tier , Gender , City

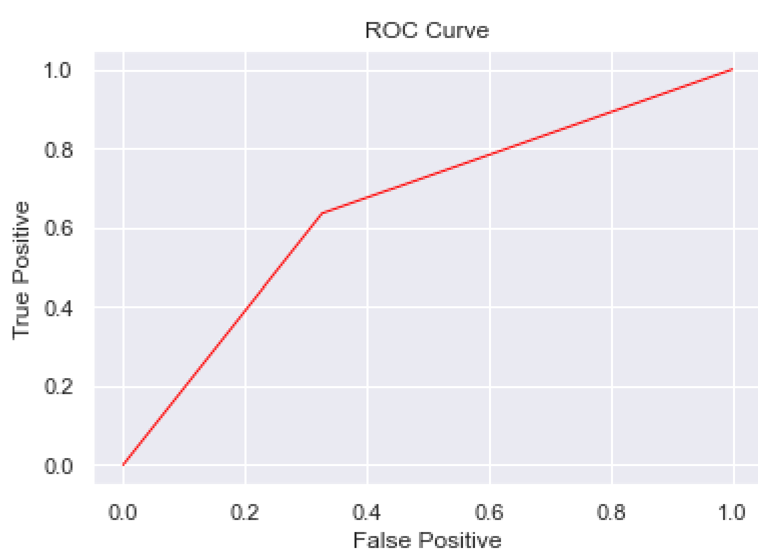
10-GaussianNB

In [44]:
```
GNB = GaussianNB()
GNB.fit(X_train, Y_train)
Y_pred_gnb =GNB.predict(X_test)
print("F1-Score:",metrics.f1_score(Y_test, Y_pred_gnb))
print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred_gnb))
print("Precision:",metrics.precision_score(Y_test, Y_pred_gnb))
print("Recall:",metrics.recall_score(Y_test, Y_pred_gnb))
print("AUC:",metrics.roc_auc_score(Y_test, Y_pred_gnb))
print(classification_report(Y_test, Y_pred_gnb))
cutoff_grid = np.linspace(0.0,1.0,100)
TPR = []
FPR = []
cutoff_grid
FPR, TPR, cutoffs = metrics.roc_curve(Y_test, Y_pred_gnb,pos_label=1)
plt.plot(FPR,TPR,c='red',linewidth=1.0)
plt.xlabel('False Positive')
plt.ylabel('True Positive')
plt.title('ROC Curve')
plt.show()
```

```
F1-Score: 0.6453781512605041
Accuracy: 0.6546644844517185
Precision: 0.6552901023890785
Recall: 0.6357615894039735
AUC: 0.6544503739900127
              precision    recall  f1-score   support

           0       0.65      0.67      0.66       618
           1       0.66      0.64      0.65       604

    accuracy                           0.65      1222
   macro avg       0.65      0.65      0.65      1222
weighted avg       0.65      0.65      0.65      1222
```



In [45]:
```
def testModel():
    edu = int(input("Please,Enter Education level\n0-Bachelors\n1-Masters\n2-PHD\
    year = int(input("Please,Enter Joining year\n"))
    city = int(input("Please,Enter City\n0-Bangalore\n1-New Delhi\n2-Pune\n"))
    payment = int(input("Please,Enter Payment Tier\n1-Highest\n2-Mid Level\n3-Low
    age = int(input("Please,Enter Age\n"))
    gender = int(input("Please,Enter Gender\n0-Female\n1-Male\n"))
    benched = int(input("Please,Enter if employee ever Benched\n0-No\n1-Yes\n"))
    exper = int(input("Please,Enter Experience In Current Domain\n"))
    data = [[edu,year,city,payment,age,gender,benched,exper]]
    data = sc.transform(data)
    pred = clf.predict(data)
    if (pred == 1):
        print("Employee Will Leave\n")
        suge = int(input("Would you like to know the suggetions to make him stay?
        if(suge == 1):
            from random import choice
            while (1):
                data[0][1] = choice(X[1])
                data[0][2] = choice(X[2])
                data[0][3] = choice(X[3])
                data[0][6] = choice(X[6])
                sugPred = clf.predict(data)
                if (sugPred == 0):
                    data = (sc.inverse_transform(data)).astype(int)
                    data = data.astype(str)
                    if (data[0][2] == "0"):
                        data[0][2] = "Bangalore"
                    elif (data[0][2] == "1"):
                        data[0][2] = "New Delhi"
                    elif (data[0][2] == "2"):
                        data[0][2] = "Pune"
                    if (data[0][3] == "1"):
                        data[0][3] = "Highest"
                    elif (data[0][3] == "2"):
                        data[0][3] = "Mid"
                    elif (data[0][3] == "3"):
                        data[0][3] = "Lowest"
                    if (data[0][6] == "0"):
                        data[0][6] = " not "
                    elif (data[0][6] == "1"):
                        data[0][6] = " "
                    print("We suggest to deal with the employee like %s,\nmove th
                    break
    if (pred == 0):
        print("Employee will not leave")
testModel()
```

```
Please,Enter Education level
0-Bachelors
1-Masters
2-PHD
0
Please,Enter Joining year
2018
Please,Enter City
```

```
0-Bangalore
1-New Delhi
2-Pune
0
Please,Enter Payment Tier
1-Highest
2-Mid Level
3-Lowest
3
Please,Enter Age
28
Please,Enter Gender
0-Female
1-Male
1
Please,Enter if employee ever Benched
0-No
1-Yes
1
Please,Enter Experience In Current Domain
2
Employee Will Leave

Would you like to know the suggetions to make him stay?
1-Yes
2-No
1
We suggest to deal with the employee like 2012,
move the employee to office in New Delhi,
make employee payment in Lowest level
and not make the employee benched
```

In [ ]: