Titanic - Machine Learning from Disaster

Predict survival on the Titanic and get familiar with ML basics

In [1]:

```
### importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objs as go
import cufflinks as cf
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
init_notebook_mode(connected=True)
cf.go_offline()

### importing All models
from sklearn.ensemble import RandomForestClassifier,GradientBoostingClassifier,AdaB
from xgboost import XGBClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import GridSearchCV
from lightgbm import LGBMClassifier

### importing Data preprocessing tools
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedKFold, cross_val_score

### importing metrices
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

sns.set(rc = {'figure.figsize':(8,5)})
sns.set_palette('husl')
%matplotlib inline
```

In [2]:

```
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
subm = pd.read_csv('gender_submission.csv')
```

In [3]:
```
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 [4]:
```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Pclass       418 non-null    int64  
 2   Name         418 non-null    object 
 3   Sex          418 non-null    object 
 4   Age          332 non-null    float64
 5   SibSp        418 non-null    int64  
 6   Parch        418 non-null    int64  
 7   Ticket       418 non-null    object 
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object 
 10  Embarked     418 non-null    object 
dtypes: float64(2), int64(4), object(5)
memory usage: 36.0+ KB
```

In [5]:
```
train.isnull().sum()
```

Out[5]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

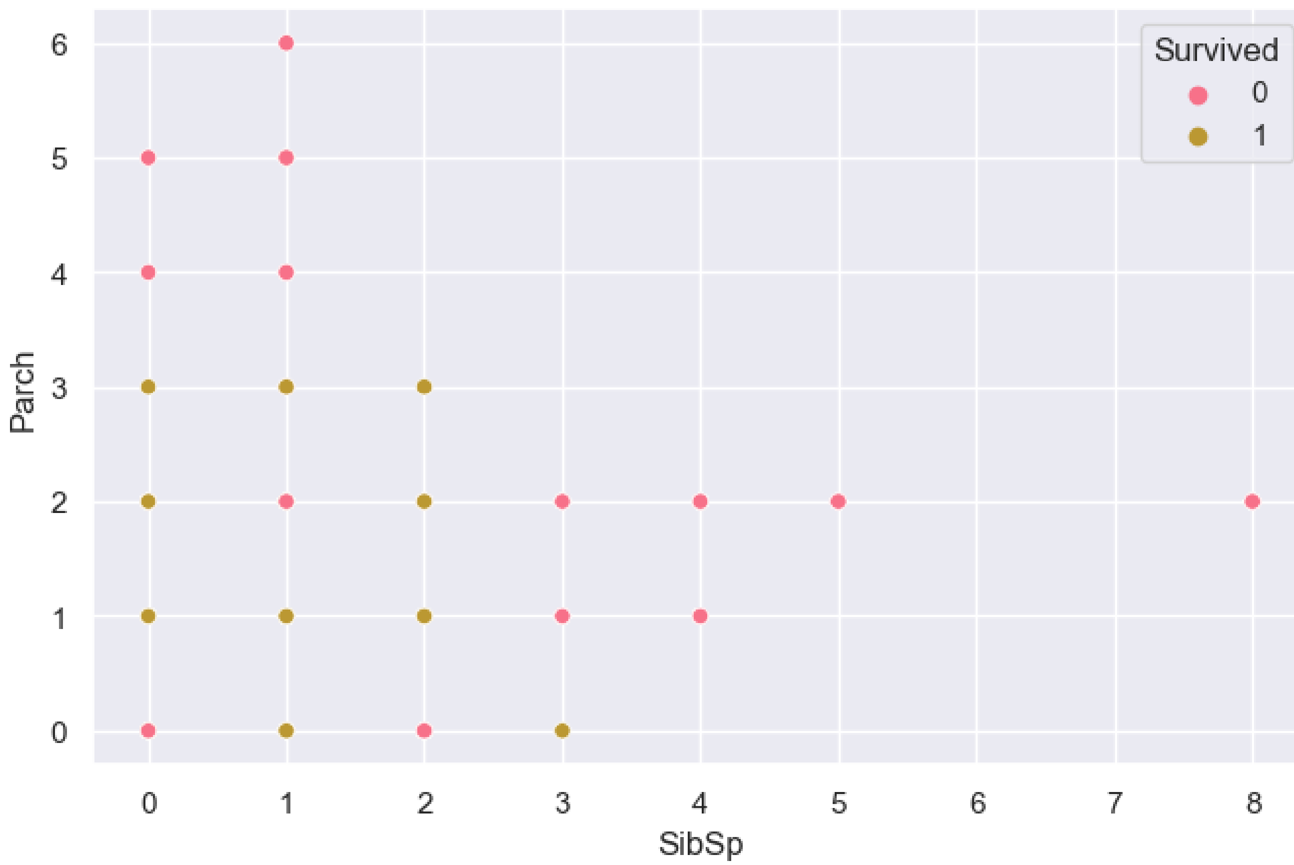
In [6]:
```
test.isnull().sum()
```

Out[6]:
```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

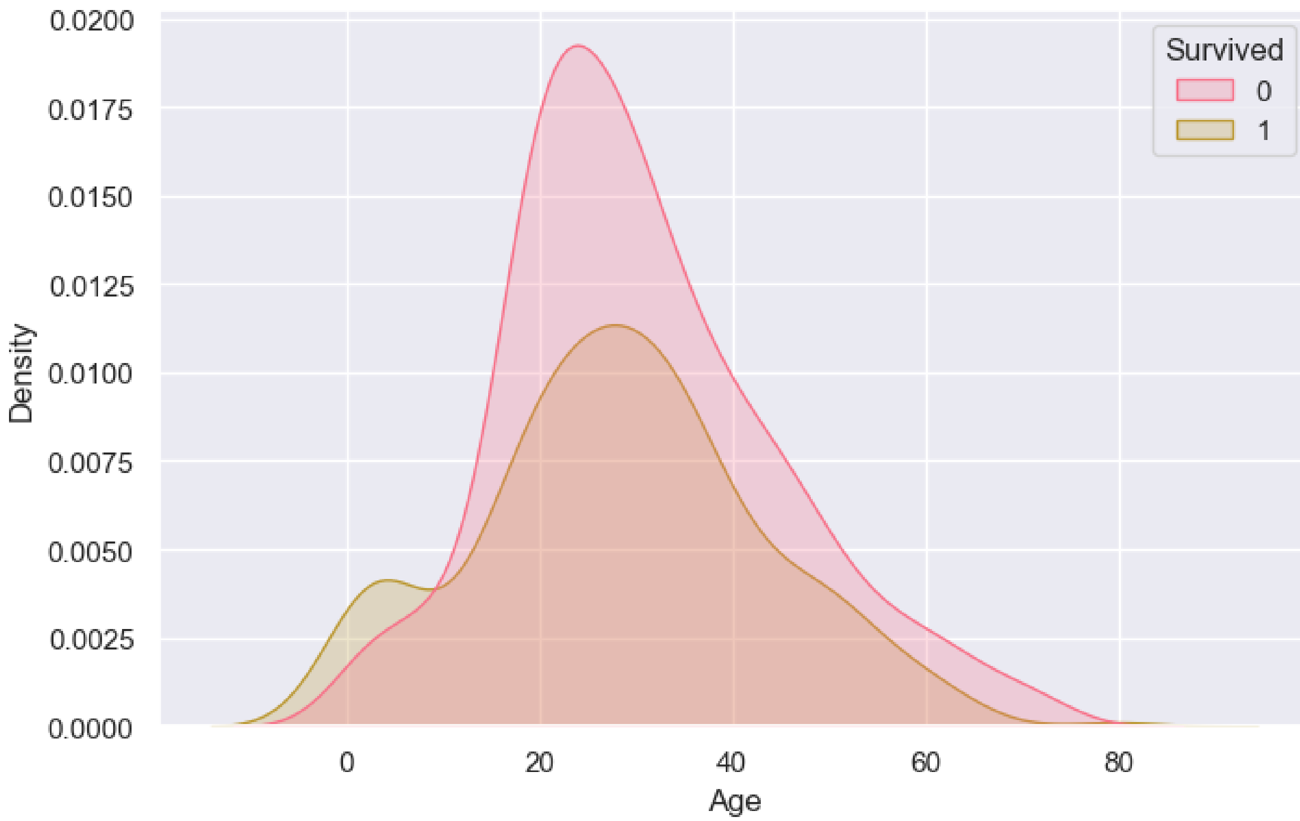
Data cleaning , visualization and EDA

In [7]:
```
sns.scatterplot(data=train, x='SibSp', y='Parch', hue='Survived')
```

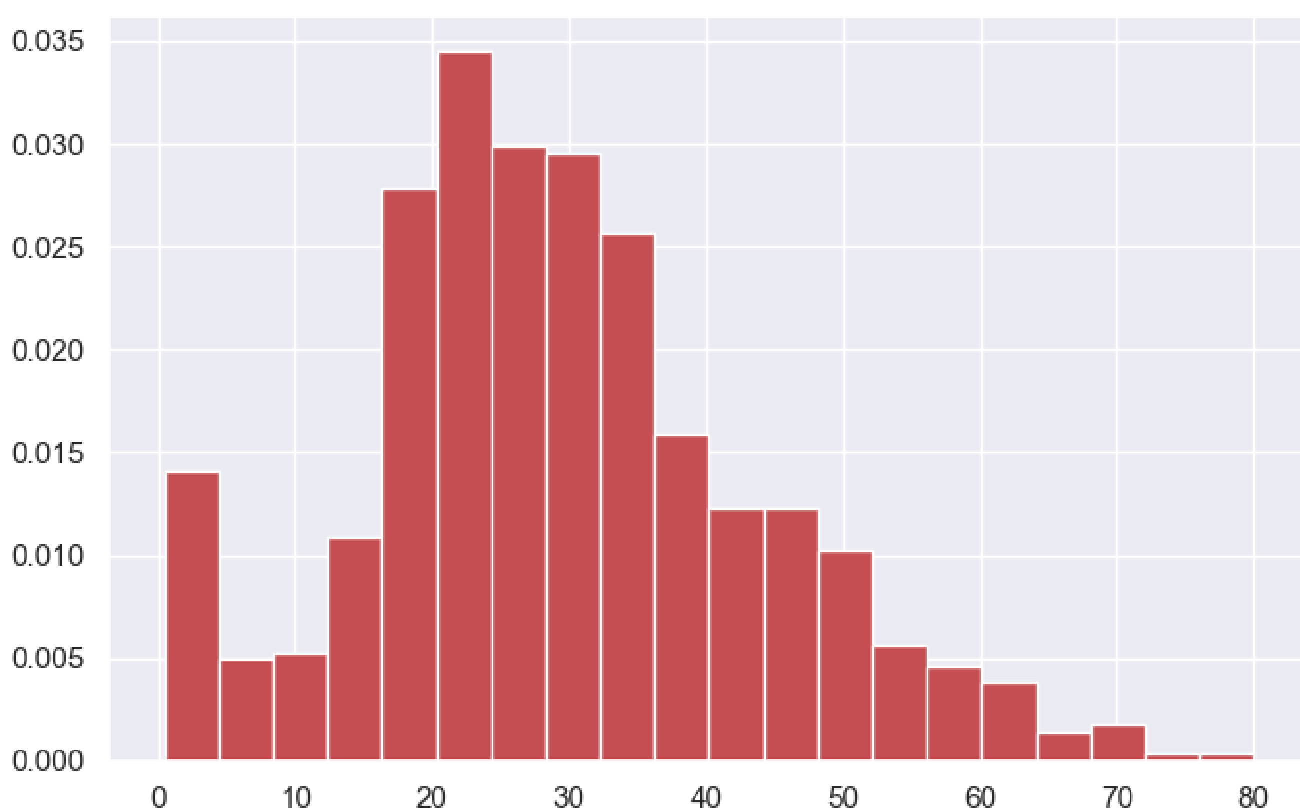
Out[7]:
```
<Axes: xlabel='SibSp', ylabel='Parch'>
```



