In [57]:

```
import pandas as pd
from datetime import datetime
import numpy as np
import datetime as dt
import matplotlib.pyplot as plt

import seaborn as sns
import plotly.express as px

from sklearn import preprocessing
from sklearn.metrics import mean_squared_error, f1_score, precision_score, recall_score, accuracy_score
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
```

In [58]:

```
#Original Data
test = pd.read_csv(r'OneDrive\Desktop\test.csv')
train = pd.read_csv(r'OneDrive\Desktop\train.csv')
```

In [59]:

```
test
```

Out[59]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...
413	1305	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500	NaN	S
414	1306	1	Oliva y Ocana, Dona. Fermina	female	39.0	0	0	PC 17758	108.9000	C105	C
415	1307	3	Saether, Mr. Simon Sivertsen	male	38.5	0	0	SOTON/O.Q. 3101262	7.2500	NaN	S
416	1308	3	Ware, Mr. Frederick	male	NaN	0	0	359309	8.0500	NaN	S
417	1309	3	Peter, Master. Michael J	male	NaN	1	1	2668	22.3583	NaN	C

418 rows × 11 columns

In [60]:

```
train
```

Out[60]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	Q

891 rows × 12 columns

EDA

Cleaning the Data

In [61]:

```
train.describe()
```

Out[61]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

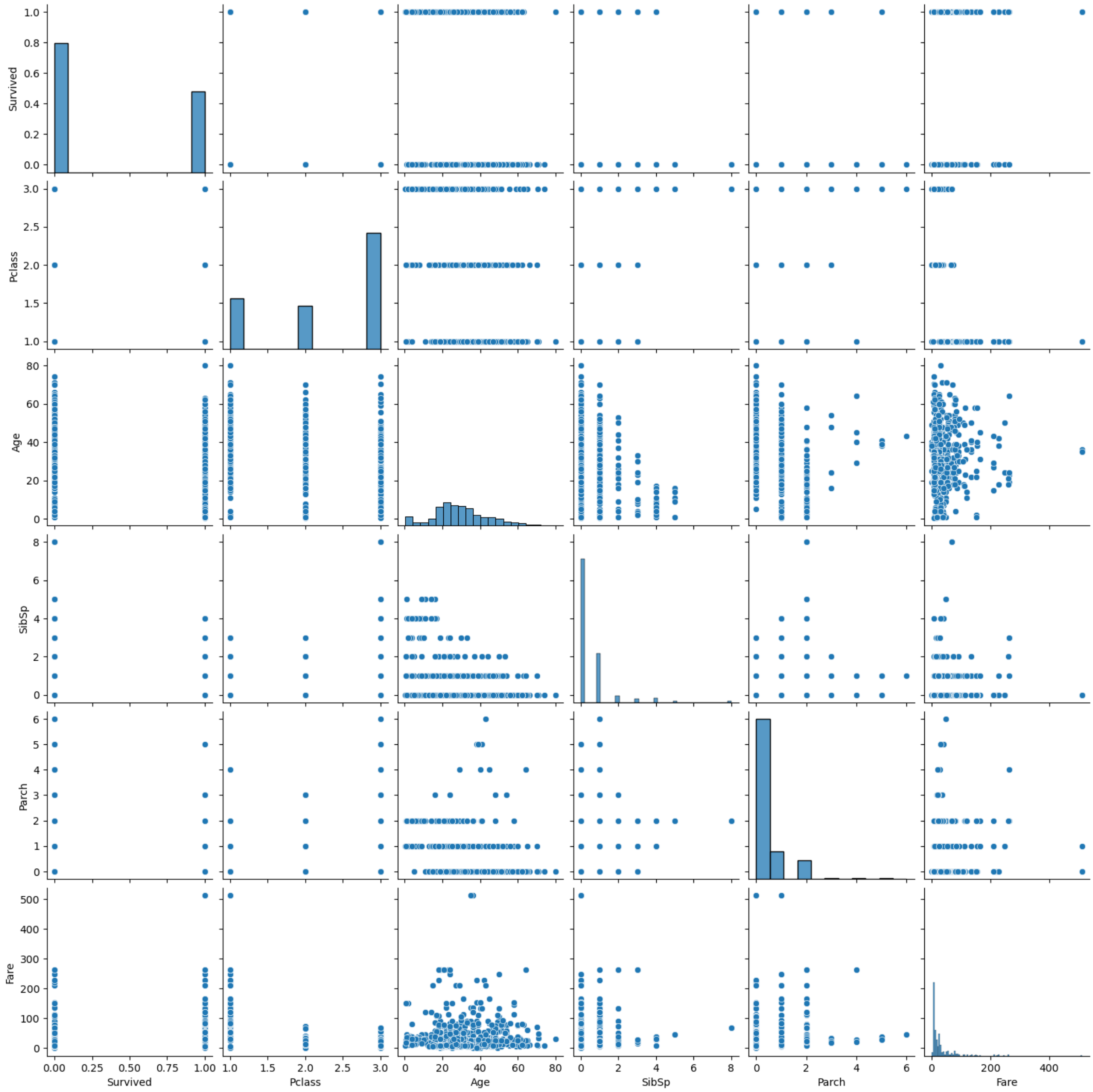
In [62]:

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

In [63]:

```
#correlation of non-numeric features
sns.pairplot(train.drop(columns=['PassengerId']))
plt.show()
```



In [64]:

```
#remove outlier high fare, remove id, name, ticket (ticket #) /drop fare >= 400 in test and train?
```

In [65]:

```
np.where(train.Fare >= 400, 1, 0).sum()
```

Out[65]:

3

In [66]:

```
np.where(test.Fare >= 400, 1, 0).sum()
```

Out[66]:

1

In [67]:

```
np.where(train.Fare >= 200, 1, 0).sum()
```

Out[67]:

20

In [68]:

```
np.where(test.Fare >= 200, 1, 0).sum()
```

Out[68]:

18

In [69]:

```
#Removing outliers and removing unnecessary columns (cleaning the data)
test = test.query("Fare < 400").drop(columns=['PassengerId', 'Name', 'Ticket'])
train = train.query("Fare < 400").drop(columns=['PassengerId', 'Name', 'Ticket'])
```

In [70]:

```
test
```

Out[70]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Cabin	Embarked
0	3	male	34.5	0	0	7.8292	NaN	Q
1	3	female	47.0	1	0	7.0000	NaN	S
2	2	male	62.0	0	0	9.6875	NaN	Q
3	3	male	27.0	0	0	8.6625	NaN	S
4	3	female	22.0	1	1	12.2875	NaN	S
...	...	...	...	...	...	...	...	...
413	3	male	NaN	0	0	8.0500	NaN	S
414	1	female	39.0	0	0	108.9000	C105	C
415	3	male	38.5	0	0	7.2500	NaN	S
416	3	male	NaN	0	0	8.0500	NaN	S
417	3	male	NaN	1	1	22.3583	NaN	C

416 rows × 8 columns

In [71]:

```
train
```

Out[71]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Cabin	Embarked
0	0	3	male	22.0	1	0	7.2500	NaN	S
1	1	1	female	38.0	1	0	71.2833	C85	C
2	1	3	female	26.0	0	0	7.9250	NaN	S
3	1	1	female	35.0	1	0	53.1000	C123	S
4	0	3	male	35.0	0	0	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...
886	0	2	male	27.0	0	0	13.0000	NaN	S
887	1	1	female	19.0	0	0	30.0000	B42	S
888	0	3	female	NaN	1	2	23.4500	NaN	S
889	1	1	male	26.0	0	0	30.0000	C148	C
890	0	3	male	32.0	0	0	7.7500	NaN	Q

