Visualization on Titanic Dataset

February 9, 2024

0.0.1 About Dataset:

0.0.2 Context:

The data contains the details of passengers onboard in Titanic and its shipwreck details.Contains demographics and passenger information from 891 of the 2224 passengers and crew on board the Titanic.

0.0.3 Contents:

Passenger details: Age, Gender, Socio Economic Class, Adults and Kids with their relation between, Cabin Number.

0.0.4 Problem:

Analyse and Visualize the dataset.

*Variable**	**Definition**	**Key**
Survived	Survival	0 = No, 1 = Yes
Pclass	Ticket class	1 = 1st, 2 = 2nd, 3 = 3rd
Sex	Sex	
Age	Age in years	
Sibsp	# of siblings / spouses aboard the Titanic	
Parch	# of parents / children aboard the Titanic	
Ticket	Ticket number	
Fare	Passenger fare	
Cabin	Cabin number	
Embarked	Port of Embarkation	C = Cherbourg, Q = Queenstown,S = Southampton

Pclass: A proxy for socio-economic status (SES)
1st = Upper
2nd = Middle
3rd = Lower

Age: Age is fractional if less than 1. If the age is estimated, is it in the form of xx.5

Sibsp: The dataset defines family relations in this way...
Sibling = brother, sister, stepbrother, stepsister
Spouse = husband, wife (mistresses and fiancés were ignored)

Parch: The dataset defines family relations in this way...
Parent = mother, father
Child = daughter, son, stepdaughter, stepson
Some children travelled only with a nanny, therefore parch=0 for them.

[1]:
```
# Importing Libraries:
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
# Defing default sizes for plots:
SMALL_SIZE = 13
MEDIUM_SIZE = 14
BIGGER_SIZE = 16

plt.rc('font', size=SMALL_SIZE)          # controls default text sizes
plt.rc('axes', titlesize=SMALL_SIZE)     # fontsize of the axes title
plt.rc('axes', labelsize=MEDIUM_SIZE)    # fontsize of the x and y labels
plt.rc('xtick', labelsize=MEDIUM_SIZE)    # fontsize of the tick labels
plt.rc('ytick', labelsize=MEDIUM_SIZE)    # fontsize of the tick labels
plt.rc('legend', fontsize=SMALL_SIZE)    # legend fontsize
```

0.0.5 Data Acquisition

[3]:
```
#Load the CSV into a Pandas Dataframe
titanic_data = pd.read_csv("C:/Users/amitm/Desktop/New folder/Task Impetus/
 ↪Class/Python/Case Study/titanic-data.csv")
```

[4]:
```
# Data Description:
titanic_data.head(10)
```

[4]:

	PassengerId	Survived	Pclass	\
0	1	0	3	
1	2	1	1	
2	3	1	3	
3	4	1	1	
4	5	0	3	
5	6	0	3	
6	7	0	1	
7	8	0	3	
8	9	1	3	
9	10	1	2	

```
                                                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
5                                   Moran, Mr. James    male   NaN      0
6                            McCarthy, Mr. Timothy J    male  54.0      0
7                     Palsson, Master. Gosta Leonard    male   2.0      3
8  Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)  female  27.0      0
9                Nasser, Mrs. Nicholas (Adele Achem)  female  14.0      1

   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
5      0            330877   8.4583   NaN        Q
6      0             17463  51.8625   E46        S
7      1            349909  21.0750   NaN        S
8      2            347742  11.1333   NaN        S
9      0            237736  30.0708   NaN        C
```

[5]:
```
titanic_data.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
```

0.0.6 Data Cleaning and Transformation:

[6]:
```
#Dropping Columns(Cabin,Ticket, Name,Fare,PassengerId- missing common values)
n_titanic_data=titanic_data.drop(['Cabin','Ticket','Name',
                                  'Fare','PassengerId'],axis=1)
```

[7]:
```
titanic_data
```

[7]:

	PassengerId	Survived	Pclass	\
0	1	0	3	
1	2	1	1	
2	3	1	3	
3	4	1	1	
4	5	0	3	
..	…	…	…	
886	887	0	2	
887	888	1	1	
888	889	0	3	
889	890	1	1	
890	891	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	
..	…	…	…	…	
886	Montvila, Rev. Juozas	male	27.0	0	
887	Graham, Miss. Margaret Edith	female	19.0	0	
888	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	
889	Behr, Mr. Karl Howell	male	26.0	0	
890	Dooley, Mr. Patrick	male	32.0	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
..	…	…	…	…	…
886	0	211536	13.0000	NaN	S
887	0	112053	30.0000	B42	S
888	2	W./C. 6607	23.4500	NaN	S
889	0	111369	30.0000	C148	C
890	0	370376	7.7500	NaN	Q

```
[891 rows x 12 columns]
```

[8]:
```
n_titanic_data.head()
```

[8]:
```
   Survived  Pclass     Sex   Age  SibSp  Parch Embarked
0         0       3    male  22.0      1      0        S
1         1       1  female  38.0      1      0        C
2         1       3  female  26.0      0      0        S
3         1       1  female  35.0      1      0        S
4         0       3    male  35.0      0      0        S
```

[9]:
```
n_titanic_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Survived  891 non-null    int64
 1   Pclass    891 non-null    int64
 2   Sex       891 non-null    object
 3   Age       714 non-null    float64
 4   SibSp     891 non-null    int64
 5   Parch     891 non-null    int64
 6   Embarked  889 non-null    object
dtypes: float64(1), int64(4), object(2)
memory usage: 48.9+ KB
```

We have only 714 -Age values out of 891 of the entries and 2 values missing from Embarked Variable and choose to drop them as there is lack of consistency between analyzed subsets.

0.0.7 Analysis and Visualization

[10]:
```
#Changing keys to readable format and exploring initial composition of the␣
 ↪passengers.
descript = n_titanic_data.copy()

#Change the embarked keys to better readable ones
descript.loc[:,'Embarked'].
 ↪replace(['C','S','Q'],['Cherbourg','Southampton','Queenstown'],inplace=True)

#And the survived keys
descript.loc[:,'Survived'].replace([0,1],['No','Yes'],inplace=True)
```

[11]:
```
descript.head(10)
```

[11]:
```
  Survived  Pclass     Sex   Age  SibSp  Parch     Embarked
0       No       3    male  22.0      1      0  Southampton
```

```
1      Yes       1  female  38.0      1      0    Cherbourg
2      Yes       3  female  26.0      0      0  Southampton
3      Yes       1  female  35.0      1      0  Southampton
4       No       3    male  35.0      0      0  Southampton
5       No       3    male   NaN      0      0   Queenstown
6       No       1    male  54.0      0      0  Southampton
7       No       3    male   2.0      3      1  Southampton
8      Yes       3  female  27.0      0      2  Southampton
9      Yes       2  female  14.0      1      0    Cherbourg
```

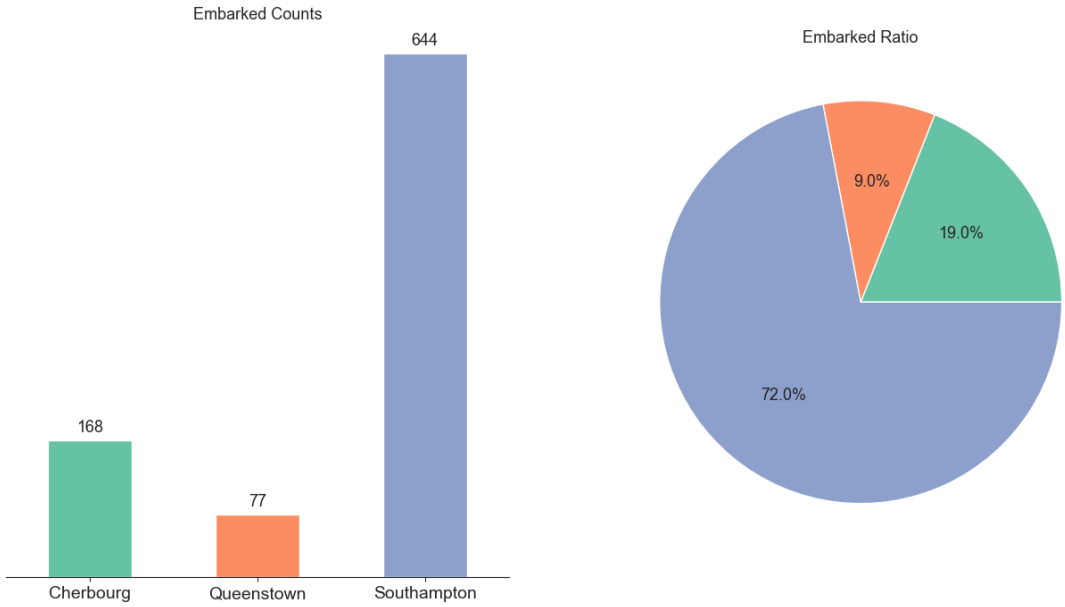
Analysis for Embarked variable.

[12]:
```
def Groupby_OneCol_comp_plot(df, col, plt_style='ticks', color_palette='Set2'):
    '''
    Group by col1, sort by size , return and plot the dataframe with a bar and␣
 ↪pie plot
    '''
    gr = pd.DataFrame()
    gr['{} No'.format(col)] = df.groupby(col).size()
    gr['{} Ratio'.format(col)] = np.round(gr['{} No'.format(col)].divide(gr['{}␣
 ↪No'.format(col)].sum()) * 100, 0)

    print('Total No. of {}:{}'.format(col, gr['{} No'.format(col)].sum()))

    sns.set_style(plt_style)
    sns.set_palette(sns.color_palette(color_palette))

    fig = plt.figure()
    plt.axis('off')

    fig.add_subplot(121)

    ax = gr['{} No'.format(col)].plot(kind='bar', title='{} Counts'.
 ↪format(col), figsize=(16, 8),
                                      color=sns.color_palette())
    plt.setp(ax.get_xticklabels(), rotation=0)
    for p in ax.patches:
        ax.annotate(np.round(p.get_height(), decimals=2),
                    (p.get_x() + p.get_width() / 2., p.get_height()),
                    ha='center', va='center', xytext=(0, 10),␣
 ↪textcoords='offset points')
    ax.get_yaxis().set_ticks([])
    plt.xlabel('')

    fig.add_subplot(122)
    plt.axis('off')
    gr.loc[:, '{} Ratio'.format(col)].plot(kind='pie',
```

```
                                                autopct='%1.1f%%', shadow=False,
                                                title='{} Ratio'.format(col),␣
↪legend=False, labels=None);
    sns.despine(top=True, right=True, left=True, bottom=False);
```

[13]:
```
Groupby_OneCol_comp_plot(descript, 'Embarked')
```

```
Total No. of Embarked:889
```



- Majority of passengers (644 of 889 :72%) embarked in Southampton.
- Less number of passengers(77 of 889:9%) embarked in Queenstown.

