kaggle competition - titanic machine learning from disaster

March 12, 2021

I'll be compiling and experimenting with various methods of prediction. Also I want to experiment and learn the best practices on how to approach a problem. This may also serve as a "tutorial" for others. The competition solution workflow goes through seven stages described in the Data Science Solutions book.

- Question or problem definition.
- Acquire training and testing data.
- Wrangle, prepare, cleanse the data.
- Analyze, identify patterns, and explore the data.
- Model, predict and solve the problem.
- Visualize, report, and present the problem solving steps and final solution.
- Supply or submit the results.

The sinking of the Titanic is one of the most infamous shipwrecks in history.

On April 15, 1912, during her maiden voyage, the widely considered "unsinkable" RMS Titanic sank after colliding with an iceberg. Unfortunately, there weren't enough lifeboats for everyone onboard, resulting in the death of 1502 out of 2224 passengers and crew.

While there was some element of luck involved in surviving, it seems some groups of people were more likely to survive than others.

In this challenge, we ask you to build a predictive model that answers the question: "what sorts of people were more likely to survive?" using passenger data (ie name, age, gender, socio-economic class, etc).

0.0.1 Importing libraries

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

0.0.2 Loading available data

[2]:
```
train_data = pd.read_csv('Downloads/titanic/train.csv')
test_data = pd.read_csv('Downloads/titanic/test.csv')

train_data.head()
```

```
[2]:    PassengerId  Survived  Pclass  \
     0            1         0       3
     1            2         1       1
     2            3         1       3
     3            4         1       1
     4            5         0       3

                                                     Name     Sex   Age  SibSp  \
     0                            Braund, Mr. Owen Harris    male  22.0      1
     1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
     2                             Heikkinen, Miss. Laina  female  26.0      0
     3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
     4                           Allen, Mr. William Henry    male  35.0      0

        Parch            Ticket     Fare Cabin Embarked
     0      0         A/5 21171   7.2500   NaN        S
     1      0          PC 17599  71.2833   C85        C
     2      0  STON/O2. 3101282   7.9250   NaN        S
     3      0            113803  53.1000  C123        S
     4      0            373450   8.0500   NaN        S
```

1 EDA

EDA techniques allow for effective manipulation of data sources, enabling data scientists to find the answers they need by discovering data patterns, spotting anomalies, checking assumptions, or testing a hypothesis.

Data specialists primarily use exploratory data analysis to discern what datasets can reveal further beyond formal modeling of data or hypothesis testing tasks. This enables them to gain in-depth knowledge of the variables in datasets and their relationships.

Exploratory data analysis can help detect obvious errors, identify outliers in datasets, understand relationships, unearth important factors, find patterns within data, and provide new insights. It's about finding correlations between features. By doing this, we can gain a strong insight into which feature should be used. We need to create the ability to interpret pictures.

There are four exploratory data analysis techniques that data experts use, which include:

Univariate Non-Graphical

This is the simplest type of EDA, where data has a single variable. Since there is only one variable, data professionals do not have to deal with relationships.

Univariate Graphical

Non-graphical techniques do not present the complete picture of data. Therefore, for comprehensive EDA, data specialists implement graphical methods, such as stem-and-leaf plots, box plots, and histograms.

Multivariate Non-Graphical

Multivariate data consists of several variables. Non-graphic multivariate EDA methods illustrate relationships between 2 or more data variables using statistics or cross-tabulation.

Multivariate Graphical

This EDA technique makes use of graphics to show relationships between 2 or more datasets. The widely-used multivariate graphics include bar chart, bar plot, heat map, bubble chart, run chart, multivariate chart, and scatter plot.

[3]:
```
df = train_data



def all_about_my_data(df):
    print("Here is some Basic Ground Info about the data:\n")

    # Shape of the data
    print("Number of Instances:",df.shape[0])
    print("Number of Features:",df.shape[1])

    # Summary Stats
    print("\nSummary Stats:")
    print(df.describe())

    # Missing Value Inspection
    print("\nMissing Values:")
    print(df.isna().sum())
    #percentage if i want (df.isna().sum()/df.shape[0])*100))

    print("\nFeatures Types:")
    for column in df.columns:
        print("Column ", column, "is dtype:", df[column].dtype.name)

all_about_my_data(df)
```

```
Here is some Basic Ground Info about the data:

Number of Instances: 891
Number of Features: 12

Summary Stats:
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000
```

```
            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200

Missing Values:
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

Features Types:
Column  PassengerId is dtype: int64
Column  Survived is dtype: int64
Column  Pclass is dtype: int64
Column  Name is dtype: object
Column  Sex is dtype: object
Column  Age is dtype: float64
Column  SibSp is dtype: int64
Column  Parch is dtype: int64
Column  Ticket is dtype: object
Column  Fare is dtype: float64
Column  Cabin is dtype: object
Column  Embarked is dtype: object
```