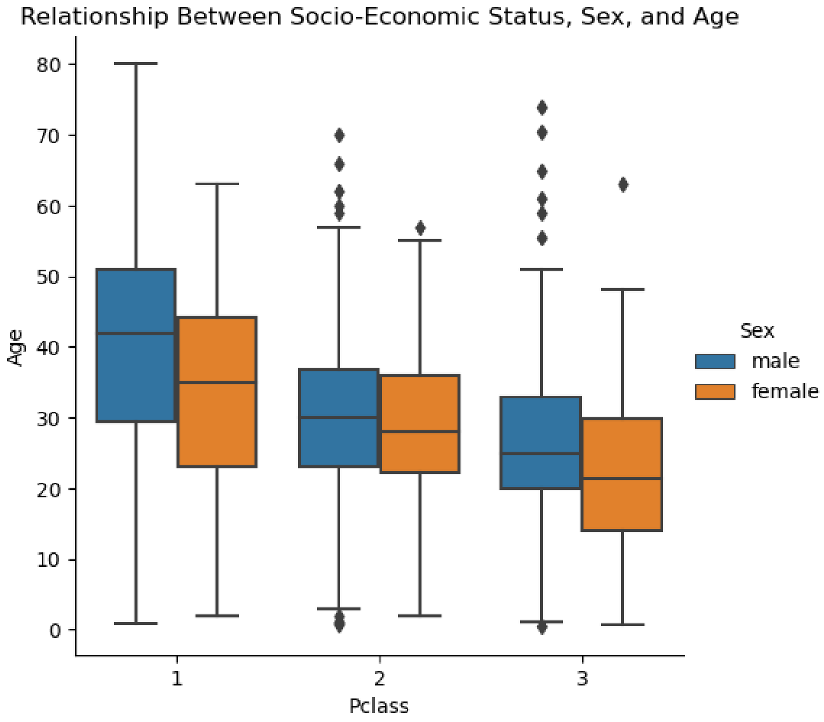
888 rows × 9 columns

Relation Between Socio-Economic Status and Other Features

In [72]:

```
es class relate to age, sex and family member on board
d ppl in class 1 so no outliers, but in 2 and 3 there are so many more oyung ppl that the old ppl become outliers


lot(data=train, x="Pclass", y="Age", kind="box", hue="Sex").set(title="Relationship Between Socio-Economic Status, Sex, and Age
()
```



In [73]:

```
#
train.groupby(['Pclass'])['Fare'].mean()
```

Out[73]:

```
Pclass
1    78.124061
2    20.662183
3    13.675550
Name: Fare, dtype: float64
```

In [74]:

```
train.groupby(['Pclass', 'Parch'])['Fare'].mean()
```

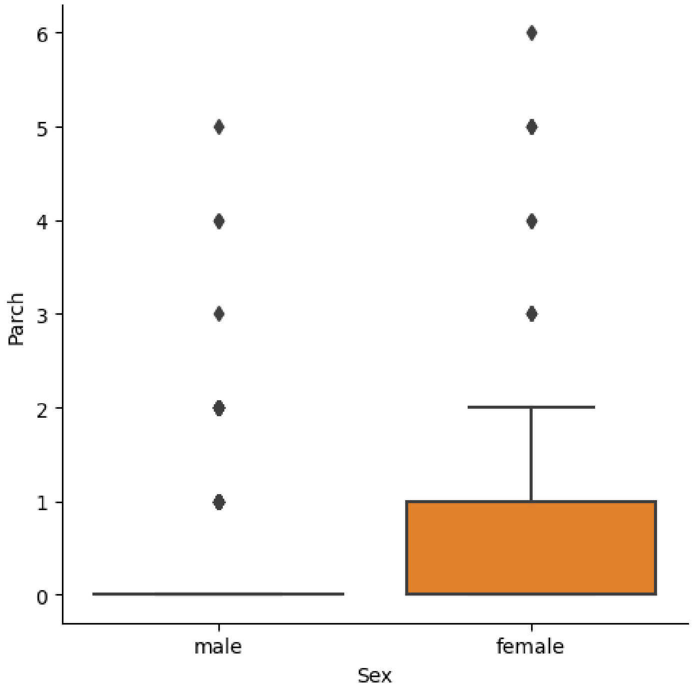
Out[74]:

```
Pclass  Parch
1       0         63.128312
        1        101.885000
        2        150.343648
        4        263.000000
2       0         17.467132
        1         27.609506
        2         33.499488
        3         20.875000
3       0         10.023412
        1         19.408033
        2         33.809300
        3         29.336100
        4         25.625000
        5         32.550000
        6         46.900000
Name: Fare, dtype: float64
```

