Survivor PREDICTION

3-survivors-transported-prediction

June 8, 2025

```
[1]: import numpy
    import pandas
    from sklearn.preprocessing import OneHotEncoder
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.model_selection import train_test_split
    from sklearn.metrics import classification_report
    from sklearn.preprocessing import StandardScaler
    from sklearn.model_selection import GridSearchCV
    from xgboost import XGBClassifier
    import matplotlib.pyplot as mat
    import seaborn as sns
    from sklearn.svm import SVC

# To remove the warnings for deperacations of the functions
    pandas.set_option('future.no_silent_downcasting', True)
```

[2]: # Bringing Data main_train_data = pandas.read_csv(r"/kaggle/input/spaceship-titanic/train.csv") main_test_data = pandas.read_csv(r"/kaggle/input/spaceship-titanic/test.csv") main_test_data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4277 entries, 0 to 4276
Data columns (total 13 columns):

#	Column	Non-Null Count	Dtype
0	PassengerId	4277 non-null	object
1	HomePlanet	4190 non-null	object
2	CryoSleep	4184 non-null	object
3	Cabin	4177 non-null	object
4	Destination	4185 non-null	object
5	Age	4186 non-null	float64
6	VIP	4184 non-null	object
7	RoomService	4195 non-null	float64
8	FoodCourt	4171 non-null	float64
9	${\tt ShoppingMall}$	4179 non-null	float64
10	Spa	4176 non-null	float64

```
11 VRDeck 4197 non-null float64
12 Name 4183 non-null object
```

dtypes: float64(6), object(7)
memory usage: 434.5+ KB

24133.000000

max

```
[3]: main_train_data.describe()
```

```
[3]:
                           RoomService
                                            FoodCourt
                                                        ShoppingMall
                     Age
                                                                                 Spa \
            8514.000000
                                                         8485.000000
                           8512.000000
                                          8510.000000
                                                                        8510.000000
     count
     mean
              28.827930
                            224.687617
                                           458.077203
                                                          173.729169
                                                                         311.138778
     std
              14.489021
                            666.717663
                                          1611.489240
                                                          604.696458
                                                                        1136.705535
     min
               0.000000
                              0.000000
                                             0.000000
                                                            0.000000
                                                                           0.000000
     25%
              19.000000
                              0.000000
                                             0.000000
                                                            0.000000
                                                                           0.000000
     50%
              27.000000
                              0.000000
                                             0.000000
                                                            0.000000
                                                                           0.00000
     75%
              38.000000
                             47.000000
                                            76.000000
                                                           27.000000
                                                                          59.000000
              79.000000
                          14327.000000
                                         29813.000000
                                                        23492.000000
                                                                       22408.000000
     max
                   VRDeck
             8505.000000
     count
     mean
              304.854791
             1145.717189
     std
                0.000000
     min
     25%
                0.00000
     50%
                 0.000000
     75%
                46.000000
```

```
[4]: fig, ax = mat.subplots(1, 5, figsize=(25, 6))

sns.histplot(main_train_data['RoomService'], bins=30, ax=ax[0])
sns.histplot(main_train_data['FoodCourt'], bins=30, ax=ax[1])
sns.histplot(main_train_data['ShoppingMall'], bins=30, ax=ax[2])
sns.histplot(main_train_data['Spa'], bins=30, ax=ax[3])
sns.histplot(main_train_data['VRDeck'], bins=30, ax=ax[4])

fig, axis = mat.subplots(1, 5, figsize=(25, 6))

sns.boxplot(main_train_data['RoomService'], ax=axis[0])
sns.boxplot(main_train_data['FoodCourt'], ax=axis[1])
sns.boxplot(main_train_data['ShoppingMall'], ax=axis[2])
sns.boxplot(main_train_data['Spa'], ax=axis[3])
sns.boxplot(main_train_data['VRDeck'], ax=axis[4])
```

/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

with pd.option_context('mode.use_inf_as_na', True):
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119: FutureWarning:

use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

with pd.option_context('mode.use_inf_as_na', True):

/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

with pd.option_context('mode.use_inf_as_na', True):

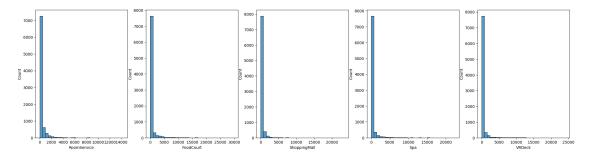
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

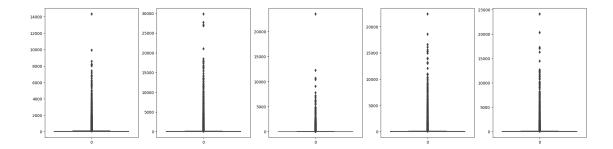
with pd.option_context('mode.use_inf_as_na', True):

/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

with pd.option_context('mode.use_inf_as_na', True):

[4]: <Axes: >





- We have a little bot of outliers and thus we cannot remove them now.
- Identical pattern can be seen

[5]: # Feature Engineering

Total Bill Generated during the journey

def engineeringfeature(data):