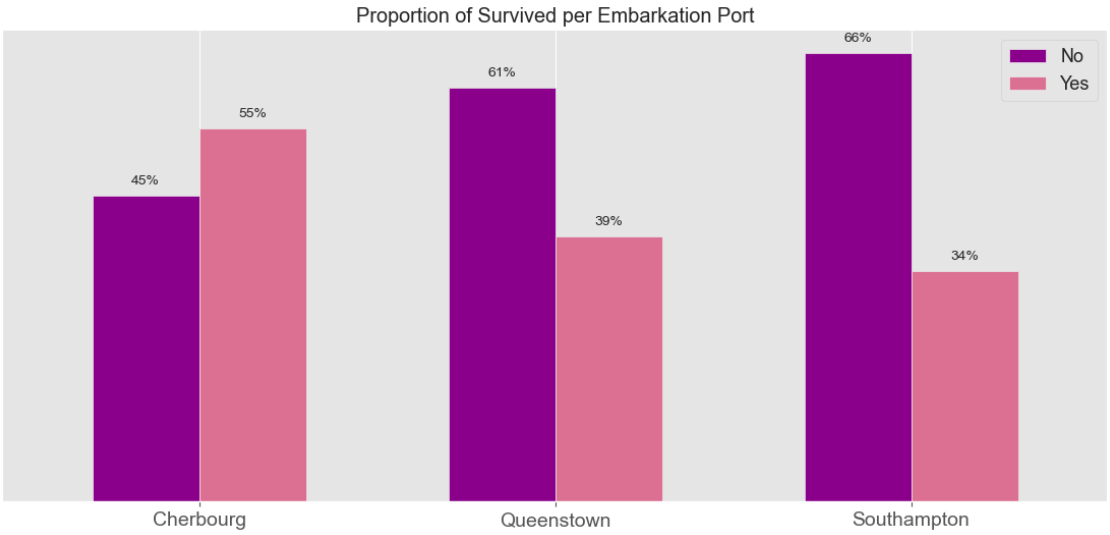
Correlation between Survived with Embarked.

[14]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

def plot(table, legloc='upper right', plt_style='ticks', color_palette="dark",
         sorter=None, stacked=False, kind='bar', percentage=True,␣
↪custom_title=None,
         minimal=True, figsize=(19, 10), width=0.7):

    grouped = table

    if percentage:
        grouped = np.round(grouped.divide(grouped['Total'], axis=0) * 100, 0)
```

```
    try:
        del grouped['Total']
    except:
        pass

    if sorter:
        grouped = grouped[sorter]

    plt.style.use(plt_style)
    sns.set_palette(sns.color_palette(color_palette))
    ax = grouped.plot(kind=kind, stacked=stacked, figsize=figsize, width=width)
    _ = plt.setp(ax.get_xticklabels(), rotation=0)
    plt.legend(loc=legloc)

    if percentage:
        for p in ax.patches:
            ax.annotate('{}%'.format(int(np.round(p.get_height(), decimals=2))),
                        (p.get_x() + p.get_width() / 2., p.get_height()),␣
 ↪ha='center', va='center',
                        xytext=(0, 10), textcoords='offset points')
    else:
        for p in ax.patches:
            ax.annotate(np.round(p.get_height(), decimals=2),
                        (p.get_x() + p.get_width() / 2., p.get_height()),␣
 ↪ha='center', va='center',
                        xytext=(0, 10), textcoords='offset points')

    if minimal:
        ax.get_yaxis().set_ticks([])
        plt.xlabel('')
        sns.despine(top=True, right=True, left=True, bottom=False)

    plt.title(custom_title)

def Groupby_TwoCol_Plot(df, col1, col2, legloc='upper right',␣
 ↪plt_style='ggplot',
                        color_palette="dark", sorter=None, stacked=False,
                        kind='bar', percentage=True, custom_title=None,
                        minimal=True, figsize=(14, 6), width=0.6):

    grouped = df.groupby([col2,col1]).size().unstack(col2)
    grouped['Total'] = grouped.sum(axis=1)