In [8]:
```
sns.kdeplot(data=train, x='Age', hue='Survived', fill=True)
```
Out[8]: <Axes: xlabel='Age', ylabel='Density'>



In [9]:
```
plt.hist(train.Age, density=True, bins=20, color='r')
plt.show()
```



In [10]:

```
df = train[(train.Pclass == 1) & ((train.Fare > 80) & (train.Fare < 100)) ]
df.head()
```

Out[10]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
34	35	0	1	Meyer, Mr. Edgar Joseph	male	28.0	1	0	PC 17604	82.1708	NaN	C
62	63	0	1	Harris, Mr. Henry Birkhardt	male	45.0	1	0	36973	83.4750	C83	S
224	225	1	1	Hoyt, Mr. Frederick Maxfield	male	38.0	1	0	19943	90.0000	C93	S
230	231	1	1	Harris, Mrs. Henry Birkhardt (Irene Wallach)	female	35.0	1	0	36973	83.4750	C83	S
245	246	0	1	Minahan, Dr. William Edward	male	44.0	2	0	19928	90.0000	C78	Q

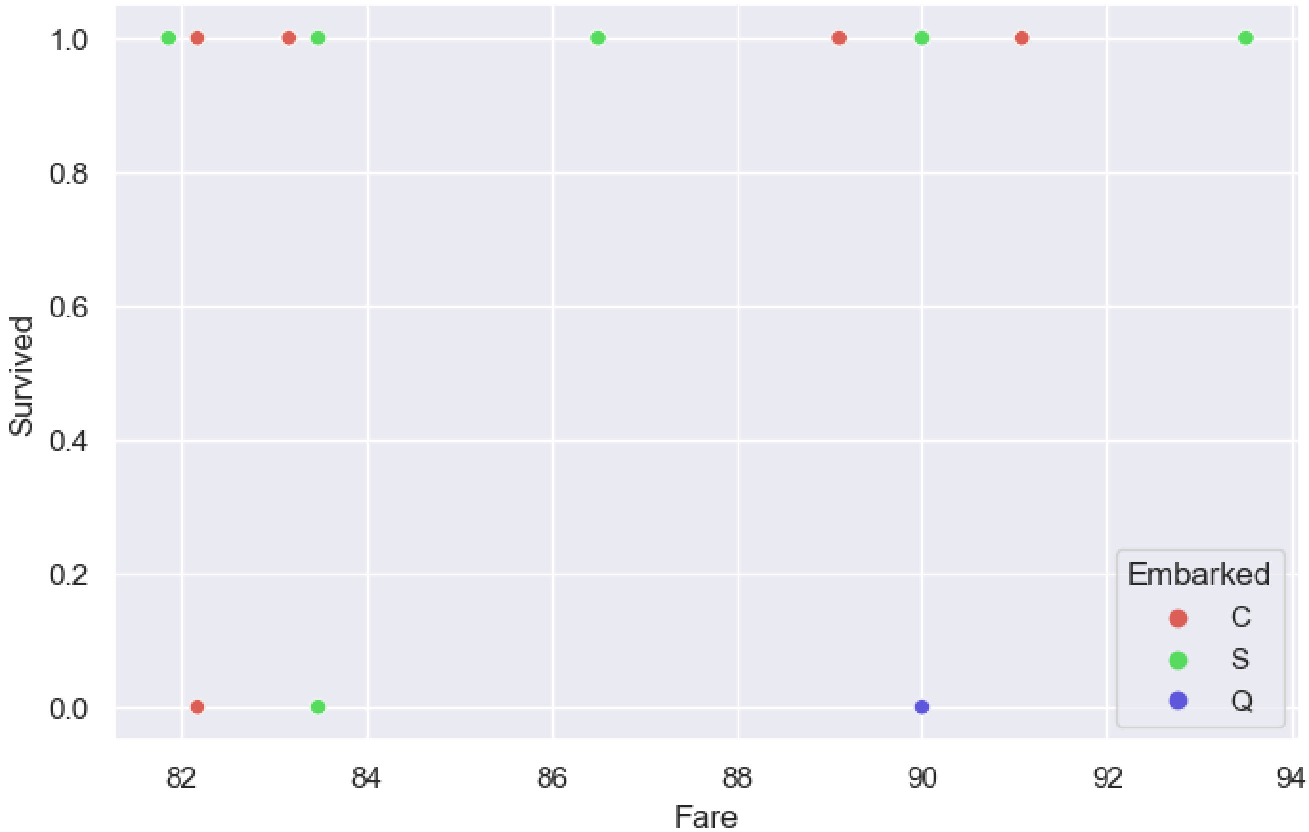
In [11]:

```
1  sns.pairplot(data=df, diag_kind='kde', hue='Embarked', palette='hls')
```

Out[11]: <seaborn.axisgrid.PairGrid at 0x2ad2137c460>

In [12]:
```
sns.scatterplot(x='Fare', y='Survived', data=df, hue='Embarked', palette='hls')
```

Out[12]: <Axes: xlabel='Fare', ylabel='Survived'>

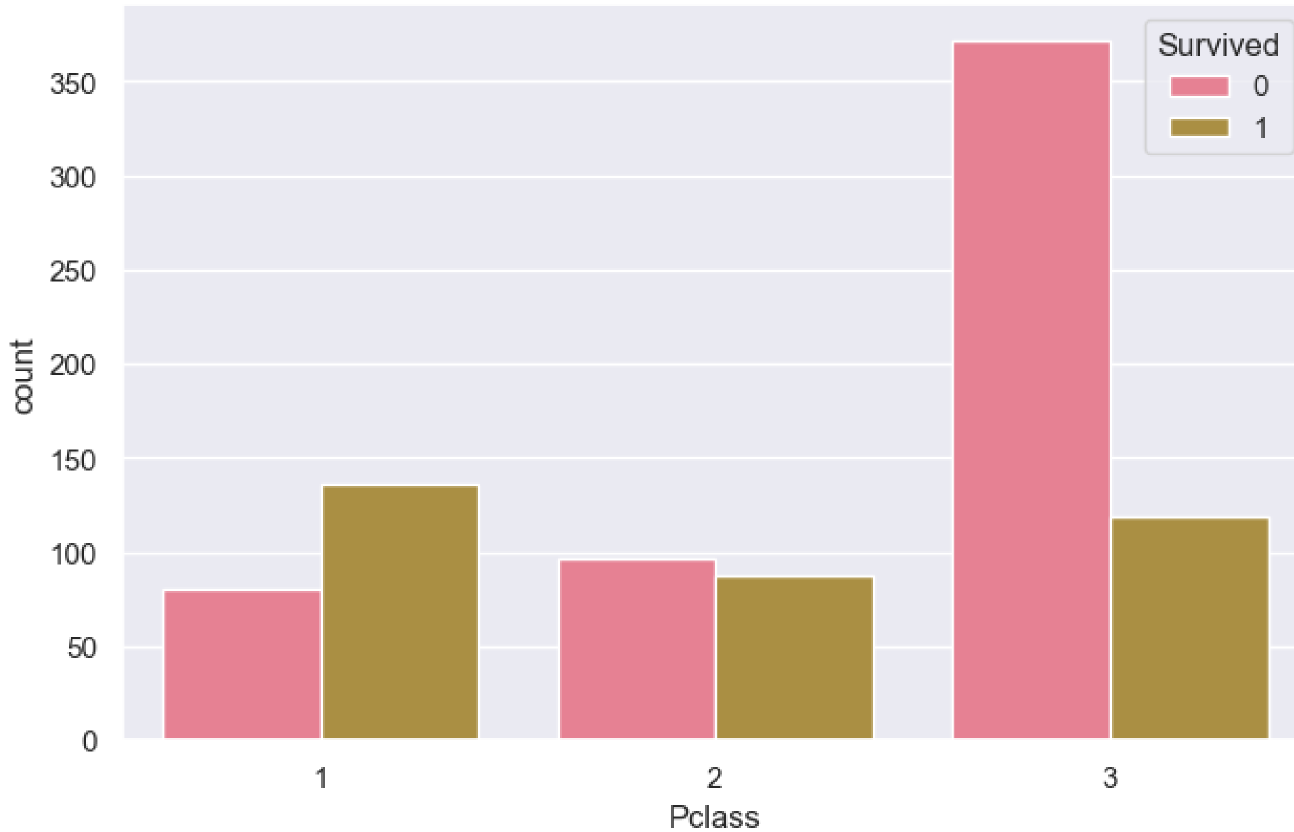


In [13]:
```
train.Embarked.fillna('C', inplace=True)
```

In [14]:

```
sns.countplot(data=train, x='Pclass', hue='Survived')
```

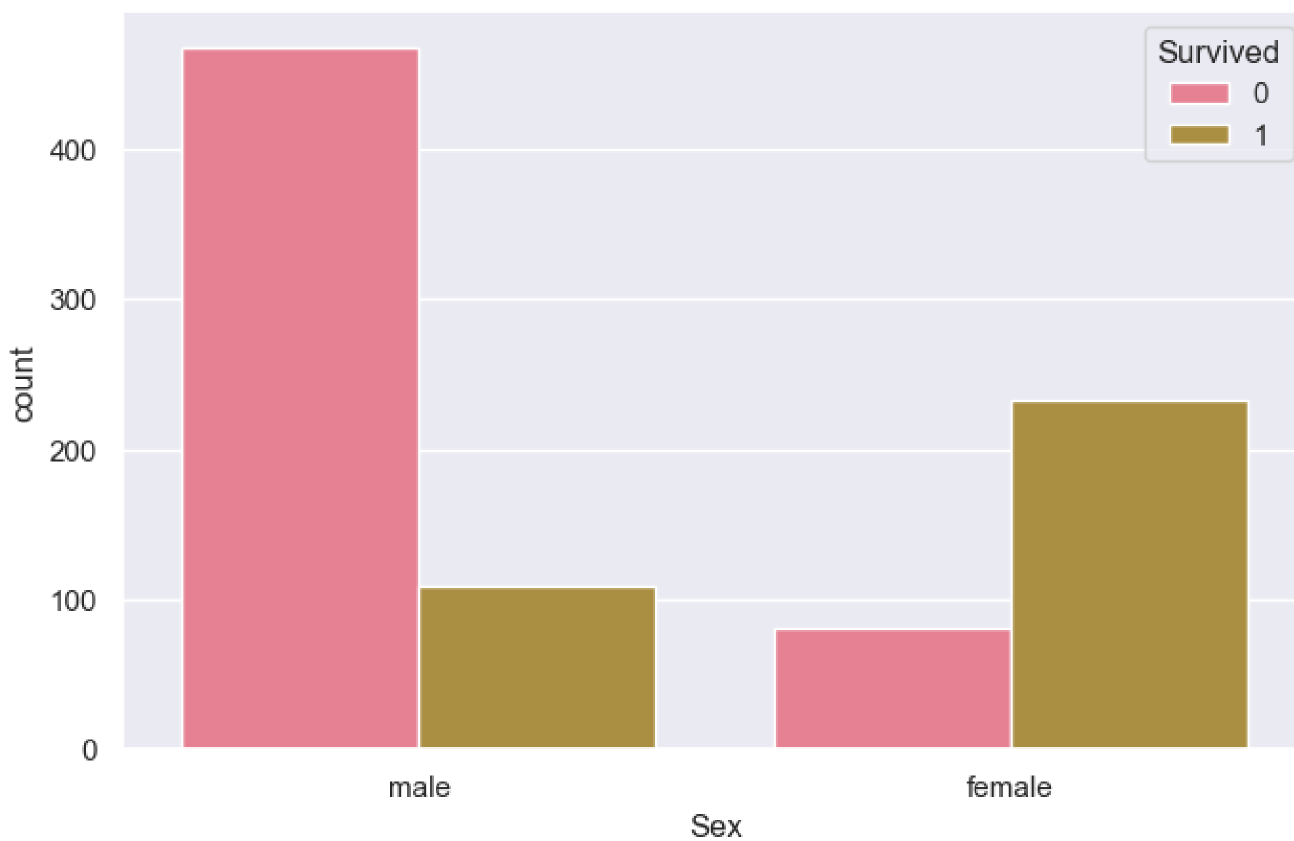
Out[14]: <Axes: xlabel='Pclass', ylabel='count'>