Done Done

0.1 - Handling the missing values for train dataset

```
[6]: transported_train = main_train_data['Transported']
[7]: # Function that handles both of the sets
encoder = OneHotEncoder(sparse_output=False)

def missing_value_handling(data, set):

    # Dividing the set into two parts
    categorical_fet = data.select_dtypes(include='object')
    continous_fet = data.select_dtypes(include=['float', 'int'])

# Using interpolate function for numerical features
interpolated_num = continous_fet.interpolate()

# Using mode for categorical fetures to fill the missing values
data['Cabin'] = data['Cabin'].fillna(data['Cabin'].mode()[0])
listings = categorical_fet.columns

for feature_name in listings:
    categorical_fet[feature_name] = categorical_fet[feature_name].

Gillna(categorical_fet[feature_name].mode()[0])
```

```
# One Hot Encoder
   cat_encoded = encoder.fit_transform(categorical_fet[['HomePlanet',_
 categorical_fet = pandas.DataFrame(
       cat encoded,
       columns = encoder.get_feature_names_out(['HomePlanet', 'CryoSleep',__
 ⇔'Destination', 'VIP'])
   )
   # Condition for knowing the dataset
   if set == 'train':
       data = pandas.concat(
           [categorical_fet, interpolated_num, transported_train,_

data[['PassengerId', 'Cabin']]], axis=1

   else:
       data = pandas.concat(
           [categorical_fet, interpolated_num, data[['PassengerId', __
 return data
train_data = missing_value_handling(data=main_train_data, set='train')
test_data = missing_value_handling(data=main_test_data, set='test')
```

```
print(passenger_id(main_data=main_test_data, data=test_data)) # For the

Graining Set
```

Done Done

```
[9]: scaler = StandardScaler()
     def transformer(data):
         splitted_data = []
         for all in data['Cabin']:
             splitted_data.append(all.split('/'))
         first = []
         second = []
         third = []
         for all in splitted_data:
             first.append(all[0])
             second.append(all[1])
             third.append(all[2])
         data['cabin_num'] = second
         return 'Done'
     print(transformer(data=train_data))
     print(transformer(data=test_data))
```

Done Done

```
[10]: train_data = train_data.drop(columns='Cabin')
test_data = test_data.drop(columns='Cabin')
```

0.1.1 Training Set Model Training and Model Prediction

```
# Training and predicting using training dataset
     X_train, X_test, y_train, y_test = train_test_split(
         Х, у,
         random_state=25,
         test_size=0.2
     )
     scaler = StandardScaler()
     X_train_scaled = scaler.fit_transform(X_train)
     X_test_scaled = scaler.fit_transform(X_test)
     # Training the model
     randomforest.fit(X_train_scaled, y_train)
     # Predictions
     predict = randomforest.predict(X_test_scaled)
      # Classification Report
     classification_repo = classification_report(y_test, predict, output_dict=True)
     cls_repo = pandas.DataFrame(classification_repo)
[12]: print('Classification Report :')
     cls_repo
     Classification Report :
[12]:
                     False
                                  True accuracy
                                                    macro avg weighted avg
     precision
                  0.675771
                              0.802980 0.719954
                                                     0.739376
                                                                   0.738169
     recall
                  0.865688
                              0.568581 0.719954
                                                     0.717135
                                                                   0.719954
     f1-score
                  0.759030
                              0.665752 0.719954
                                                     0.712391
                                                                   0.713276
     support
                886.000000 853.000000 0.719954 1739.000000
                                                               1739.000000
[13]: print('Out-Of-Bag Score ')
     print(randomforest.oob_score_)
     Out-Of-Bag Score
     0.7361230946218004
     XGBoost
[14]: # XGBOOST - X_training
     parameters = {
          'estimators':[100, 101, 103, 104],
          'learning_rate':[0.23, 0.24, 0.25, 0.26],
          'max_depth':[1, 2, 1, 3],
     }
```

```
listi = ['estimators', 'learning_rate', 'max_depth']
      reports = []
      itr = 0
      while itr < 1:
          for index in range(len(parameters['estimators'])):
              xg = XGBClassifier(
                  random_state=42,
                  colsample_bylevel=1,
                  colsample_bytree=1,
                  n_estimators=parameters[listi[itr]][index],
                  max_depth=parameters[listi[itr + 2]][index],
                  learning_rate=parameters[listi[itr + 1]][index]
              )
              xg.fit(X_train_scaled, y_train) # Training the model
              predict = xg.predict(X_test_scaled)
              classificationreport = classification_report(y_test, predict,__
       →output_dict=True)
              cls_reports = reports.append(classificationreport)
              print(f'Done {cls_reports}')
          break
     Done None
     Done None
     Done None
     Done None
[15]: def score_checker(
          report_list, # A list of report
          lookup_score, # What score we want
          type, # both True and false or True or False
```

if lookup_score != 'accuracy':

report=None # A simple report also can be given

if isinstance(report_list, list):

if lookup_score:

):

if report_list:

try:

```
for report in report_list:
                            true_val = report['True']
                            false_val = report['False']
                            true_sorted = sorted(true_val.items(), key=lambda__
 →item: item[1])
                            false_sorted = sorted(false_val.items(), key=lambda_
 →item: item[1])
                            if type == 'both':
                                return {
                                         'True Value':true_sorted,
                                         'False Value':false_sorted
                            elif type == 'true':
                                return true_sorted
                            else:
                                return false_sorted
                    else:
                        for report in report_list:
                            accuracy = report[lookup_score]
                            return accuracy
            except (TypeError):
                print('There should be a string given like\nprecision, recall∟
 →and so on')
        else:
            pass
    elif report != None:
        pass
    else:
        pass
accuracy = score_checker(report_list=reports, type='true',__
 →lookup_score='accuracy')
print('Accuracy -', round(accuracy, 3))
```

Accuracy - 0.75

1 Original Predictions

1.1 Random Forest

Out-of-box score: 0.735649373058783

1.2 XG Boost Classifier

```
[17]: xgboost = XGBClassifier(
    n_estimators=100,
    max_depth=1,
    learning_rate=0.01,
    random_state=41
)

xgboost.fit(X_scaled, y)

predict_values = xgboost.predict(scaler.fit_transform(test_data.
    drop(columns='PassengerId')))

predict_values
```

```
[17]: array([1, 0, 1, ..., 1, 0, 1])
```

1.3 SVM (Support Vector Machine)