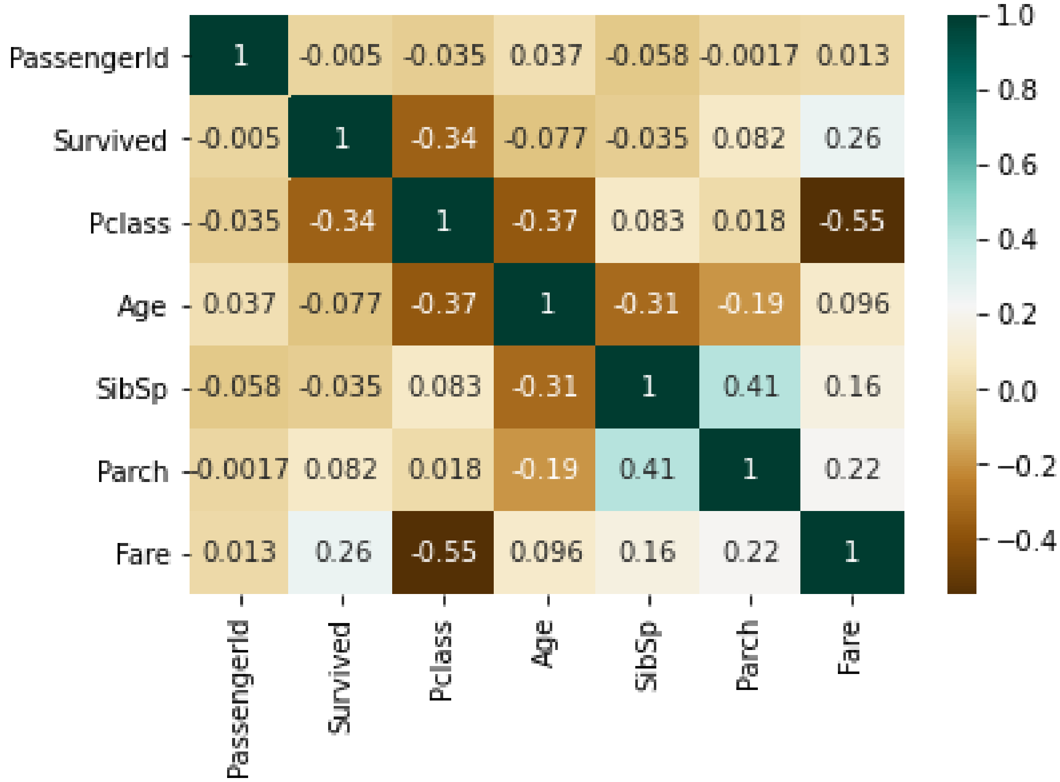
1.1 Feature Selection

Target variable: survived, 0 or 1

Relevant features related to the surviving rate: Fare and Pclass.

[4]:
```
# Filter method: Pearson correlation all features
correlation_mat = train_data.corr()
```

```
sns.heatmap(correlation_mat, annot = True, cmap="BrBG")
plt.show()

#highest corr with survival: pclass, fare
#fare-pclass, age-pclass, parch-sibsp

print(train_data[['Pclass', 'Survived']].corr())
print(train_data[['Fare', 'Survived']].corr())
```




```
            Pclass  Survived
Pclass    1.000000 -0.338481
Survived -0.338481  1.000000
              Fare  Survived
Fare      1.000000  0.257307
Survived  0.257307  1.000000
```

[5]:
```
train_data[["Sex", "Survived"]].groupby(['Sex'], as_index=False).mean().
↪sort_values(by='Survived', ascending=False)
```

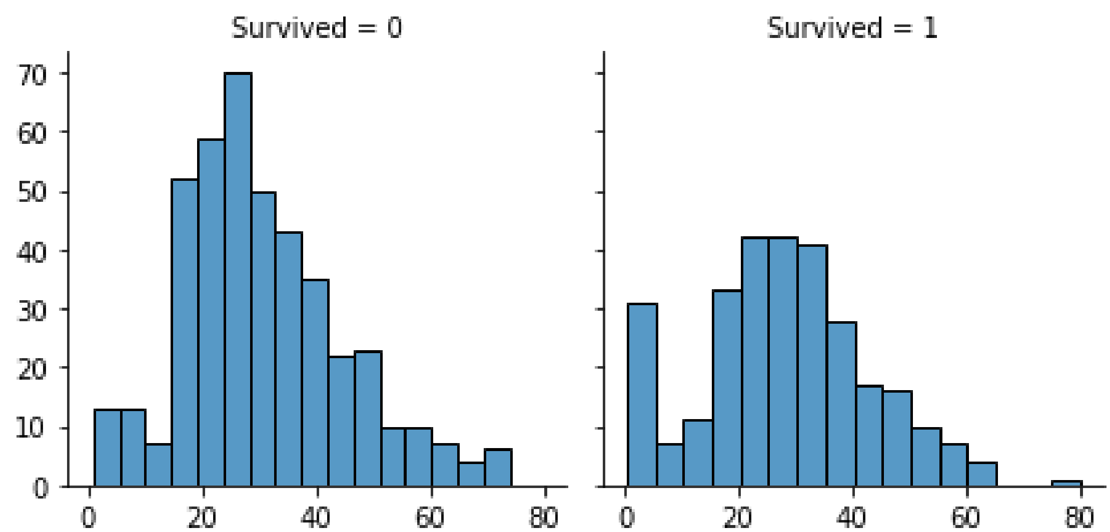
[5]:
```
      Sex  Survived
0  female  0.742038
1    male  0.188908
```

1.2 Visualizations

Histograms, Distplots, kdeplots are your friends

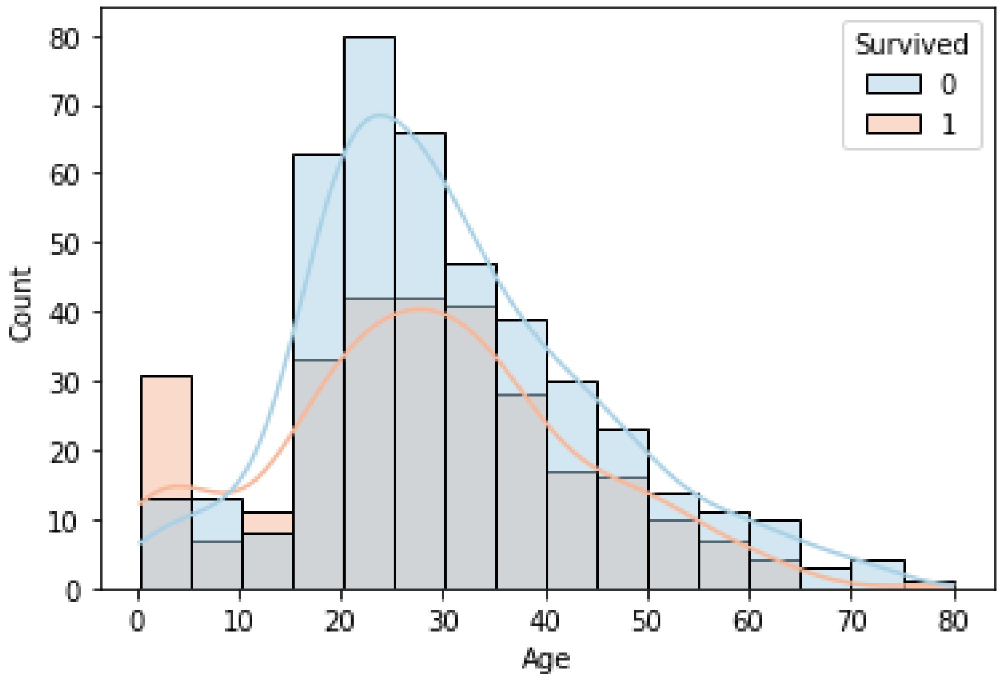
[6]:
```python
#Facetgrid is like a multi-plot grid for plotting conditional relationships.␣
↪This class maps a dataset onto multiple axes arrayed in a grid of rows and␣
↪columns that correspond to levels of variables in the dataset.
#Histplot is only about the COUNT (or density, or probability) of a column/
↪feature.

#Histogram of survival(1) and death (0) by age.
survived_grid = sns.FacetGrid(train_data, col='Survived')
survived_grid.map_dataframe(sns.histplot, x='Age', bins=16)
```

[6]:
```
<seaborn.axisgrid.FacetGrid at 0x7f6fff3a0640>
```



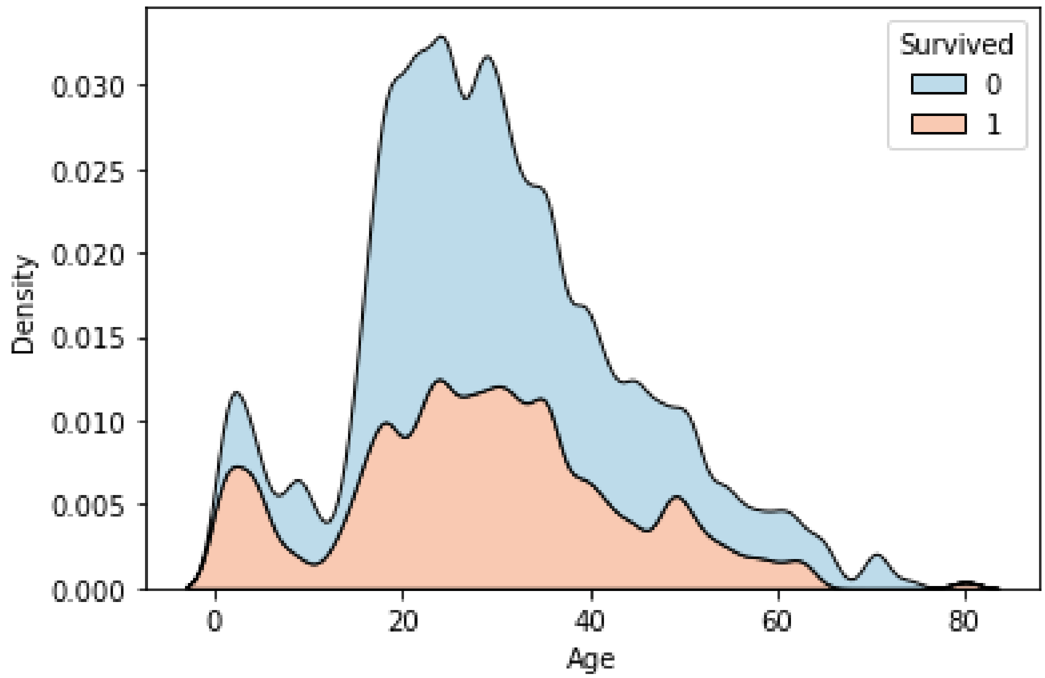
[7]:
```python
#Another graphical representation of survival by age
sns.histplot(train_data, x='Age', hue='Survived',multiple="layer", bins=16,␣
↪palette='RdBu_r', kde=True)
```

[7]:
```
<AxesSubplot:xlabel='Age', ylabel='Count'>
```



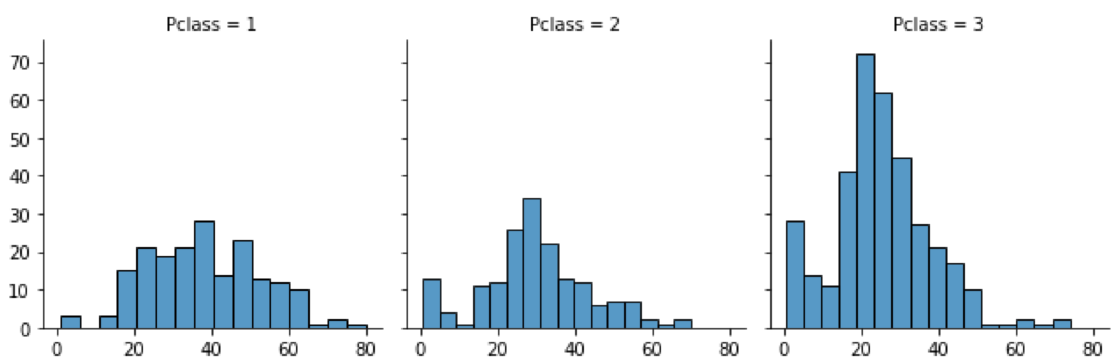
[8]:
```
#kde plot (continuous probability density curve in one or more dimensions) but
 ↪less smooth
sns.kdeplot(data=train_data, x='Age', hue='Survived', bw_adjust=.3,
 ↪multiple='stack', palette='RdBu_r')
```

[8]: <AxesSubplot:xlabel='Age', ylabel='Density'>



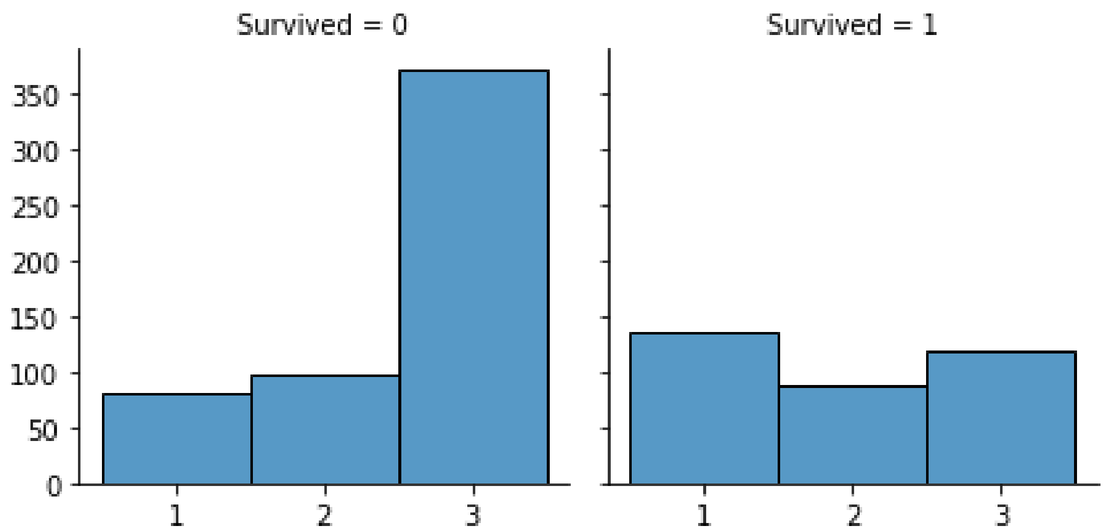
[9]:
```
#Histogram of Passenger Class by age.
pclass_grid = sns.FacetGrid(train_data, col='Pclass')
pclass_grid.map_dataframe(sns.histplot, x='Age', bins=16)
```

[9]: <seaborn.axisgrid.FacetGrid at 0x7f6ffe8d6730>



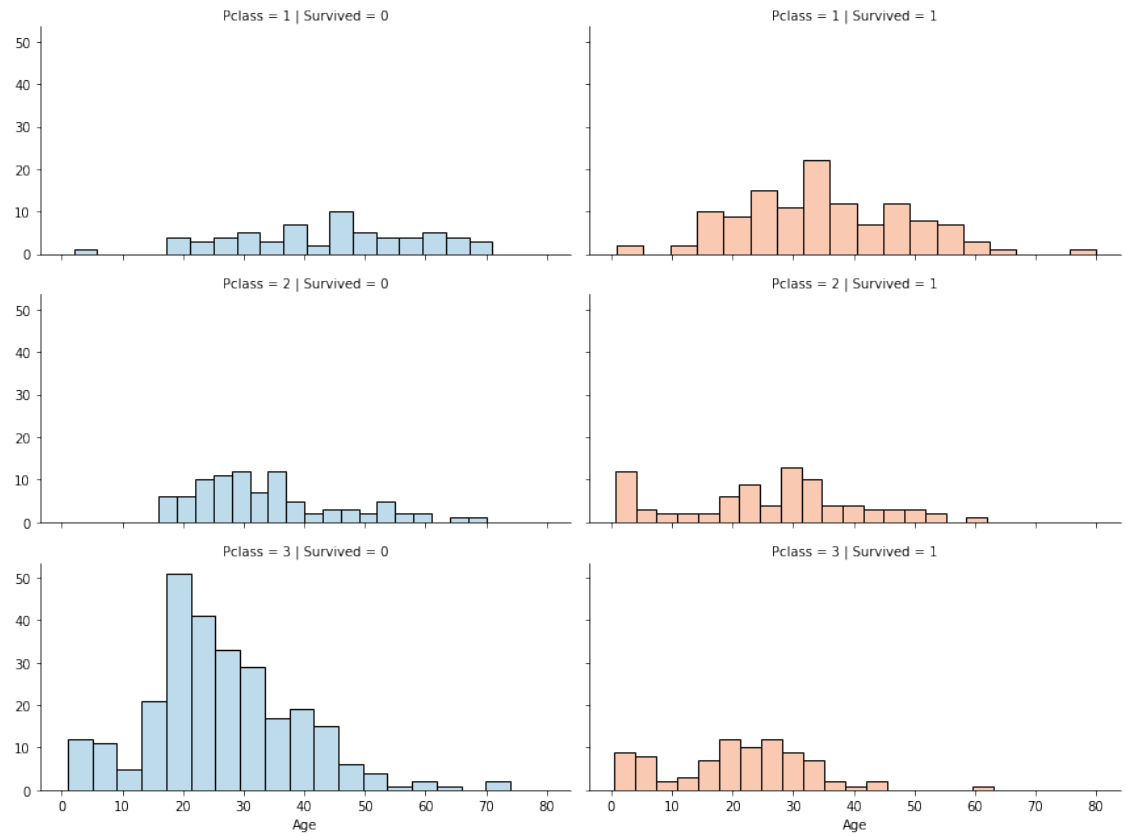
[10]:
```
#Survival by Passenger Class
survived_p_grid = sns.FacetGrid(train_data, col='Survived')
survived_p_grid.map_dataframe(sns.histplot, x='Pclass', bins=3, discrete=True)
```

