jun28

July 18, 2019

In [1]:
```
# Guides used
# https://www.kaggle.com/jatturat/finding-important-factors-to-survive-titanic]
# https://www.youtube.com/watch?v=COUWKVf6zKY
```

In [60]:
```
# Load libraries.
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC

from xgboost import XGBClassifier

from sklearn.model_selection import KFold, cross_val_score, GridSearchCV, cross_val_p
from sklearn.metrics import accuracy_score
from sklearn import preprocessing
```

In [3]:
```
# Load main datasets.
raw_train_dataset = pd.read_csv('data/train.csv', index_col='PassengerId', header=0)
raw_test_dataset = pd.read_csv('data/test.csv', index_col='PassengerId', header=0)

# Describe raw datasets.
print('Train dataset, Columns:\n{0}\n'.format(raw_train_dataset.columns.values))
print('Train dataset, Shape:\n{0}\n'.format(raw_train_dataset.shape))  # (891, 11)
print('Train dataset, Head:\n')
display(raw_train_dataset.head())
print('Train dataset, Describe:\n')
display(raw_train_dataset.describe())
```

```python
        print('Test dataset, Columns:\n{0}\n'.format(raw_test_dataset.columns.values))
        print('Test dataset, Shape:\n{0}\n'.format(raw_test_dataset.shape))  # (418, 10)
        print('Test dataset, Head:\n')
        display(raw_test_dataset.head())
        print('Test dataset, Describe:\n')
        display(raw_test_dataset.describe())
```

```
Train dataset, Columns:
['Survived' 'Pclass' 'Name' 'Sex' 'Age' 'SibSp' 'Parch' 'Ticket' 'Fare'
 'Cabin' 'Embarked']

Train dataset, Shape:
(891, 11)

Train dataset, Head:
```

```
             Survived  Pclass  \
PassengerId
1                   0       3
2                   1       1
3                   1       3
4                   1       1
5                   0       3

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

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

```
Train dataset, Describe:
```

```
         Survived      Pclass         Age       SibSp       Parch        Fare
count  891.000000  891.000000  714.000000  891.000000  891.000000  891.000000
```

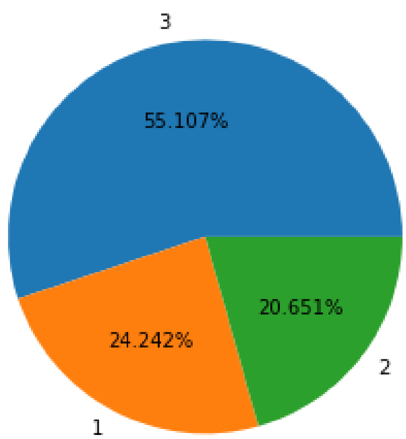
```
mean     0.383838    2.308642   29.699118    0.523008    0.381594   32.204208
std      0.486592    0.836071   14.526497    1.102743    0.806057   49.693429
min      0.000000    1.000000    0.420000    0.000000    0.000000    0.000000
25%      0.000000    2.000000   20.125000    0.000000    0.000000    7.910400
50%      0.000000    3.000000   28.000000    0.000000    0.000000   14.454200
75%      1.000000    3.000000   38.000000    1.000000    0.000000   31.000000
max      1.000000    3.000000   80.000000    8.000000    6.000000  512.329200


Test dataset, Columns:
['Pclass' 'Name' 'Sex' 'Age' 'SibSp' 'Parch' 'Ticket' 'Fare' 'Cabin'
 'Embarked']

Test dataset, Shape:
(418, 10)

Test dataset, Head:



             Pclass                                          Name     Sex  \
PassengerId
892               3                              Kelly, Mr. James    male
893               3              Wilkes, Mrs. James (Ellen Needs)  female
894               2                     Myles, Mr. Thomas Francis    male
895               3                              Wirz, Mr. Albert    male
896               3  Hirvonen, Mrs. Alexander (Helga E Lindqvist)  female

              Age  SibSp  Parch   Ticket     Fare Cabin Embarked
PassengerId
892          34.5      0      0   330911   7.8292   NaN        Q
893          47.0      1      0   363272   7.0000   NaN        S
894          62.0      0      0   240276   9.6875   NaN        Q
895          27.0      0      0   315154   8.6625   NaN        S
896          22.0      1      1  3101298  12.2875   NaN        S


Test dataset, Describe:



           Pclass         Age       SibSp       Parch        Fare
count  418.000000  332.000000  418.000000  418.000000  417.000000
mean     2.265550   30.272590    0.447368    0.392344   35.627188
std      0.841838   14.181209    0.896760    0.981429   55.907576
min      1.000000    0.170000    0.000000    0.000000    0.000000
25%      1.000000   21.000000    0.000000    0.000000    7.895800
50%      3.000000   27.000000    0.000000    0.000000   14.454200
75%      3.000000   39.000000    1.000000    0.000000   31.500000
```

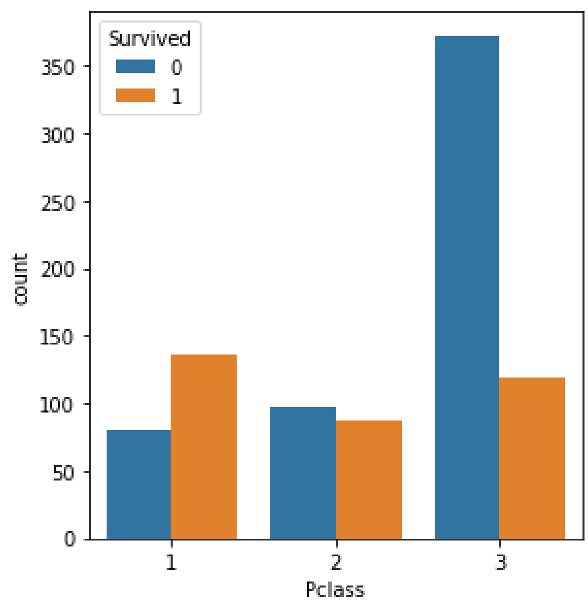
```
max      3.000000   76.000000    8.000000    9.000000  512.329200
```

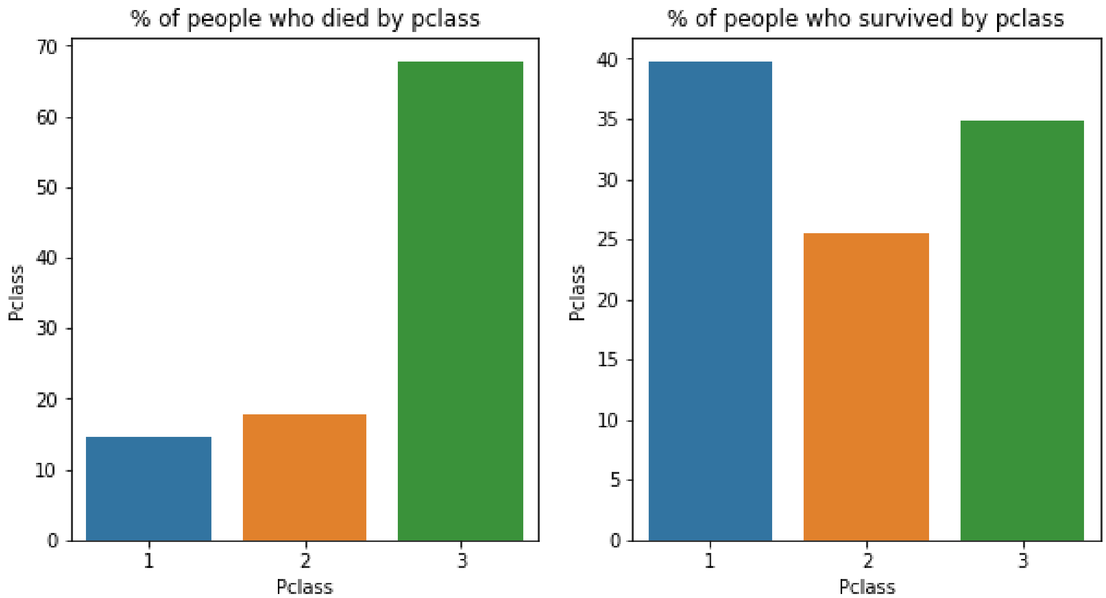
In [4]:
```python
# Explore the data
def plot_continuous_data(dataset_df, feature_name, target_name):
    dataset_copy_df = dataset_df.copy()
    dataset_copy_df['Counts'] = ""  # Trick to skip using an axis (x or y) on splittin
    fig, [axis0, axis1] = plt.subplots(1, 2, figsize=(10, 5))
    sns.distplot(dataset_copy_df[feature_name],
                 ax=axis0)
    sns.violinplot(data=dataset_copy_df,
                   x=feature_name, y="Counts",
                   hue=target_name, split=True, orient='h', ax=axis1)
    plt.show()

def plot_categorical_data(dataset_df, feature_name, target_name):
    fig, [axis0, axis1] = plt.subplots(1, 2, figsize=(10, 5))
    feature_count_data = dataset_df[feature_name].value_counts()
    piechart_labels = feature_count_data.index.values
    piechart_values = feature_count_data.values
    axis0.pie(x=piechart_values, labels=piechart_labels,
              autopct="%1.3f%%")
    sns.countplot(data=dataset_df,
                  x=feature_name,
                  hue=target_name, ax=axis1)
    plt.show()
```

In [5]:
```python
# Ticket class data, column 'Pclass'
# values: 1: high class, 2: middle class, 3: lowest class.

# To note from this chart:
# - class 1 has the most survivors
# - regardless of numbers of people, the higher class is, the higher chance of surviva
# - being in class 3 singificantly reduces the chance of survival

plot_categorical_data(raw_train_dataset, 'Pclass', 'Survived')


# Display percentage of survived/dead passengers by seat class.

# To note from this chart: percentage of people who survived is higher in 3rd class th

fig, [axis0, axis1] = plt.subplots(1, 2, figsize=(10, 5))
passengers_pclass_survived = raw_train_dataset[['Pclass', 'Survived']].copy()

dead_filter, survived_filter = [passengers_pclass_survived['Survived'] == survived_valu
                                for survived_value in [0, 1]]
```

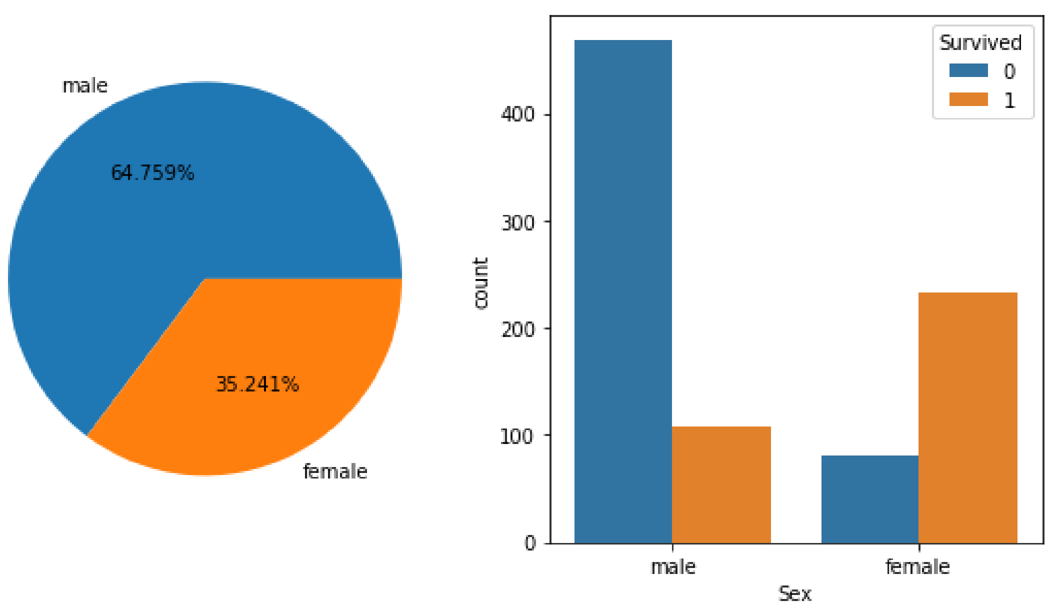
```
passengers_dead = passengers_pclass_survived[dead_filter]
sns.barplot(data=passengers_dead,
            x="Pclass", y="Pclass",
            estimator=lambda x: len(x) / len(passengers_dead.index) * 100,
            ax=axis0)
axis0.set_title("% of people who died by pclass")
passengers_survived = passengers_pclass_survived[survived_filter]
sns.barplot(data=passengers_survived,
            x="Pclass", y="Pclass",
            estimator=lambda x: len(x) / len(passengers_survived.index) * 100,
            ax=axis1)
axis1.set_title("% of people who survived by pclass")
plt.show()

# Conclusion: Pclass matters for each person to survive or not therefore is an importa
```



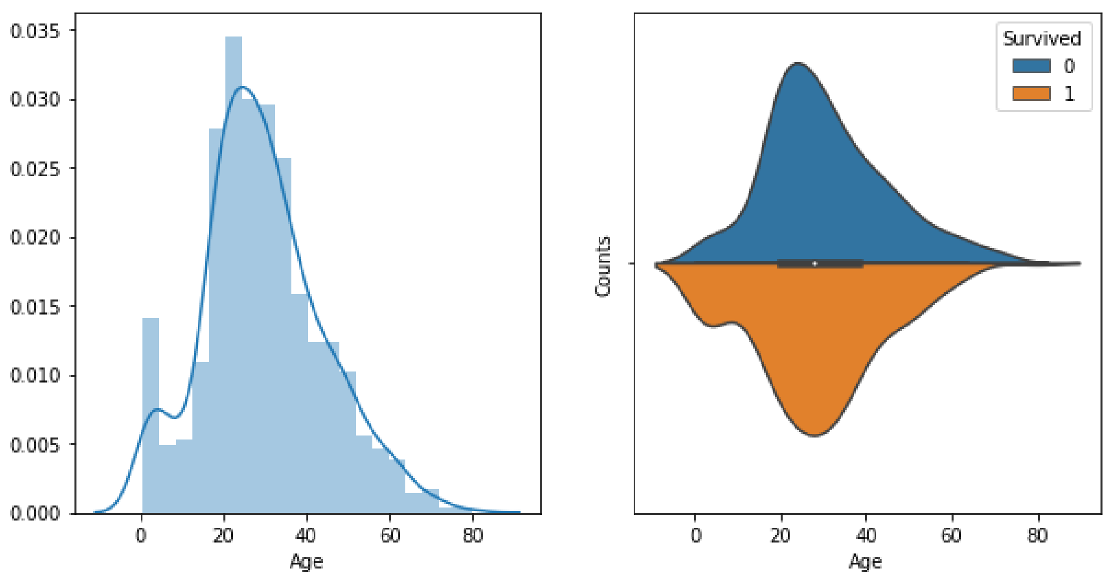




In [6]:
```python
# Sex data, column 'Sex'
# values: 'female', 'male'

# To note from this chart:
# - being a female increases chance for survival and vice-versa for male.
# - males: 2/3 of amount of passengers, females: 1/3

plot_categorical_data(raw_train_dataset, 'Sex', 'Survived')

# Conclusion: 'Sex' is an important feature.
```

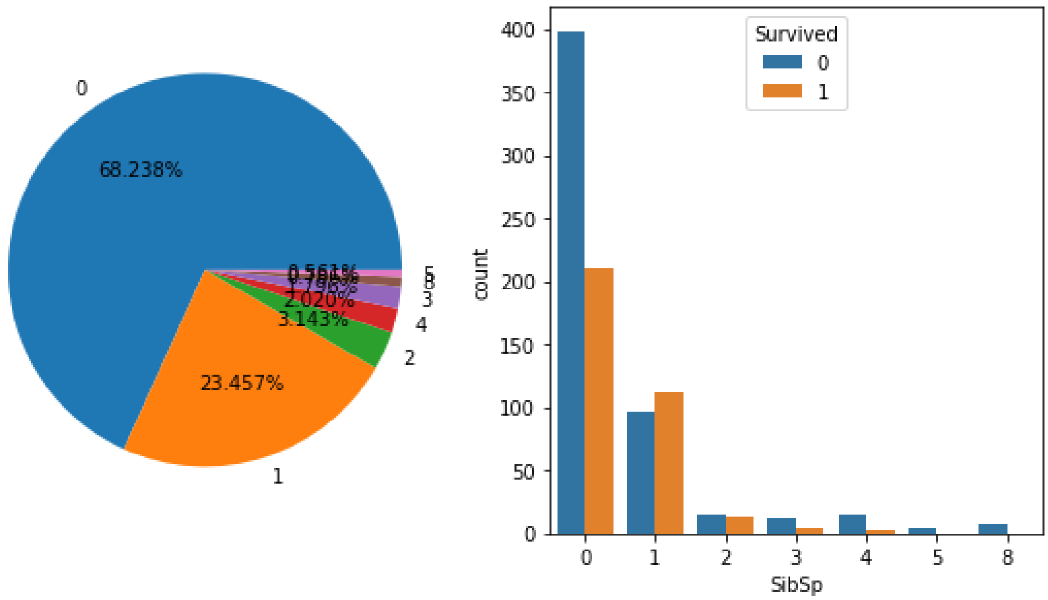


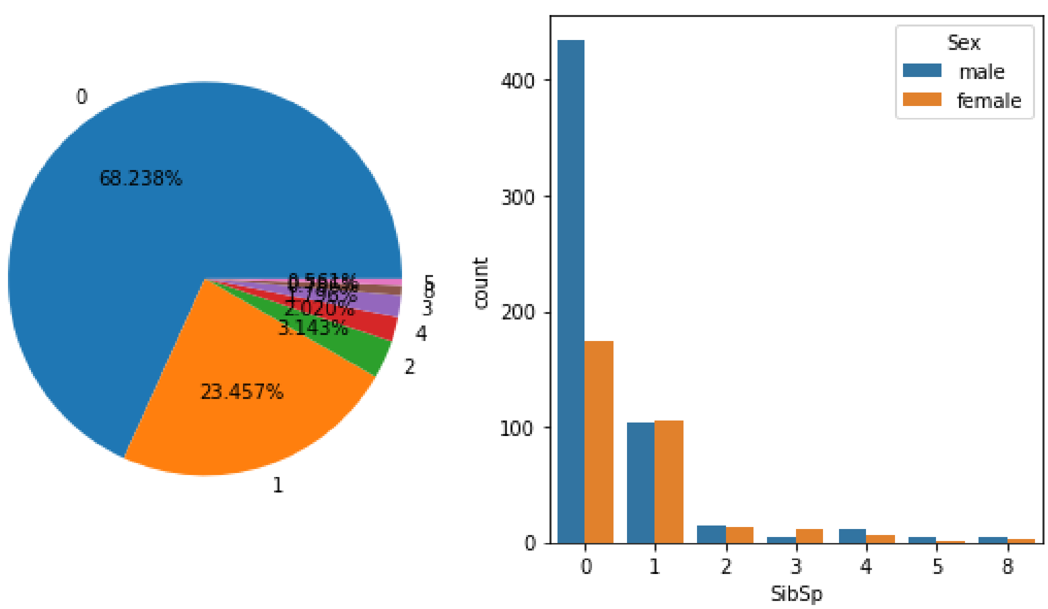
```
In [7]: # Age data, column 'Age'
        # values: integer, indicates passenger's age in years.

        # To note from this chart:
        # - chart values distribution shifts to the left side of Age=0.
        # - passengers aged 0-5 had pretty good chance for survival
        # - significantly more person died aged between 20 and 35
        # - people aged 60-80 had lowest chance for survival

        age_set_nonan = raw_train_dataset[['Age', 'Survived']].copy().dropna(axis=0)
        plot_continuous_data(age_set_nonan, 'Age', 'Survived')

        # Conclusion:
        # 'Age' is an important feature;
        # 'Age' could be divided in different ranges and considered as categorical feature.
```



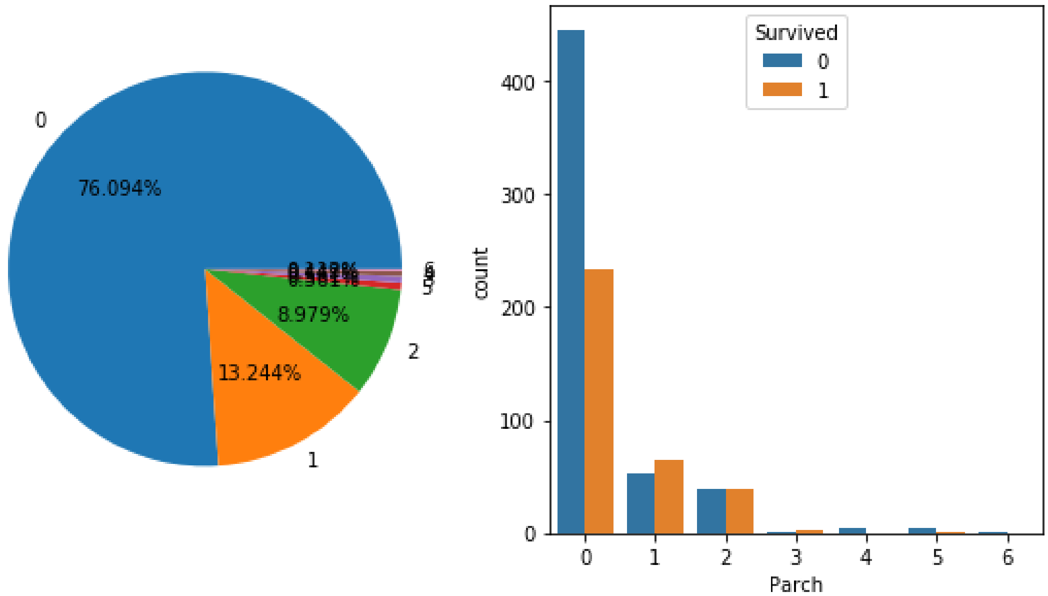

```
In [8]: # Number of siblings/spouses aboard the Titanic, column 'SipSp'

        # To note from this chart:
        # - Only people with 1 SipSp have a bit more survivors compared to the all others
        #   People with 2 SipSp - equal chances to survive
        #   People with 0 SipSp - 1/2 chance to survive
        # - ~33% to survive if 0 SiSp

        plot_categorical_data(raw_train_dataset, 'SibSp', 'Survived')
```

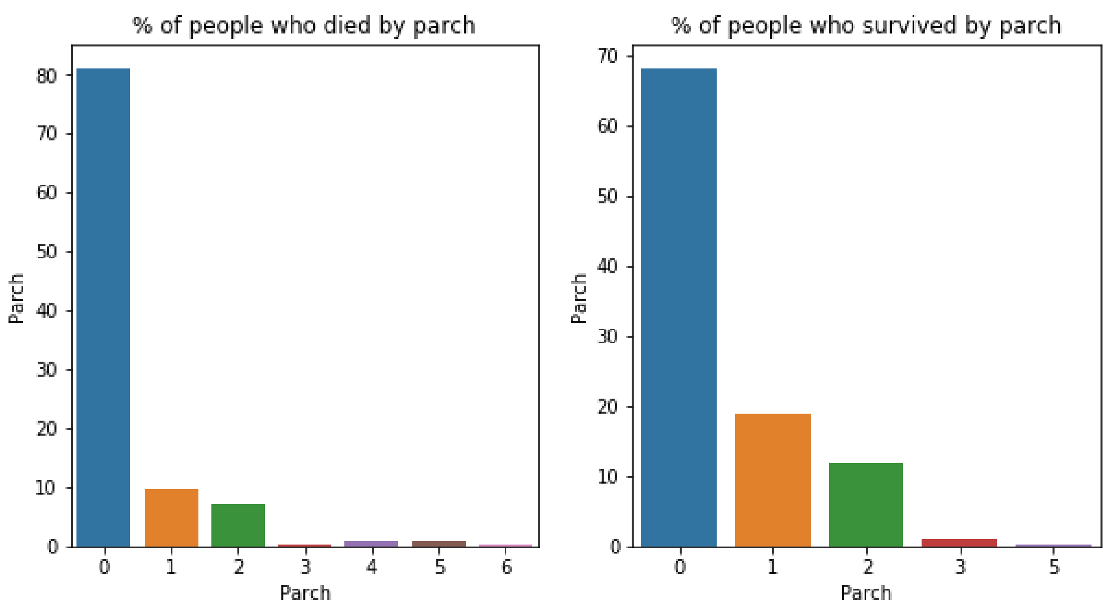
```python
# To note from this chart:
# - approximately same amount of females/males had 1 child
#   0 children - most of them are men
#   3 children - the only category where females outnumber males

plot_categorical_data(raw_train_dataset, 'SibSp', 'Sex')

# Conclusion:
# 'SipSp' is an important feature to count on
```





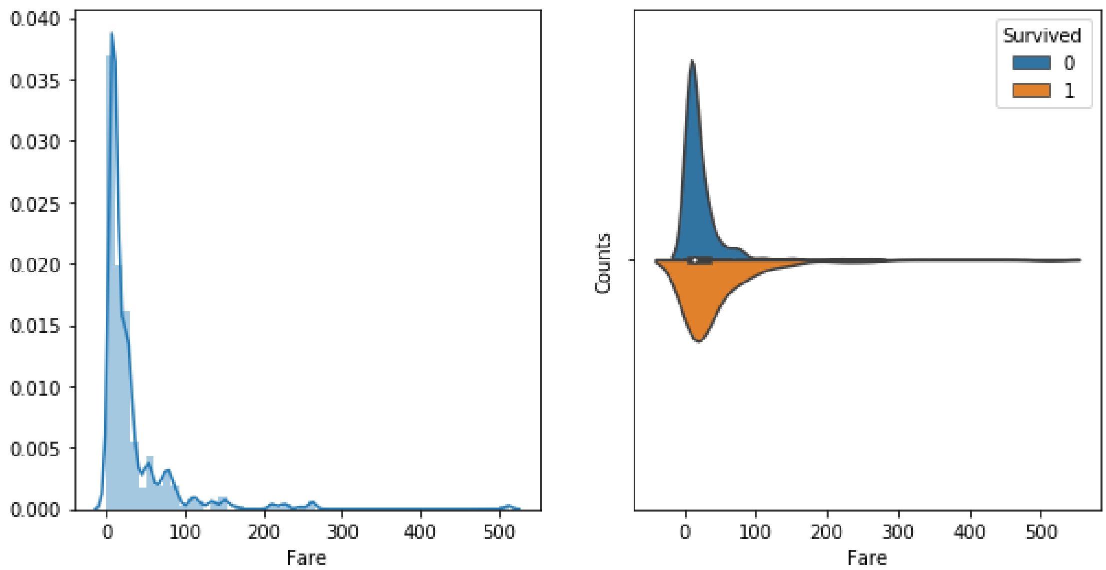
```
In [9]: # Number of parents/children aboard the Titanic, column 'Parch'

        # To note from this chart:
        # - Having 1,2,3 people as parents/children is a 50/50 factor to stay alive
        # - ... (todo)

        plot_categorical_data(raw_train_dataset, 'Parch', 'Survived')

        # To note from this chart:
        # - ... (todo)

        fig, [axis0, axis1] = plt.subplots(1, 2, figsize=(10, 5))
        passengers_parch_survived = raw_train_dataset[['Parch', 'Survived']].copy()
        dead_filter, survived_filter = [passengers_parch_survived['Survived'] == survived_valu
                                        for survived_value in [0, 1]]

        passengers_dead = passengers_parch_survived[dead_filter]
        sns.barplot(data=passengers_dead,
                    x="Parch", y="Parch",
                    estimator=lambda x: len(x) / len(passengers_dead.index) * 100,
                    ax=axis0)
        axis0.set_title("% of people who died by parch")
        passengers_survived = passengers_parch_survived[survived_filter]
        sns.barplot(data=passengers_survived,
                    x="Parch", y="Parch",
                    estimator=lambda x: len(x) / len(passengers_survived.index) * 100,
                    ax=axis1)
        axis1.set_title("% of people who survived by parch")
        plt.show()

        # Conclusion:
        # - 'Parch' and 'SipSp' are very similar: try to combine them into a single feature.
```






```
In [10]: # Passenger fare, column 'Fare'

         # To note from this plot:
         # - we can try to categorize 'Fare' into several categories:
         #   fare < 10; 10<fare<50; fare>50
```

```
passenger_fare_survived = raw_train_dataset[['Fare', 'Survived']].copy().dropna(axis=
plot_continuous_data(passenger_fare_survived, 'Fare', 'Survived')
```



In [11]:
```
# Passenger cabin, column 'Cabin'

display(raw_train_dataset['Cabin'].value_counts().head(10))
display(raw_test_dataset['Cabin'].value_counts().head(10))

# Idea 1: throw away the column 'Cabin' because of mess in it

# Idea 2: todo

# drop NA data
passengers_cabin = raw_train_dataset[['Cabin']].copy()
passengers_cabin['cabin_data'] = passengers_cabin['Cabin'].isnull().apply(lambda x: no

display(passengers_cabin)
```

```
B96 B98        4
C23 C25 C27    4
G6             4
E101           3
F33            3
C22 C26        3
F2             3
D              3
E24            2
B35            2
```

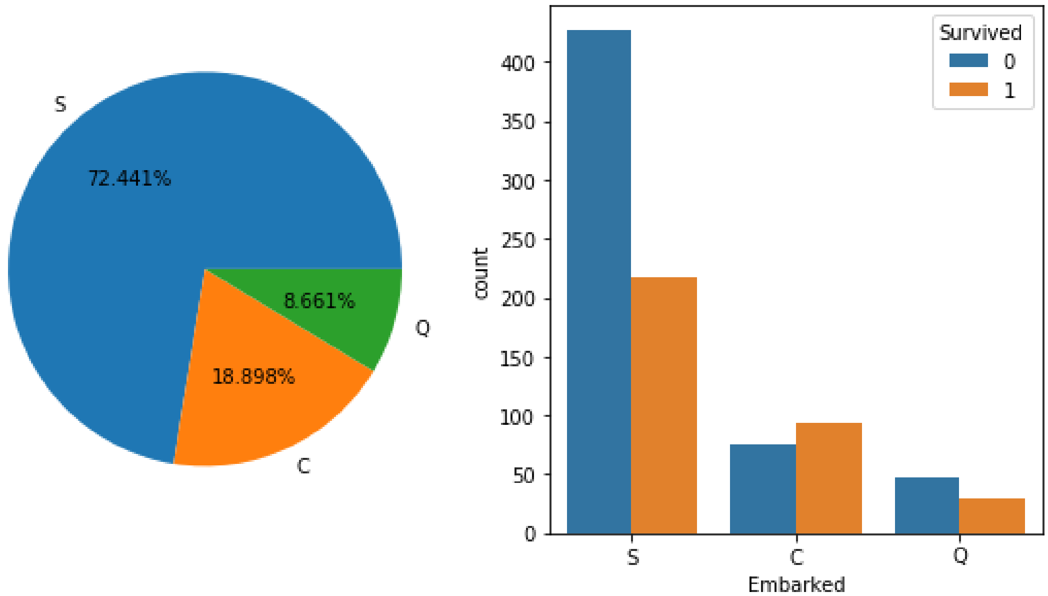
```
Name: Cabin, dtype: int64
```

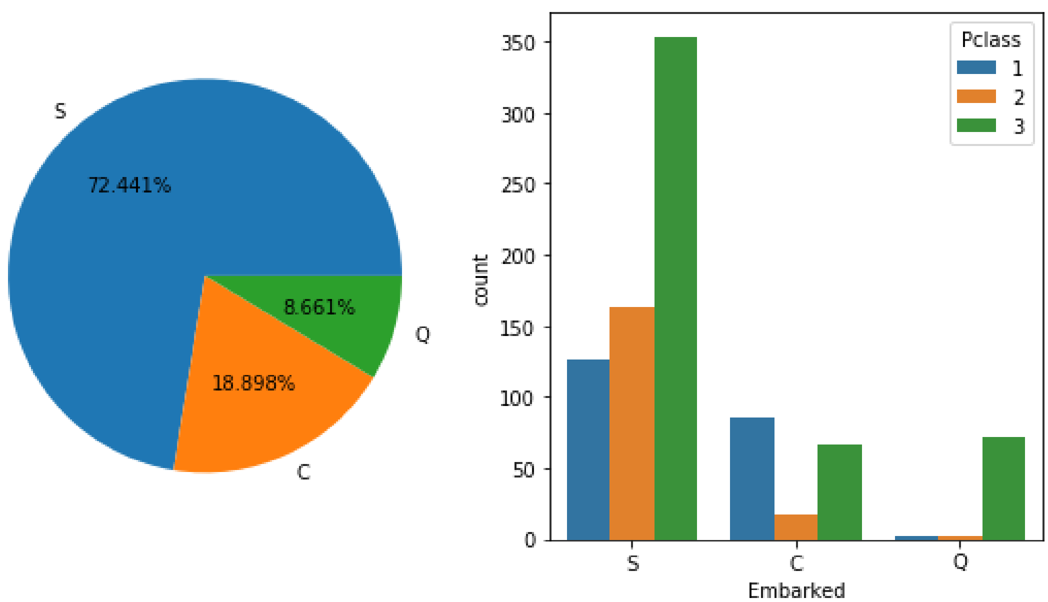
```
B57 B59 B63 B66    3
B45                2
A34                2
C116               2
E34                2
C6                 2
C31                2
C89                2
C80                2
C55 C57            2
Name: Cabin, dtype: int64
```

```
                   Cabin  cabin_data
PassengerId
1                    NaN       False
2                    C85        True
3                    NaN       False
4                   C123        True
5                    NaN       False
6                    NaN       False
7                    E46        True
8                    NaN       False
9                    NaN       False
10                   NaN       False
11                    G6        True
12                  C103        True
13                   NaN       False
14                   NaN       False
15                   NaN       False
16                   NaN       False
17                   NaN       False
18                   NaN       False
19                   NaN       False
20                   NaN       False
21                   NaN       False
22                   D56        True
23                   NaN       False
24                    A6        True
25                   NaN       False
26                   NaN       False
27                   NaN       False
28           C23 C25 C27        True
29                   NaN       False
30                   NaN       False
```

```
...                   ...      ...
862                   NaN    False
863                   D17     True
864                   NaN    False
865                   NaN    False
866                   NaN    False
867                   NaN    False
868                   A24     True
869                   NaN    False
870                   NaN    False
871                   NaN    False
872                   D35     True
873           B51 B53 B55     True
874                   NaN    False
875                   NaN    False
876                   NaN    False
877                   NaN    False
878                   NaN    False
879                   NaN    False
880                   C50     True
881                   NaN    False
882                   NaN    False
883                   NaN    False
884                   NaN    False
885                   NaN    False
886                   NaN    False
887                   NaN    False
888                   B42     True
889                   NaN    False
890                  C148     True
891                   NaN    False

[891 rows x 2 columns]
```

In [12]:
```
# Port of Embarkation, column 'Embarked'

# To note:
# - City C: only city to survive more than died
plot_categorical_data(raw_train_dataset, 'Embarked', 'Survived')

# To note:
# - City Q: only 3rd class;
# - City C: mostly 1st and 3rd class
# - City S: different, but mostly 3rd class
plot_categorical_data(raw_train_dataset, 'Embarked', 'Pclass')

# Empty values: fill with S, the major port
```





In [13]:
```
# Check dataset for null values.

display(raw_train_dataset.isnull().sum())  # age:177, cabin:687, embarked:2
display(raw_test_dataset.isnull().sum())  # age:86, fare:1, cabin:327
```

```
Survived      0
```

```
Pclass        0
Name          0
Sex           0
Age         177
SibSp         0
Parch         0
Ticket        0
Fare          0
Cabin       687
Embarked      2
dtype: int64
```

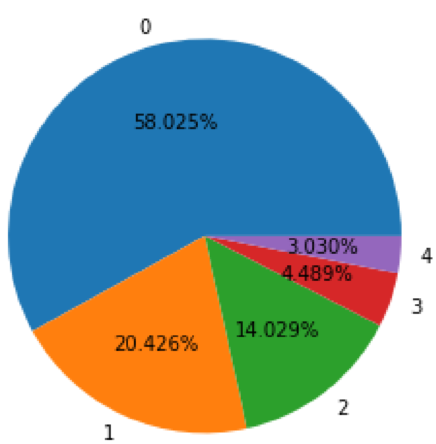
```
Pclass        0
Name          0
Sex           0
Age          86
SibSp         0
Parch         0
Ticket        0
Fare          1
Cabin       327
Embarked      0
dtype: int64
```

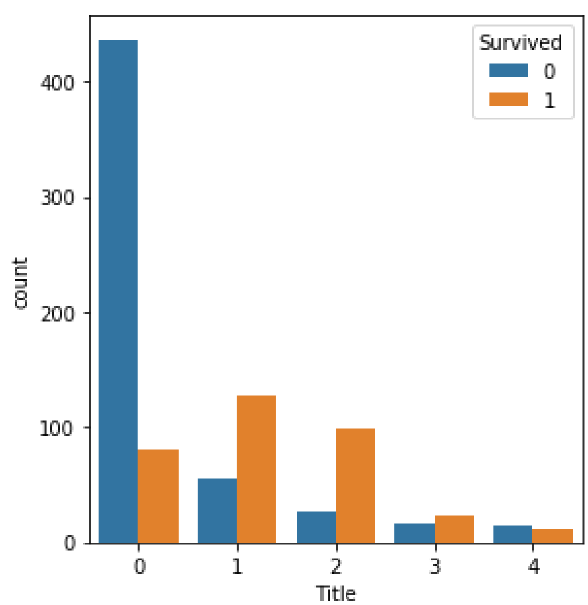
In [14]:
```
# Work on 'Name' feature in datasets.

train_dataset = raw_train_dataset.copy()
test_dataset = raw_test_dataset.copy()

for dataset in [train_dataset, test_dataset]:
    dataset['Title'] = dataset['Name'].str.extract('([A-Za-z]+)\.', expand=False)

display(train_dataset[['Name', 'Title']].head(3))

print('Train dataset "Title" value_counts:')
display(train_dataset['Title'].value_counts())

print('Test dataset "Title" value_counts:')
display(test_dataset['Title'].value_counts())

# Map 'Title' feature
for dataset in [train_dataset, test_dataset]:
    title_mapping = {
        title_value: 4
        for title_value in dataset['Title'].unique()
    }
```

```
        title_mapping['Mr'] = 0
        title_mapping['Miss'] = 1
        title_mapping['Mrs'] = 2
        title_mapping['Master'] = 3
        dataset['Title'] = dataset['Title'].map(title_mapping)

    display(train_dataset.head(5))

    plot_categorical_data(train_dataset, 'Title', 'Survived')
```

```
                                                         Name Title
PassengerId
1                                     Braund, Mr. Owen Harris    Mr
2            Cumings, Mrs. John Bradley (Florence Briggs Th...   Mrs
3                                      Heikkinen, Miss. Laina  Miss


Train dataset "Title" value_counts:


Mr          517
Miss        182
Mrs         125
Master       40
Dr            7
Rev           6
Mlle          2
Major         2
Col           2
Don           1
Capt          1
Lady          1
Ms            1
Sir           1
Mme           1
Countess      1
Jonkheer      1
Name: Title, dtype: int64


Test dataset "Title" value_counts:


Mr        240
Miss       78
Mrs        72
Master     21
Col         2
Rev         2
```

```
Dona        1
Ms          1
Dr          1
Name: Title, dtype: int64

             Survived  Pclass  \
PassengerId
1                   0       3
2                   1       1
3                   1       3
4                   1       1
5                   0       3

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

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



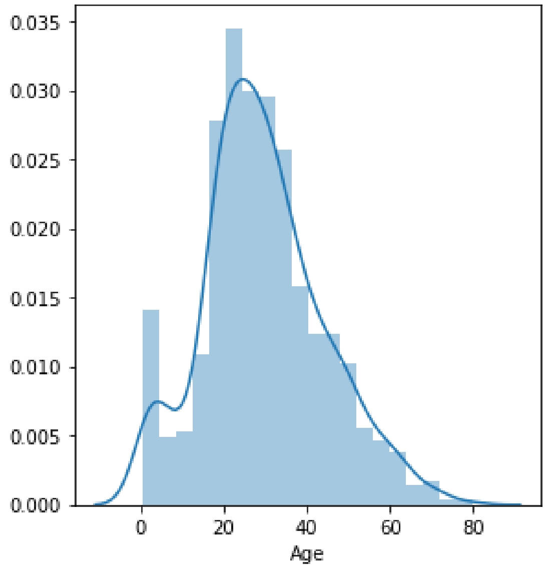


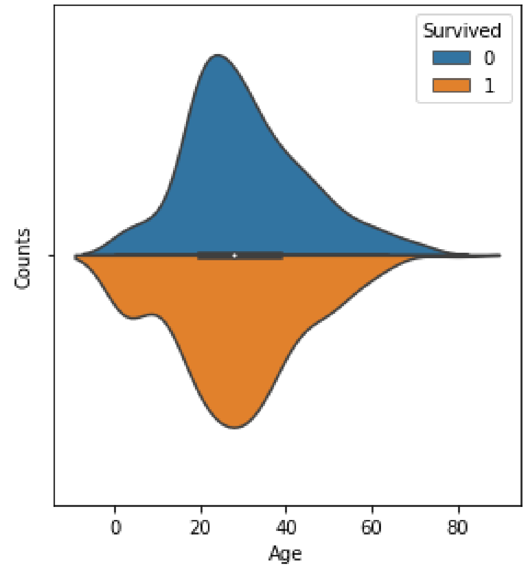
```
In [15]: # Work on 'Sex' feature in datasets.

         for dataset in [train_dataset, test_dataset]:
             sex_mapping = {'male': 0, 'female': 1}
             dataset['Sex'] = dataset['Sex'].map(sex_mapping)

         display(train_dataset.head(10))
```

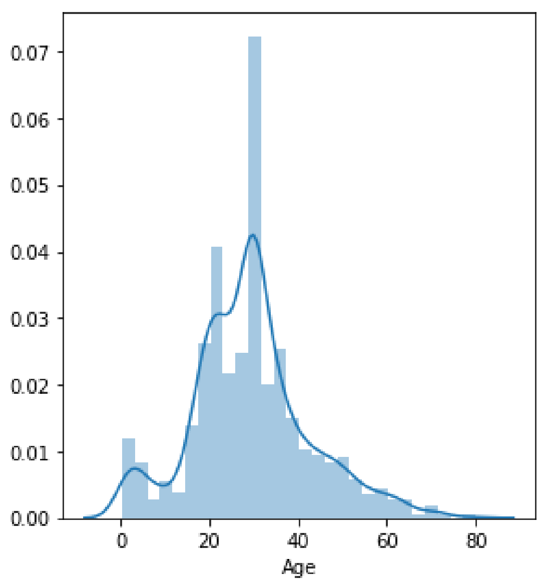
```
             Survived  Pclass  \
PassengerId
1                   0       3
2                   1       1
3                   1       3
4                   1       1
5                   0       3
6                   0       3
7                   0       1
8                   0       3
9          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

                                                          Name  Sex   Age  \
PassengerId
1                                      Braund, Mr. Owen Harris    0  22.0
2            Cumings, Mrs. John Bradley (Florence Briggs Th...    1  38.0
3                                       Heikkinen, Miss. Laina    1  26.0
4                 Futrelle, Mrs. Jacques Heath (Lily May Peel)    1  35.0
5                                     Allen, Mr. William Henry    0  35.0
6                                             Moran, Mr. James    0   NaN
7                                      McCarthy, Mr. Timothy J    0  54.0
8                               Palsson, Master. Gosta Leonard    0   2.0
9            Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)    1  27.0
10                         Nasser, Mrs. Nicholas (Adele Achem)    1  14.0

             SibSp  Parch            Ticket     Fare Cabin Embarked  Title
PassengerId
1                1      0         A/5 21171   7.2500   NaN        S      0
2                1      0          PC 17599  71.2833   C85        C      2
3                0      0  STON/O2. 3101282   7.9250   NaN        S      1
4                1      0            113803  53.1000  C123        S      2
5                0      0            373450   8.0500   NaN        S      0
6                0      0            330877   8.4583   NaN        Q      0
7                0      0             17463  51.8625   E46        S      0
8                3      1            349909  21.0750   NaN        S      3
9                0      2            347742  11.1333   NaN        S      2
```

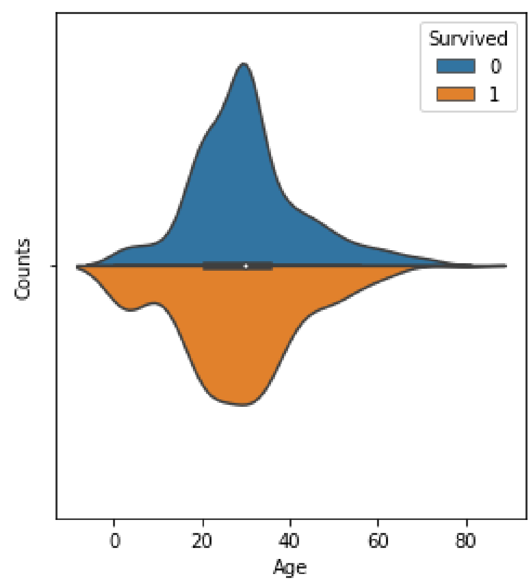
```
10                1      0            237736   30.0708    NaN         C      2
```

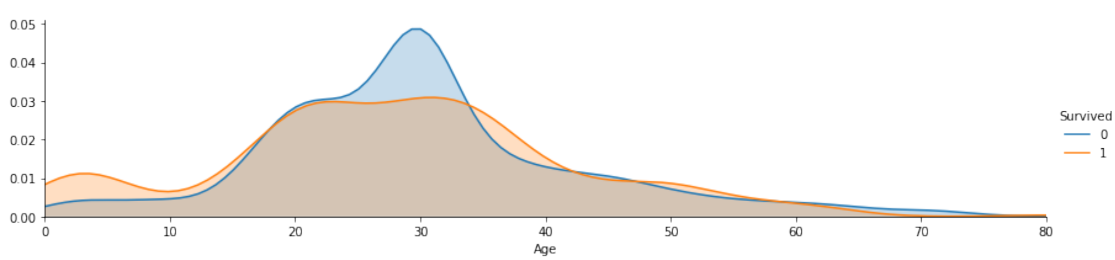
```
In [16]: # Work on 'Age' feature in datasets.

         # fill up missing Age values with median age by title
         for dataset in [train_dataset, test_dataset]:
             dataset['Age'].fillna(
                 dataset.groupby('Title')['Age'].transform('median'),
                 inplace=True
             )

         # Draw chart to view 'Age' and 'Survival' rate again

         # Plot, type1
         age_set_nonan = raw_train_dataset[['Age', 'Survived']].copy().dropna(axis=0)
         plot_continuous_data(age_set_nonan, 'Age', 'Survived')

         passengers_age_survived = train_dataset[['Age', 'Survived']].copy()
         plot_continuous_data(passengers_age_survived, 'Age', 'Survived')

         # Plot, type2
         facet = sns.FacetGrid(train_dataset, hue='Survived', aspect=4)
         facet.map(sns.kdeplot, 'Age', shade=True)
         facet.set(xlim=(0, train_dataset['Age'].max()))
         facet.add_legend()
         plt.show()

         # Bin the continuous data 'Age': create a categorical variable
         for dataset in [train_dataset, test_dataset]:
             dataset.loc[dataset['Age'] <= 15, 'Age'] = 0
             dataset.loc[(dataset['Age'] > 15) & (dataset['Age'] <= 25), 'Age'] = 1
             dataset.loc[(dataset['Age'] > 25) & (dataset['Age'] <= 35), 'Age'] = 2
             dataset.loc[(dataset['Age'] > 35) & (dataset['Age'] <= 65), 'Age'] = 3
             dataset.loc[dataset['Age'] > 65, 'Age'] = 4

         display(train_dataset.head(5))

         print('Division by age intervals (bins):')
         fig, ax = plt.subplots()
         feature_count_data = train_dataset['Age'].value_counts()
         piechart_labels = feature_count_data.index.values
         piechart_values = feature_count_data.values
         ax.pie(x=piechart_values, labels=piechart_labels, autopct="%1.3f%%")
         plt.show()
```


0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
20
40
60
80
Age


Survived
0
1
Counts
0
20
40
60
80
Age

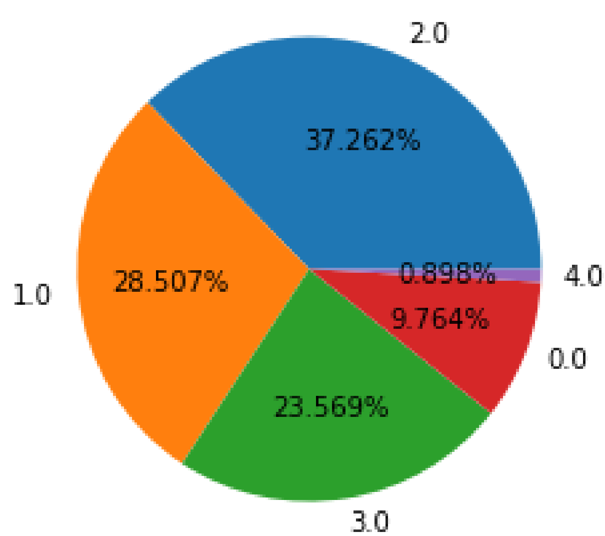

0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
20
40
60
80
Age


Survived
0
1
Counts
0
20
40
60
80
Age


0.05
0.04
0.03
0.02
0.01
0.00
0
10
20
30
40
50
60
70
80
Age
Survived
0
1

```
             Survived  Pclass  \
PassengerId
1                   0       3
2                   1       1
3                   1       3
4                   1       1
5                   0       3

                                                          Name  Sex  Age  \
PassengerId
1                                      Braund, Mr. Owen Harris    0  1.0
2            Cumings, Mrs. John Bradley (Florence Briggs Th...    1  3.0
3                                       Heikkinen, Miss. Laina    1  2.0
4                 Futrelle, Mrs. Jacques Heath (Lily May Peel)    1  2.0
5                                     Allen, Mr. William Henry    0  2.0

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

```
Division by age intervals (bins):
```

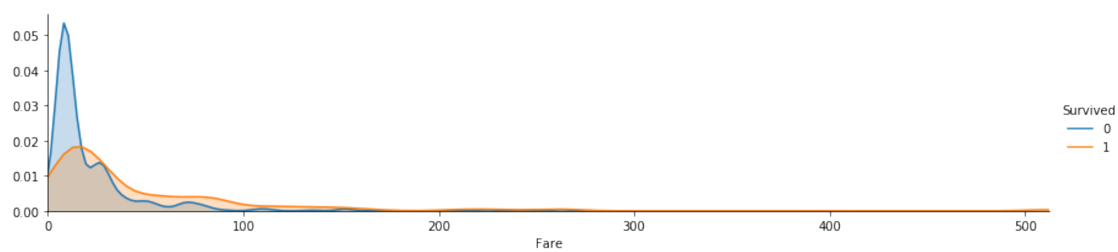


In [17]:
```
# Work on 'Embarked' feature

for dataset in [train_dataset, test_dataset]:
    # Fix missing values with 'S' - the majority of passengers are from there
    dataset['Embarked'] = dataset['Embarked'].fillna('S')
    # Map embarked feature values
    embarked_mapping = {'S': 0, 'C': 1, 'Q': 2}
    dataset['Embarked'] = dataset['Embarked'].map(embarked_mapping)

display(train_dataset.head(5))
```

```
             Survived  Pclass  \
PassengerId
1                   0       3
2                   1       1
3                   1       3
4                   1       1
5                   0       3

                                                          Name  Sex  Age  \
PassengerId
1                                      Braund, Mr. Owen Harris    0  1.0
2            Cumings, Mrs. John Bradley (Florence Briggs Th...    1  3.0
3                                       Heikkinen, Miss. Laina    1  2.0
4                 Futrelle, Mrs. Jacques Heath (Lily May Peel)    1  2.0
5                                     Allen, Mr. William Henry    0  2.0

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

In [18]:
```
# Work on 'Fare' feature

for dataset in [train_dataset, test_dataset]:
    # Fix missing values with median value by certain class, not by the whole dataset
    dataset['Fare'].fillna(
        dataset.groupby('Pclass')['Fare'].transform('median'),
        inplace=True
    )
```

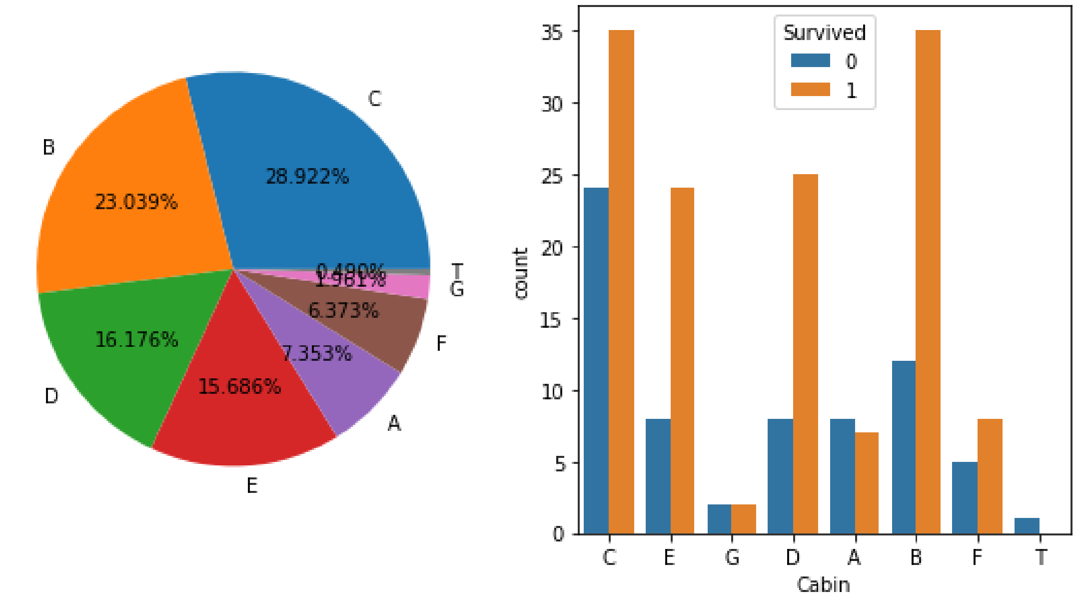
```python
# Draw plot to see how exactly divide this continuous data to intervals (bins)
facet = sns.FacetGrid(train_dataset, hue='Survived', aspect=4)
facet.map(sns.kdeplot, 'Fare', shade=True)
facet.set(xlim=(0, train_dataset['Fare'].max()))
facet.add_legend()
plt.show()

for dataset in [train_dataset, test_dataset]:
    dataset.loc[dataset['Fare'] <= 17, 'Fare'] = 0
    dataset.loc[(dataset['Fare'] > 17) & (dataset['Fare'] <= 30), 'Fare'] = 1
    dataset.loc[(dataset['Fare'] > 30) & (dataset['Fare'] <= 95), 'Fare'] = 2
    dataset.loc[dataset['Fare'] > 95, 'Fare'] = 3

display(train_dataset.head(5))
```