In [75]:

```
#Bad plot tbh

sns.catplot(data=train, x="Sex", y="Parch", kind="box")
plt.show()
```



In [76]:

```
train.query("Sex == 'female' & Parch > 0").shape
```

Out[76]:

```
(120, 9)
```

In [77]:

```
train.groupby(['Pclass','Sex']).size()
```

Out[77]:

```
Pclass  Sex
1       female     93
        male      120
2       female     76
        male      108
3       female    144
        male      347
dtype: int64
```

In [78]:

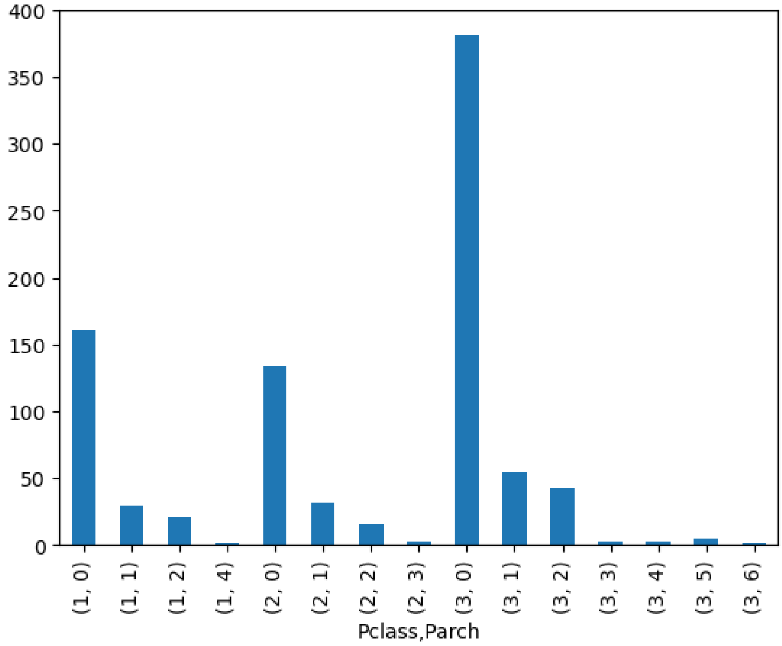
```
#Bad table tbh
train.groupby(['Pclass','Age']).size()
```

Out[78]:

```
Pclass  Age
1       0.92     1
        2.00     1
        4.00     1
        11.00    1
        14.00    1
                ..
3       61.00    1
        63.00    1
        65.00    1
        70.50    1
        74.00    1
Length: 182, dtype: int64
```

In [79]:

