Московский государственный технический университет им. Н.Э. Баумана

Факультет «Информатика и системы управления»
Кафедра ИУ5 «Системы обработки информации и управления»

Курс «Парадигмы и конструкции языков программирования» Отчет по ДЗ

Выполнил:	Проверил:
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Подпись и дата:	Подпись и дата:

Москва, 2023г.

Задача:
Задача взята с сайта https://www.kaggle.com/competitions/titanic,
Цель:
создание модели бинарной классификации, предсказывающей выжил ли пассажир Титаника или нет
Метрика:
точность(accuracy)

Решение:

1) Заполнить пропуски
2) Закодировать категориальные признаки
3) Визуализировать данные
4) Приведение данных к нормальному распределению
5) Тренировка моделей
6) Подбор гиперпараметров

1) и 2)

```
dict_ = {'male':True, 'female':False}
train['is_male'] = train['Sex'].replace(dict_)
test['is_male'] = test['Sex'].replace(dict_)

train.Embarked.fillna('S', inplace=True)

df = pd.concat([train,test])
encoder = OneHotEncoder()
encoder.fit(df.Embarked.to_numpy().reshape(-1,1))
temp = encoder.transform(train.Embarked.to_numpy().reshape(-1,1))
temp = pd.DataFrame(temp.astype(int).toarray())
for i, u in enumerate(list(encoder.categories_[0])):
    train[u] = temp[i]
    train[u] = train[u].astype(bool)
temp = encoder.transform(test.Embarked.to_numpy().reshape(-1,1))
temp = pd.DataFrame(temp.astype(int).toarray())
for i, u in enumerate(list(encoder.categories_[0])):
    test[u] = temp[i]
    test[u] = test[u].astype(bool)

temp = encoder.transform(df.Embarked.to_numpy().reshape(-1,1))
temp = pd.DataFrame(temp.astype(int).toarray())
for i, u in enumerate(list(encoder.categories_[0])):
    df[u] = temp[i]
    df[u] = df[u].astype(bool)
```

```python
train['stat'] = train.Name.str.split(',').apply(lambda x:x[1].split('.')[0])
test['stat'] = test.Name.str.split(',').apply(lambda x:x[1].split('.')[0])

fullnames = ['Mister', 'Missis', 'Miss', 'Master', 'Don', 'Reverend', 'Doctor', 'Madame',
             'Miss', 'Major', 'Lady', 'Sir', 'Madmuaselle', 'Colonel', 'Captain',
             'Countess',  'Jonkheer']
dict_ = dict(zip(train.stat.unique(), fullnames))

train['stat'] = train.stat.replace(dict_)
test['stat'] = test.stat.replace(dict_)

train['family_size'] = train.SibSp + train.Parch
test['family_size'] = test.SibSp + test.Parch

dict_ = {'Mister': 'Sir',
         'Missis': 'Lady',
         'Miss': 'Kid',
         'Master': 'Kid',
         'Don': 'Sir',
         'Reverend': 'Rare',
         'Doctor': 'Rare',
         'Madame': 'Lady',
         'Major': 'Rare',
         'Madmuaselle': 'Kid',
         'Colonel': 'Rare',
         'Captain': 'Rare',
         'Countess': 'Lady',
         'Jonkheer': 'Rare',
         ' Dona': 'Lady'
         }

train['is_civil'] = train.stat.replace(dict_)
test['is_civil'] = test.stat.replace(dict_)


train = pd.concat([train.drop('is_civil', axis=1), pd.get_dummies(train['is_civil'])], axis=1)
test = pd.concat([test.drop('is_civil', axis=1), pd.get_dummies(test['is_civil'])], axis=1)
```

```python
X['deck'] = X.Cabin.str[0]

temp = X.Ticket.value_counts().loc[X.Ticket.value_counts()>1]
for i in temp.index:
  t = X.loc[(X.Ticket==i)]
  if (t.Cabin.count()!=t.shape[0])&(t.Cabin.count()!=0):
    id = t.loc[t.Cabin.isna()].index
    X.loc[id, 'Cabin'] = t.Cabin.mode().iloc[0]
    X.loc[id, 'deck'] = t.deck.mode().iloc[0]



X['deck'] = X['Cabin'].apply(lambda s: s[0] if pd.notnull(s) else 'M')
X['deck'] = np.where((X.deck == 'T'),'A',X.deck)

X['deck'].replace(['A', 'B', 'C'], 'ABC', inplace=True)
X['deck'].replace(['D', 'E'], 'DE', inplace=True)
X['deck'].replace(['F', 'G'], 'FG', inplace=True)

train = X.iloc[:train.shape[0]]
test = X.drop('Survived',axis=1).iloc[train.shape[0]:]
```

```
def size(x):
    if x<1: return 'alone'
    elif x>4: return '1-3'
    else: return '4+'
train['family_cat'] = train.family_size.apply(size)
test['family_cat'] =test.family_size.apply(size)


X = pd.concat([train,test]).drop('Survived', axis=1)
temp = pd.get_dummies(X.family_cat)

train = pd.concat([train, temp.iloc[:train.shape[0]]], axis=1)
test = pd.concat([test, temp.iloc[train.shape[0]:]], axis=1)
```

```
X = pd.concat([train,test]).drop('Survived', axis=1)
temp = pd.get_dummies(X.Pclass)

train = pd.concat([train, temp.iloc[:train.shape[0]]], axis=1)
test = pd.concat([test, temp.iloc[train.shape[0]:]], axis=1)

train = train.rename({1:'1st class', 2:'2nd class', 3:'3rd class'}, axis=1)
test = test.rename({1:'1st class', 2:'2nd class', 3:'3rd class'}, axis=1)
```

```
X = pd.concat([train,test]).drop('Survived', axis=1)[['Ticket', 'Fare']]
tickets_count = X.Ticket.value_counts().to_dict()

X['tickcount'] = X.Ticket.replace(tickets_count)
X['Fare'] = X['Fare']/X['tickcount']
train['Fare'] = X['Fare'].iloc[:train.shape[0]]
test['Fare'] = X['Fare'].iloc[train.shape[0]:]
# test.loc[test.loc[test.Fare.isna()].index, 'Age'] = df.loc[(df.Pclass==3)&(df.Sex=='male')].Age.median()
test['Fare'].fillna(df.loc[(df.Pclass==3)&(df.Sex=='male')].Age.median(), inplace = True)
```


```
test['Fare'].fillna(df.loc[(df.Pclass==3)&(df.Sex=='male')].Age.median(), inplace = True)
```


```
df = pd.concat([train,test])
for k in df.is_male.unique():
  for i in df.Pclass.unique():
    id = df.loc[(df.Pclass==i)&(df.Age.isna())&(df.is_male==k)].index
    temp = df.loc[(df.Pclass == i)&(df.is_male==k)].Age
    std = temp.std()
    mean = temp.mean()
    repl_arr = np.random.normal(mean,len(id))
    df.loc[id, 'Age'] = repl_arr

df['Age'] = df.Age.round()
train['Age'] = df.Age.iloc[:train.shape[0]].astype(int)
test['Age'] = df.Age.iloc[train.shape[0]:].astype(int)
```

```
X = pd.concat([X, pd.get_dummies(X.deck)], axis=1)
train['Age'] = X.Age.iloc[:train.shape[0]].astype(int)
test['Age'] = X.Age.iloc[train.shape[0]:].astype(int)
```

```
X = pd.concat([X, pd.get_dummies(X.deck)], axis=1)
train =  X.iloc[:train.shape[0]]
test = X.iloc[train.shape[0]:]
lst = ['Sex', 'Embarked', 'Name', 'Ticket', 'Cabin', 'stat', 'family_cat', 'Pclass',
       'SibSp', 'Parch', 'Sir', 'deck', 'family_size']
train.drop(lst,axis=1, inplace=True)
test.drop(lst,axis=1, inplace=True)
```

4)Привидение к нормальному виду

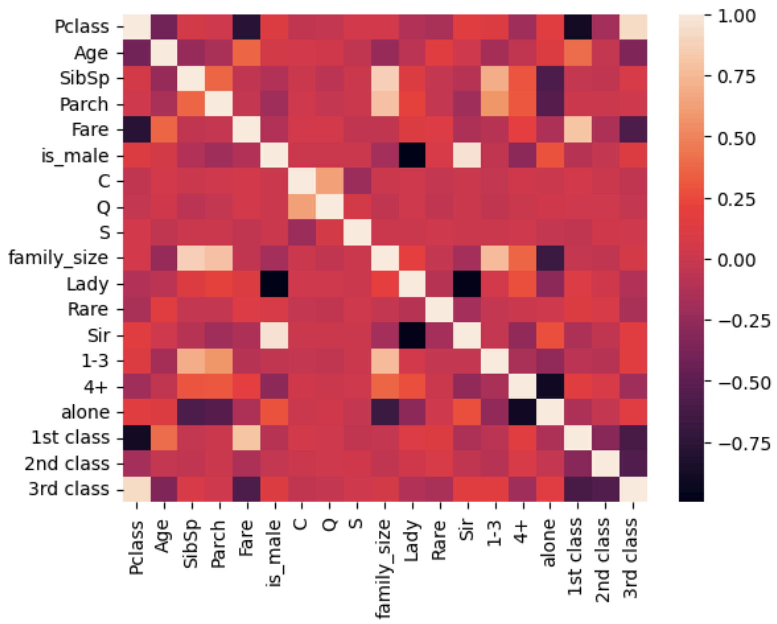
scaling

```
lst =['Age', 'Fare']#, 'family_size']
scaler = StandardScaler()
temp = scaler.fit_transform(train[lst])
temp = pd.DataFrame(temp, columns=lst).set_index(train.index)
train = pd.concat([train.drop(lst, axis=1), temp], axis=1)

temp = scaler.transform(test[lst])
temp = pd.DataFrame(temp, columns=lst).set_index(test.index)
test = pd.concat([test.drop(lst, axis=1), temp], axis=1)
```

```
df = pd.concat([train.drop('Survived', axis=1), test])
sns.heatmap(df.corr())
```

```
<ipython-input-39-cc734fa1c52f>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(df.corr())
```

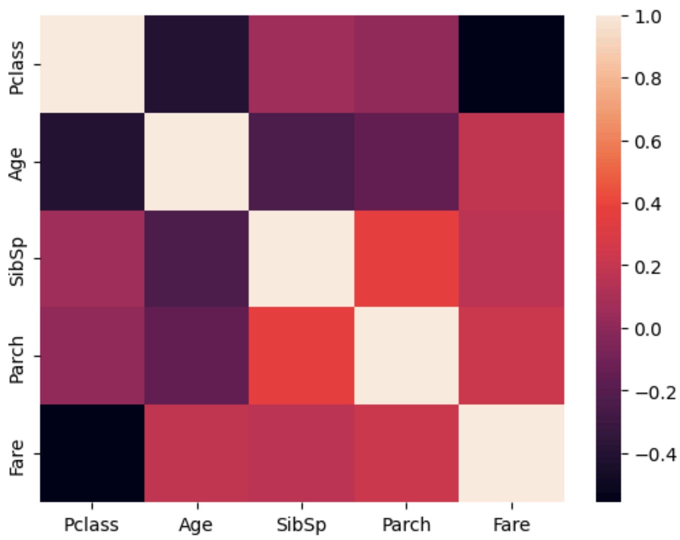
```
<Axes: >
```




```
sns.heatmap(df.corr())
```

```
<ipython-input-155-aa4f4450a243>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(df.corr())
```

```
<Axes: >
```

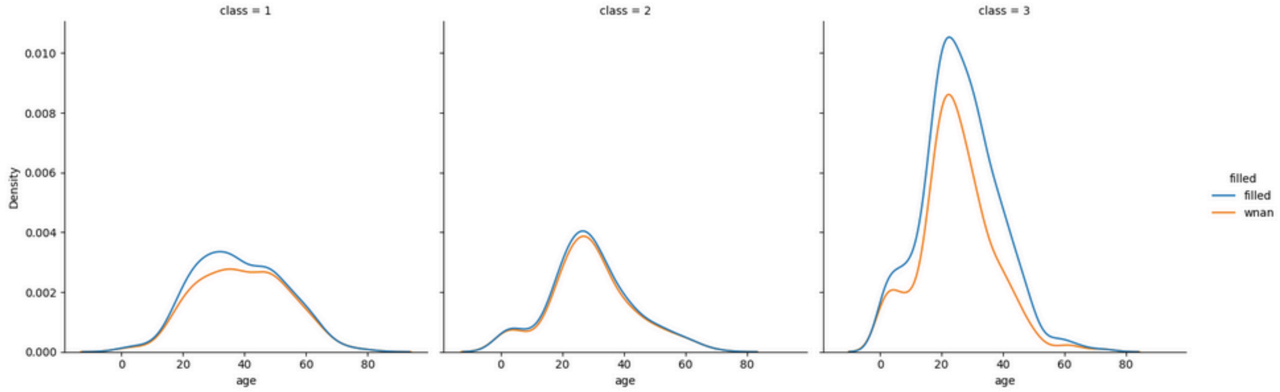


```python
train['stat'] = train.Name.str.split(',').apply(lambda x:x[1].split('.')[0])
test['stat'] = test.Name.str.split(',').apply(lambda x:x[1].split('.')[0])

fullnames = ['Mister', 'Missis', 'Miss', 'Master', 'Don', 'Reverend', 'Doctor', 'Madame',
             'Miss', 'Major', 'Lady', 'Sir', 'Madmuaselle', 'Colonel', 'Captain',
             'Countess',  'Jonkheer']
dict_ = dict(zip(train.stat.unique(), fullnames))

train['stat'] = train.stat.replace(dict_)
test['stat'] = test.stat.replace(dict_)

df = pd.concat([train,test])

for i in df.loc[df.Age.isna()].stat.unique():
  id = df.loc[(df.stat==i)&(df.Age.isna())].index
  if i == 'Doctor':
    df.loc[id,'Age'] = df.loc[df.stat == i].Age.median()
  else:
    temp = df.loc[df.stat == i].Age
    if temp.isna().sum()!=temp.shape[0]:
      std = temp.std()
      mean = temp.mean()
    else:
      std = df.Age.std()
      mean = df.Age.mean()
    # id = df.loc[(df.stat==i)&(df.Age.isna())].index
    repl_arr = np.random.normal(mean,std,len(id))
    while (repl_arr<2).sum() != 0:
      repl_arr = np.random.normal(mean,std,len(id))
    # repl_arr = [k if k>1 else mean for k in repl_arr]
    df.loc[id, 'Age'] = repl_arr
df['Age'] = df.Age.round()

train['Age'] = df.Age.iloc[:train.shape[0]].astype(int)
test['Age'] = df.Age.iloc[train.shape[0]:].astype(int)
```

```python
df = pd.concat([train,test])

for i in df.Pclass:
  id = df.loc[(df.Pclass==i)&(df.Age.isna())].index
  temp = df.loc[df.Pclass == i].Age
  std = temp.std()
  mean = temp.mean()
  repl_arr = np.random.normal(mean,std,len(id))
  df.loc[id, 'Age'] = repl_arr
df['Age'] = df.Age.round()

train['Age'] = df.Age.iloc[:train.shape[0]].astype(int)
test['Age'] = df.Age.iloc[train.shape[0]:].astype(int)
```

```python
train_age = pd.concat([train['Age'], train_bu.Age, ], axis=1)
test_age = pd.concat([test['Age'], test_bu.Age], axis=1)

train_age.columns=['filled_train',  'wnan_train']#'Sex',
test_age.columns=['filled_test', 'wnan_test']

sex_col =  pd.concat([train.Sex, train.Sex, test.Sex, test.Sex]).reset_index(drop=True)
class_col = pd.concat([train.Pclass, train.Pclass, test.Pclass, test.Pclass]).reset_index(drop=True)


d1 = {'filled_train':'train',
         'filled_test':'test',
         'wnan_test':'test',
         'wnan_train':'train' }
d2 = {'filled_train':'filled',
         'filled_test':'filled',
         'wnan_test':'wnan',
         'wnan_train':'wnan'}
temp = pd.concat([train_age.melt(), test_age.melt()]).reset_index(drop=True)
temp = pd.concat([temp['value'],temp['variable'].replace(d1), temp['variable'].replace(d2), sex_col, class_col],

temp.columns = ['age', 'subset', 'filled', 'sex', 'class']
```

```python
]: a = sns.displot(data=temp, x='age', hue='filled', col='class', kind='kde')
```



