Fundamentals of AI & ML

Monsoon Semester V 2021-22

Lab - 3

Date: 22nd October 2021

Topic: Exploratory Data Analysis

AIM

Perform Exploratory Data Analysis (EDA) on the **"TITANIC"** dataset shared. Please make use of the information given in the *Dataset_Information file*.

Try to find below Exploratory Data Analysis (EDA) Steps

1. Identification of Missing Values.
2. Identification of All The Numerical Variables.
3. Distribution Of the Numerical Variables.
4. Identification of Categorical Variables.
5. Cardinality of Categorical Variables.
6. Identification of Outliers.
7. Relationship between independent and dependent variables.

EXPERIMENT

Program CODE

In [1]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
plt.style.use('ggplot')
import seaborn as sns
sns.set_style('dark')
```

In [2]:
```
titanic_df = pd.read_csv(".\Titanic_Dataset.csv")
titanic_df.head()
```

Out[2]:

	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 Th...	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

In [3]:
```
titanic_df.shape
```

Out[3]:
```
(891, 12)
```

In [4]:
```
titanic_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

In [19]:
```
missing_n = titanic_df.isna().sum()[titanic_df.isna().sum().apply(lambda count: count > 0)]

missing_values = pd.DataFrame({
    'amount': missing_n,
})

missing_values
```

Out[19]:

	amount
Age	177
Cabin	687
Embarked	2

In [23]:
```
numerical_features = titanic_df.select_dtypes(include=['int64', 'float64'])
numerical_features.head()
```

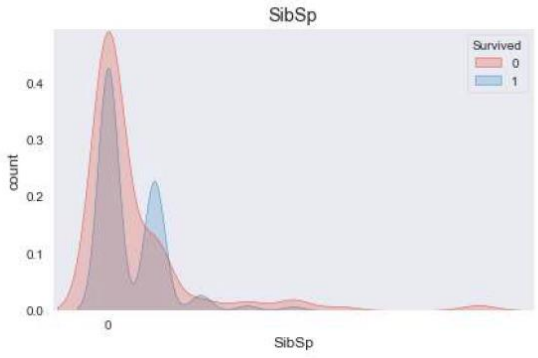
Out[23]:

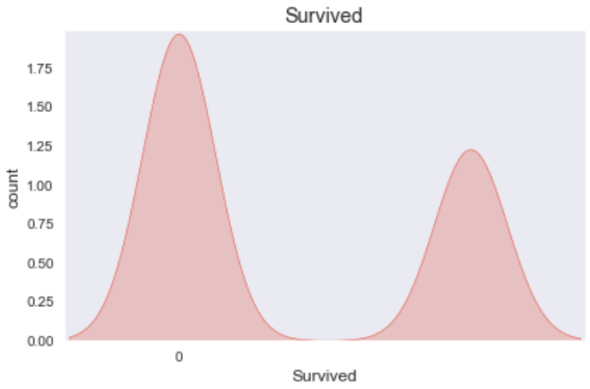
	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
0	1	0	3	22.0	1	0	7.2500
1	2	1	1	38.0	1	0	71.2833
2	3	1	3	26.0	0	0	7.9250
3	4	1	1	35.0	1	0	53.1000
4	5	0	3	35.0	0	0	8.0500

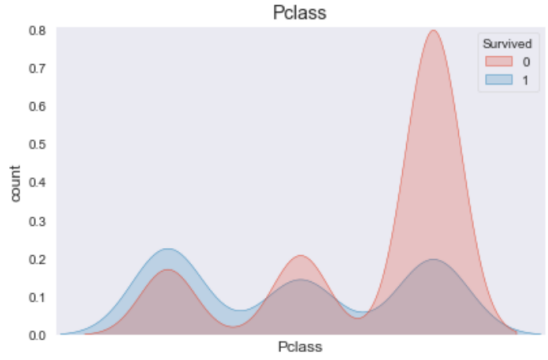
In [11]:
```
numerical_features.columns
```