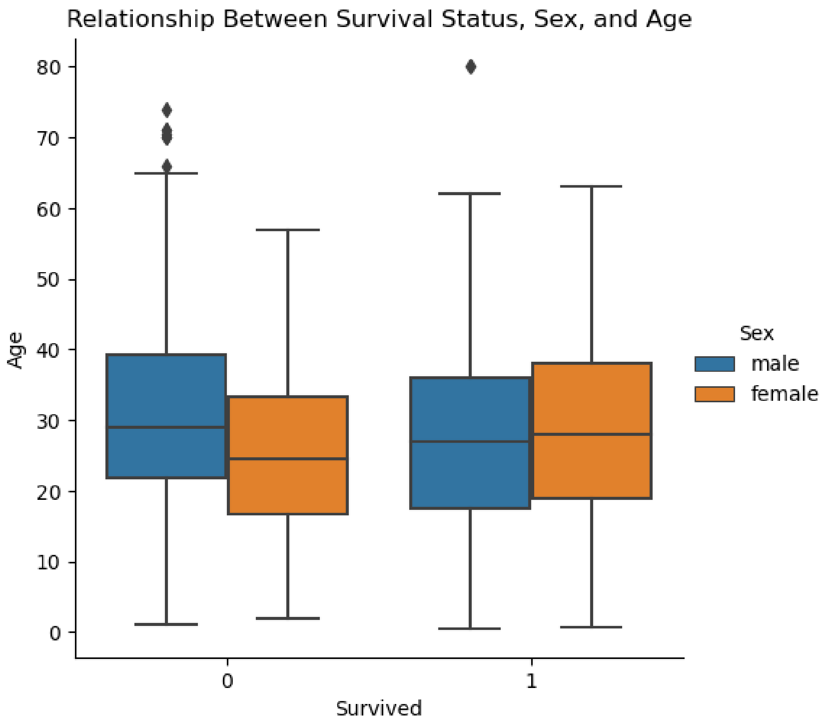
```
train.groupby(['Pclass','Parch']).size().plot.bar()
plt.show()
```



Relation Between Survival Status and Other Features

In [80]:

```
sns.catplot(data=train, x="Survived", y="Age", kind="box", hue="Sex").set(title="Relationship Between Survival Status, Sex, and
plt.show()
```



In [81]:

```
train.groupby(['Survived'])['Fare'].mean()
```

Out[81]:

```
Survived
0    22.117887
1    44.289799
Name: Fare, dtype: float64
```

In [82]:

```
train.groupby(['Survived','Sex']).size()
```

Out[82]:

```
Survived  Sex
0         female     81
          male      468
1         female    232
          male      107
dtype: int64
```

Correlation Between All Numeric Features

In [83]:

```
#CORRELATION STUFF
train.corr()
```

Out[83]:

	Survived	Pclass	Age	SibSp	Parch	Fare
Survived	1.000000	-0.334068	-0.079472	-0.033395	0.082157	0.261742
Pclass	-0.334068	1.000000	-0.368625	0.080937	0.018212	-0.604960
Age	-0.079472	-0.368625	1.000000	-0.307639	-0.189194	0.100396
SibSp	-0.033395	0.080937	-0.307639	1.000000	0.415141	0.211816
Parch	0.082157	0.018212	-0.189194	0.415141	1.000000	0.263910
Fare	0.261742	-0.604960	0.100396	0.211816	0.263910	1.000000

In [84]:

```
test
```

Out[84]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Cabin	Embarked
0	3	male	34.5	0	0	7.8292	NaN	Q
1	3	female	47.0	1	0	7.0000	NaN	S
2	2	male	62.0	0	0	9.6875	NaN	Q
3	3	male	27.0	0	0	8.6625	NaN	S
4	3	female	22.0	1	1	12.2875	NaN	S
...	...	...	...	...	...	...	...	...
413	3	male	NaN	0	0	8.0500	NaN	S
414	1	female	39.0	0	0	108.9000	C105	C
415	3	male	38.5	0	0	7.2500	NaN	S
416	3	male	NaN	0	0	8.0500	NaN	S
417	3	male	NaN	1	1	22.3583	NaN	C

416 rows × 8 columns

In [85]:

```
train
```

Out[85]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Cabin	Embarked
0	0	3	male	22.0	1	0	7.2500	NaN	S
1	1	1	female	38.0	1	0	71.2833	C85	C
2	1	3	female	26.0	0	0	7.9250	NaN	S
3	1	1	female	35.0	1	0	53.1000	C123	S
4	0	3	male	35.0	0	0	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...
886	0	2	male	27.0	0	0	13.0000	NaN	S
887	1	1	female	19.0	0	0	30.0000	B42	S
888	0	3	female	NaN	1	2	23.4500	NaN	S
889	1	1	male	26.0	0	0	30.0000	C148	C
890	0	3	male	32.0	0	0	7.7500	NaN	Q

888 rows × 9 columns

In [86]:

```
#logistic, KNN and 1 more (random_forest)
```

In [87]:

```
train.isnull().sum()
```

Out[87]:

```
Survived      0
Pclass        0
Sex           0
Age         177
SibSp         0
Parch         0
Fare          0
Cabin       686
Embarked      2
dtype: int64
```

In [88]:

```
train.columns
```

Out[88]:

```
Index(['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Cabin',
       'Embarked'],
      dtype='object')
```

Modeling and Question Answering

Prepping the Data for Modeling

In [103]:

```
prepped_data = prep_data(train)
prepped_data_x = prepped_data.drop(columns = ['Survived'])
prepped_data_y = prepped_data['Survived']

train_test_list = train_test_split(prepped_data)
my_train = train_test_list[0]
my_test = train_test_list[1]
```

In [116]:

```
my_train
```

Out[116]:

	Survived	Pclass	Age	SibSp	Parch	Fare	male	Q	S
582	0	2	54.0	0	0	26.0000	1	0	1
404	0	3	20.0	0	0	8.6625	0	0	1
9	1	2	14.0	1	0	30.0708	0	0	0
559	1	3	36.0	1	0	17.4000	0	0	1
540	1	1	36.0	0	2	71.0000	0	0	1
...	...	...	...	...	...	...	...	...	...
498	0	1	25.0	1	2	151.5500	0	0	1
595	0	3	36.0	1	1	24.1500	1	0	1
858	1	3	24.0	0	3	19.2583	0	0	0
742	1	1	21.0	2	2	262.3750	0	0	0
491	0	3	21.0	0	0	7.2500	1	0	1

531 rows × 9 columns

Functions for Modeling

In [105]:

```
def prep_data(data):
    droped_train = data.drop(columns=['Cabin']).dropna()
    sex_dummies = pd.get_dummies(droped_train.Sex, drop_first=True)
    embarked_dummies = pd.get_dummies(droped_train.Embarked, drop_first=True)

    new_train = pd.concat([droped_train.drop(columns=['Sex','Embarked']), sex_dummies, embarked_dummies], axis = 1)
    return new_train

def build_model(train_x, train_y, test_x, model_type, data_for_cv_x, data_for_cv_y):
    if model_type == "logistic_regression":
        model = LogisticRegression()
        cv_scores = cross_val_score(model, data_for_cv_x, data_for_cv_y, cv=5)

    elif model_type == "KNN":
        model  = KNeighborsClassifier(n_neighbors=3)
        cv_scores = cross_val_score(model, data_for_cv_x, data_for_cv_y, cv=5)
    else:
        model = RandomForestClassifier(random_state = 0)
        cv_scores = cross_val_score(model, data_for_cv_x, data_for_cv_y, cv=5)

    model.fit(train_x, train_y)
    res = model.predict(test_x)
    return res, cv_scores
```

Creating the 3 Models: Logistic Regression, K-Nearest-Neighbors, and Random Forest

In [106]:

```
my_train_x = my_train.drop(columns=['Survived'])
my_train_y = my_train['Survived']

my_test_x = my_test.drop(columns=['Survived'])
my_test_y = my_test['Survived']

lr_model = build_model(my_train_x, my_train_y, my_test_x, "logistic_regression", prepped_data_x, prepped_data_y)
lr_pred, lr_cv_scores = lr_model


knn_model = build_model(my_train_x, my_train_y, my_test_x, "KNN", prepped_data_x, prepped_data_y)
knn_pred, knn_cv_scores = knn_model

rf_model = build_model(my_train_x, my_train_y, my_test_x, "Random Forest", prepped_data_x, prepped_data_y)
rf_pred, rf_cv_scores = rf_model
```

```
C:\Users\ukolv\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs fail
ed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/preproce
ssing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/stab
le/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
C:\Users\ukolv\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs fail
ed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/preproce
ssing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/stab
le/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
C:\Users\ukolv\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs fail
ed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/preproce
ssing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/stab
le/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
C:\Users\ukolv\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs fail
ed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/preproce
ssing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/stab
le/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
C:\Users\ukolv\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs fail
ed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/preproce
ssing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/stab
le/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
C:\Users\ukolv\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs fail
ed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/preproce
ssing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/stab
le/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
C:\Users\ukolv\anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:228: FutureWarning: Unlike other
reduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves the axis it ac
ts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `ax
is` over which the statistic is taken will be eliminated, and the value None will no longer be accepted. Set `ke
epdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\Users\ukolv\anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:228: FutureWarning: Unlike other
reduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves the axis it ac
ts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `ax
is` over which the statistic is taken will be eliminated, and the value None will no longer be accepted. Set `ke
epdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\Users\ukolv\anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:228: FutureWarning: Unlike other
reduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves the axis it ac
ts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `ax
is` over which the statistic is taken will be eliminated, and the value None will no longer be accepted. Set `ke
epdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