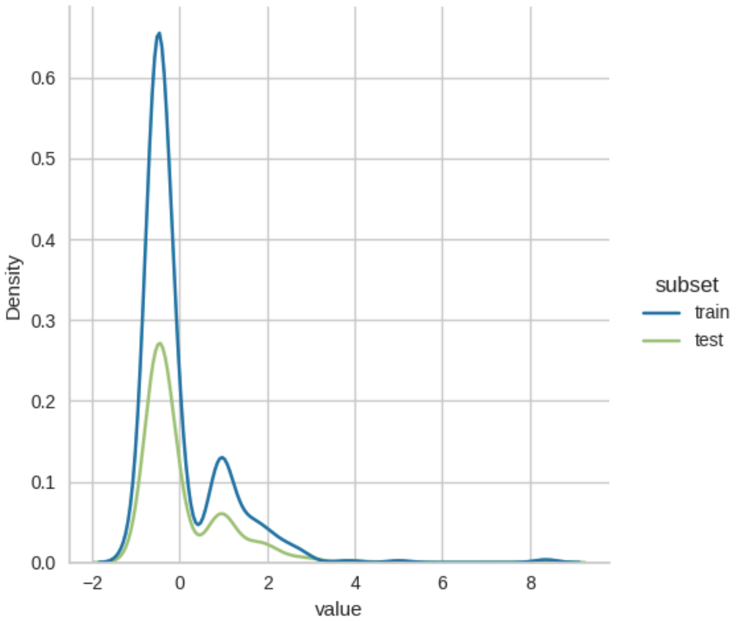

```python
: t1 = pd.Series(np.random.choice(t, a1.shape))
a1.reset_index(drop=True, inplace=True)
```

```python
def get_best_distribution(data):
    dist_names = ["norm", "exponweib", "weibull_max", "weibull_min", "pareto", "genextreme"]
    dist_results = []
    params = {}
    for dist_name in dist_names:
        dist = getattr(st, dist_name)
        param = dist.fit(data)

        params[dist_name] = param
        # Applying the Kolmogorov-Smirnov test
        D, p = st.kstest(data, dist_name, args=param)
        print("p value for "+dist_name+" = "+str(p))
        dist_results.append((dist_name, p))

    # select the best fitted distribution
    best_dist, best_p = (max(dist_results, key=lambda item: item[1]))
    # store the name of the best fit and its p value

    print("Best fitting distribution: "+str(best_dist))
    print("Best p value: "+ str(best_p))
    print("Parameters for the best fit: "+ str(params[best_dist]))

    return best_dist, best_p, params[best_dist]
get_best_distribution(data.loc[~data.isna()])
```

```
p value for norm = 4.090734030520837e-06
p value for exponweib = 0.0010394734025497118
p value for weibull_max = 0.00036793342881385316
p value for weibull_min = 9.937416623563527e-06
p value for pareto = 1.749205034758647e-86
p value for genextreme = 0.0003678772194694297
Best fitting distribution: exponweib
Best p value: 0.0010394734025497118
Parameters for the best fit: (15.26537334292596, 2.860196772430548, -82.61306733997591, 74.93359349480347)

('exponweib',
 0.0010394734025497118,
 (15.26537334292596, 2.860196772430548, -82.61306733997591, 74.93359349480347))
```

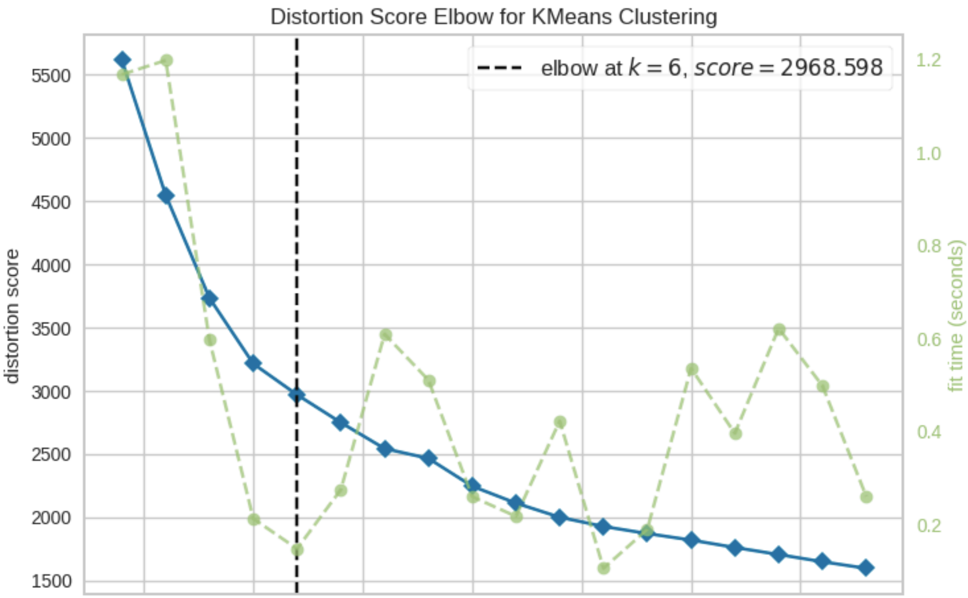
]:
```
a = pd.Series(['train' if i<test.shape[0] else 'test' for i in range(temp.shape[0])])
temp = pd.concat([pd.Series(np.random.choice(train.Fare, test.Fare.shape[0])), test.Fare])

temp = pd.concat([train.Fare, test.Fare]).reset_index(drop=True)
a = pd.Series(['train' if i<train.shape[0] else 'test' for i in range(temp.shape[0])])
temp = pd.concat([temp, a], axis=1)
temp.columns = ['value', 'subset']
sns.displot(data=temp, x='value', kind='kde', hue='subset', )
```