[10]: <seaborn.axisgrid.FacetGrid at 0x7f6ffa4dd670>



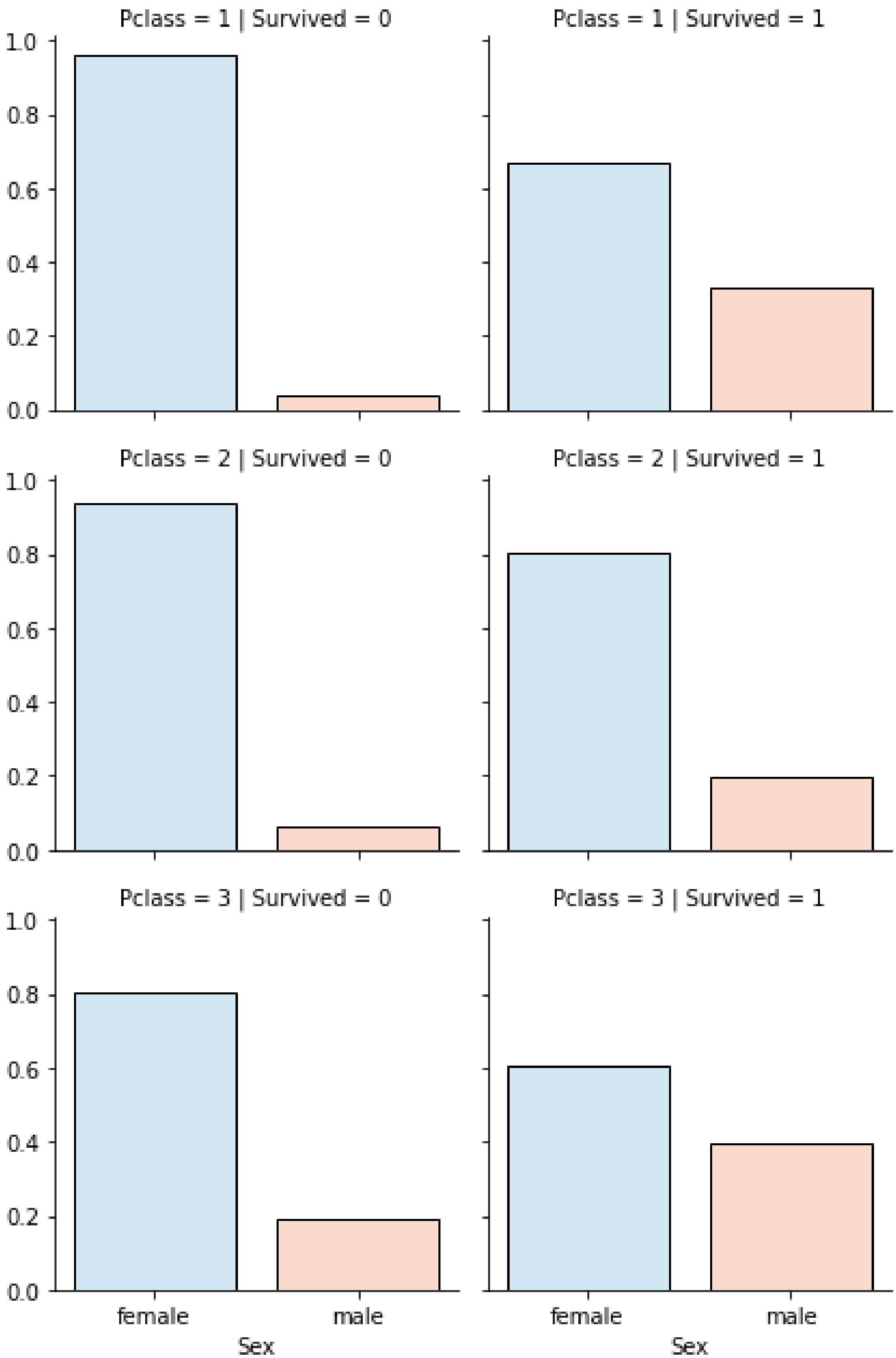
[11]:
```
#Combining age, survival, pclass
triple_grid = sns.FacetGrid(train_data, col='Survived', row='Pclass',␣
 ↪hue='Survived', aspect=2, palette='RdBu_r')
triple_grid.map_dataframe(sns.histplot, 'Age', bins=18)
```