```
C:\Users\ukolv\anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:228: FutureWarning: Unlike other
reduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves the axis it ac
ts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `ax
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  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\Users\ukolv\anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:228: FutureWarning: Unlike other
reduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves the axis it ac
ts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `ax
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epdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\Users\ukolv\anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:228: FutureWarning: Unlike other
reduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves the axis it ac
ts along. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `ax
is` over which the statistic is taken will be eliminated, and the value None will no longer be accepted. Set `ke
epdims` to True or False to avoid this warning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

In [107]:

```
lr_pred
```

Out[107]:

```
array([0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0,
       1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1,
       1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1,
       0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1,
       1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1,
       0, 1], dtype=int64)
```

In [108]:

```
knn_pred
```

Out[108]:

```
array([1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0,
       1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0,
       0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1,
       1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1,
       0, 0], dtype=int64)
```

In [109]:

```
rf_pred
```

Out[109]:

```
array([0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1,
       1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1,
       1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1,
       0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1,
       0, 1], dtype=int64)
```

In [110]:

```
def print_all(test_y, y_prediction):
    my_f1_score = round(f1_score(test_y, y_prediction) , 4)
    my_recall_score = round(recall_score(test_y, y_prediction), 4)
    my_precision_score = round(precision_score(test_y, y_prediction), 4)
    my_accuracy_score = round(accuracy_score(test_y, y_prediction), 4)


    print('f1_score: {}'.format(my_f1_score))
    print('recall_score: {}'.format(my_recall_score))
    print('precision_score: {}'.format(my_precision_score))
    print('accuracy_score: {}'.format(my_accuracy_score))
```

Evaluating the Performance of Each Model

In [111]:

```
print_all(my_test_y, lr_pred)
```

```
f1_score: 0.752
recall_score: 0.7705
precision_score: 0.7344
accuracy_score: 0.8258
```

In [112]:

```
print_all(my_test_y, knn_pred)
```

```
f1_score: 0.688
recall_score: 0.7049
precision_score: 0.6719
accuracy_score: 0.7809
```

In [113]:

```
print_all(my_test_y, rf_pred)
```

```
f1_score: 0.7377
recall_score: 0.7377
precision_score: 0.7377
accuracy_score: 0.8202
```

Evaluating Performance After Cross Validation

In [114]:

```
#Accuracy of Model with Cross Validation
lr_cv_mean = round(np.mean(lr_cv_scores),4)
knn_cv_mean = round(np.mean(knn_cv_scores),4)
rf_cv_mean = round(np.mean(rf_cv_scores),4)

print('Mean Accuracy with Cross Validation Set of Logistic Regression Model: {}'.format(lr_cv_mean))
print('Mean Accuracy with Cross Validation Set of K-Nearest-Neighbors Model: {}'.format(knn_cv_mean))
print('Mean Accuracy with Cross Validation Set of Random Forest Model: {}'.format(rf_cv_mean))
```

```
Mean Accuracy with Cross Validation Set of Logistic Regression Model: 0.7885
Mean Accuracy with Cross Validation Set of K-Nearest-Neighbors Model: 0.6926
Mean Accuracy with Cross Validation Set of Random Forest Model: 0.7913
```

In [ ]:

```
```