?]: <seaborn.axisgrid.FacetGrid at 0x79780921d870>



clustering vis

]:
```
from yellowbrick.cluster import KElbowVisualizer

X = pd.concat([train.drop('Survived', axis=1),test])

km = KMeans(random_state=42)
visualizer = KElbowVisualizer(km, k=(2,20))

visualizer.fit(X)        # Fit the data to the visualizer
visualizer.show()
```



Подбор моделей, обучение

testing models

од [ ]:
```python
x_train, x_test, y_train, y_test = train_test_split(train.drop('Survived', axis=1),train.Survived,
                                                    test_size=.25, random_state=42, shuffle=True,
                                                    stratify=train.Survived)
```

од [ ]:
```python
model_1 = LogisticRegression(max_iter=1000)
model_1.fit(x_train, y_train)
y_preds = model_1.predict(x_test)
# result_list[0] = (f'f1: {round(f1_score(y_test,y_preds),4)}\naccuracy: {round(accuracy_score(y_test,y_preds),
print(f'f1: {round(f1_score(y_test,y_preds),4)}\naccuracy: {round(accuracy_score(y_test,y_preds), 4)}')
```

```
f1: 0.75
accuracy: 0.8117
```

од [ ]:
```python
model_2 = RandomForestClassifier(random_state=42)
model_2.fit(x_train, y_train)
y_preds = model_2.predict(x_test)
print(f'f1: {round(f1_score(y_test,y_preds),4)}\naccuracy: {round(accuracy_score(y_test,y_preds), 4)}')
```

```
f1: 0.6795
accuracy: 0.7758
```

од [ ]:
```python
model_3 = DecisionTreeClassifier(random_state=42)
model_3.fit(x_train, y_train)
y_preds = model_3.predict(x_test)
print(f'f1: {round(f1_score(y_test,y_preds),4)}\naccuracy: {round(accuracy_score(y_test,y_preds), 4)}')
```

```
f1: 0.7232
accuracy: 0.7803
```

од [ ]:
```python
model_4 = LinearSVC(max_iter=2000, random_state=42)
model_4.fit(x_train, y_train)
y_preds = model_4.predict(x_test)
print(f'f1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
# print(result_list[3])
```

од [ ]:
```python
from xgboost import XGBClassifier, XGBRFClassifier
model_8 = XGBClassifier(random_state=42)
model_8.fit(x_train, y_train)
y_preds = model_8.predict(x_test)
print(f'XGBC /nf1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')

model_9 = XGBRFClassifier(random_state=42)
model_9.fit(x_train, y_train)
y_preds = model_9.predict(x_test)
print(f'XGBRFC /nf1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
```

```
XGBC /nf1: 0.75449
accuracy: 0.81614
XGBRFC /nf1: 0.725
accuracy: 0.80269
```

од [ ]:
```python
from sklearn.linear_model import SGDClassifier
model_10 = SGDClassifier(random_state=42)
model_10.fit(x_train, y_train)
y_preds = model_10.predict(x_test)
print(f'SGDC /nf1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
```

```
SGDC /nf1: 0.74713
accuracy: 0.80269
```

од [ ]:
```python
from sklearn.linear_model import PassiveAggressiveClassifier
model_11 = PassiveAggressiveClassifier(random_state=42)
model_11.fit(x_train, y_train)
y_preds = model_11.predict(x_test)
print(f'SGDC /nf1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
```

```
SGDC /nf1: 0.71628
accuracy: 0.72646
```

[ ]:

```
from sklearn.linear_model import RidgeClassifier
model_12 = RidgeClassifier(random_state=42)
model_12.fit(x_train, y_train)
y_preds = model_12.predict(x_test)
print(f'SGDC /nf1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
```

```
SGDC /nf1: 0.75862
accuracy: 0.81166
```