[11]: <seaborn.axisgrid.FacetGrid at 0x7f6ffa46b3a0>

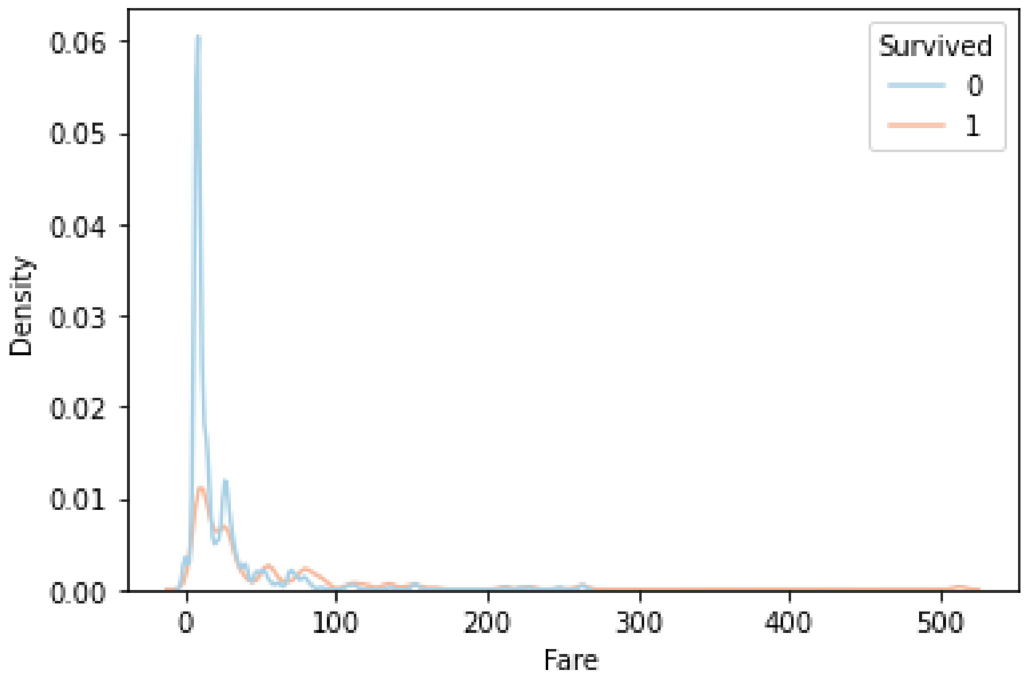


[12]:
```python
#Combining age, survival, pclass
triple_grid = sns.FacetGrid(train_data, col='Survived', row='Pclass')
triple_grid.map_dataframe(sns.histplot, 'Sex', shrink=0.8, stat="density",␣
↪hue='Sex',  palette='RdBu_r')


   # count shows the number of observations

  #  frequency shows the number of observations divided by the bin width

 #   density normalizes counts so that the area of the histogram is 1

#    probability normalizes counts so that the sum of the bar heights is 1
```

[12]:
```
<seaborn.axisgrid.FacetGrid at 0x7f6ffa007820>
```


Pclass = 1 | Survived = 0
Pclass = 1 | Survived = 1
Pclass = 2 | Survived = 0
Pclass = 2 | Survived = 1
Pclass = 3 | Survived = 0
Pclass = 3 | Survived = 1
1.0
0.8
0.6
0.4
0.2
0.0
female
male
Sex

[13]:
```
#Another graphical representation of survival by FARE - we can see an outlier
survived_fare = sns.kdeplot(data=train_data, x='Fare', hue='Survived',␣
↪bw_adjust=.2, palette='RdBu_r', levels=100)
```



2 Dealing with missing values

Age 177 SibSp 0 Parch 0 Ticket 0 Fare 0 Cabin 687 Embarked 2

[14]:
```
#state of things

combined_data = [train_data, test_data]

def visual_report(combined_data):
    for data in combined_data:
        print(data.isnull().sum())
        print('*' * 20)

visual_report(combined_data)
```

```
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
********************
PassengerId       0
Pclass            0
Name              0
Sex               0
Age              86
SibSp             0
Parch             0
Ticket            0
Fare              1
Cabin           327
Embarked          0
dtype: int64
********************
```

[15]:
```python
# filling the nan values fo Age and fare column with the mean while Embarked␣
↪column with most_frequent value
for data in combined_data:
    data.Age.fillna(data.Age.mean(), inplace = True)
    data.Fare.fillna(data.Fare.mean(), inplace = True)

# from visualization we know that Southamptom is most frequent Embarked place␣
↪so, filling the missing value
# with 'S'
train_data.Embarked.fillna('S', inplace = True)

#Mapping dual categorical data
train_data.Sex = train_data.Sex.map({'female':1, 'male':0})
test_data.Sex = test_data.Sex.map({'female':1, 'male':0})
```

[16]:
```python
#Mapping 3 categorie data
change = {'S':1,'C':2,'Q':0}
train_data.Embarked = train_data.Embarked.map(change)
test_data.Embarked = test_data.Embarked.map(change)

train_data.Embarked.fillna(train_data.Embarked.mean(), inplace=True)
```

[17]:
```
# before filling the missing values, let's drop Cabin column from both data.
train_data.drop('Cabin', axis = 1, inplace = True)
test_data.drop('Cabin', axis = 1, inplace = True)
```

[18]:
```
# now lets drop SibSp and Parch column for both training and testing data
train_data.drop(['SibSp','Parch'], axis = 1, inplace = True)
test_data.drop(['SibSp','Parch'], axis = 1, inplace = True )

columns_to_drop = ['PassengerId','Ticket','Name']
train_data.drop(columns_to_drop, axis = 1, inplace = True)
test_data.drop(columns_to_drop[1:], axis = 1, inplace = True)

visual_report(combined_data)
```

```
Survived    0
Pclass      0
Sex         0
Age         0
Fare        0
Embarked    0
dtype: int64
********************
PassengerId    0
Pclass         0
Sex            0
Age            0
Fare           0
Embarked       0
dtype: int64
********************
```

[ ]:

[ ]:

[19]:
```
#binning

for dataset in combined_data:
    dataset.loc[ dataset['Age'] <= 16, 'Age'] = 0
    dataset.loc[(dataset['Age'] > 16) & (dataset['Age'] <= 32), 'Age'] = 1
    dataset.loc[(dataset['Age'] > 32) & (dataset['Age'] <= 48), 'Age'] = 2
    dataset.loc[(dataset['Age'] > 48) & (dataset['Age'] <= 64), 'Age'] = 3
    dataset.loc[ dataset['Age'] > 64, 'Age'] = 4


for data in combined_data:
    data.loc[data['Fare'] < 30, 'Fare'] = 1
```

```
    data.loc[(data['Fare'] >= 30) & (data['Fare'] < 50),'Fare'] = 2
    data.loc[(data['Fare'] >= 50) & (data['Fare'] < 100),'Fare'] = 3
    data.loc[(data['Fare'] >= 100),'Fare'] = 4

visual_report(combined_data)
```

```
Survived    0
Pclass      0
Sex         0
Age         0
Fare        0
Embarked    0
dtype: int64
********************
PassengerId    0
Pclass         0
Sex            0
Age            0
Fare           0
Embarked       0
dtype: int64
********************
```