In [15]:

```
sns.countplot(data=train, x='Sex', hue='Survived')
```

Out[15]: <Axes: xlabel='Sex', ylabel='count'>



In [16]:

```
train.groupby('Pclass', as_index=False).mean()
```

```
C:\Users\Nayan\AppData\Local\Temp\ipykernel_1196\997615993.py:1: FutureWarning:

The default value of numeric_only in DataFrameGroupBy.mean is deprecated. In a future
version, numeric_only will default to False. Either specify numeric_only or select onl
y columns which should be valid for the function.
```

Out[16]:

	Pclass	PassengerId	Survived	Age	SibSp	Parch	Fare
0	1	461.597222	0.629630	38.233441	0.416667	0.356481	84.154687
1	2	445.956522	0.472826	29.877630	0.402174	0.380435	20.662183
2	3	439.154786	0.242363	25.140620	0.615071	0.393075	13.675550

In [17]:

```
# assinging Age
def fill_age(colls):
    Age = colls[0]
    Pclass = colls[1]

    if pd.isnull(Age):
        if Pclass == 1:
            return 38
        elif Pclass == 2:
            return 29
        elif Pclass == 3:
            return 24
    else:
        return Age
```

In [18]:

```
train.Age = train[['Age', 'Pclass']].apply(fill_age, axis=1)
test.Age = test[['Age', 'Pclass']].apply(fill_age, axis=1)
```

In [19]:

```
test.Fare.fillna(value=test.Fare.mean(), inplace=True)
```

In [20]:

```
train['Titels'] = train['Name'].apply(lambda x: x.split(',')[1].split('.')[0].strip
test['Titels'] = test['Name'].apply(lambda x: x.split(',')[1].split('.')[0].strip()
```

In [21]:

```
# Most Common Titels
def Title_change(title):
    if title in ['Lady', 'the Countess', 'Capt', 'Col', 'Don', 'Dr', 'Major', 'Rev'
        return 'Others'
    elif title in ['Mlle', 'Ms']:
        return 'Miss'
    elif title == 'Mme':
        return 'Mrs'
    return title
```

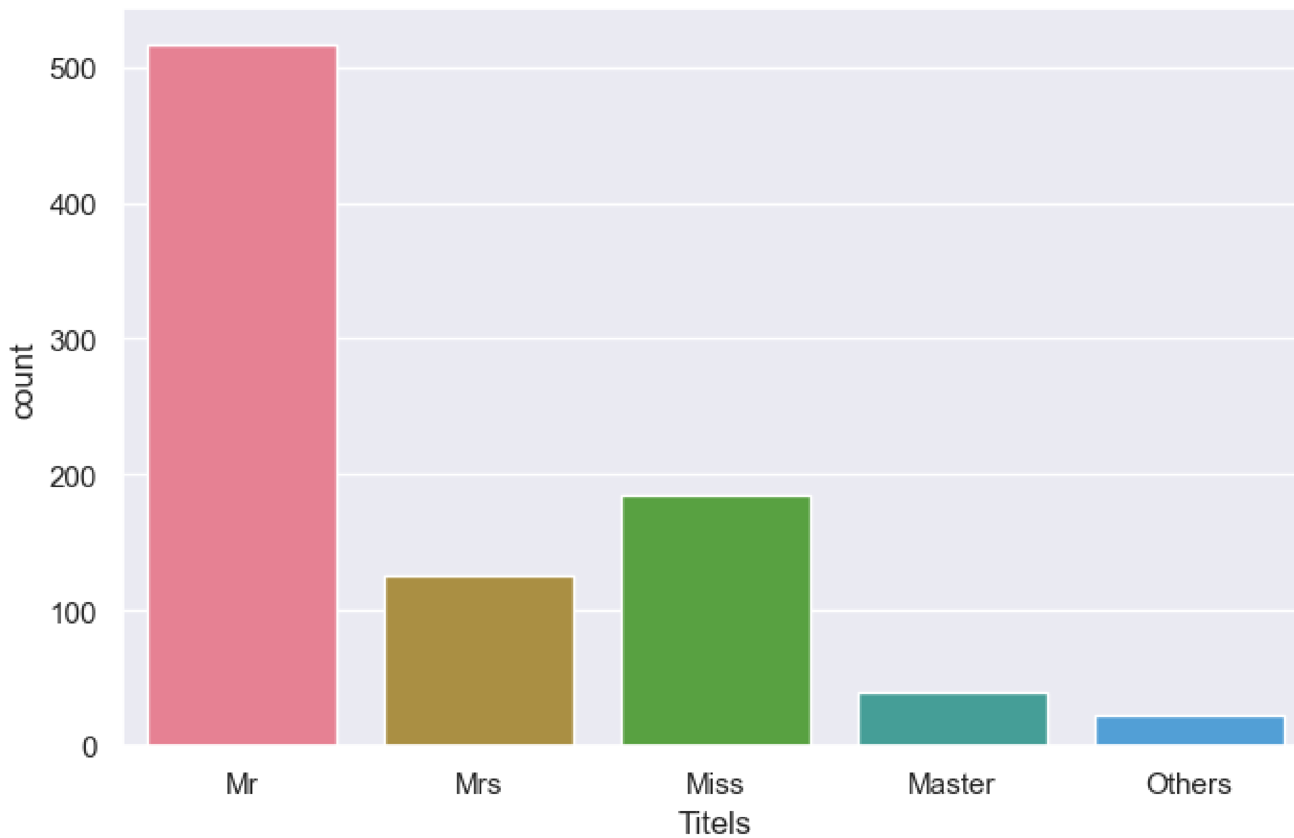
In [22]:

```
train.Titels = train.Titels.apply(Title_change)
test.Titels = test.Titels.apply(Title_change)
```

In [23]:

```
plt.figure(figsize=(8,5))
sns.countplot(train,x='Titels')
```

Out[23]: <Axes: xlabel='Titels', ylabel='count'>



In [24]:

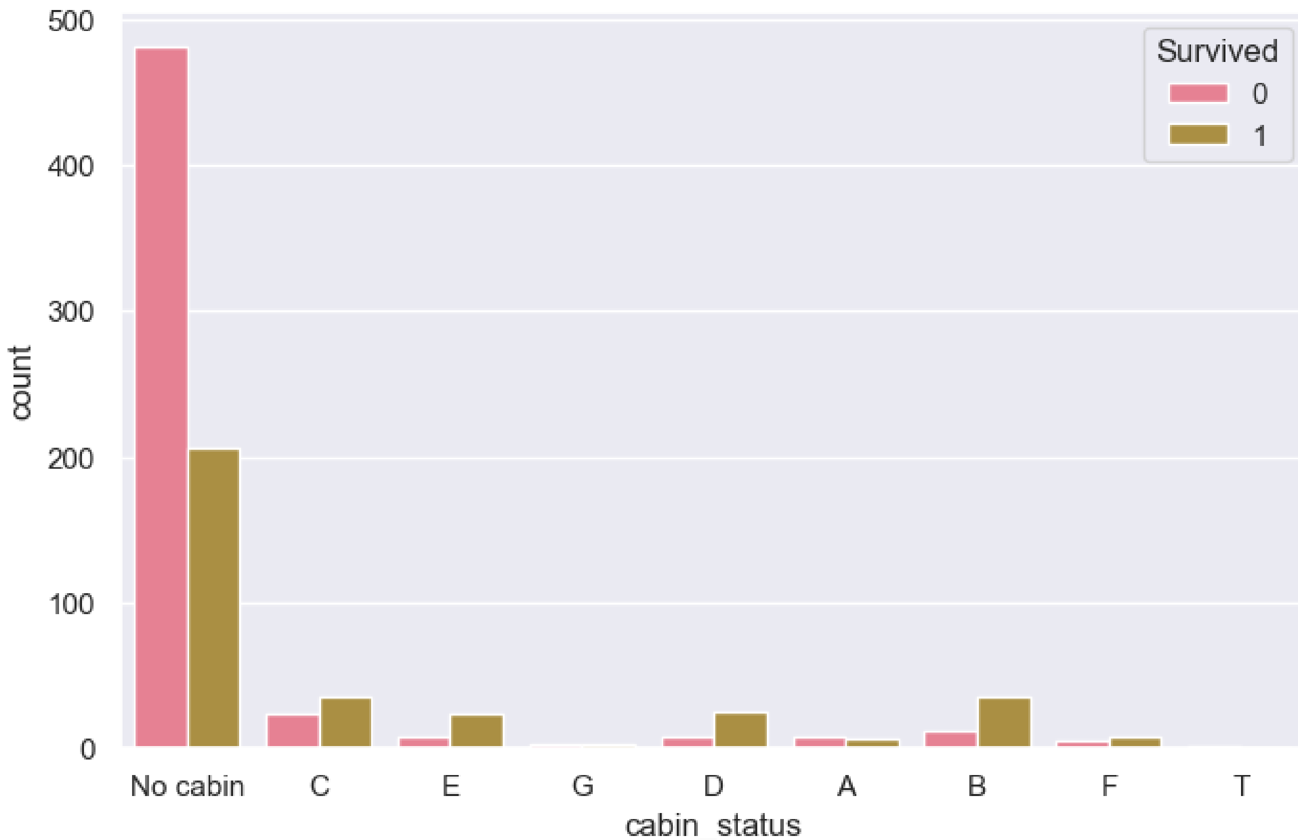
```
def cabin_class(cabin):
    if pd.isnull(cabin):
        return 'No cabin'
    return cabin[0]
```

In [25]:

```
train['cabin_status']=train.Cabin.apply(cabin_class)
test['cabin_status']=test.Cabin.apply(cabin_class)
```

In [26]:
```
sns.countplot(data=train, x='cabin_status', hue='Survived')
```

Out[26]: <Axes: xlabel='cabin_status', ylabel='count'>

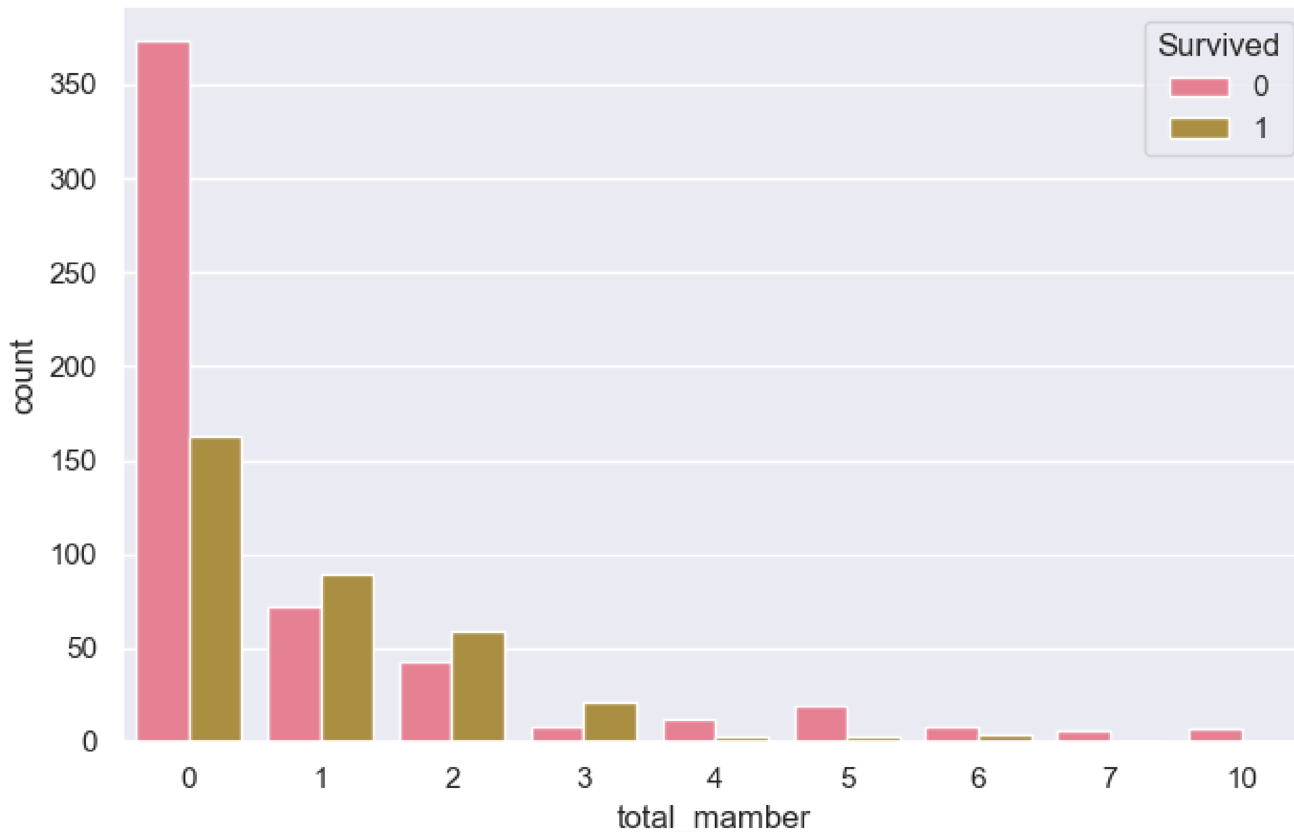


In [27]:
```
train.drop(train[train.cabin_status == 'T'].index, inplace=True)
```