[ ]:

```
from sklearn.neural_network import MLPClassifier
model_13 = MLPClassifier(random_state=42)
model_13.fit(x_train, y_train)
y_preds = model_13.predict(x_test)
print(f'SGDC /nf1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
```

```
SGDC /nf1: 0.70064
accuracy: 0.78924
```

[ ]:

```
from sklearn.svm import NuSVC
model_14 = NuSVC(random_state=42, probability=True)
model_14.fit(x_train, y_train)
y_preds = model_14.predict(x_test)
print(f'SGDC /nf1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
```

```
SGDC /nf1: 0.76471
accuracy: 0.82063
```

[ ]:

```
from catboost import CatBoostClassifier
model_15 =  CatBoostClassifier(random_state=42, verbose=False)
model_15.fit(x_train, y_train)
y_preds = model_15.predict(x_test)
print(f'catboost /nf1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}
```

```
Collecting catboost
catboost /nf1: 0.73418
accuracy: 0.81166
```

[ ]:

```
from lightgbm import LGBMClassifier
model_16 = LGBMClassifier(num_leaves=25, verbose=-1, random_state=42)
model_16.fit(x_train, y_train)
y_preds = model_16.predict(x_test)
print(f'catboost /nf1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}
```

```
catboost /nf1: 0.73054
accuracy: 0.79821
```

[ ]:

```
ests = [('logreg' ,model_1), ('tree' ,model_3), ('linsvc' ,model_4), ('gbc' ,model_5), ('knn' ,model_7),
        ('rf' ,model_2), ('abc', model_6), ('XGBC', model_8), ('XGBRFC', model_9), ('SGDC', model_10), ('PAC', m
         ('RC', model_12), ('MLPC', model_13), ('NuSVC',model_14), ('cbc', model_15), ('lightgbm',model_16)]
ensemble_1 = VotingClassifier(estimators=ests)#, voting='soft')
ensemble_1.fit(x_train, y_train)
y_preds = ensemble_1.predict(x_test)
print(f'f1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
```

```
f1: 0.77576
accuracy: 0.83408
```

[ ]:

```
# ests = [('logreg' ,model_1), ('tree' ,model_3), ('linsvc' ,model_4), ('gbc' ,model_5), ('knn' ,model_7)]#, ('a
ensemble_2 = StackingClassifier(estimators=ests)#, final_estimator=model_4)
ensemble_2.fit(x_train, y_train)
y_preds = ensemble_2.predict(x_test)
print(f'f1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
```

```
f1: 0.7619
accuracy: 0.82063
```

[ ]:

```
from sklearn.naive_bayes import CategoricalNB
ensemble_3 = StackingClassifier(estimators=ests, final_estimator=model_1)
ensemble_3.fit(x_train, y_train)
y_preds = ensemble_3.predict(x_test)
print(f'f1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
```

```
f1: 0.76836
accuracy: 0.81614
```

[ ]:

```
ests = [('logreg' ,model_1), ('tree' ,model_3), ('gbc' ,model_5), ('knn' ,model_7),
        ('rf' ,model_2), ('abc', model_6), ('XGBC', model_8), ('XGBRFC', model_9), ('MLPC', model_13), ('NuSVC',
         ('cbc', model_15), ('lightgbm',model_16)]
ensemble_4 = VotingClassifier(estimators=ests, voting='soft')
ensemble_4.fit(x_train, y_train)
y_preds = ensemble_4.predict(x_test)
print(f'f1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
```

```
f1: 0.76829
accuracy: 0.8296
```

[ ]:

```
from sklearn.ensemble import BaggingClassifier
ensemble_5 = BaggingClassifier(estimator=model_2)
ensemble_5.fit(x_train, y_train)
y_preds = ensemble_5.predict(x_test)
print(f'f1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
```

```
f1: 0.74699
accuracy: 0.81166
```

6) Подбор гиперпараметров

optimizers

```
model_5 =  GradientBoostingClassifier(cv.best_params_)
model_5.fit(x_train, y_train)
y_preds = model_5.predict(x_test)
print(f'f1: {round(f1_score(y_test,y_preds),5)}\naccuracy: {round(accuracy_score(y_test,y_preds), 5)}')
```

...

```
gbc_params = {
    'loss': ['exponential', 'log_loss'],
    'learning_rate': [.07, .06, .05, .04, .03 ],
    'n_estimators': [i for i in range(83, 89, 2)],
    'criterion': ['friedman_mse', 'squared_error'],
    'tol': [1e-4, 9e-5, 2e-4]
}

cv = GridSearchCV(model_5, param_grid= gbc_params, scoring='accuracy')

cv.fit(x_train, y_train)
cv.best_score_
```

[389]: 0.8278083267871171

```
model_1 = LogisticRegression()
model_1.fit(x_train, y_train)
y_preds = model_1.predict(x_test)
# result_list[0] = (f'f1: {round(f1_score(y_test,y_preds),4)}\naccuracy: {round(accuracy_score(y_test,y_preds),
print(f'f1: {round(f1_score(y_test,y_preds),4)}\naccuracy: {round(accuracy_score(y_test,y_preds), 4)}')

lr_params = {
    'penalty': ['l1', 'l2', 'elasticnet'],
    'tol': [1e-4, 5e-5, 1e-5, 1e-3, 5e-4],
    'solver': ['lbfgs', 'liblinear', 'newton-cg', 'newton-cholesky', 'sag', 'saga'],# ['liblinear', 'saga'],
    'max_iter':[100,  500, 1000, 1500, 2000]

}
model = LogisticRegression()
cv = GridSearchCV(model, param_grid= lr_params, scoring='accuracy')

cv.fit(train.drop(['Survived',], axis=1),  train.Survived)
cv.best_score_
```

```
cv.best_params_
```

12]: {'max_iter': 100, 'penalty': 'l1', 'solver': 'saga', 'tol': 0.0001}

```
lr_params = {
    'penalty': ['l1', 'l2', 'elasticnet'],
    'tol': [1e-4, 5e-5, 1e-5, 1e-3, 5e-4],
    'solver': ['lbfgs', 'liblinear', 'newton-cg', 'newton-cholesky', 'sag', 'saga'],# ['liblinear', 'saga'],
    'max_iter':[10, 15, 20, 25, 50, 60, 70, 80, 90, 100, 150, 200, 250, 300, 350, 400]

}
model = LogisticRegression()
cv = HalvingGridSearchCV(model, param_grid= lr_params, scoring='accuracy', verbose=2)
cv.fit(train.drop(['Survived',], axis=1),  train.Survived)
```

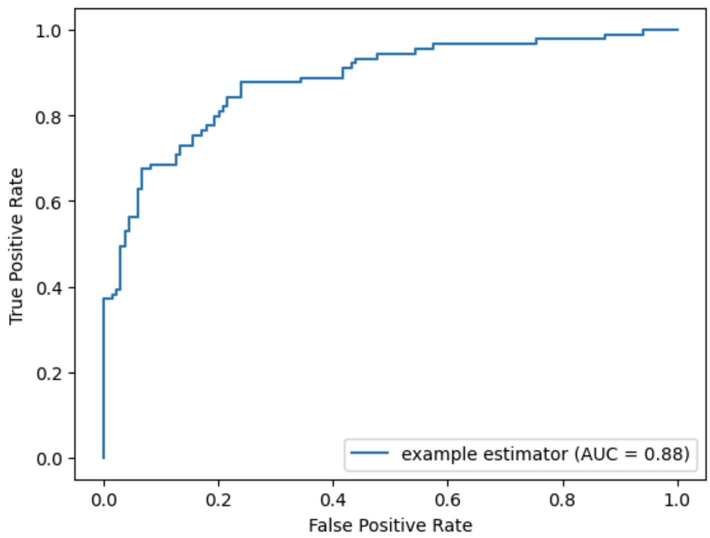
```
cv.best_score_
```

97]: 0.7984942886812045

```
cv.best_params_
```

52]: {'n_neighbors': 12, 'weights': 'uniform'}

```python
from sklearn import metrics

y_score = model_1.predict_proba(x_test)

fpr, tpr, _ = metrics.roc_curve(y_test, y_score[:,1])

roc_auc = metrics.auc(fpr, tpr)
display = metrics.RocCurveDisplay(fpr=fpr, tpr=tpr, roc_auc=roc_auc,
                                  estimator_name='example estimator')
display.plot()

plt.show()
```



Результат:

Несмотря на хорошие результаты большого колическтва моделей на тренировочной выборке. На тестовой выборке лучше всего себя проявила Логистическая регрессия с минимумом обработка данных,
0.78468

Модель	Результат
Логистическая регрессия	0.78468
KNN	0.77272
Градиентный бусины	0.76076
Стэкинг	0.75598