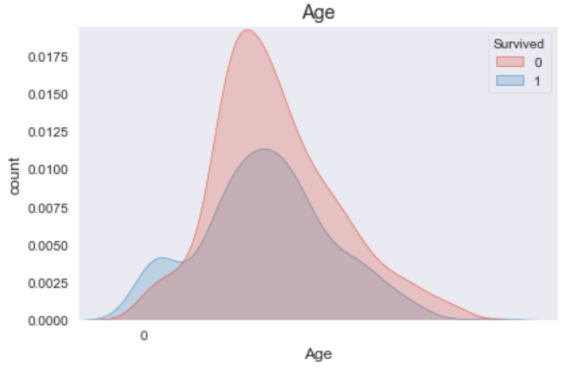
Out[11]:
```
Index(['Age', 'Fare'], dtype='object')
```

In [24]:
```
for numerical_feature in numerical_features:
    sns.kdeplot(x=numerical_feature,
    hue='Survived' if numerical_feature != 'Survived' else None,
    data=titanic_df, shade=True)
    sns.countplot()
    plt.title(numerical_feature)
    plt.margins(x=0.01, y=0.01)
    plt.tight_layout()
    plt.show()
```









From the graphs we can make some simple and direct observations:

- About **half as many people survived as compared to the amount that died**
- The rate of survival is almost similar for each Pclass except for **Pclass 3**, where almost **4 times as many people in Pclass 3 died than**
- **survived**
- The **age distribution** for the ones who survived and died are **fairly similar**, both having a mean of 30-35
- More passengers that did not have any **siblings/significant others** died than the ones that do not have any siblings/significant others
- on board
- Passengers who did and did not have any **parents/children** on board had the same survival rate
- Passengers who survived paid **a little more for the fare** had a slightly higher survival rate

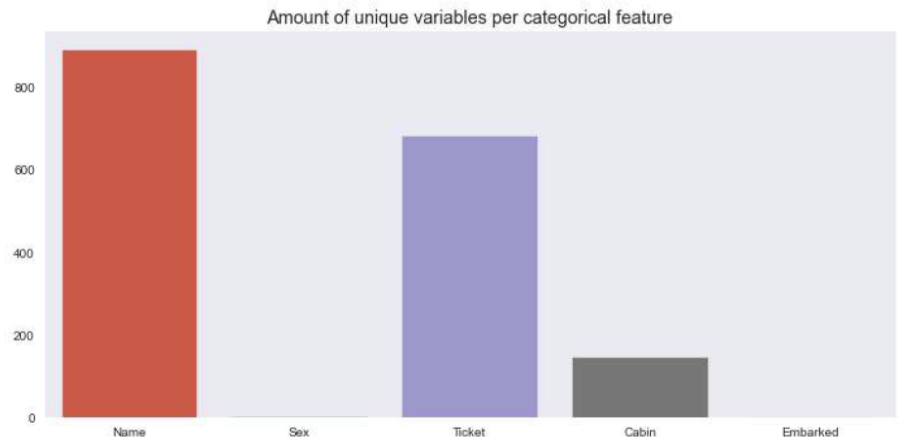
In [26]:
```
categorical_variable = titanic_df.select_dtypes(include=['object'])
categorical_variable.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   Name      891 non-null    object
 1   Sex       891 non-null    object
 2   Ticket    891 non-null    object
 3   Cabin     204 non-null    object
 4   Embarked  889 non-null    object
dtypes: object(5)
memory usage: 34.9+ KB
```

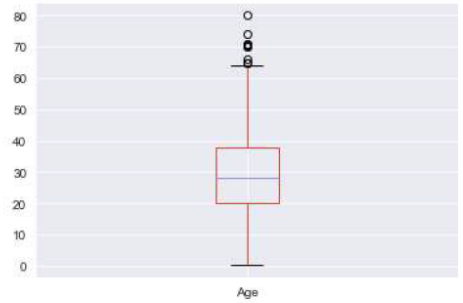
In [29]:
```
n_unique_vars = titanic_df[categorical_variable.keys()].nunique()
n_unique_vars
```