[ ]:

```

```

[20]:

```
X_train = train_data.drop("Survived", axis=1) #fit

Y_train = train_data["Survived"] #predict

X_test = test_data.drop("PassengerId", axis = 1) #evaluate

print("shape of X_train",X_train.shape)
print("Shape of Y_train",Y_train.shape)
print("Shape of x_test",X_test.shape)
```

```
shape of X_train (891, 5)
Shape of Y_train (891,)
Shape of x_test (418, 5)
```

3 Neural Networks

[21]:

```
import tensorflow as tf
import keras
from keras.layers import Dense, Dropout, Input
from keras.models import Sequential
```

3.0.1 First try

[22]:
```
model = Sequential()
model.add(Dense(units = 32, input_shape = (5,), activation = 'relu'))
model.add(Dense(units = 64, activation = 'relu', kernel_initializer =␣
 ↪'he_normal', use_bias = False))
model.add(tf.keras.layers.BatchNormalization())
model.add(Dense(units = 128, activation = 'relu',kernel_initializer =␣
 ↪'he_normal', use_bias = False))
model.add(Dropout(0.1))
model.add(Dense(units = 64, activation = 'relu',kernel_initializer =␣
 ↪'he_normal', use_bias = False))
model.add(Dropout(0.1))
model.add(Dense(units = 32, activation = 'relu'))
model.add(Dropout(0.15))
model.add(Dense(units = 16, activation = 'relu'))
model.add(Dense(units = 8, activation = 'relu',kernel_initializer =␣
 ↪'he_normal', use_bias = False))
model.add(Dense(units =1 , activation = 'sigmoid'))
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 32)                192
_________________________________________________________________
dense_1 (Dense)              (None, 64)                2048
_________________________________________________________________
batch_normalization (BatchNo (None, 64)                256
_________________________________________________________________
dense_2 (Dense)              (None, 128)               8192
_________________________________________________________________
dropout (Dropout)            (None, 128)               0
_________________________________________________________________
dense_3 (Dense)              (None, 64)                8192
_________________________________________________________________
dropout_1 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_4 (Dense)              (None, 32)                2080
_________________________________________________________________
dropout_2 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_5 (Dense)              (None, 16)                528
_________________________________________________________________
dense_6 (Dense)              (None, 8)                 128
_________________________________________________________________
```

```
dense_7 (Dense)              (None, 1)                 9
=================================================================
Total params: 21,625
Trainable params: 21,497
Non-trainable params: 128
_________________________________________________________________
```

[23]:
```
model.compile(loss = tf.keras.losses.binary_crossentropy, optimizer = tf.keras.
 ↪optimizers.Adam(), metrics = ['acc'])
```

[24]:
```
model.fit(X_train, Y_train, batch_size = 32, verbose = 2, epochs = 50)
```

```
Epoch 1/50
28/28 - 1s - loss: 0.6840 - acc: 0.5892
Epoch 2/50
28/28 - 0s - loss: 0.5919 - acc: 0.7452
Epoch 3/50
28/28 - 0s - loss: 0.5007 - acc: 0.7778
Epoch 4/50
28/28 - 0s - loss: 0.4560 - acc: 0.7957
Epoch 5/50
28/28 - 0s - loss: 0.4521 - acc: 0.8081
Epoch 6/50
28/28 - 0s - loss: 0.4604 - acc: 0.7991
Epoch 7/50
28/28 - 0s - loss: 0.4315 - acc: 0.8193
Epoch 8/50
28/28 - 0s - loss: 0.4240 - acc: 0.8092
Epoch 9/50
28/28 - 0s - loss: 0.4378 - acc: 0.8103
Epoch 10/50
28/28 - 0s - loss: 0.4266 - acc: 0.8081
Epoch 11/50
28/28 - 0s - loss: 0.4239 - acc: 0.8148
Epoch 12/50
28/28 - 0s - loss: 0.4280 - acc: 0.8092
Epoch 13/50
28/28 - 0s - loss: 0.4234 - acc: 0.8204
Epoch 14/50
28/28 - 0s - loss: 0.4185 - acc: 0.8227
Epoch 15/50
28/28 - 0s - loss: 0.4265 - acc: 0.8025
Epoch 16/50
28/28 - 0s - loss: 0.4219 - acc: 0.8114
Epoch 17/50
28/28 - 0s - loss: 0.4247 - acc: 0.8148
Epoch 18/50
28/28 - 0s - loss: 0.4271 - acc: 0.8193
```

```
Epoch 19/50
28/28 - 0s - loss: 0.4032 - acc: 0.8204
Epoch 20/50
28/28 - 0s - loss: 0.4101 - acc: 0.8193
Epoch 21/50
28/28 - 0s - loss: 0.4079 - acc: 0.8238
Epoch 22/50
28/28 - 0s - loss: 0.4235 - acc: 0.8092
Epoch 23/50
28/28 - 0s - loss: 0.4150 - acc: 0.8204
Epoch 24/50
28/28 - 0s - loss: 0.4076 - acc: 0.8182
Epoch 25/50
28/28 - 0s - loss: 0.4054 - acc: 0.8081
Epoch 26/50
28/28 - 0s - loss: 0.4145 - acc: 0.8148
Epoch 27/50
28/28 - 0s - loss: 0.4144 - acc: 0.8283
Epoch 28/50
28/28 - 0s - loss: 0.4270 - acc: 0.8137
Epoch 29/50
28/28 - 0s - loss: 0.4102 - acc: 0.8171
Epoch 30/50
28/28 - 0s - loss: 0.4081 - acc: 0.8159
Epoch 31/50
28/28 - 0s - loss: 0.4112 - acc: 0.8137
Epoch 32/50
28/28 - 0s - loss: 0.4117 - acc: 0.7980
Epoch 33/50
28/28 - 0s - loss: 0.3945 - acc: 0.8215
Epoch 34/50
28/28 - 0s - loss: 0.4080 - acc: 0.8249
Epoch 35/50
28/28 - 0s - loss: 0.4056 - acc: 0.8249
Epoch 36/50
28/28 - 0s - loss: 0.4131 - acc: 0.8148
Epoch 37/50
28/28 - 0s - loss: 0.4082 - acc: 0.8272
Epoch 38/50
28/28 - 0s - loss: 0.4095 - acc: 0.8171
Epoch 39/50
28/28 - 0s - loss: 0.4111 - acc: 0.8294
Epoch 40/50
28/28 - 0s - loss: 0.4028 - acc: 0.8249
Epoch 41/50
28/28 - 0s - loss: 0.3968 - acc: 0.8238
Epoch 42/50
28/28 - 0s - loss: 0.3986 - acc: 0.8193
```

```
Epoch 43/50
28/28 - 0s - loss: 0.4062 - acc: 0.8148
Epoch 44/50
28/28 - 0s - loss: 0.4133 - acc: 0.8137
Epoch 45/50
28/28 - 0s - loss: 0.4047 - acc: 0.8193
Epoch 46/50
28/28 - 0s - loss: 0.3978 - acc: 0.8193
Epoch 47/50
28/28 - 0s - loss: 0.4098 - acc: 0.8159
Epoch 48/50
28/28 - 0s - loss: 0.4037 - acc: 0.8171
Epoch 49/50
28/28 - 0s - loss: 0.4017 - acc: 0.8182
Epoch 50/50
28/28 - 0s - loss: 0.3983 - acc: 0.8272
```