In [28]:
```
train['total_mamber']=train.Parch + train.SibSp
test['total_mamber']=test.Parch + test.SibSp
```

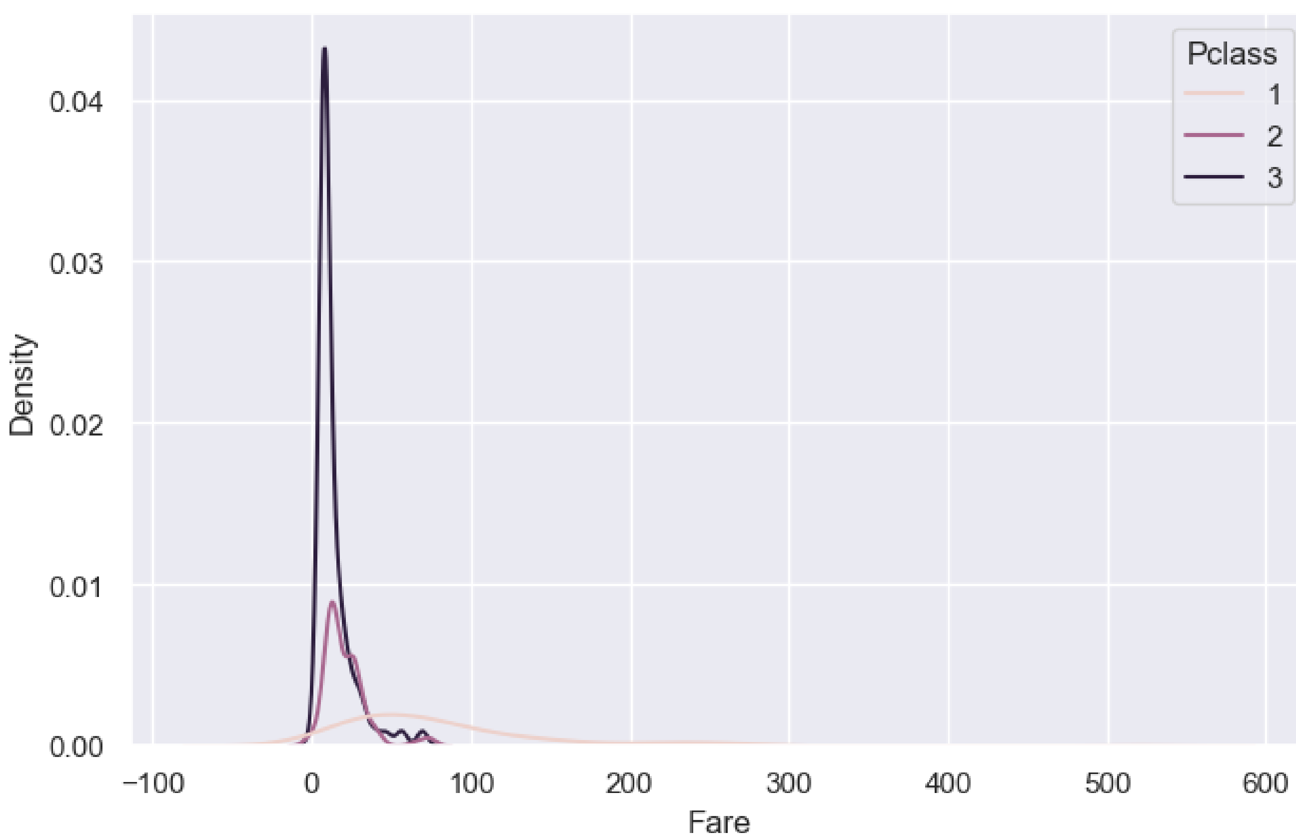
In [29]:
```
sns.countplot(data=train, x='total_mamber', hue='Survived')
```

Out[29]: <Axes: xlabel='total_mamber', ylabel='count'>



In [30]:
```
sns.kdeplot(data=train, x='Fare', hue='Pclass')
```

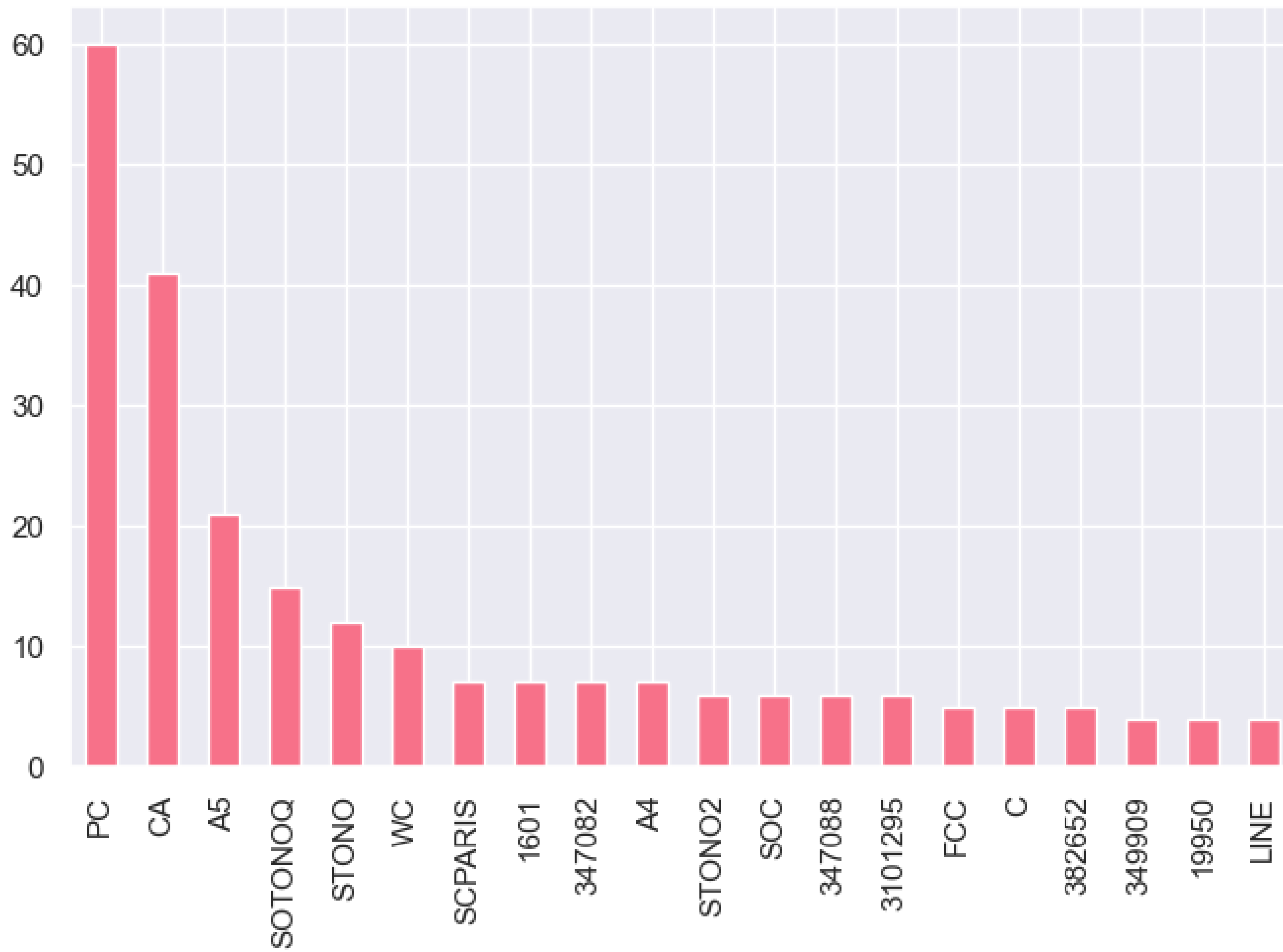
Out[30]: <Axes: xlabel='Fare', ylabel='Density'>



In [31]:
```
train['most_common_ticket'] = train.Ticket.apply(lambda x: x.replace('/', '').repla
test['most_common_ticket'] = test.Ticket.apply(lambda x: x.replace('/', '').replace
```

In [32]:
```
train.most_common_ticket.value_counts().head(20).plot(kind='bar') # 20 most common
```

Out[32]: <Axes: >

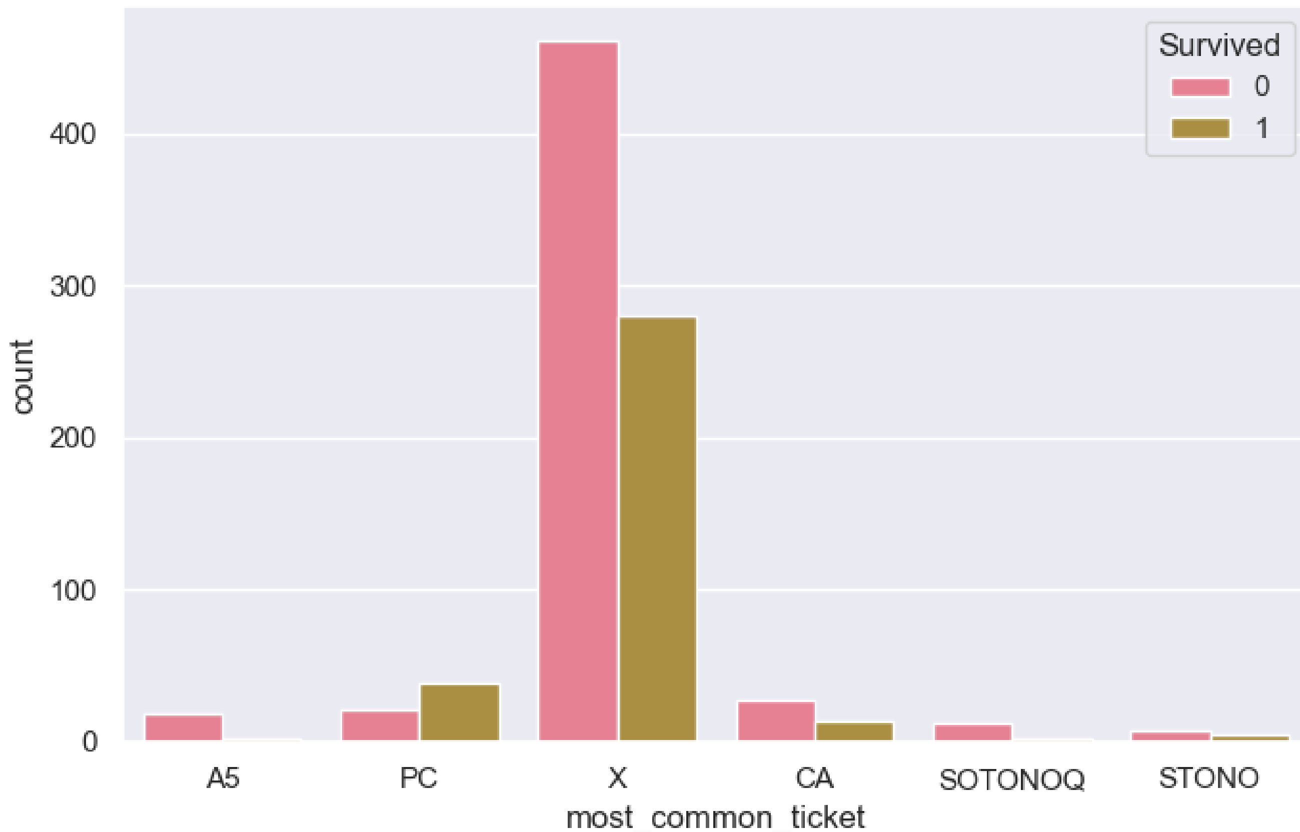


In [33]:
```
most_common_tickets = ['PC', 'CA', 'A5', 'SOTONOQ', 'STONO']
```

In [34]:
```
train.most_common_ticket = train.most_common_ticket.apply(lambda item: item if item
test.most_common_ticket = test.most_common_ticket.apply(lambda item: item if item i
```

