Data Visualization I

- Use the inbuilt dataset 'titanic'. The dataset contains 891 rows and contains information about the passengers who boarded the unfortunate Titanic ship. Use the Seaborn library to see if we can find any patterns in the data.
- Write a code to check how the price of the ticket (column name: 'fare') for each passenger is distributed by plotting a histogram.

Titanic: Dataset

Workflow:

- Exploratory Data Analysis.
  - Surviving rate
  - Pclass
  - Name
  - Sex
  - Age
  - SibSp, Parch
  - Ticket
  - Fare
  - Cabin
  - Embarked
- Feature Engineering
  - Imputation on Embarked and Age columns
  - Title extraction
  - Ticket first letters
  - Cabin first letters
  - Encoding sex column
  - Family size
  - One Hot Encoding for all categorical variables
- Machine Learning
  - Split data into train and test sets
  - Initialize a Random Forest Classifier
  - Hyperparameter Tuning with Grid Search
  - Prediction

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

1. Exploratory Data Analysis

In [2]:
```
train = pd.read_csv("train.csv")

display(train.head())

print(train.info())
print(train.info())
print(train.describe())
```

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

```
<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
None
<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
None
       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  
```

Notes:

- There are some missing values in Age, Embarked and Cabin columns.
- We do not need PassengerId column
- The surviving rate is 38.3% in our dataset

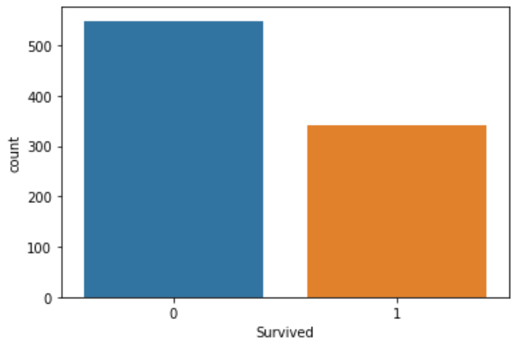
Survived

Let's start with Survived column. It contains integer 1 or 0 which correspond to surviving (1 = Survived, 0 = Not Survived)

In [3]:

```
# Visualize with a countplot
sns.countplot(x="Survived", data=train)
plt.show()

# Print the proportions
print(train["Survived"].value_counts(normalize=True))
```



```
0    0.616162
1    0.383838
Name: Survived, dtype: float64
```

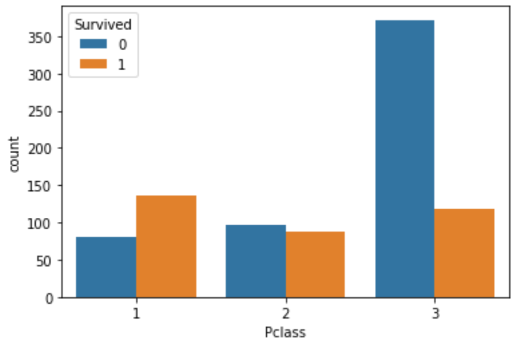
Pclass

Pclass column contains the socioeconomic status of the passengers. It might be predictive for our model
1 = Upper
2 = Middle
3 = Lower

In [4]:
```
# Visualize with a countplot
sns.countplot(x="Pclass", hue="Survived", data=train)
plt.show()

# Proportion of people survived for each class
print(train["Survived"].groupby(train["Pclass"]).mean())

# How many people we have in each class?
print(train["Pclass"].value_counts())
```




```
Pclass
1    0.629630
2    0.472826
3    0.242363
Name: Survived, dtype: float64
3    491
1    216
2    184
Name: Pclass, dtype: int64
```

As I expected, first class passengers have higher surviving rate. We will use this information in our training data.

Name

At a first glance, I thought that I would use the titles.

In [5]:
```
# Display first five rows of the Name column
display(train[["Name"]].head())
```

	Name
0	Braund, Mr. Owen Harris
1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)
2	Heikkinen, Miss. Laina
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)
4	Allen, Mr. William Henry

We can extract the titles from names.