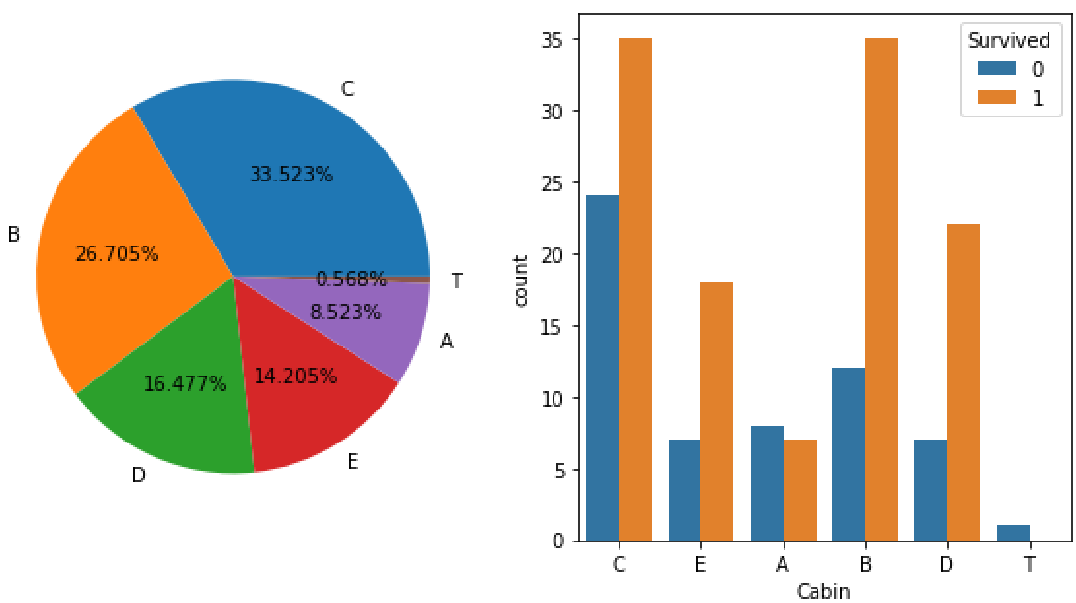

```
             Survived  Pclass  \
PassengerId
1                   0       3
2                   1       1
3                   1       3
4                   1       1
5                   0       3

                                                          Name  Sex  Age  \
PassengerId
1                                      Braund, Mr. Owen Harris    0  1.0
2            Cumings, Mrs. John Bradley (Florence Briggs Th...    1  3.0
3                                       Heikkinen, Miss. Laina    1  2.0
4                 Futrelle, Mrs. Jacques Heath (Lily May Peel)    1  2.0
5                                     Allen, Mr. William Henry    0  2.0

             SibSp  Parch            Ticket  Fare Cabin  Embarked  Title
PassengerId
1                1      0         A/5 21171   0.0   NaN         0      0
2                1      0          PC 17599   2.0   C85         1      2
3                0      0  STON/O2. 3101282   0.0   NaN         0      1
```

```
4                 1      0             113803    2.0   C123          0       2
5                 0      0             373450    0.0    NaN          0       0
```

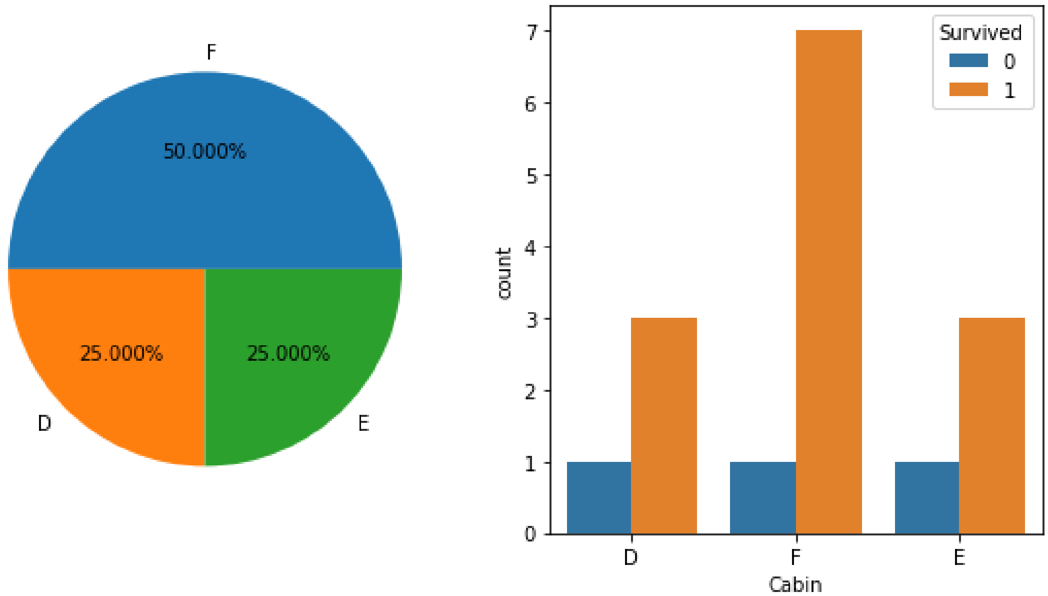
In [19]:
```python
# Work on 'Cabin' feature

# for now, leave only first character
for dataset in [train_dataset, test_dataset]:
    dataset['Cabin'] = dataset['Cabin'].str[:1]

plot_categorical_data(train_dataset, 'Cabin', 'Survived')

for key, df_by_pclass in train_dataset.groupby(['Pclass']):
    display('Class {0}'.format(key))
    plot_categorical_data(df_by_pclass, 'Cabin', 'Survived')

# Add a simple feature 'HasCabin', it might help
for dataset in [train_dataset, test_dataset]:
    dataset['HasCabin'] = dataset['Cabin'].notnull().astype(int)

# Map cabines with scaled bins on ragne [0;3]
for dataset in [train_dataset, test_dataset]:
    cabin_mapping = {
        'A': 0, 'B': 0.4, 'C': 0.8, 'D': 1.2, 'E': 1.6, 'F': 2, 'G': 2.4, 'T': 2.8
    }
    dataset['Cabin'] = dataset['Cabin'].map(cabin_mapping)
    # Fill NaN values with median for each Pclass
    dataset['Cabin'].fillna(
        dataset.groupby('Pclass')['Cabin'].transform('median'),
        inplace=True
    )

# todo cabin: https://www.kaggle.com/ccastleberry/titanic-cabin-features

display(train_dataset.head(5))
```



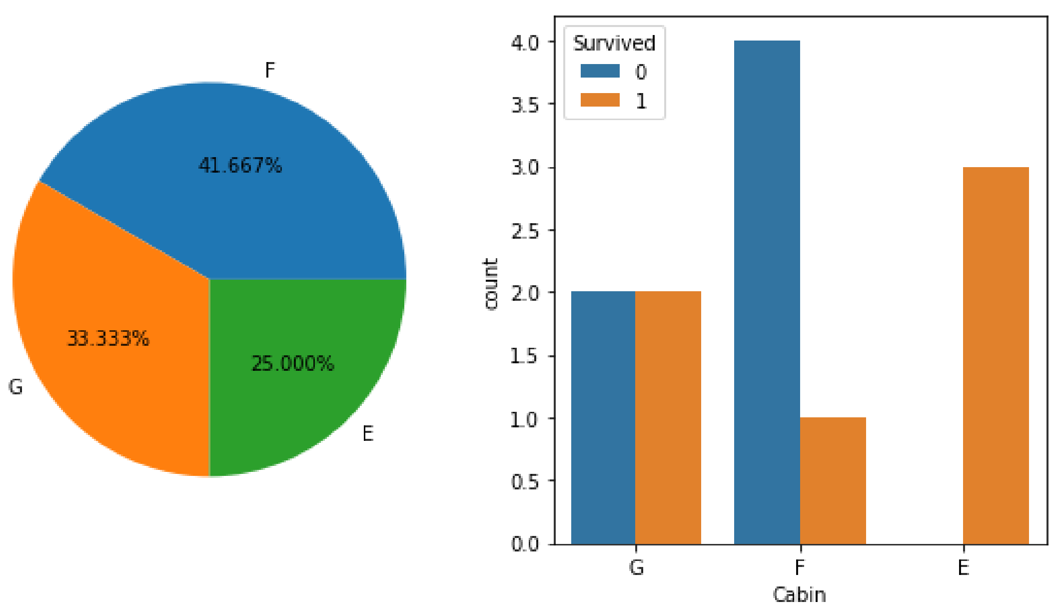
'Class 1'



'Class 2'



'Class 3'



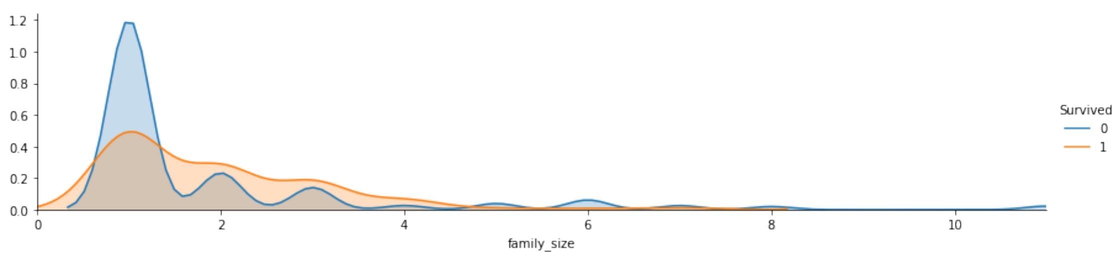

```
             Survived  Pclass  \
PassengerId
1                   0       3
```

```
2                    1       1
3                    1       3
4                    1       1
5                    0       3

                                                          Name  Sex  Age  \
PassengerId
1                                      Braund, Mr. Owen Harris    0  1.0
2            Cumings, Mrs. John Bradley (Florence Briggs Th...    1  3.0
3                                       Heikkinen, Miss. Laina    1  2.0
4                 Futrelle, Mrs. Jacques Heath (Lily May Peel)    1  2.0
5                                     Allen, Mr. William Henry    0  2.0

             SibSp  Parch            Ticket  Fare  Cabin  Embarked  Title  \
PassengerId
1                1      0         A/5 21171   0.0    2.0         0      0
2                1      0          PC 17599   2.0    0.8         1      2
3                0      0  STON/O2. 3101282   0.0    2.0         0      1
4                1      0            113803   2.0    0.8         0      2
5                0      0            373450   0.0    2.0         0      0

             HasCabin
PassengerId
1                   0
2                   1
3                   0
4                   1
5                   0
```

In [20]:
```
# Work on ticket numbers, column 'Ticket'

# todo

# https://www.kaggle.com/c/titanic/discussion/11127
# Seems to help find family members or potential nannies.
# Example:
# Jensen, Mr. Hans Peder: TktNum = 350050
# Jensen, Mr. Svend Lauritz: TktNum = 350048
# Jensen, Mr. Niels Peder: TktNum = 350047

# It could mean that tickets sharing the same prefixes could be booked for
# cabins placed together. It could therefore lead to the actual placement
# of the cabins within the ship.

# Also this matters more for females.
# The males have low survival irrespective of their cabin placement.
```

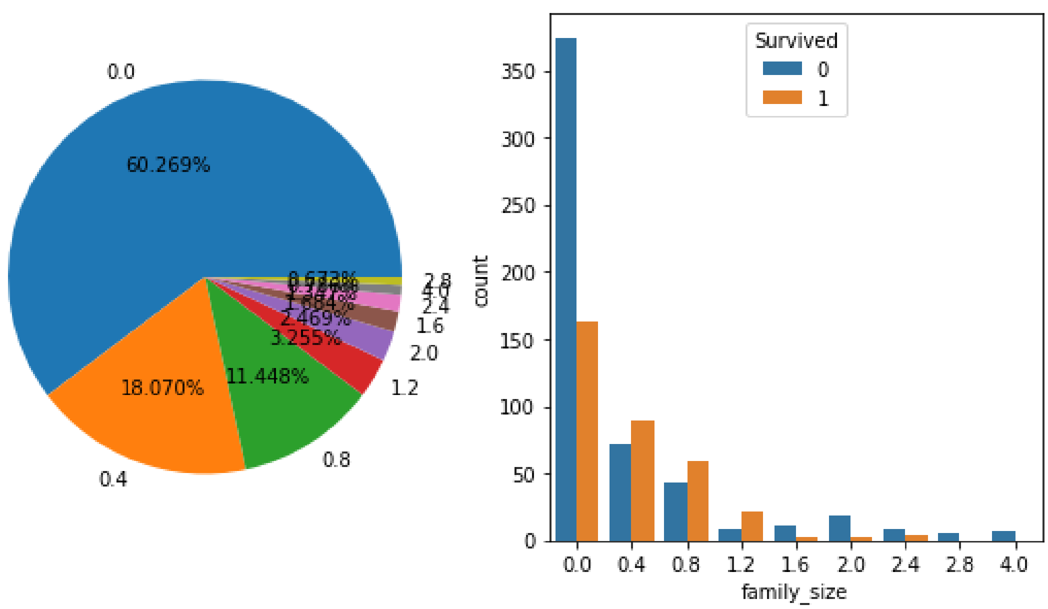
```
        # I would imagine that the ones containing SOTON were boarded
        # at Southampton (Soton is a common abbreviation for Southampton in the UK).
```