    plot(grouped, legloc=legloc, plt_style=plt_style,␣
 ↪color_palette=color_palette,
         sorter=sorter, stacked=stacked, kind=kind, percentage=percentage,
```

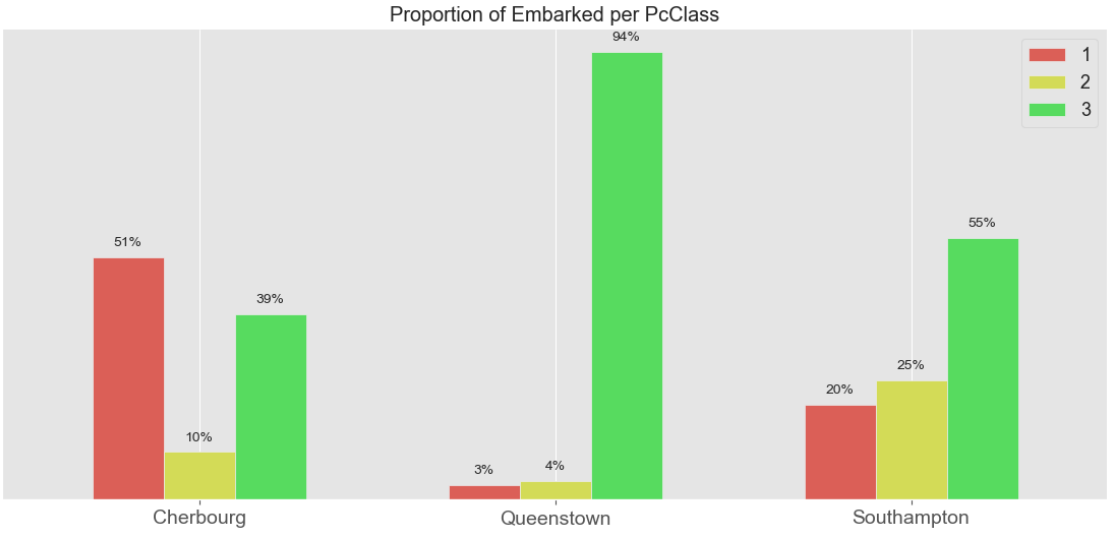
```
        custom_title=custom_title, minimal=minimal, figsize=figsize,␣
↪width=width)
```

[15]:
```
Groupby_TwoCol_Plot(descript, 'Embarked', 'Survived',␣
↪color_palette=('darkmagenta','palevioletred'),
                    custom_title='Proportion of Survived per Embarkation Port')
```



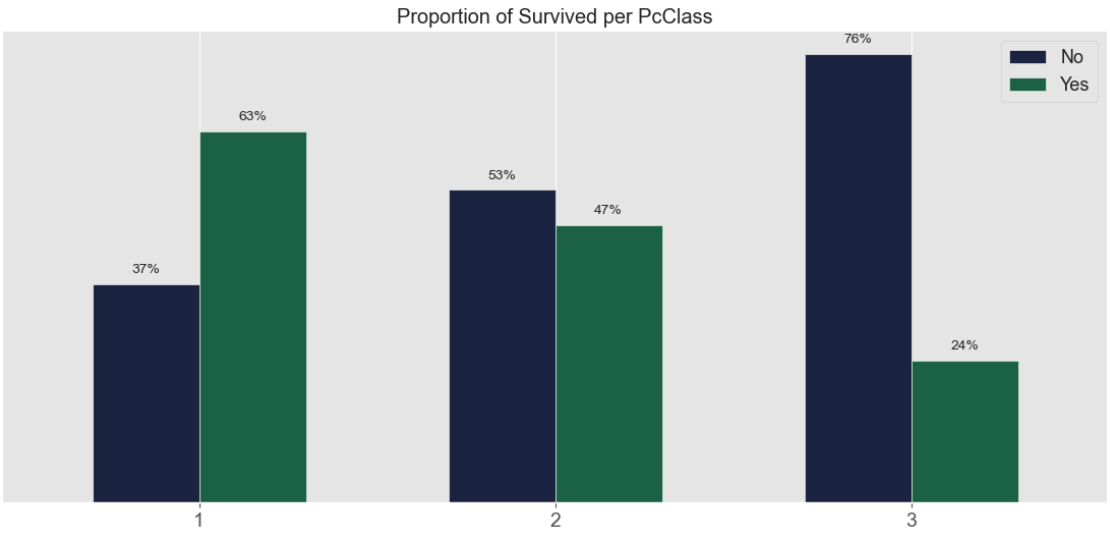
- 55% of passengers embarked in Cherbourg survived compared to 34% and 39% at Southampton and Queensberg respectively.

[16]:
```
Groupby_TwoCol_Plot(descript, 'Embarked', 'Pclass', color_palette=('hls'),
                    custom_title='Proportion of Embarked per PcClass',␣
↪sorter=[1,2,3])
```



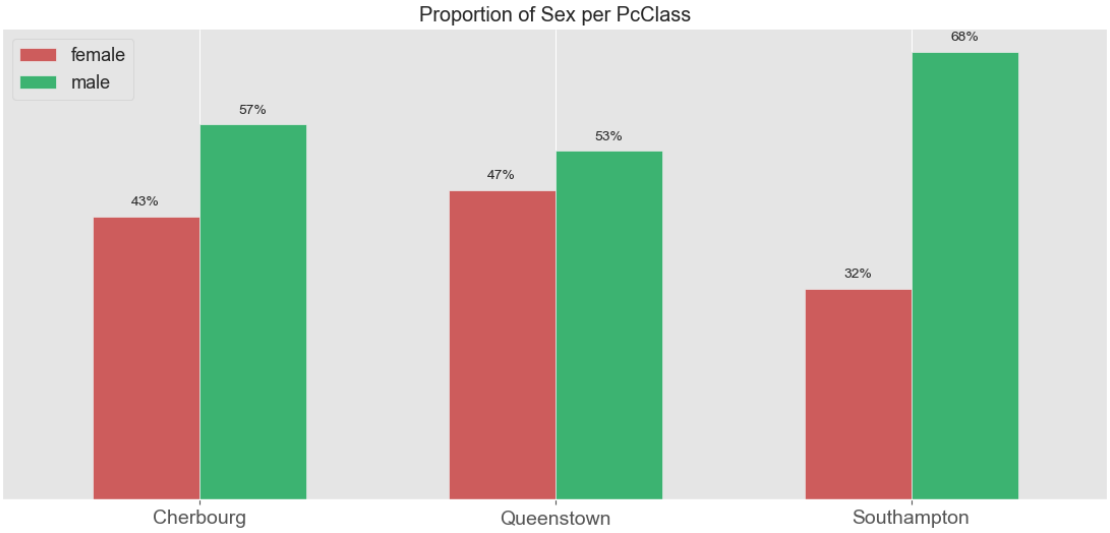
- 51% of the passengers embarked in Cherbourg are in the 1st Pclass compared to 20% and 3% respectively for Southhampton and Queenstown.
- It looks like the class may play a role in port of embarkation's relationship with survibability.

[17]:
```
# Correlation of Survived with Pclass
Groupby_TwoCol_Plot(descript, 'Pclass', 'Survived', color_palette=('cubehelix'),
                    custom_title='Proportion of Survived per PcClass')
```



- 63% of 1st class passengers survived compared to 47% and 24% for the 2nd and 3rd class respectively.
- Survivability seems to be correlated with the Pcclass and this could be the main factor behind the correlation with the port of embarkation as well.

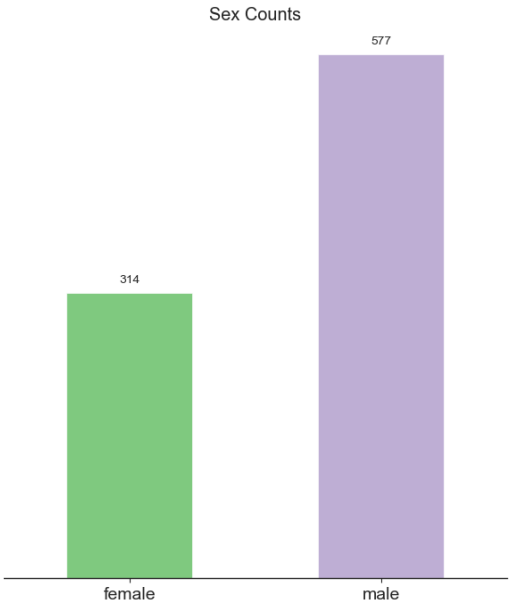
[18]:
```
# Correlation of Embarked with Sex.
#Calculate percentages of port passengers per Sex
Groupby_TwoCol_Plot(descript, 'Embarked', 'Sex',␣
 ↪color_palette=('indianred','mediumseagreen'),
                    custom_title='Proportion of Sex per PcClass', legloc='upper␣
 ↪left')
```

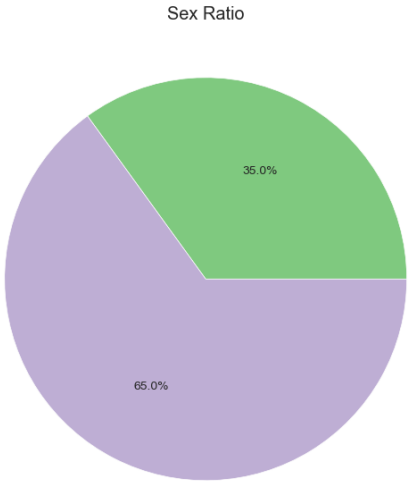


There does not seem to be a clear pattern related to Gender that could be contributing to the increased survivability of the Cherbourg passengers.

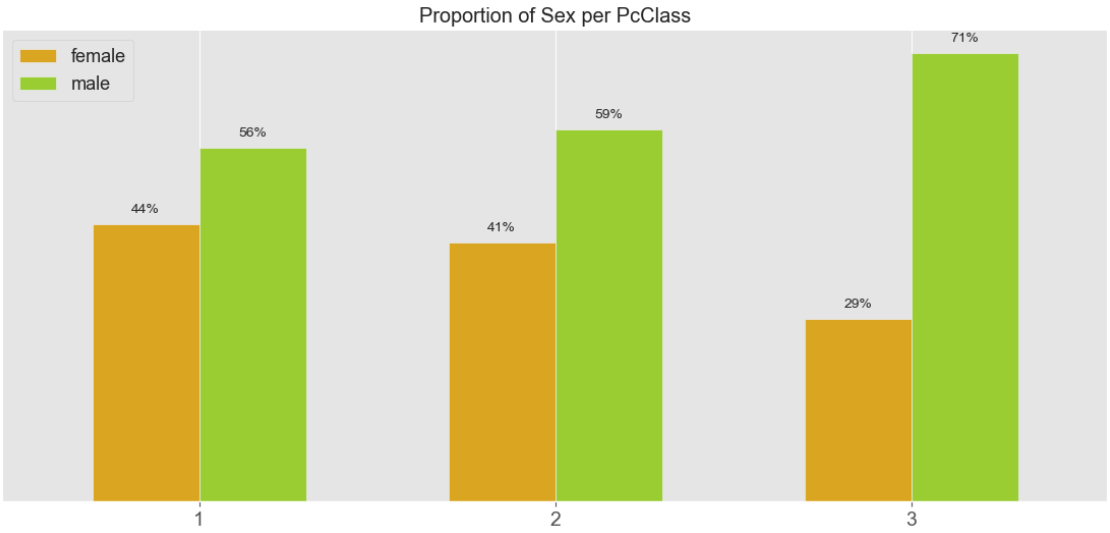
[19]:
```
# Sex ratio of passengers
Groupby_OneCol_comp_plot(descript, 'Sex', color_palette = ('Accent') )
```

```
Total No. of Sex:891
```



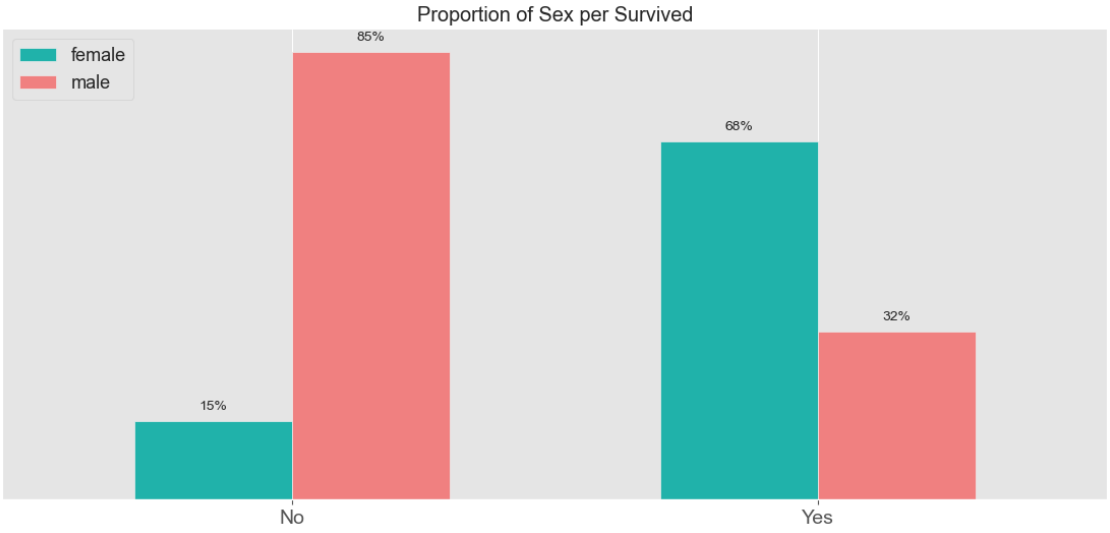


[20]:
```
# Correlation of Sex with Pclass.
# Calculate percentages of Pclass per Sex
Groupby_TwoCol_Plot(descript, 'Pclass', 'Sex',␣
 ↪color_palette=('goldenrod','yellowgreen'),
                    custom_title='Proportion of Sex per PcClass', legloc='upper␣
 ↪left')
```



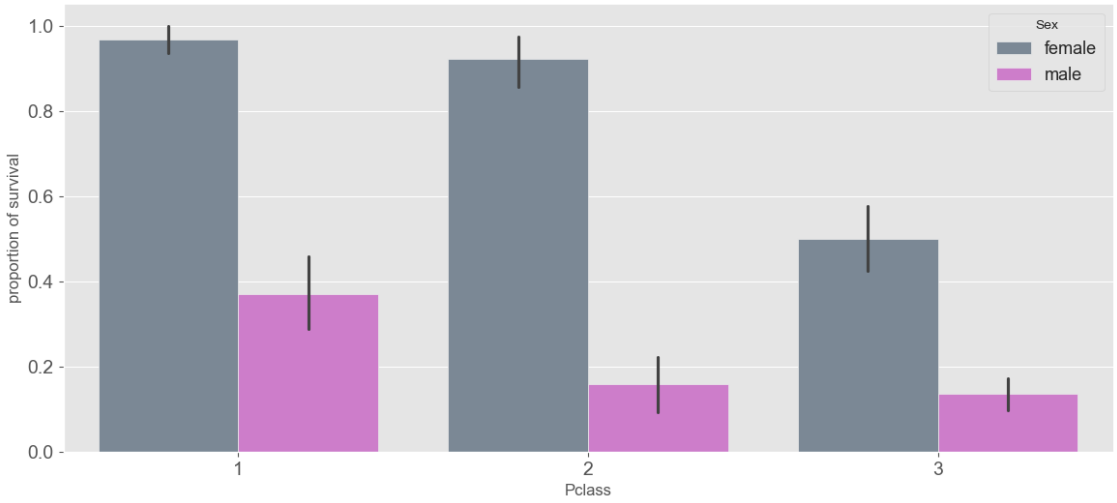
- We observe that the 3rd class has a higher than average (71 % vs 65%) male percentage.

[21]:
```
# Correlation of Sex with Survived
Groupby_TwoCol_Plot(descript, 'Survived', 'Sex',␣
 ↪color_palette=('lightseagreen','lightcoral'),
                    custom_title='Proportion of Sex per Survived',␣
 ↪legloc='upper left')
```



- 74% of females survived compared to 19% for males.
- 44% of the 1st class(which had a 65% survivability) comprised of females compared to 29% of the third class (24% survivability).

[22]:
```
# Correlation of Survived with Sex and Pclass.

plt.figure(figsize=(14,6))
sns.set_palette(sns.color_palette(('lightslategrey','orchid')))
sns.barplot(data=n_titanic_data, x="Pclass", hue='Sex', y='Survived',␣
 ↪estimator=np.mean);
plt.ylabel('proportion of survival')
sns.despine(top=True, right=True, left=False, bottom=False);
```



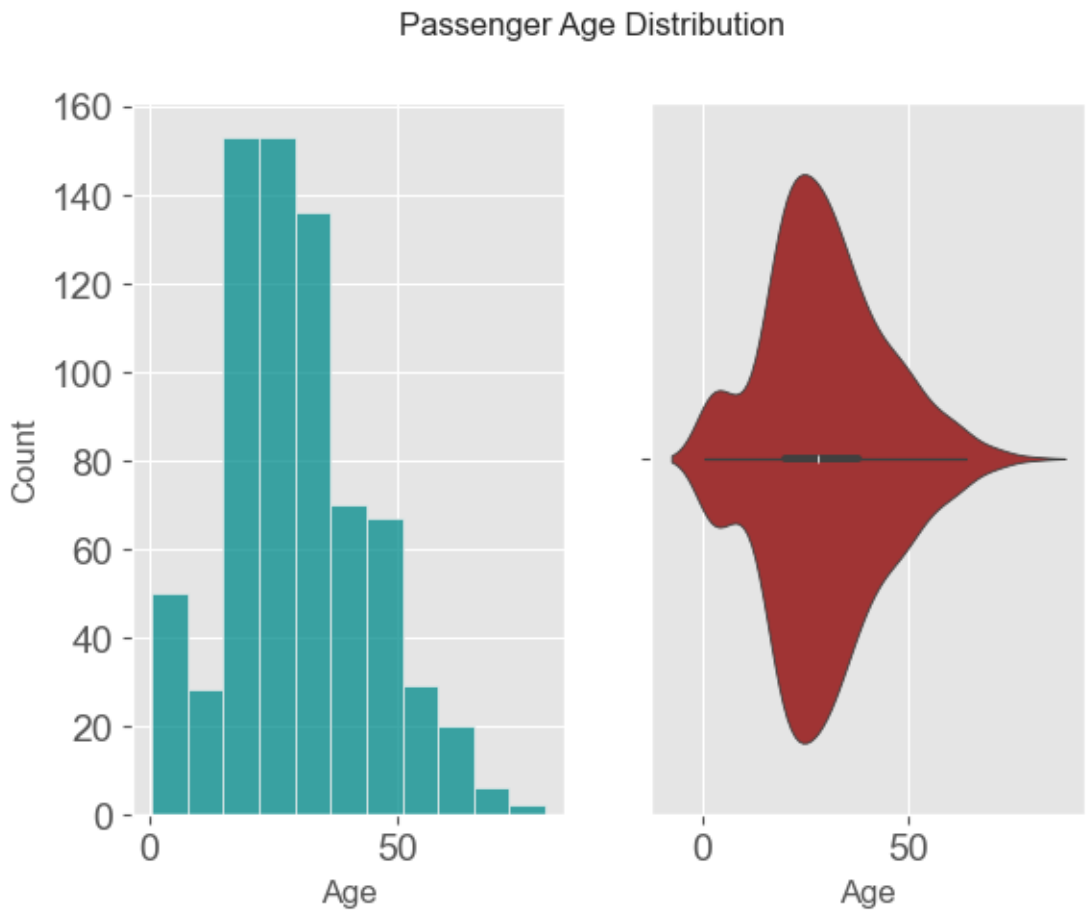
- The proportion of survival for females in the first class was almost 100% in the first class compared to 50% in the third class.
- Age together with the Class have a compound effect on survivability as well as on the correlation of other variables to survivability.

[23]:
```
# Analysis of the Age variable
# Make a dataframe for non-missing 'Age' values
not_missing = n_titanic_data[n_titanic_data['Age'].notnull()].copy()

# Replace the 'Survived' values with 'No' and 'Yes'
not_missing['Survived'].replace({0: 'No', 1: 'Yes'}, inplace=True)
```

[24]:
```
print ('No. of Passengers with not missing Age Values:{}'.
  ↪format(len(not_missing)))
```

```
No. of Passengers with not missing Age Values:714
```

[25]:
```
fig = plt.figure()
plt.suptitle('Passenger Age Distribution')

ax1 = fig.add_subplot(121)
sns.histplot(not_missing['Age'], bins=11, ax=ax1,color='darkcyan')

ax2 = fig.add_subplot(122)
sns.violinplot(x=not_missing['Age'], ax=ax2,color='firebrick')

plt.show()
```



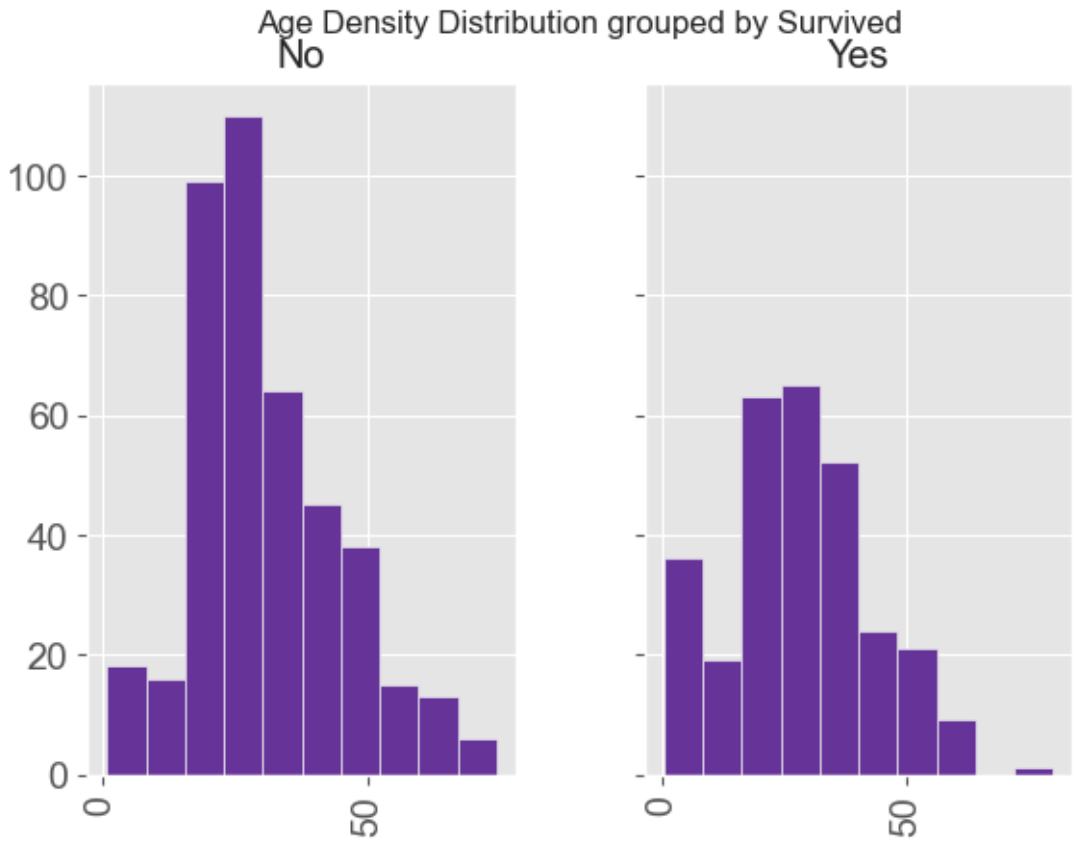
[26]:
```
# Get summary descriptive statistics
v= pd.DataFrame(not_missing['Age'].describe())

#Change the index labels and round the values reported
v.index = ['Population Size', 'Mean', 'Std. Deviation', 'Min', '25% Qt',␣
 ↪'Median',\
               '75% Qt', 'Max']
v = v.round(decimals=3)
v
```

[26]:

	Age
Population Size	714.000
Mean	29.699
Std. Deviation	14.526
Min	0.420
25% Qt	20.125
Median	28.000
75% Qt	38.000

```
Max                80.000
```

[27]:
```
# The density distribution and boxplot of the Age variable depending by␣
 ↪survivability.
not_missing.hist(column="Age", by="Survived", sharey=True,␣
 ↪color='rebeccapurple')
plt.suptitle('Age Density Distribution grouped by Survived');
```



- We observe that the percentage of children below 10 that survived was significantly higher and almost nobody over 70 year's old survived.
- This could be because of underlying reason:'Women and Children first' rule.

[28]:
```
#Make a datframe with the sample populations
age = pd.DataFrame()
age['all'] = not_missing['Age']
not_survived = age['Not-survived'] =␣
 ↪not_missing['Age'][not_missing['Survived']=='No']
survived = age['Survived'] = not_missing['Age'][not_missing['Survived']=='Yes']

#Get the summary statistics
```

```
var = age.describe()

#Change the index labels and round the values reported
var.index = ['Sample Size', 'Mean', 'Std. Deviation', 'Min', '25% Qt',␣
 ↪'Median',\
               '75% Qt', 'Max']
var = var.round(decimals=3)
```

[29]:
```
var.loc[:,['Not-survived','Survived']]
```

[29]:

	Not-survived	Survived
Sample Size	424.000	290.000
Mean	30.626	28.344
Std. Deviation	14.172	14.951
Min	1.000	0.420
25% Qt	21.000	19.000
Median	28.000	28.000
75% Qt	39.000	36.000
Max	74.000	80.000

- The not-survived and survived age populations have the above descriptive statistics:

Statistical Chi-Squared Test for Survived and Age

[30]:
```
#Create age-groups
age_labels = ['0-9', '10-19', '20-29', '30-39', '40-49', '50-59', '60-69',
              '70-80']
age_group_values = pd.cut(not_missing.Age, range(0,81,10),
                                  right=False, labels=age_labels)
not_missing.loc[:,'age-groups'] = age_group_values

#Set the value for the one 80-year old outside the bins
#chi-squared is notvalid for no of observations below 5
not_missing.loc[not_missing['Age']>=80, 'age-groups'] = '70-80'

#Make an observed-table for chi-squared test
obs_table = pd.crosstab([not_missing['Survived']],[not_missing['age-groups']])
```

[31]:
```
obs_table
```

[31]:

age-groups	0-9	10-19	20-29	30-39	40-49	50-59	60-69	70-80
Survived								
No	24	61	143	94	55	28	13	6
Yes	38	41	77	73	34	20	6	1

[32]:
```
from scipy.stats import chi2_contingency

# Compute Chi-square statistic
chi2, p, dof, expected = chi2_contingency(obs_table)
```

```
# Report results
print(' Chi-square: {}\n Degrees of Freedom: {}\n P-Value: {}'.format(chi2,␣
 ↪dof, p))
```

```
Chi-square: 17.42772160585894
Degrees of Freedom: 7
P-Value: 0.014836878112813482
```

- P-value is lesser than 0.05, therefore we reject the Null-Hypothesis and accept that Survived and Age are dependent variables and there is indeed a relationship between age and survivability.