In [6]:
```
# Get titles
train["Title"] = train['Name'].str.split(', ', expand=True)[1].str.split('.', expand=True)[0]

# Print title counts
print(train["Title"].value_counts())
```

```
Mr              517
Miss            182
Mrs             125
```

```
Master           40
Dr                7
Rev               6
Mlle              2
Major             2
Col               2
the Countess      1
Capt              1
Ms                1
Sir               1
Lady              1
Mme               1
Don               1
Jonkheer          1
Name: Title, dtype: int64
```

Is there any relationship between titles and surviving

In [7]:

```
# Print the Surviving rates by title
print(train["Survived"].groupby(train["Title"]).mean().sort_values(ascending=False))
```

```
Title
the Countess    1.000000
Mlle            1.000000
Sir             1.000000
Ms              1.000000
Lady            1.000000
Mme             1.000000
Mrs             0.792000
Miss            0.697802
Master          0.575000
Col             0.500000
Major           0.500000
Dr              0.428571
Mr              0.156673
Jonkheer        0.000000
Rev             0.000000
Don             0.000000
Capt            0.000000
Name: Survived, dtype: float64
```

Apparently, there is relationship between titles and surviving rate. In feature engineering part, I will group title by their surviving rates like following

higher = the Countess, Mlle, Lady, Ms , Sir, Mme, Mrs, Miss, Master
neutral = Major, Col, Dr
lower = Mr, Rev, Jonkheer, Don, Capt

Age

In [8]:

```
# Print the missing values in Age column
print(train["Age"].isnull().sum())
```

```
177
```

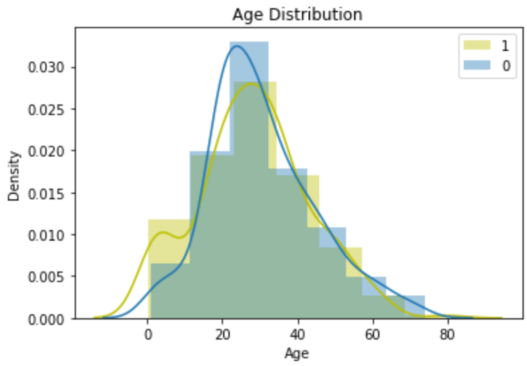
There are 177 missing values in Age column, we will impute them in Feature engineering part. Now, let's look at the distribution of ages by surviving

In [9]:

```
# Survived by age
sns.distplot(train[train.Survived==1]["Age"],color="y", bins=7, label="1")

# Death by age
sns.distplot(train[train.Survived==0]["Age"], bins=7, label="0")
plt.legend()
plt.title("Age Distribution")
plt.show()
```

```
/home/ihack-pc/.local/lib/python3.8/site-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
/home/ihack-pc/.local/lib/python3.8/site-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



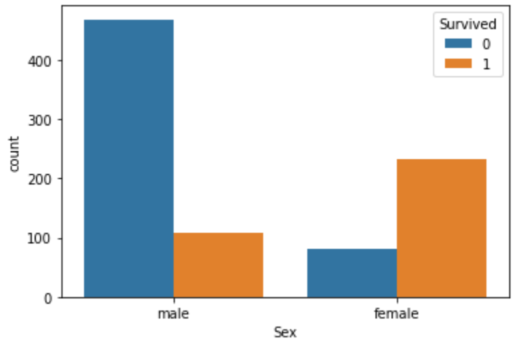
Sex

Is sex important for surviving?

In [10]:
```
# Visualize with a countplot
sns.countplot(x="Sex", hue="Survived", data=train)
plt.show()

# Proportion of people survived for each class
print(train["Survived"].groupby(train["Sex"]).mean())

# How many people we have in each class?
print(train["Sex"].value_counts())
```




```
Sex
female    0.742038
male      0.188908
Name: Survived, dtype: float64
male      577
female    314
Name: Sex, dtype: int64
```

Obviously, there is a relationship between sex and surviving.

SibSp & Parch

SibSp = Sibling or Spouse number
Parch = Parent or Children number

I decided to make a new feature called family size by summing the SibSp and Parch columns

In [11]:
```
print(train["SibSp"].value_counts())

print(train["Parch"].value_counts())

train["family_size"] = train["SibSp"] + train["Parch"]

print(train["family_size"].value_counts())

# Proportion of people survived for each class
print(train["Survived"].groupby(train["family_size"]).mean().sort_values(ascending=False))
```

```
0    608
1    209
```

```
2     28
4     18
3     16
8      7
5      5
Name: SibSp, dtype: int64
0    678
1    118
2     80
5      5
3      5
4      4
6      1
Name: Parch, dtype: int64
0     537
1     161
2     102
3      29
5      22
4      15
6      12
10      7
7       6
Name: family_size, dtype: int64
family_size
3     0.724138
2     0.578431
1     0.552795
6     0.333333
0     0.303538
4     0.200000
5     0.136364
7     0.000000
10    0.000000
Name: Survived, dtype: float64
```

Apparently, family size is important to survive. I am going to group them in feature engineering step like following

big family = if family size > 3
small family = if family size > 0 and family size < =3
alone = family size == 0

Ticket

At first, I thought that I would drop this column but after exploration I found useful features.

In [12]:
```
# Print the first five rows of the Ticket column
print(train["Ticket"].head(15))
```

```
0            A/5 21171
1             PC 17599
2     STON/O2. 3101282
3               113803
4               373450
5               330877
6                17463
7               349909
8               347742
9               237736
10             PP 9549
11              113783
12           A/5. 2151
13              347082
14              350406
Name: Ticket, dtype: object
```

I extracted only first letters of the tickets because I thought that they would indicate the ticket type.

In [13]:
```
# Get first letters of the tickets
train["Ticket_first"] = train["Ticket"].apply(lambda x: str(x)[0])

# Print value counts
print(train["Ticket_first"].value_counts())

# Surviving rates of first letters
print(train.groupby("Ticket_first")["Survived"].mean().sort_values(ascending=False))
```

```
3    301
2    183
1    146
P     65
S     65
C     47
A     29
W     13
4     10
7      9
F      7
```

```
6      6
L      4
5      3
8      2
9      1
Name: Ticket_first, dtype: int64
Ticket_first
9    1.000000
P    0.646154
1    0.630137
F    0.571429
2    0.464481
C    0.340426
S    0.323077
L    0.250000
3    0.239203
4    0.200000
6    0.166667
W    0.153846
7    0.111111
A    0.068966
5    0.000000
8    0.000000
Name: Survived, dtype: float64
```

The first letters of the tickets are correlated with surviving rate somehow. I am going to group them like following

higher surviving rate = F, 1, P , 9
neutral = S, C, 2
lower surviving rate = else

Fare

We can plot a histogram to see Fare distribution

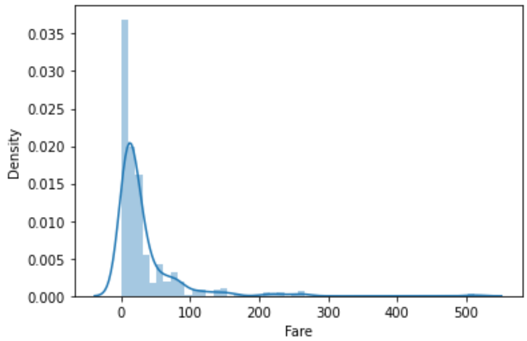
In [14]:
```python
# Print 3 bins of Fare column
print(pd.cut(train['Fare'], 3).value_counts())

# Plot the histogram
sns.distplot(train["Fare"])
plt.show()

# Print binned Fares by surviving rate
print(train['Survived'].groupby(pd.cut(train['Fare'], 3)).mean())
```

```
(-0.512, 170.776]     871
(170.776, 341.553]     17
(341.553, 512.329]      3
Name: Fare, dtype: int64
```

```
/home/ihack-pc/.local/lib/python3.8/site-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```




```
Fare
(-0.512, 170.776]     0.376579
(170.776, 341.553]    0.647059
(341.553, 512.329]    1.000000
Name: Survived, dtype: float64
```

There is also a correlation between ticket fares and surviving

Cabin

I found this figure wikiwand.com. The figure shows us the most affacted parts of the Titanic and the Cabin locations. Although there are many missing value in Cabin column, I decided to extract the Cabin information to try whether it works or not.