In [21]:
```
# Work on 'family_size': combine 'SibSp' and 'Parch' similar features
for dataset in [train_dataset, test_dataset]:
    dataset['family_size'] = dataset['SibSp'] + dataset['Parch'] + 1

facet = sns.FacetGrid(train_dataset, hue='Survived', aspect=4)
facet.map(sns.kdeplot, 'family_size', shade=True)
facet.set(xlim=(0, train_dataset['family_size'].max()))
facet.add_legend()
plt.show()

for dataset in [train_dataset, test_dataset]:
    familysize_mapping = {
        1:0, 2:.4, 3:.8,
        4:1.2, 5:1.6,
        6:2, 7:2.4, 8:2.8,
        9:3.2, 10:3.6, 11:4
    }
    dataset['family_size'] = dataset['family_size'].map(familysize_mapping)

display(train_dataset.head(5))

# To note: similar to 'SibSp' and 'Parch' plots
plot_categorical_data(train_dataset, 'family_size', 'Survived')
```




```
             Survived  Pclass  \
PassengerId
1                   0       3
2                   1       1
3                   1       3
4                   1       1
5                   0       3

                                                     Name  Sex  Age  \
PassengerId
```

```
1                                      Braund, Mr. Owen Harris    0  1.0
2            Cumings, Mrs. John Bradley (Florence Briggs Th...    1  3.0
3                                       Heikkinen, Miss. Laina    1  2.0
4                 Futrelle, Mrs. Jacques Heath (Lily May Peel)    1  2.0
5                                     Allen, Mr. William Henry    0  2.0

             SibSp  Parch            Ticket  Fare  Cabin  Embarked  Title  \
PassengerId
1                1      0         A/5 21171   0.0    2.0         0      0
2                1      0          PC 17599   2.0    0.8         1      2
3                0      0  STON/O2. 3101282   0.0    2.0         0      1
4                1      0            113803   2.0    0.8         0      2
5                0      0            373450   0.0    2.0         0      0

             HasCabin  family_size
PassengerId
1                   0          0.4
2                   1          0.4
3                   0          0.0
4                   1          0.4
5                   0          0.0
```



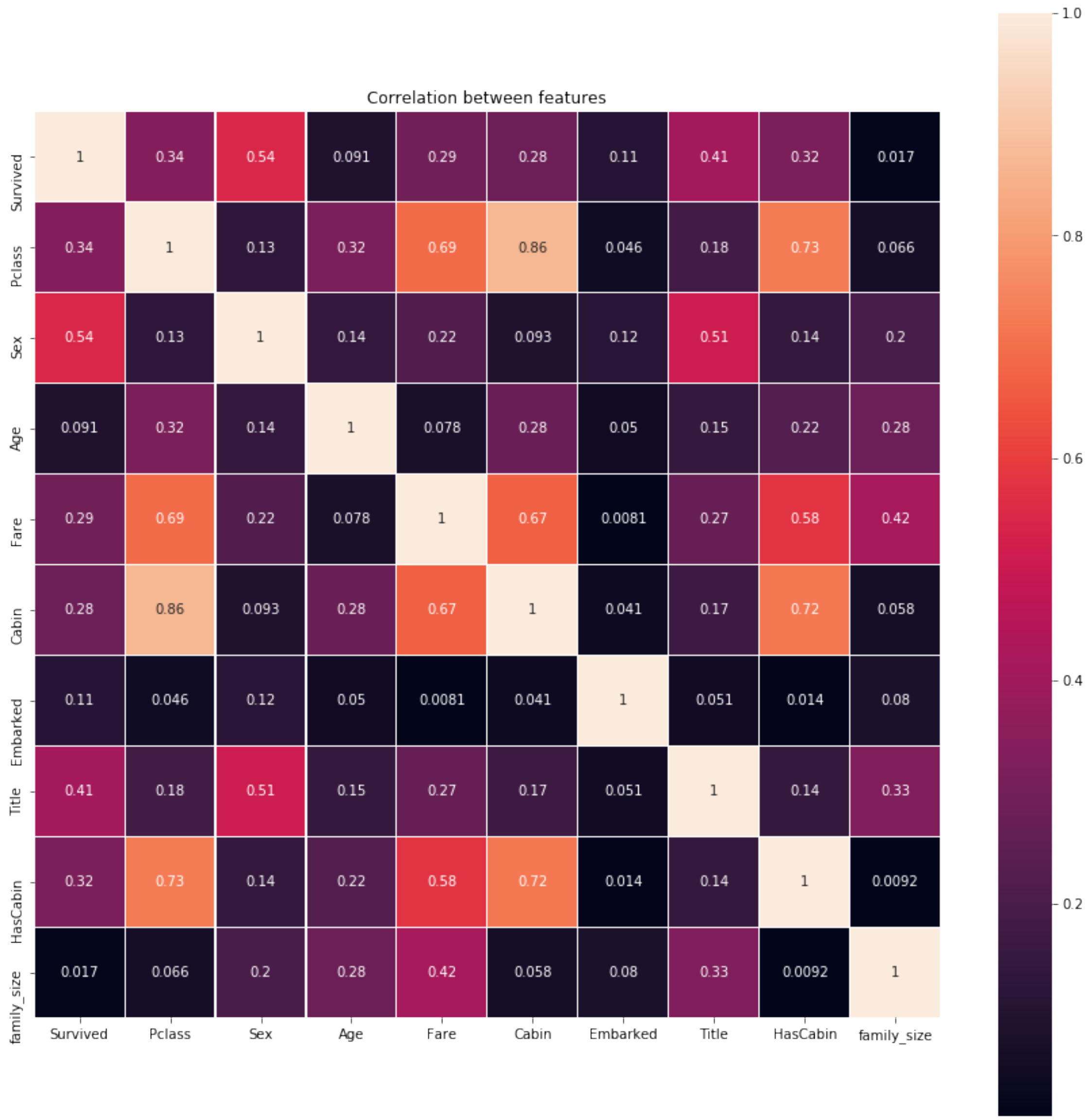

```
In [22]: # Drop cols

         for dataset in [train_dataset, test_dataset]:
             # Drop unnecessary features
```

```
            features_to_drop = ['Ticket', 'SibSp', 'Parch', 'Name']
            dataset.drop(features_to_drop, axis=1, inplace=True)
            # Final check of the datasets
            display(dataset.head(5))
```

```
             Survived  Pclass  Sex  Age  Fare  Cabin  Embarked  Title  \
PassengerId
1                   0       3    0  1.0   0.0    2.0         0      0
2                   1       1    1  3.0   2.0    0.8         1      2
3                   1       3    1  2.0   0.0    2.0         0      1
4                   1       1    1  2.0   2.0    0.8         0      2
5                   0       3    0  2.0   0.0    2.0         0      0

             HasCabin  family_size
PassengerId
1                   0          0.4
2                   1          0.4
3                   0          0.0
4                   1          0.4
5                   0          0.0


             Pclass  Sex  Age  Fare  Cabin  Embarked  Title  HasCabin  \
PassengerId
892               3    0  2.0   0.0    2.0         2      0         0
893               3    1  3.0   0.0    2.0         0      2         0
894               2    0  3.0   0.0    2.0         2      0         0
895               3    0  2.0   0.0    2.0         0      0         0
896               3    1  1.0   0.0    2.0         0      2         0

             family_size
PassengerId
892                  0.0
893                  0.4
894                  0.0
895                  0.0
896                  0.8
```

In [23]:
```
# Check for correlations

# 0.34 - Pclass
# 0.54 - Sex
# 0.41 - Title
# 0.32 - HasCabin

plt.figure(figsize=(15, 15))
plt.title('Correlation between features')
```

```
sns.heatmap(
    train_dataset.corr().abs(),
    annot=True, linecolor='white', square=True, vmax=1.0, linewidths=0.1
)
plt.show()
```




```
In [24]: # Prepare data for modelling

         X_train = train_dataset.drop('Survived', axis=1)
         Y_train = train_dataset['Survived']

         print(X_train.shape, Y_train.shape)
```

```
(891, 9) (891,)
```

```
In [25]: display(X_train.isnull().sum())
         display(Y_train.isnull().sum())
```

```
Pclass         0
Sex            0
Age            0
Fare           0
Cabin          0
Embarked       0
Title          0
HasCabin       0
family_size    0
dtype: int64
```

```
0
```

```
In [26]: # Prepare for cross-validation

         k_fold = KFold(n_splits=10, shuffle=True, random_state=0)

         def try_classifier(clf):
             scoring = 'accuracy'
             score = cross_val_score(clf,
                                     X_train, Y_train,
                                     cv=k_fold, n_jobs=-1, scoring=scoring)
             print(score)
             print(np.mean(score) * 100, 2)
```

```
In [27]: # Check feature importances
         rforest_checker = RandomForestClassifier(random_state=0, n_estimators=100)
         rforest_checker.fit(X_train, Y_train)
         importances_df = pd.DataFrame(rforest_checker.feature_importances_,
                                       columns=['feature_importance'],
                                       index=X_train.columns)
         importances_df.sort_values(by=['feature_importance'], ascending=False, inplace=True)
         display(importances_df)

         # Title: 0.245
         # Sex: 0.199
         # family_size: 0.131
         # Cabin: 0.103
```

```
             feature_importance
Title                  0.245140
```

```
Sex                     0.198682
family_size             0.130600
Cabin                   0.103836
Age                     0.091108
Fare                    0.076010
Pclass                  0.062412
Embarked                0.053970
HasCabin                0.038241
```

```
In [51]: # Create classifiers
         classifiers = {
             'knn_clf': KNeighborsClassifier(n_neighbors=100),
             'logreg_clf': LogisticRegression(solver='lbfgs'),
             'gnb_clf': GaussianNB(),
             'dtc_clf': DecisionTreeClassifier(),
             'rfc_clf': RandomForestClassifier(n_estimators=100),
             'svc_clf': SVC()
         }
         for clf_name, clf_obj in classifiers.items():
             print('clf_name: {0}'.format(clf_name))
             try_classifier(clf_obj)
             print('\n')
```

```
clf_name: knn_clf
[0.77777778 0.79775281 0.75280899 0.69662921 0.7752809  0.83146067
 0.7752809  0.76404494 0.74157303 0.78651685]
76.99126092384519 2


clf_name: logreg_clf
[0.8        0.78651685 0.80898876 0.7752809  0.78651685 0.80898876
 0.82022472 0.83146067 0.82022472 0.85393258]
80.92134831460675 2


clf_name: gnb_clf
[0.83333333 0.7752809  0.73033708 0.73033708 0.74157303 0.80898876
 0.73033708 0.76404494 0.85393258 0.82022472]
77.88389513108615 2


clf_name: dtc_clf
[0.77777778 0.8988764  0.76404494 0.76404494 0.83146067 0.79775281
 0.84269663 0.76404494 0.74157303 0.7752809 ]
79.57553058676655 2
```

```
clf_name: rfc_clf
[0.83333333 0.87640449 0.79775281 0.79775281 0.83146067 0.84269663
 0.83146067 0.78651685 0.75280899 0.82022472]
81.70411985018727 2


clf_name: svc_clf
[0.84444444 0.80898876 0.82022472 0.82022472 0.84269663 0.82022472
 0.84269663 0.85393258 0.83146067 0.85393258]
83.38826466916353 2
```

```
In [29]: # # Try removing features with low importance: try to reduce noise
         X_train_2 = train_dataset.drop(['Survived', 'HasCabin', 'Embarked'], axis=1)

         def try_classifier_2(clf):
             scoring = 'accuracy'
             score = cross_val_score(clf,
                                     X_train_2, Y_train,
                                     cv=k_fold, n_jobs=-1, scoring=scoring)
             print(score)
             print(np.mean(score) * 100, 2)

         for clf_name, clf_obj in classifiers.items():
             print('clf_name: {0}'.format(clf_name))
             try_classifier_2(clf_obj)
             print('\n')
```

```
clf_name: knn_clf
[0.75555556 0.80898876 0.7752809  0.74157303 0.74157303 0.83146067
 0.82022472 0.79775281 0.80898876 0.82022472]
79.01622971285892 2


clf_name: gnb_clf
[0.83333333 0.74157303 0.74157303 0.75280899 0.70786517 0.79775281
 0.74157303 0.79775281 0.85393258 0.82022472]
77.88389513108615 2


clf_name: dtc_clf
[0.8        0.86516854 0.82022472 0.79775281 0.82022472 0.7752809
 0.82022472 0.78651685 0.74157303 0.83146067]
80.58426966292134 2
```

```
clf_name: rfc_clf
[0.83333333 0.84269663 0.82022472 0.78651685 0.85393258 0.7752809
 0.83146067 0.79775281 0.78651685 0.86516854]
81.92883895131085 2


clf_name: svc_clf
[0.84444444 0.80898876 0.82022472 0.82022472 0.84269663 0.80898876
 0.83146067 0.85393258 0.83146067 0.83146067]
82.93882646691635 2
```