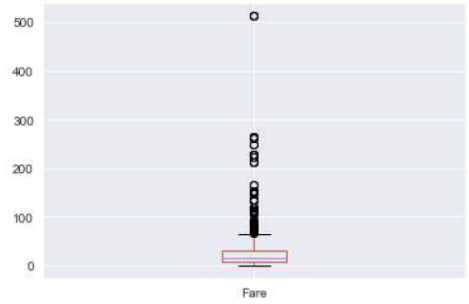
Out[29]:
```
Name        891
Sex           2
Ticket      681
Cabin       147
Embarked      3
dtype: int64
```

In [30]:
```
plt.figure(figsize=(10, 5))
sns.barplot(x=n_unique_vars.keys(), y=n_unique_vars.values)
plt.title("Amount of unique variables per categorical feature")
plt.tight_layout()
plt.show()
```

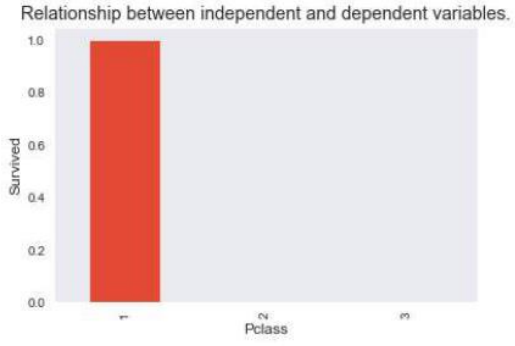


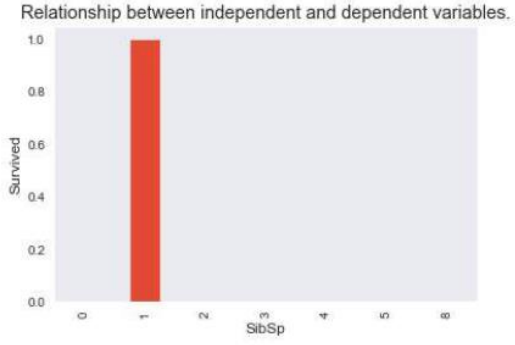
In [38]:
```
numerical_df = titanic_df.select_dtypes(include=['float64'])
for feature in numerical_df:
    numerical_df.boxplot(column=feature)
    plt.show()
```

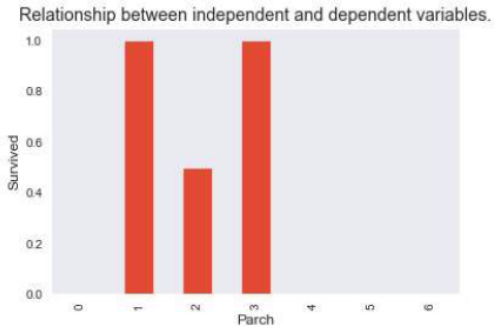




In [43]:
```
dis_var = titanic_df.select_dtypes(include=['int64'])
for features in dis_var:
    if features != 'PassengerId' and features !="Survived":
        dis_var.groupby(features)['Survived'].median().plot.bar()
        plt.xlabel(features)
        plt.ylabel("Survived")
        plt.title("Relationship between independent and dependent variables.")
        plt.show()
```







CONCLUSION

A couple of key points can be derived:

- About half as many more peopled died than survived.
- Chances of survival is affected depending on the Pclass of the passenger.
- Sex of the passengers matters.
- Age of the passengers matter as well.
- Passengers who did not have any parents/siblings/spouses/children on board, had a higher chance of survival.
- Passengers who have embarked from S survived more than passengers that have embarked from other locations.
- However, the same applies to the death count. Passengers who've embarked from S had a higher death toll.