In [15]:
```
# Print the unique values in the Cabin column
print(train["Cabin"].unique())

# Get the first letters of Cabins
train["Cabin_first"] = train["Cabin"].apply(lambda x: str(x)[0])

# Print value counts of first letters
print(train["Cabin_first"].value_counts())

# Surviving rate of Cabin first letters
print(train.groupby("Cabin_first")["Survived"].mean().sort_values(ascending=False))
```

```
[nan 'C85' 'C123' 'E46' 'G6' 'C103' 'D56' 'A6' 'C23 C25 C27' 'B78' 'D33'
 'B30' 'C52' 'B28' 'C83' 'F33' 'F G73' 'E31' 'A5' 'D10 D12' 'D26' 'C110'
 'B58 B60' 'E101' 'F E69' 'D47' 'B86' 'F2' 'C2' 'E33' 'B19' 'A7' 'C49'
 'F4' 'A32' 'B4' 'B80' 'A31' 'D36' 'D15' 'C93' 'C78' 'D35' 'C87' 'B77'
 'E67' 'B94' 'C125' 'C99' 'C118' 'D7' 'A19' 'B49' 'D' 'C22 C26' 'C106'
 'C65' 'E36' 'C54' 'B57 B59 B63 B66' 'C7' 'E34' 'C32' 'B18' 'C124' 'C91'
 'E40' 'T' 'C128' 'D37' 'B35' 'E50' 'C82' 'B96 B98' 'E10' 'E44' 'A34'
 'C104' 'C111' 'C92' 'E38' 'D21' 'E12' 'E63' 'A14' 'B37' 'C30' 'D20' 'B79'
 'E25' 'D46' 'B73' 'C95' 'B38' 'B39' 'B22' 'C86' 'C70' 'A16' 'C101' 'C68'
 'A10' 'E68' 'B41' 'A20' 'D19' 'D50' 'D9' 'A23' 'B50' 'A26' 'D48' 'E58'
 'C126' 'B71' 'B51 B53 B55' 'D49' 'B5' 'B20' 'F G63' 'C62 C64' 'E24' 'C90'
 'C45' 'E8' 'B101' 'D45' 'C46' 'D30' 'E121' 'D11' 'E77' 'F38' 'B3' 'D6'
 'B82 B84' 'D17' 'A36' 'B102' 'B69' 'E49' 'C47' 'D28' 'E17' 'A24' 'C50'
 'B42' 'C148']
n    687
C     59
B     47
D     33
E     32
A     15
F     13
G      4
T      1
Name: Cabin_first, dtype: int64
Cabin_first
D    0.757576
E    0.750000
B    0.744681
F    0.615385
C    0.593220
G    0.500000
A    0.466667
n    0.299854
T    0.000000
Name: Survived, dtype: float64
```

According to surviving rates. I will group the Cabins like following

higher surviving rate = D, E, B, F, C
neutral = G, A
lower surviving rate else

Embarked

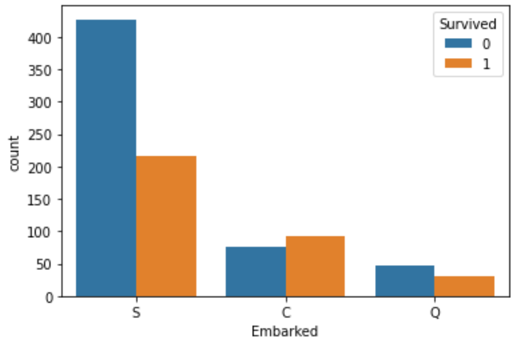
Embarked is a categorical features which shows us the port of embarkation.

C = Cherbourg, Q = Queenstown, S = Southampton

In [16]:
```
# Make a countplot
sns.countplot(x="Embarked", hue="Survived", data=train)
plt.show()

# Print the value counts
print(train["Embarked"].value_counts())

# Surviving rates of Embarked
print(train["Survived"].groupby(train["Embarked"]).mean())
```




```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
Embarked
C    0.553571
Q    0.389610
S    0.336957
Name: Survived, dtype: float64
```

No doubt, C has the higher surviving rate. We will definetely use this information.

2. Feature Engineering

We have learned a lot from exploratory data analysis. Now we can start feature engineering. Firstly, let's load the train and the test sets.

In [17]:
```
# Load the train and the test datasets
train = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")

print(test.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Pclass       418 non-null    int64  
 2   Name         418 non-null    object 
 3   Sex          418 non-null    object 
 4   Age          332 non-null    float64
 5   SibSp        418 non-null    int64  
 6   Parch        418 non-null    int64  
 7   Ticket       418 non-null    object 
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object 
 10  Embarked     418 non-null    object 
dtypes: float64(2), int64(4), object(5)
memory usage: 36.0+ KB
None
```

There is one missing value in the Fare column of the test set. I imputed it by using mean.

In [18]:
```
# Put the mean into the missing value
```

```
test['Fare'].fillna(train['Fare'].mean(), inplace = True)
```

I have used two types of Imputer from sklearn. Iterative imputer for age imputation, and Simple imputer (with most frequent strategy) for Embarked

In [19]:
```
from sklearn.impute import SimpleImputer
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer

# Imputers
imp_embarked = SimpleImputer(missing_values=np.nan, strategy="most_frequent")
imp_age = IterativeImputer(max_iter=100, random_state=34, n_nearest_features=2)

# Impute Embarked
train["Embarked"] = imp_embarked.fit_transform(train[["Embarked"]])
test["Embarked"] = imp_embarked.transform(test[["Embarked"]])

# Impute Age
train["Age"] = np.round(imp_age.fit_transform(train[["Age"]]))
test["Age"] = np.round(imp_age.transform(test[["Age"]]))
```

We also encode the sex column.

In [20]:
```
from sklearn.preprocessing import LabelEncoder

# Initialize a Label Encoder
le = LabelEncoder()

# Encode Sex
train["Sex"] = le.fit_transform(train[["Sex"]].values.ravel())
test["Sex"] = le.fit_transform(test[["Sex"]].values.ravel())
```

In EDA, we decided to use family size feature

In [21]:
```
# Family Size
train["Fsize"] = train["SibSp"] + train["Parch"]
test["Fsize"] = test["SibSp"] + test["Parch"]
```

Ticket first letters and Cabin first letters are also needed

In [22]:
```
# Ticket first letters
train["Ticket"] = train["Ticket"].apply(lambda x: str(x)[0])
test["Ticket"] = test["Ticket"].apply(lambda x: str(x)[0])

# Cabin first letters
train["Cabin"] = train["Cabin"].apply(lambda x: str(x)[0])
test["Cabin"] = test["Cabin"].apply(lambda x: str(x)[0])
```

Extract the titles from the names

In [23]:
```
# Titles
train["Title"] = train['Name'].str.split(', ', expand=True)[1].str.split('.', expand=True)[0]
test["Title"] = test['Name'].str.split(', ', expand=True)[1].str.split('.', expand=True)[0]
```