In [35]:
```
sns.countplot(data=train, x='most_common_ticket', hue='Survived')
```

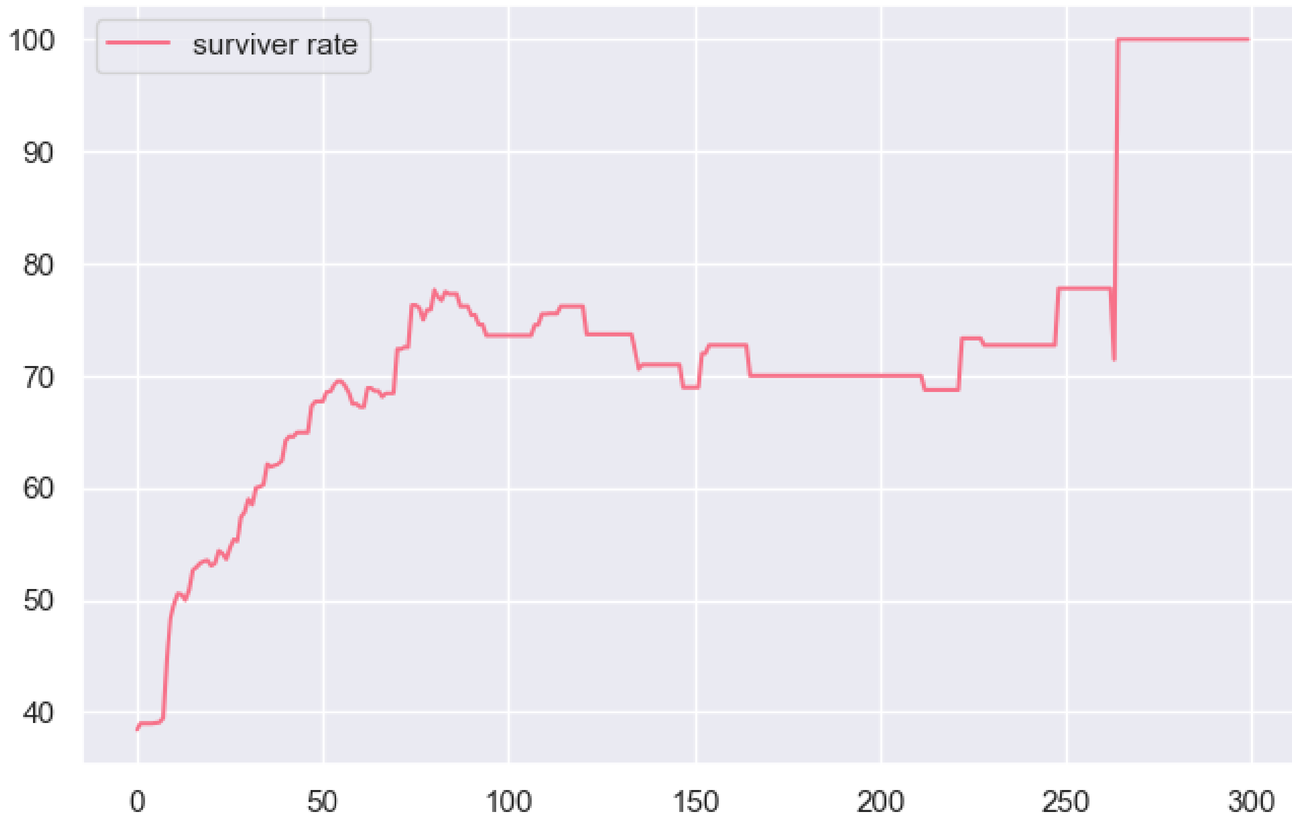
Out[35]: <Axes: xlabel='most_common_ticket', ylabel='count'>



In [36]:

```
prob = []
d = {}
for i in range(300):

    prob.append((train[train.Fare >= i].describe().transpose()['mean'][1])*100)

d = {'surviver rate':prob}

pd.DataFrame(d).plot()
```

Out[36]: <Axes: >



In [37]:

```
def is_alone(total_mamber):

    if total_mamber == 0:
        return 0
    return 1
```

In [ ]:

```

```

In [38]:

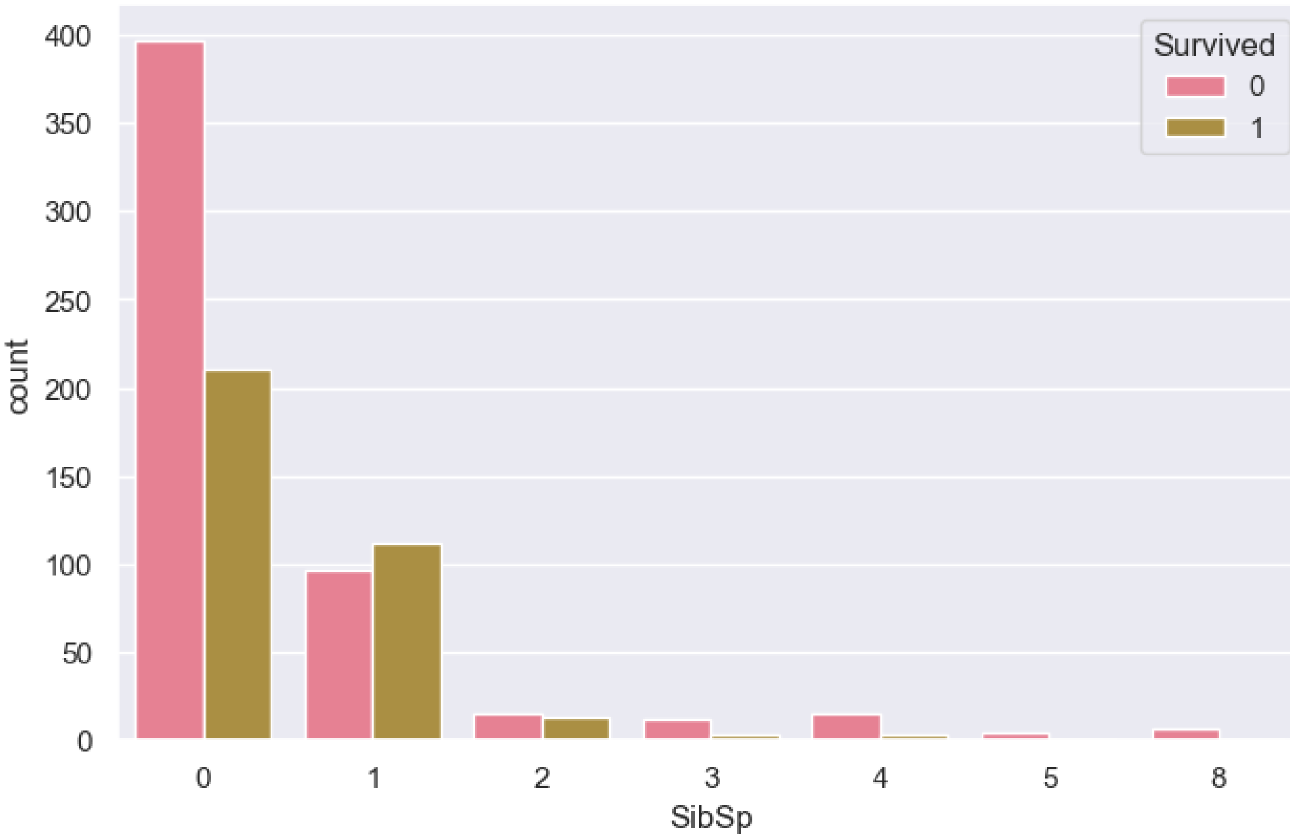
```
train['is_alone'] = train.total_mamber.apply(lambda item: 1 if item == 0 else 0)
test['is_alone'] = test.total_mamber.apply(lambda item: 1 if item == 0 else 0)
```

In [ ]:

```

```

In [39]:
```
sns.countplot(data=train, x='SibSp', hue='Survived')
```

Out[39]: <Axes: xlabel='SibSp', ylabel='count'>



In [40]:
```
train.SibSp = train.SibSp.apply(lambda item: 'more than three' if item >2 else item
```

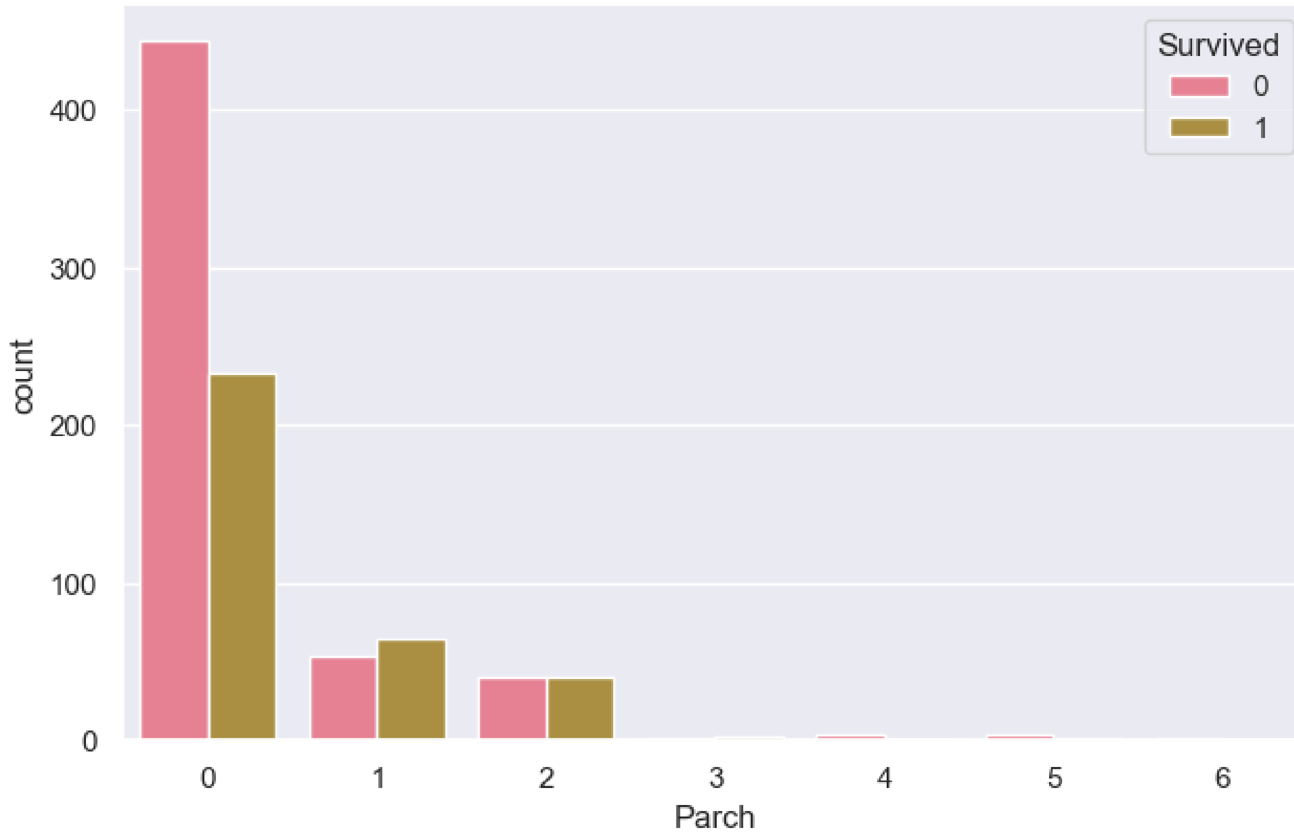
In [41]:
```
test.SibSp = test.SibSp.apply(lambda item: 'more than three' if item >2 else item)
```

In [42]:

```python
sns.countplot(data=train, x='Parch', hue='Survived')
```

Out[42]:

```
<Axes: xlabel='Parch', ylabel='count'>
```



In [43]:

```python
test.Parch = test.Parch.apply(lambda item: 'more than three' if item >2 else item)
train.Parch = train.Parch.apply(lambda item: 'more than three' if item >2 else item
```

In [44]:
```
train.head()
```

Out[44]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embark
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	

Data preprocessing

In [45]:
```
X_train = train.drop(['PassengerId', 'Name', 'Ticket', 'Cabin', 'Survived', 'Embark
y_train = train.Survived
X_test = test.drop(['PassengerId', 'Name', 'Ticket', 'Cabin', 'Embarked','most_comm
y_test = subm.Survived
```

In [46]:
```
X_train
```

Out[46]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Titels	cabin_status	is_alone
0	3	male	22.0	1	0	7.2500	Mr	No cabin	0
1	1	female	38.0	1	0	71.2833	Mrs	C	0
2	3	female	26.0	0	0	7.9250	Miss	No cabin	1
3	1	female	35.0	1	0	53.1000	Mrs	C	0
4	3	male	35.0	0	0	8.0500	Mr	No cabin	1
...	...	...	...	...	...	...	...	...	...
886	2	male	27.0	0	0	13.0000	Others	No cabin	1
887	1	female	19.0	0	0	30.0000	Miss	B	1
888	3	female	24.0	1	2	23.4500	Miss	No cabin	0
889	1	male	26.0	0	0	30.0000	Mr	C	1
890	3	male	32.0	0	0	7.7500	Mr	No cabin	1

890 rows × 9 columns

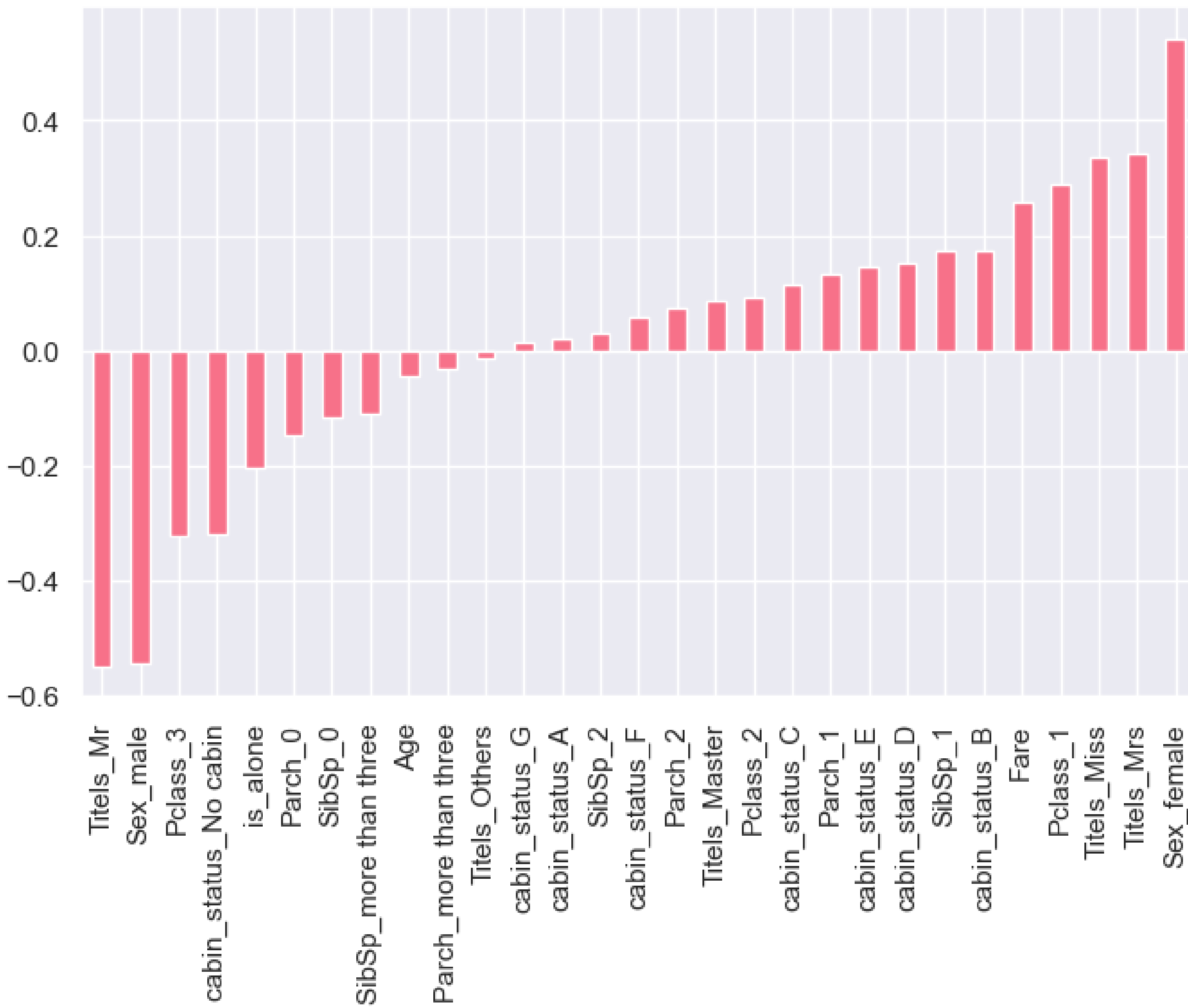
In [47]:
```
X_train.Pclass = X_train.Pclass.apply(lambda item: str(item))
X_test.Pclass = X_test.Pclass.apply(lambda item: str(item))
```

In [48]:
```
X_train = pd.get_dummies(X_train)
X_test = pd.get_dummies(X_test)
```

In [49]:

```
pd.concat([train.Survived, X_train], axis=1).corr().Survived.drop('Survived').sort_
```

Out[49]: <Axes: >



Model Emplementation and Metrics Evaluation

In [50]:
```
models=[RandomForestClassifier(), AdaBoostClassifier() ,
        GradientBoostingClassifier(), GaussianNB(), XGBClassifier(), LGBMClassifier

model_names=['RandomForestClassifier', 'AdaBoostClassifier',
             'GradientBoostingClassifier','GaussianNB', 'XGBClassifier', 'LGBMClass

acc=[]
mean_acc=[]
d={}

for model in range(len(models)):
    clf=models[model]
    clf.fit(X_train,y_train)
    pred=clf.predict(X_test)
    yprob = clf.predict_proba(X_test)[:, 1]
    acc.append(round(accuracy_score(pred,y_test)*100, 3))
    skf = StratifiedKFold(n_splits=20, shuffle=True)
    mean_acc.append(round(np.mean(cross_val_score(clf,X_train,y_train,cv=skf))*100,

d={'Modelling Algo':model_names,'Accuracy':acc, 'mean_Accuracy':mean_acc}

```

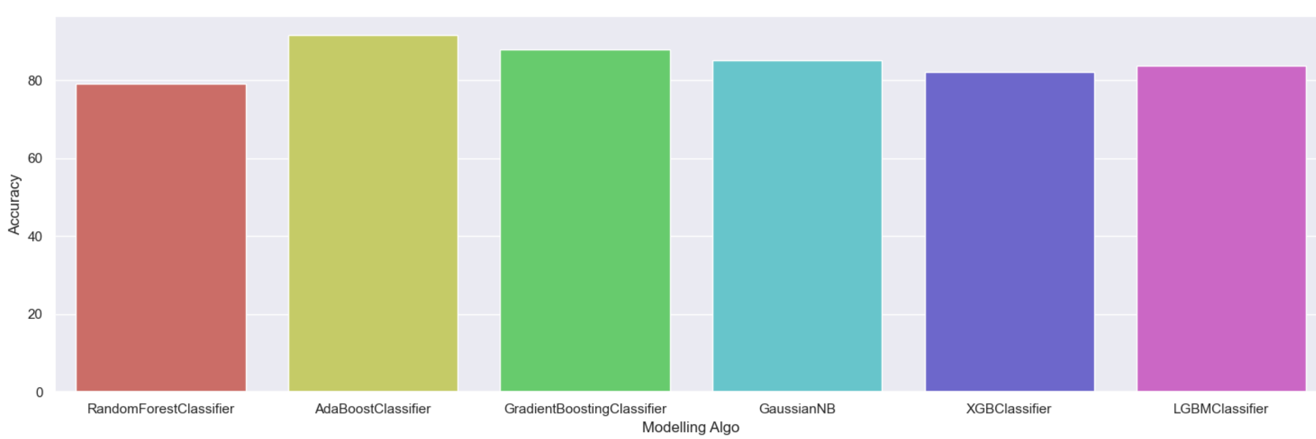
In [51]:
```
acc_df = pd.DataFrame(d)
acc_df
```

Out[51]:

	Modelling Algo	Accuracy	mean_Accuracy
0	RandomForestClassifier	79.187	81.581
1	AdaBoostClassifier	91.627	81.328
2	GradientBoostingClassifier	87.799	83.038
3	GaussianNB	85.167	77.755
4	XGBClassifier	82.057	83.018
5	LGBMClassifier	83.732	82.003

In [52]:
```
### result comperision
sns.catplot(data=acc_df, x='Modelling Algo', y='Accuracy',kind='bar', height=5,aspe
```

Out[52]: <seaborn.axisgrid.FacetGrid at 0x2ad26c89c10>



In [53]:

```
# xgb is best perfomer
from xgboost import XGBClassifier
clf = XGBClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
y_pred_train = clf.predict(X_train)
```

In [54]:

```
print(f'Testing Accuracy:{accuracy_score(y_test, y_pred)*100:.3f} %')
print(f'Training Accuracy:{accuracy_score(y_train, y_pred_train)*100:.3f} %')
print('\n')
print(confusion_matrix(y_test, y_pred))
print('\n')
print(classification_report(y_test, y_pred))
```

```
Testing Accuracy:82.057 %
Training Accuracy:97.079 %


[[224  42]
 [ 33 119]]


              precision    recall  f1-score   support

           0       0.87      0.84      0.86       266
           1       0.74      0.78      0.76       152

    accuracy                           0.82       418
   macro avg       0.81      0.81      0.81       418
weighted avg       0.82      0.82      0.82       418
```

In [55]:

```
skf = StratifiedKFold(n_splits=3, shuffle=True)
print(f'mean Accuracy:{np.mean(cross_val_score(RandomForestClassifier(),X_train,y_t
```

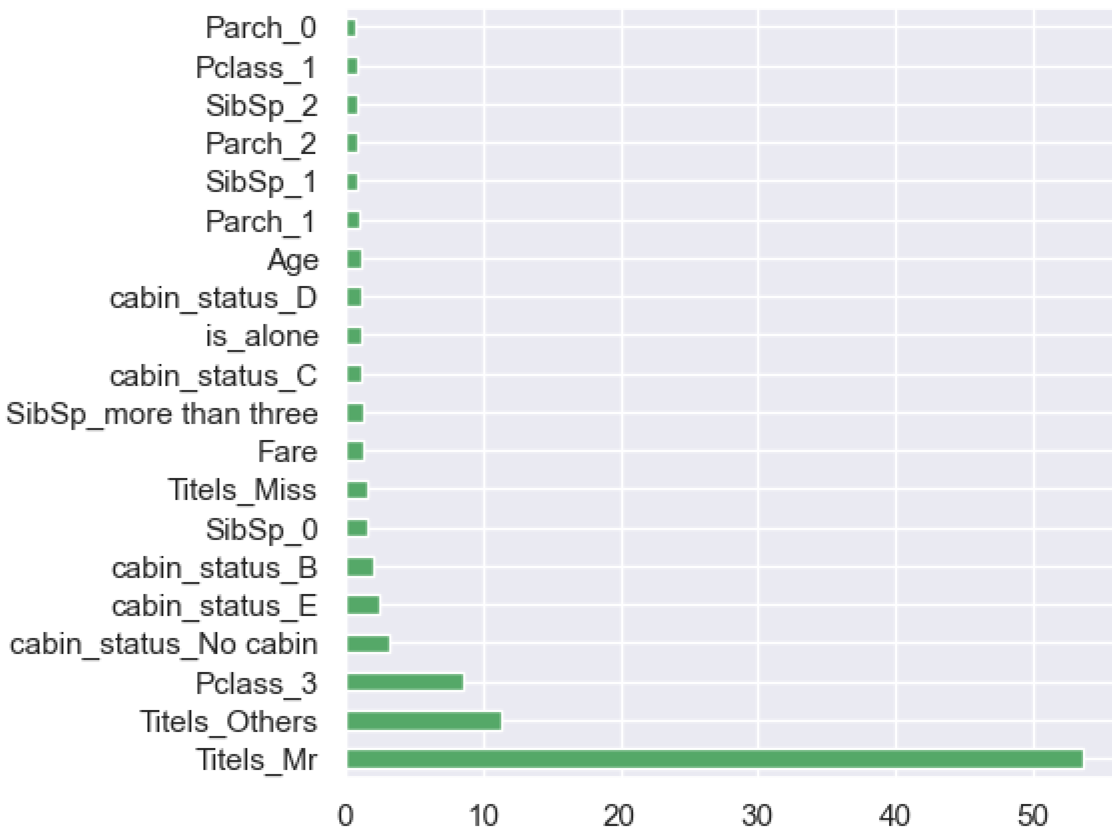
```
mean Accuracy:81.012 %
```

In [56]:

```python
f_imp = pd.Series(clf.feature_importances_*100, index=X_train.columns)
plt.figure(figsize=(5, 5))
f_imp.nlargest(20).plot(kind='barh', color = 'g')
```

Out[56]:

```
<Axes: >
```

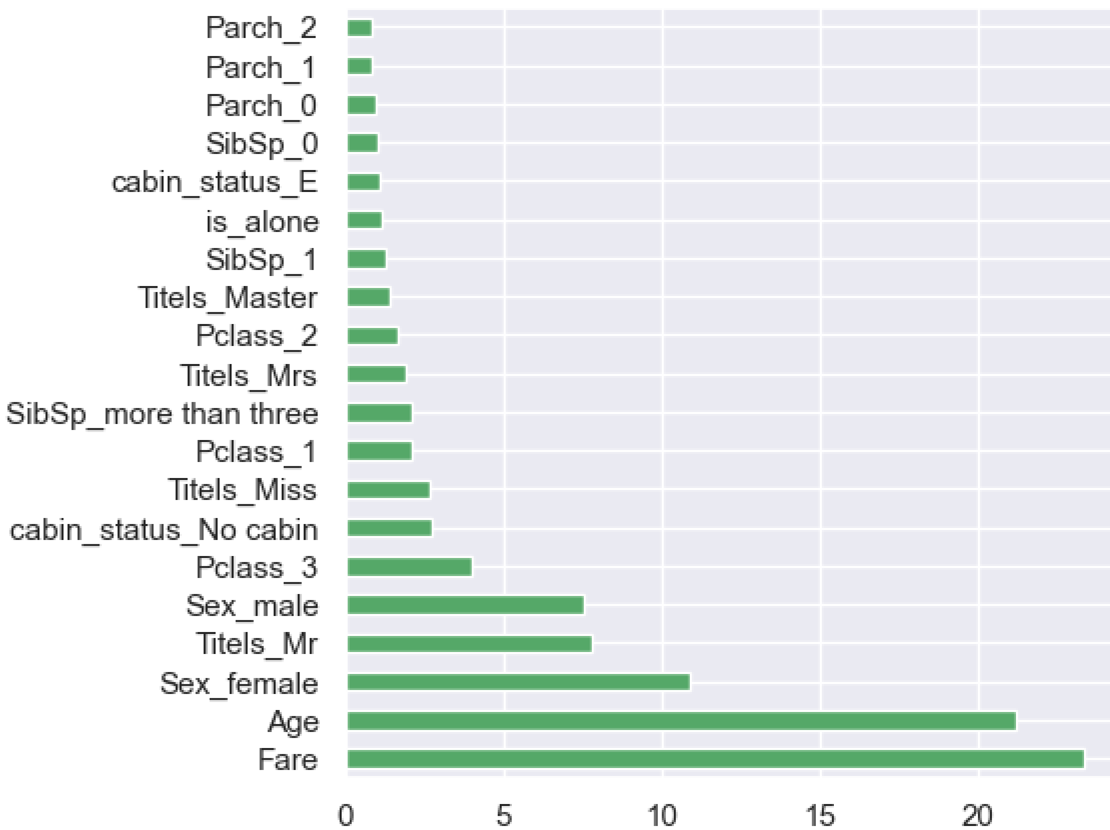


In [57]:

```python
model = RandomForestClassifier()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
y_pred_train = model.predict(X_train)
```

In [58]:
```python
f_imp = pd.Series(model.feature_importances_*100, index=X_train.columns)
plt.figure(figsize=(5, 5))
f_imp.nlargest(20).plot(kind='barh', color = 'g')
```

Out[58]: <Axes: >



In [59]:
```python
print(f'Testing Accuracy:{accuracy_score(y_test, y_pred)*100:.3f} %')
print(f'Training Accuracy:{accuracy_score(y_train, y_pred_train)*100:.3f} %')
print('\n')
print(confusion_matrix(y_test, y_pred))
print('\n')
print(classification_report(y_test, y_pred))
```

```
Testing Accuracy:78.947 %
Training Accuracy:98.764 %


[[216  50]
 [ 38 114]]


              precision    recall  f1-score   support

           0       0.85      0.81      0.83       266
           1       0.70      0.75      0.72       152

    accuracy                           0.79       418
   macro avg       0.77      0.78      0.78       418
weighted avg       0.79      0.79      0.79       418
```

In [60]:

```
RFC = RandomForestClassifier()


## Search grid for optimal parameters
rf_param_grid = {"max_depth": [None],
              "max_features": [1, 3, 10],
              "min_samples_split": [2, 3, 10],
              "min_samples_leaf": [1, 3, 10],
              "bootstrap": [False],
              "n_estimators" :[100,300],
              "criterion": ["gini"]}


gsRFC = GridSearchCV(RFC,param_grid = rf_param_grid, cv=5, scoring="accuracy", n_jo

gsRFC.fit(X_train,y_train)

RFC_best = gsRFC.best_estimator_

# Best score
gsRFC.best_score_
```

```
Fitting 5 folds for each of 54 candidates, totalling 270 fits
```

Out[60]:

```
0.8404494382022472
```

In [61]:

```
y_pred = RFC_best.predict(X_test)
y_pred_train = RFC_best.predict(X_train)
```

In [62]:

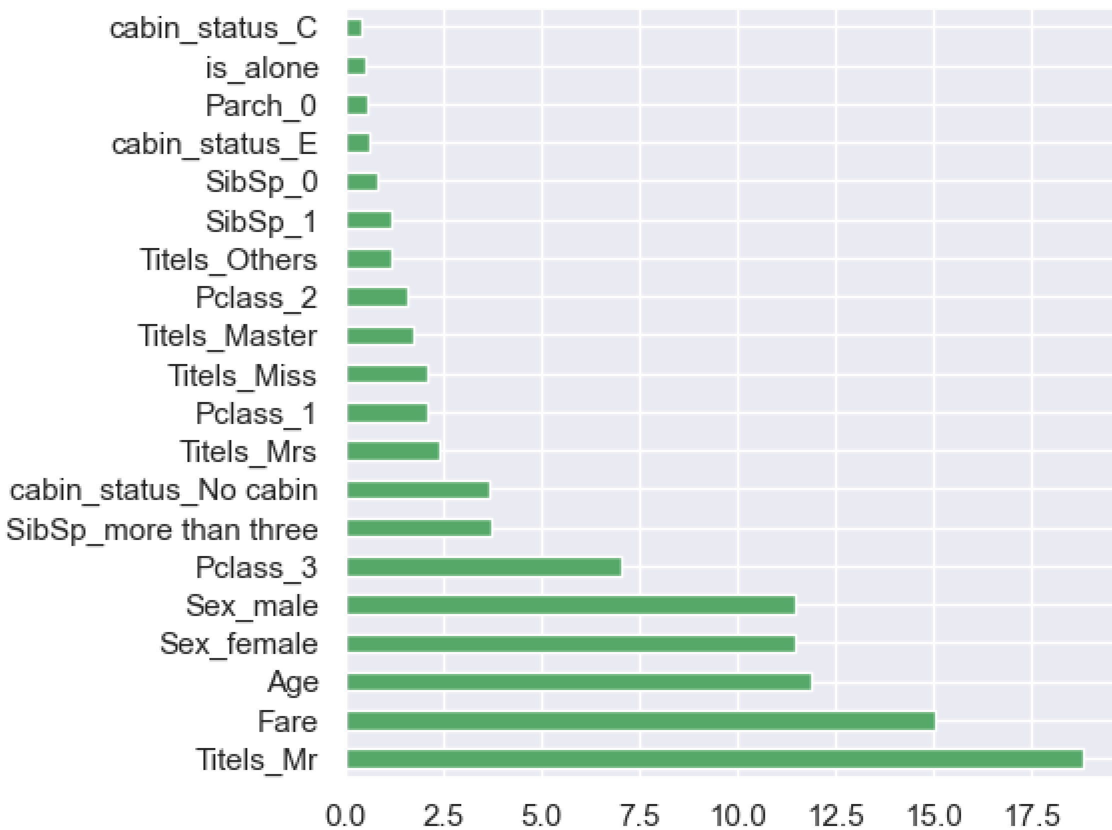
```
print(f'Testing Accuracy:{accuracy_score(y_test, y_pred)*100:.3f} %')
print(f'Training Accuracy:{accuracy_score(y_train, y_pred_train)*100:.3f} %')
print('\n')
print(confusion_matrix(y_test, y_pred))
print('\n')
print(classification_report(y_test, y_pred))
```

```
Testing Accuracy:84.450 %
Training Accuracy:91.685 %


[[235  31]
 [ 34 118]]


              precision    recall  f1-score   support

           0       0.87      0.88      0.88       266
           1       0.79      0.78      0.78       152

    accuracy                           0.84       418
   macro avg       0.83      0.83      0.83       418
weighted avg       0.84      0.84      0.84       418
```

In [63]:

```
f_imp = pd.Series(RFC_best.feature_importances_*100, index=X_train.columns)
plt.figure(figsize=(5, 5))
f_imp.nlargest(20).plot(kind='barh', color = 'g')
```

Out[63]: <Axes: >



In [64]:

```
from sklearn.ensemble import VotingClassifier

models=[RandomForestClassifier(), AdaBoostClassifier() ,
        GradientBoostingClassifier(), GaussianNB(), XGBClassifier(), LGBMClassifier

model_names=['RandomForestClassifier', 'AdaBoostClassifier',
             'GradientBoostingClassifier','GaussianNB', 'XGBClassifier', 'LGBMClass


model = VotingClassifier(estimators=list(zip(model_names, models)))
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
y_pred_train = model.predict(X_train)
```

In [ ]:

```

```

In [65]:

```
y_pred = model.predict(X_test)
y_pred_train = model.predict(X_train)
```

In [66]:

```
print(f'Testing Accuracy:{accuracy_score(y_test, y_pred)*100:.3f} %')
print(f'Training Accuracy:{accuracy_score(y_train, y_pred_train)*100:.3f} %')
print('\n')
print(confusion_matrix(y_test, y_pred))
print('\n')
print(classification_report(y_test, y_pred))
```

```
Testing Accuracy:87.081 %
Training Accuracy:93.034 %


[[244  22]
 [ 32 120]]


              precision    recall  f1-score   support

           0       0.88      0.92      0.90       266
           1       0.85      0.79      0.82       152

    accuracy                           0.87       418
   macro avg       0.86      0.85      0.86       418
weighted avg       0.87      0.87      0.87       418
```

In [67]:

```
skf = StratifiedKFold(n_splits=3, shuffle=True)
print(f'mean Accuracy:{np.mean(cross_val_score(model,X_train,y_train,cv=skf))*100:.
```

```
mean Accuracy:81.461 %
```

In [68]:

```
XGB = XGBClassifier()
n_estimators = [int(x) for x in np.linspace(start=200, stop=800, num=3)]
max_depth = [int(x) for x in np.linspace(10, 110, num=3)]
max_depth.append(None)
learning_rate=[round(float(x),2) for x in np.linspace(start=0.01, stop=0.2, num=3)]
colsample_bytree =[round(float(x),2) for x in np.linspace(start=0.1, stop=1, num=4)]

param_grid = {'n_estimators': n_estimators,
              'max_depth': max_depth,
              'learning_rate': learning_rate,
              'colsample_bytree': colsample_bytree
             }

XGB = GridSearchCV(XGB, param_grid, cv=4, verbose=1)
XGB.fit(X_train, y_train)


```

```
Fitting 4 folds for each of 144 candidates, totalling 576 fits
```

Out[68]:

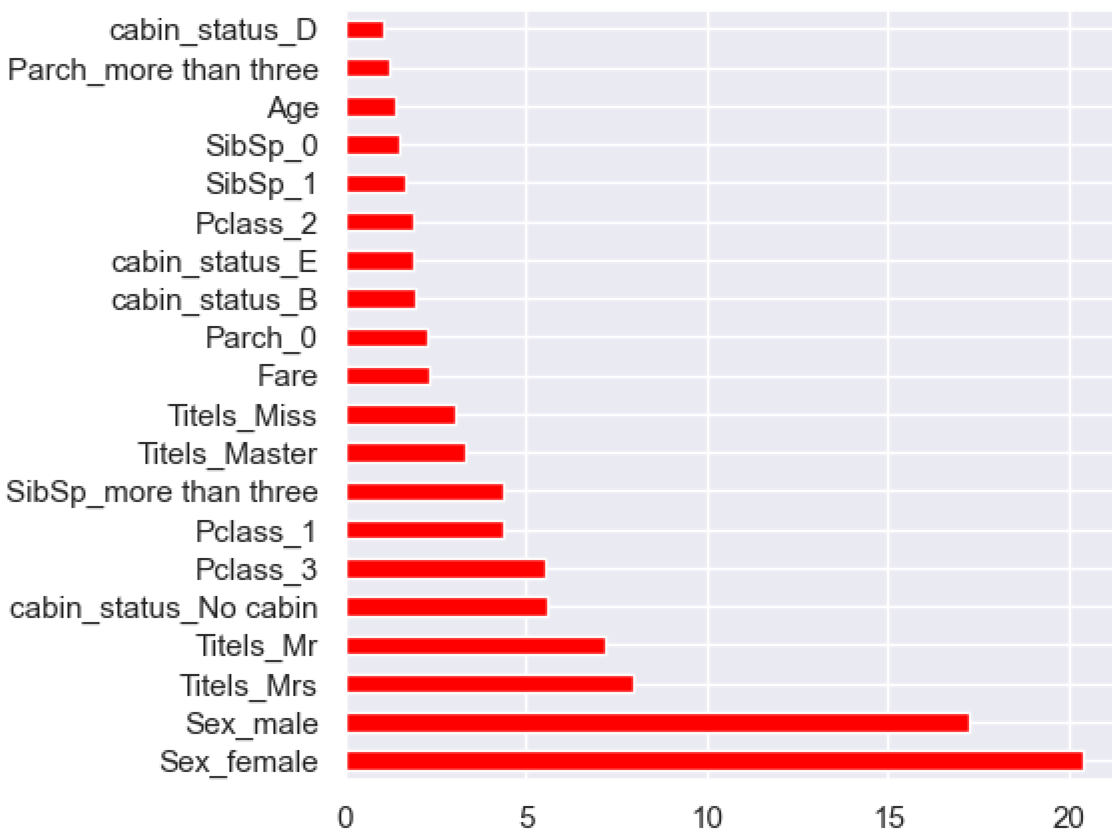
```
▸ GridSearchCV
▸ estimator: XGBClassifier
    ▸ XGBClassifier
```

In [69]:
```
model = XGB.best_estimator_
```

In [70]:
```
y_pred = model.predict(X_test)
y_pred_train = model.predict(X_train)
```

In [71]:
```
f_imp = pd.Series(model.feature_importances_*100, index=X_train.columns)
plt.figure(figsize=(5, 5))
f_imp.nlargest(20).plot(kind='barh', color = 'red')
```

Out[71]: <Axes: >



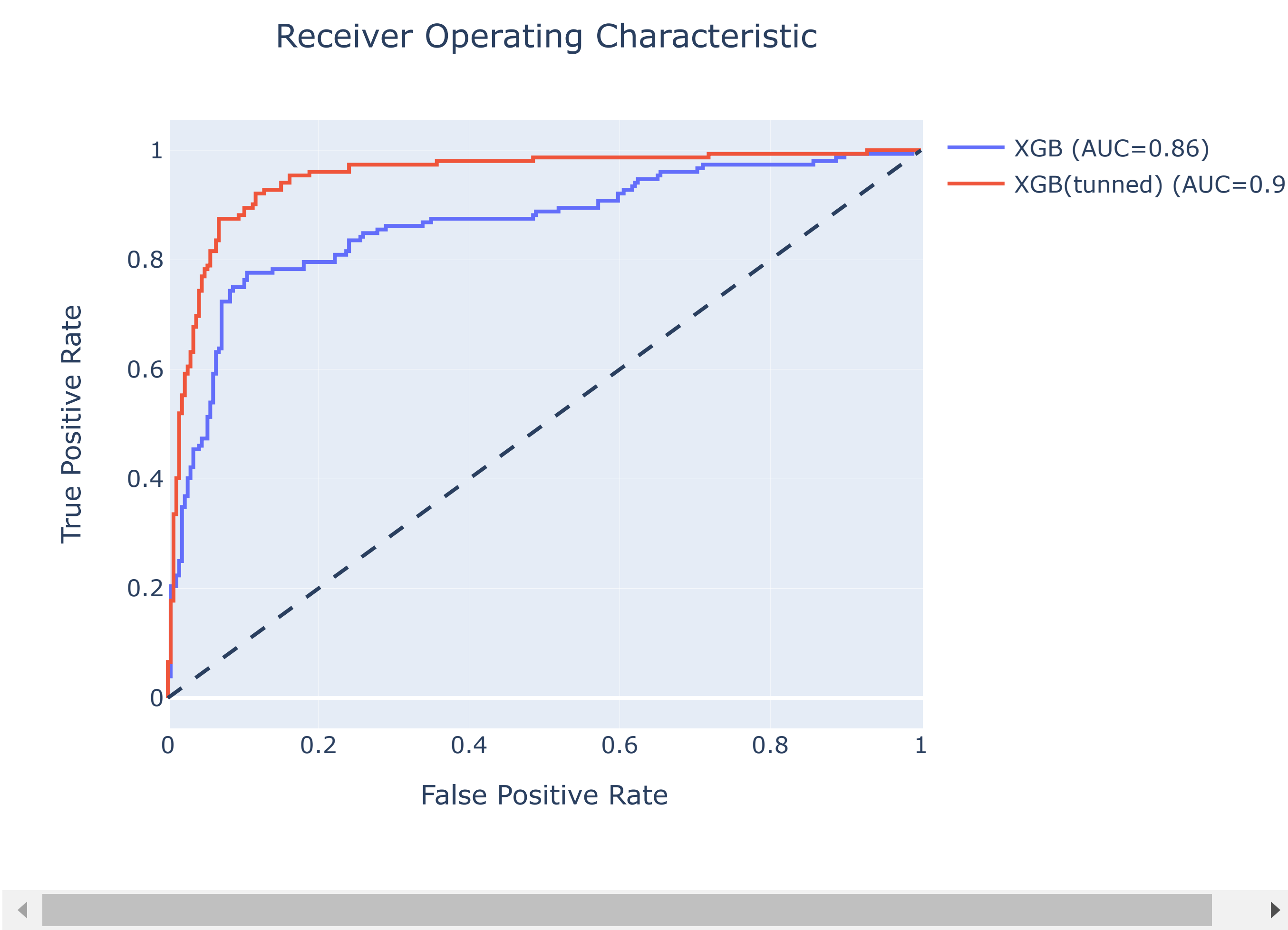
In [72]:

```
print(f'Testing Accuracy:{accuracy_score(y_test, y_pred)*100:.3f} %')
print(f'Training Accuracy:{accuracy_score(y_train, y_pred_train)*100:.3f} %')
print('\n')
print(confusion_matrix(y_test, y_pred))
print('\n')
print(classification_report(y_test, y_pred))
```

```
Testing Accuracy:90.670 %
Training Accuracy:90.000 %


[[246  20]
 [ 19 133]]


              precision    recall  f1-score   support

           0       0.93      0.92      0.93       266
           1       0.87      0.88      0.87       152

    accuracy                           0.91       418
   macro avg       0.90      0.90      0.90       418
weighted avg       0.91      0.91      0.91       418
```

In [103]:

```
fig = go.Figure()
fig.add_shape(
    type='line', line=dict(dash='dash'),
    x0=0, x1=1, y0=0, y1=1)

models = [XGBClassifier(), XGB.best_estimator_]
model_names = ['XGB', 'XGB(tunned)']

data = []
for model in range(len(models)):
    clf=models[model]
    clf.fit(X_train,y_train)
    yprob = clf.predict_proba(X_test)[:, 1]
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, yprob)
    auc_score = roc_auc_score(y_test, yprob)
    name = f"{model_names[model]} (AUC={auc_score:.2f})"
    fig.add_trace(go.Scatter(x=false_positive_rate, y=true_positive_rate, name=name


fig.update_layout(
    title = {'text':'Receiver Operating Characteristic',
             'y':0.9,
             'x':0.4,
             'xanchor': 'center',
             'yanchor': 'top'},
    xaxis_title='False Positive Rate',
    yaxis_title='True Positive Rate',
    height=500, # set height to 500 pixels
    width=700   # set width to 700 pixels
)
```



Receiver Operating Characteristic
True Positive Rate
False Positive Rate
0
0.2
0.4
0.6
0.8
1
XGB (AUC=0.86)
XGB(tunned) (AUC=0.95