In [30]:
```
# Linear models
logreg_clf = LogisticRegression(solver='lbfgs')

logreg_clf.fit(X_train, Y_train)
logreg_cvs = cross_val_score(estimator=logreg_clf,
                             X=X_train, y=Y_train,
                             cv=10)
print(logreg_cvs)
print(logreg_cvs.mean())  # mean of accuracy score
print(logreg_cvs.std())  # Standard deviation = differences of the accuracy score in
                         # the less = less variance = the better

# Try less parameters
print('\n')
logreg_clf.fit(X_train_2, Y_train)
logreg_cvs = cross_val_score(estimator=logreg_clf, X=X_train_2, y=Y_train, cv=10)
print(logreg_cvs)
print(logreg_cvs.mean())
print(logreg_cvs.std())

# Try scaling data
print('\n')
minmax_scaler = preprocessing.MinMaxScaler()
X_train_copy = X_train.copy()
for col in X_train_copy:
    X_train_copy[col] = X_train_copy[col].astype('float')
X_train_minmax = minmax_scaler.fit_transform(X_train_copy)
logreg_clf.fit(X_train_minmax, Y_train)
logreg_cvs = cross_val_score(estimator=logreg_clf, X=X_train_minmax, y=Y_train, cv=10
print(logreg_cvs)
print(logreg_cvs.mean())
print(logreg_cvs.std())
```

```
[0.82222222 0.81111111 0.7752809  0.87640449 0.84269663 0.79775281
 0.83146067 0.83146067 0.80898876 0.80681818]
```

```
0.820419645897174
0.026136623385488653


[0.8        0.82222222 0.7752809  0.87640449 0.83146067 0.78651685
 0.82022472 0.80898876 0.82022472 0.79545455]
0.8136777891272272
0.026763399515686254


[0.81111111 0.81111111 0.7752809  0.87640449 0.83146067 0.79775281
 0.84269663 0.78651685 0.80898876 0.80681818]
0.8148141527635909
0.027618670901495692
```

```
In [43]: # Hyper parameters tuning by GridSearchCV: logistic regression
         logreg_params = [
             {'penalty': ['l1'], 'solver': ['liblinear', 'saga'], 'C': [0.01, 0.1, 1, 10, 100]
             {'penalty': ['l2'], 'solver': ['lbfgs', 'sag', 'newton-cg'], 'C': [0.01, 0.1, 1,
         ]
         logreg_grid = GridSearchCV(
             estimator=LogisticRegression(random_state=0),
             param_grid=logreg_params,
             scoring='accuracy',
             cv=10,
             iid=True,
             n_jobs=-1
         )
         logreg_grid = logreg_grid.fit(X_train, Y_train)
         logreg_best_accuracy = logreg_grid.best_score_
         logreg_best_params = logreg_grid.best_params_

         print(logreg_best_accuracy)
         print(logreg_best_params)
```

```
0.8204264870931538
{'C': 1, 'penalty': 'l2', 'solver': 'lbfgs'}
```

```
In [46]: # Hyper parameters tuning by GridSearchCV: Kernel SVM

         # Because we don't have continuous feature, we need to normalize the data.
         X_train_norm = X_train.copy()
         X_train_norm = X_train_norm.apply(
             lambda x: (x - np.mean(x)) / (np.max(x) - np.min(x))
         )
```

```
params_ksvm = [
    {'C': [0.1, 1, 10, 100], 'kernel': ['linear']},
    {'C': [0.1, 1, 10, 100], 'kernel': ['rbf'], 'gamma': [0.1, 0.2, 0.3, 0.4, 0.5]},
    {'C': [0.1, 1, 10, 100], 'kernel': ['poly'], 'degree': [1, 2, 3], 'gamma': [0.1, 0
]
grid_ksvm = GridSearchCV(
    estimator = SVC(random_state=0),
    param_grid = params_ksvm,
    scoring = 'accuracy',
    cv = 10,
    n_jobs=-1,
    iid=True
)
grid_ksvm = grid_ksvm.fit(X_train_norm, Y_train)
best_acc_ksvm = grid_ksvm.best_score_
best_params_ksvm = grid_ksvm.best_params_

print(best_acc_ksvm)
print(best_params_ksvm)
```

```
0.8372615039281706
{'C': 100, 'degree': 3, 'gamma': 0.3, 'kernel': 'poly'}
```

In [48]:
```
# Hyper parameters tuning by GridSearchCV: Decision Tree
params_dtree = [{
    'min_samples_split': [5, 10, 15, 20],
    'min_samples_leaf': [1, 2, 3],
    'max_features': ['auto', 'log2']}
]
grid_dtree = GridSearchCV(
    estimator=DecisionTreeClassifier(criterion = 'gini', random_state=0),
    param_grid=params_dtree,
    scoring='accuracy',
    cv=10,
    iid=True,
    n_jobs=-1
)
grid_dtree = grid_dtree.fit(X_train, Y_train)
best_acc_dtree = grid_dtree.best_score_
best_params_dtree = grid_dtree.best_params_

print(best_acc_dtree)
print(best_params_dtree)
```

```
0.8271604938271605
{'max_features': 'auto', 'min_samples_leaf': 2, 'min_samples_split': 20}
```

In [50]:
```
# Hyper parameters tuning by GridSearchCV: Random Forest
params_rforest = [{
    'n_estimators': [10, 100, 200, 300, 500, 800],
    'max_depth': [5, 7, 10, 15, 20],
    'min_samples_split': [2, 4],
    'min_samples_leaf': [1, 2, 3],
    'max_features': ['auto', 'log2']
}]
grid_rforest = GridSearchCV(
    estimator=RandomForestClassifier(criterion='gini', random_state=0, n_jobs=-1),
    param_grid = params_rforest,
    scoring = 'accuracy',
    cv = 10,
    n_jobs=-1,
    iid=10
)
grid_rforest = grid_rforest.fit(X_train, Y_train)
best_acc_rforest = grid_rforest.best_score_
best_params_rforest = grid_rforest.best_params_

print(best_acc_rforest)
print(best_params_rforest)
```

```
0.8406285072951739
{'max_depth': 5, 'max_features': 'auto', 'min_samples_leaf': 2, 'min_samples_split': 2, 'n_esti
```

In [55]:
```
# Compare grid search scores

grid_score_dict = {
    'Best Score': [logreg_best_accuracy, best_acc_ksvm, best_acc_dtree, best_acc_rfore
    'Optimized Parameters': [logreg_best_params, best_params_ksvm, best_params_dtree,
}
grid_score_df = pd.DataFrame(
    grid_score_dict,
    index=['Logistic Regression','Kernel SVM','Decision Tree','Random Forest']
)

display(grid_score_df)
```

```
                       Best Score  \
Logistic Regression      0.820426
Kernel SVM               0.837262
Decision Tree            0.827160
Random Forest            0.840629

                                                 Optimized Parameters
Logistic Regression         {'C': 1, 'penalty': 'l2', 'solver': 'lbfgs'}
```

```
Kernel SVM           {'C': 100, 'degree': 3, 'gamma': 0.3, 'kernel'...
Decision Tree        {'max_features': 'auto', 'min_samples_leaf': 2...
Random Forest        {'max_depth': 5, 'max_features': 'auto', 'min_...
```

In [74]:
```python
# Train the best model
# # Accuracy: 82.49063670411985
# print(best_params_rforest)
# rforest = RandomForestClassifier(
#     max_depth=7,
#     max_features='auto',
#     min_samples_leaf=2,
#     min_samples_split=4,
#     n_estimators=200,
#     random_state=0
# )
# rforest.fit(X_train, Y_train)
# y_pred_train_forest = cross_val_predict(rforest, X_train, Y_train, cv=10, n_jobs=-1
# y_pred_test_forest = rforest.predict(test_dataset)

# # Accuracy: 83.27840199750312
# print(best_params_ksvm)
# ksvm = SVC(
#     C=100,
#     gamma=0.3,
#     kernel='poly',
#     random_state=0,
#     degree=3
# )
# ksvm.fit(X_train_norm, Y_train)
# y_pred_train_ksvm = cross_val_predict(ksvm, X_train_norm, Y_train, cv=10, n_jobs=-1
# y_pred_test_ksvm = ksvm.predict(test_dataset)

# # Check accuracy again
# scoring = 'accuracy'
# score = cross_val_score(ksvm, X_train_norm, Y_train, cv=k_fold, n_jobs=-1, scoring=
# print(score)
# print(np.mean(score) * 100)
```

```
{'C': 100, 'degree': 3, 'gamma': 0.3, 'kernel': 'poly'}
[0.82222222 0.83146067 0.83146067 0.85393258 0.86516854 0.84269663
 0.83146067 0.80898876 0.80898876 0.83146067]
83.27840199750312
```

In [75]:
```python
# Prepare submission for Kaggle competition
submission = pd.DataFrame({
    'PassengerId': test_dataset.index,
```

```
        'Survived': y_pred_test_ksvm
    })
    submission.to_csv('submission.csv', index=False)

    # display(test_dataset.head(5))
```

```
In [ ]: # Final result:
        # 2,289th of 11520 - top 20%
```