Now, we need some helper functions to group our categories

In [24]:
```
# Group the family_size column
def assign_passenger_label(family_size):
    if family_size == 0:
        return "Alone"
    elif family_size <=3:
        return "Small_family"
```

```python
    else:
        return "Big_family"

# Group the Ticket column
def assign_label_ticket(first):
    if first in ["F", "1", "P", "9"]:
        return "Ticket_high"
    elif first in ["S", "C", "2"]:
        return "Ticket_middle"
    else:
        return "Ticket_low"

# Group the Title column
def assign_label_title(title):
    if title in ["the Countess", "Mlle", "Lady", "Ms", "Sir", "Mme", "Mrs", "Miss", "Master"]:
        return "Title_high"
    elif title in ["Major", "Col", "Dr"]:
        return "Title_middle"
    else:
        return "Title_low"

# Group the Cabin column
def assign_label_cabin(cabin):
    if cabin in ["D", "E", "B", "F", "C"]:
        return "Cabin_high"
    elif cabin in ["G", "A"]:
        return "Cabin_middle"
    else:
        return "Cabin_low"
```

Apply the functions.

In [25]:

```python
# Family size
train["Fsize"] = train["Fsize"].apply(assign_passenger_label)
test["Fsize"] = test["Fsize"].apply(assign_passenger_label)

# Ticket
train["Ticket"] = train["Ticket"].apply(assign_label_ticket)
test["Ticket"] = test["Ticket"].apply(assign_label_ticket)

# Title
train["Title"] = train["Title"].apply(assign_label_title)
test["Title"] = test["Title"].apply(assign_label_title)

# Cabin
train["Cabin"] = train["Cabin"].apply(assign_label_cabin)
test["Cabin"] = test["Cabin"].apply(assign_label_cabin)
```

It's time to use One Hot Encoding

In [26]:

```python
train = pd.get_dummies(columns=["Pclass", "Embarked", "Ticket", "Cabin","Title", "Fsize"], data=tr
test = pd.get_dummies(columns=["Pclass", "Embarked", "Ticket", "Cabin", "Title", "Fsize"], data=te
```

Drop the colums that are no longer needed

In [27]:

```python
target = train["Survived"]
train.drop(["Survived", "SibSp", "Parch", "Name", "PassengerId"], axis=1, inplace=True)
test.drop(["SibSp", "Parch", "Name","PassengerId"], axis=1, inplace=True)
```

Final look

In [28]:

```python
display(train.head())
display(test.head())
```

```python
print(train.info())
print(test.info())
```

	Sex	Age	Fare	Pclass_2	Pclass_3	Embarked_Q	Embarked_S	Ticket_Ticket_low	Ticket_Ticket_middle	Cabin_Cabin_lo
0	1	22.0	7.2500	0	1	0	1	1	0	1
1	0	38.0	71.2833	0	0	0	0	0	0	0
2	0	26.0	7.9250	0	1	0	1	0	1	1
3	0	35.0	53.1000	0	0	0	1	0	0	0
4	1	35.0	8.0500	0	1	0	1	1	0	1

	Sex	Age	Fare	Pclass_2	Pclass_3	Embarked_Q	Embarked_S	Ticket_Ticket_low	Ticket_Ticket_middle	Cabin_Cabin_lo
0	1	34.0	7.8292	0	1	1	0	1	0	1
1	0	47.0	7.0000	0	1	0	1	1	0	1
2	1	62.0	9.6875	1	0	1	0	0	1	1
3	1	27.0	8.6625	0	1	0	1	1	0	1
4	0	22.0	12.2875	0	1	0	1	1	0	1

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Sex                   891 non-null    int64  
 1   Age                   891 non-null    float64
 2   Fare                  891 non-null    float64
 3   Pclass_2              891 non-null    uint8  
 4   Pclass_3              891 non-null    uint8  
 5   Embarked_Q            891 non-null    uint8  
 6   Embarked_S            891 non-null    uint8  
 7   Ticket_Ticket_low     891 non-null    uint8  
 8   Ticket_Ticket_middle  891 non-null    uint8  
 9   Cabin_Cabin_low       891 non-null    uint8  
 10  Cabin_Cabin_middle    891 non-null    uint8  
 11  Title_Title_low       891 non-null    uint8  
 12  Title_Title_middle    891 non-null    uint8  
 13  Fsize_Big_family      891 non-null    uint8  
 14  Fsize_Small_family    891 non-null    uint8  
dtypes: float64(2), int64(1), uint8(12)
memory usage: 31.4 KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 15 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Sex                   418 non-null    int64  
 1   Age                   418 non-null    float64
 2   Fare                  418 non-null    float64
 3   Pclass_2              418 non-null    uint8  
 4   Pclass_3              418 non-null    uint8  
 5   Embarked_Q            418 non-null    uint8  
 6   Embarked_S            418 non-null    uint8  
 7   Ticket_Ticket_low     418 non-null    uint8  
 8   Ticket_Ticket_middle  418 non-null    uint8  
 9   Cabin_Cabin_low       418 non-null    uint8  
 10  Cabin_Cabin_middle    418 non-null    uint8  
 11  Title_Title_low       418 non-null    uint8  
 12  Title_Title_middle    418 non-null    uint8  
 13  Fsize_Big_family      418 non-null    uint8  
 14  Fsize_Small_family    418 non-null    uint8  
dtypes: float64(2), int64(1), uint8(12)
memory usage: 14.8 KB
None
```

3. Machine Learning

To evaluate our model's performance, we need to split our train data into training and test sets.

In [29]:
```python
from sklearn.model_selection import train_test_split

# Select the features and the target
X = train.values
y = target.values

# Split the data info training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=34, stratify
```

I have used GridSearchCV for tuning my Random Forest Classifier

In [30]:

```
# Import Necessary libraries
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.metrics import accuracy_score, roc_auc_score, confusion_matrix, classification_report

# Initialize a RandomForestClassifier
rf = RandomForestClassifier(random_state=34)

params = {'n_estimators': [50, 100, 200, 300, 350],
          'max_depth': [3,4,5,7, 10,15,20],
          'criterion':['entropy', 'gini'],
          'min_samples_leaf' : [1, 2, 3, 4, 5, 10],
          'max_features':['auto'],
          'min_samples_split': [3, 5, 10, 15, 20],
          'max_leaf_nodes':[2,3,4,5],
          }
```

In [ ]:

```
clf = GridSearchCV(estimator=rf,param_grid=params,cv=10, n_jobs=-1)

clf.fit(X_train, y_train.ravel())

print(clf.best_estimator_)
print(clf.best_score_)

rf_best = clf.best_estimator_

# Predict from the test set
y_pred = clf.predict(X_test)

# Print the accuracy with accuracy_score function
print("Accuracy: ", accuracy_score(y_test, y_pred))

# Print the confusion matrix
print("\nConfusion Matrix\n")
print(confusion_matrix(y_test, y_pred))
```

Save the model

In [ ]:

```
pickle.dump(rf_best, open("model.pkl", 'wb'))
```

We can look at the feature importances.

In [ ]:

```
# Create a pandas series with feature importances
importance = pd.Series(rf_best.feature_importances_,index=train.columns).sort_values(ascending=Fal

sns.barplot(x=importance, y=importance.index)
# Add labels to your graph
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title("Important Features")
plt.show()
```

Train the model again with entire train data.

In [ ]:

```
last_clf = RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=4, max_features='auto',
                       max_leaf_nodes=5, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=15,
```

```python
                        min_weight_fraction_leaf=0.0, n_estimators=350,
                        n_jobs=None, oob_score=True, random_state=34, verbose=0,
                        warm_start=False)

last_clf.fit(train, target)
print("%.4f" % last_clf.oob_score_)
```

Prepare the submission file

In [ ]:

```python
# Store passenger ids
ids = pd.read_csv("test.csv")[["PassengerId"]].values

# Make predictions
predictions = last_clf.predict(test.values)

# Print the predictions
print(predictions)

# Create a dictionary with passenger ids and predictions
df = {'PassengerId': ids.ravel(), 'Survived':predictions}

# Create a DataFrame named submission
submission = pd.DataFrame(df)

# Display the first five rows of submission
display(submission.head())

# Save the file
submission.to_csv("submission_last.csv", index=False)
```