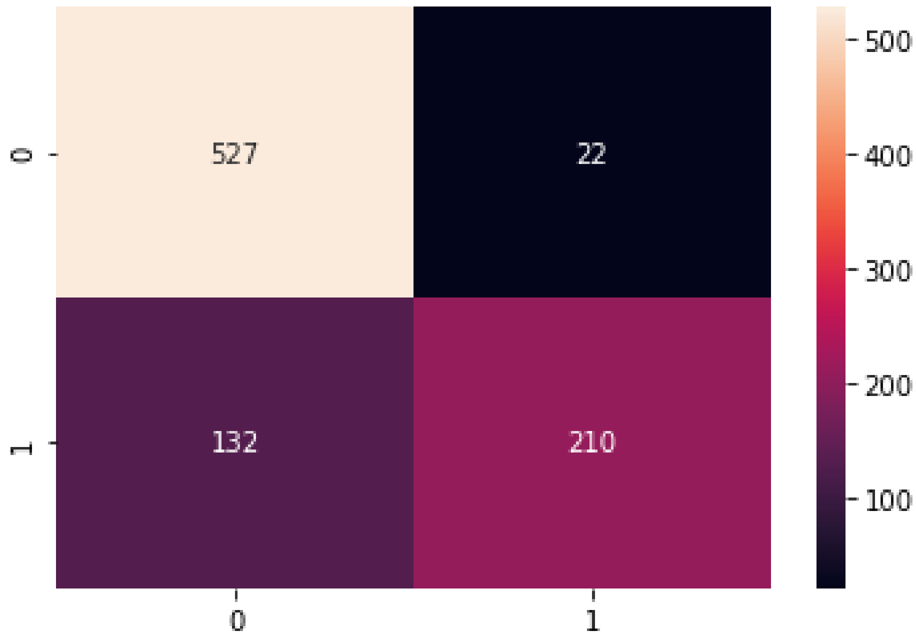
[24]:
```
<tensorflow.python.keras.callbacks.History at 0x7f6fc825c910>
```

3.0.2 Predicting for test_data

[25]:
```
predict = model.predict(X_test)
#since we have use sigmoid activation function in output layer
predict = (predict > 0.5).astype(int).ravel()
```

[26]:
```
from sklearn import metrics
Y_pred_rand = (model.predict(X_train) > 0.5).astype(int)

print('Precision : ', np.round(metrics.precision_score(Y_train,␣
↪Y_pred_rand)*100,2))
print('Accuracy : ', np.round(metrics.accuracy_score(Y_train,␣
↪Y_pred_rand)*100,2))
print('Recall : ', np.round(metrics.recall_score(Y_train, Y_pred_rand)*100,2))
print('F1 score : ', np.round(metrics.f1_score(Y_train, Y_pred_rand)*100,2))
print('AUC : ', np.round(metrics.roc_auc_score(Y_train, Y_pred_rand)*100,2))

# plotting the confusion matrix in heatmap
matrix = metrics.confusion_matrix(Y_train, Y_pred_rand)
sns.heatmap(matrix, annot = True,fmt = 'g')
plt.show()
```

```
Precision :  90.52
Accuracy :  82.72
Recall :  61.4
F1 score :  73.17
AUC :  78.7
```



[28]:
```
submit = pd.DataFrame({"PassengerId":test_data.PassengerId, 'Survived':predict})
submit.to_csv("final_submission.csv",index = False)
submit.shape
```

[28]: (418, 2)

[ ]: