CSB352: Data Mining LAB

LAB 6: Exploratory Data Analysis

2.0.1 CASE STUDY 1: [EDA] on Titanic Dataset

2.0.2 Feature Engineering in ML

Data Visualization • Data Pre-processing • Dimension Reduction : • Feature Extraction : • Feature Selection

3 Tabular data Pre-processing

Problem Statement :

Use machine learning to create a model that predicts which passengers survived the Titanic shipwreck. for more detail visit : [https://www.kaggle.com/c/titanic/overview]

```
#Currently using Jupyter Notebook
try:
  from google.colab import drive
  %tensorflow_version 2.x
  COLAB = True
  print("Hello World")
  print("Note: using Google CoLab")
except:
  print("Hello NITD")
  print("Note: not using Google CoLab")
  COLAB = False

# Print your name and Roll No.
print("Name: Rohit byas")
print("Roll Number: 181210043")
from datetime import datetime

# datetime object containing current date and time
now = datetime.now()
```

```
print("now =", now)

# dd/mm/YY H:M:S
dt_string = now.strftime("%d/%m/%Y %H:%M:%S")
print("date and time =", dt_string)
```

```
Hello World
Note: using Google CoLab
Name: Rohit byas
Roll Number: 181210043
now = 2021-02-08 09:00:21.820198
date and time = 08/02/2021 09:00:21
```

3.1 Data reading and setup

```
!gdown --id 18tm2ylYJs8m5W2xYzCUVYcFdugbQo5KV
!gdown --id 1IZ6bhCi-JLLW9vxKtRaSYNRE7OAlOFzf
```

```
Downloading...
From: https://drive.google.com/uc?id=18tm2ylYJs8m5W2xYzCUVYcFdugbQo5KV
To: /content/train.csv
100% 61.2k/61.2k [00:00<00:00, 22.5MB/s]
Downloading...
From: https://drive.google.com/uc?id=1IZ6bhCi-JLLW9vxKtRaSYNRE7OAlOFzf
To: /content/test.csv
100% 28.6k/28.6k [00:00<00:00, 51.2MB/s]
```

```
### Titanic Dataset

import numpy as np
import pandas as pd
import seaborn as sns
%matplotlib inline

from matplotlib import pyplot as plt
from matplotlib import style
from sklearn import linear_model
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.naive_bayes import GaussianNB
```

```
test_df = pd.read_csv("test.csv")
train_df = pd.read_csv("train.csv")
```

Spend some time with data

```
train_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
```

Features from Dataset - survival: Survival [0 = No, 1 = Yes] - PassengerId: Unique Id of a passenger. - pclass: Ticket class [1 = 1st, 2 = 2nd, 3 = 3rd]

- Sex: Gender (male /female)
- 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]

```
train_df.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208

```
train_df.head(8)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.250
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.283
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.925

• Catogrical Values • Different scale of numeric data • Missing values

3.1.1 Missing Values

```
total = train_df.isnull().sum().sort_values(ascending=False)
percent_1 = train_df.isnull().sum()/train_df.isnull().count()*100
percent_2 = (round(percent_1, 1)).sort_values(ascending=False)
missing_data = pd.concat([total, percent_2], axis=1, keys=['Total', '%'])
missing_data
```

	Total	%
Cabin	687	77.1
Age	177	19.9
Sex	0	0.0
Pclass	0	0.0

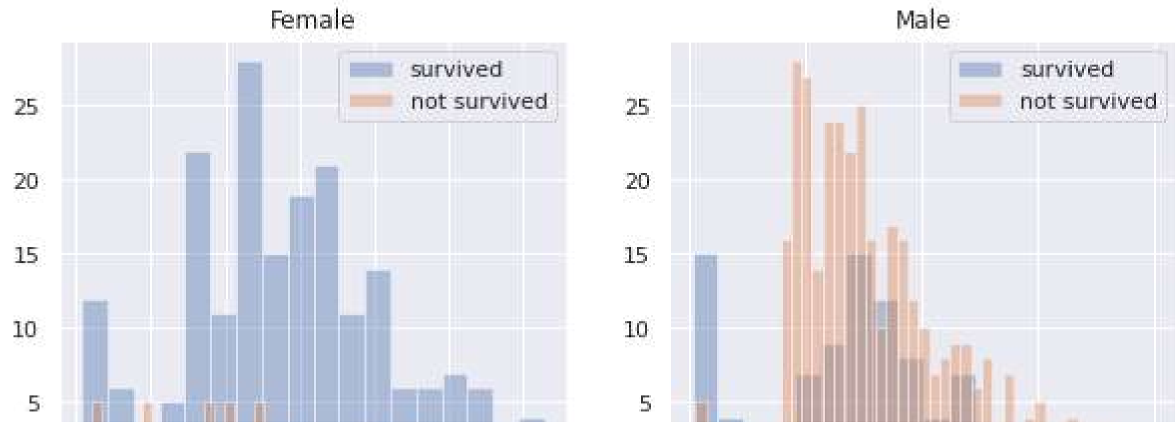
4 EDA : Exploratory Data Analysis

Exploratory Data Analysis refers to the critical process of performing initial investigations on data so as to discover patterns,to spot anomalies,to test hypothesis and to check assumptions with the help of summary statistics and graphical representations[]

Age vs Sex vs Survival

```
# Seaborn is a library that uses Matplotlib underneath to plot graphs.
# It is used to create more attractive and informative statistical graphics

import seaborn as sns
sns.set()


survived = 'survived'
not_survived = 'not survived'
fig, axes = plt.subplots(nrows=1, ncols=2,figsize=(10, 4))

women = train_df[train_df['Sex']=='female']
men = train_df[train_df['Sex']=='male']

ax = sns.distplot(women[women['Survived']==1].Age.dropna(), bins=18, label =survived, ax = ax
ax = sns.distplot(women[women['Survived']==0].Age.dropna(), bins=40, label =not_survived, ax

ax.legend()

ax.set_title('Female')

ax = sns.distplot(men[men['Survived']==1].Age.dropna(), bins=18, label =survived, ax = axes[1

ax = sns.distplot(men[men['Survived']==0].Age.dropna(), bins=40, label =not_survived, ax = ax

ax.legend()
_ = ax.set_title('Male')
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/distributions.py:2557: FutureWarning: `di
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.6/dist-packages/seaborn/distributions.py:2557: FutureWarning: `di
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.6/dist-packages/seaborn/distributions.py:2557: FutureWarning: `di
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.6/dist-packages/seaborn/distributions.py:2557: FutureWarning: `di
  warnings.warn(msg, FutureWarning)
```



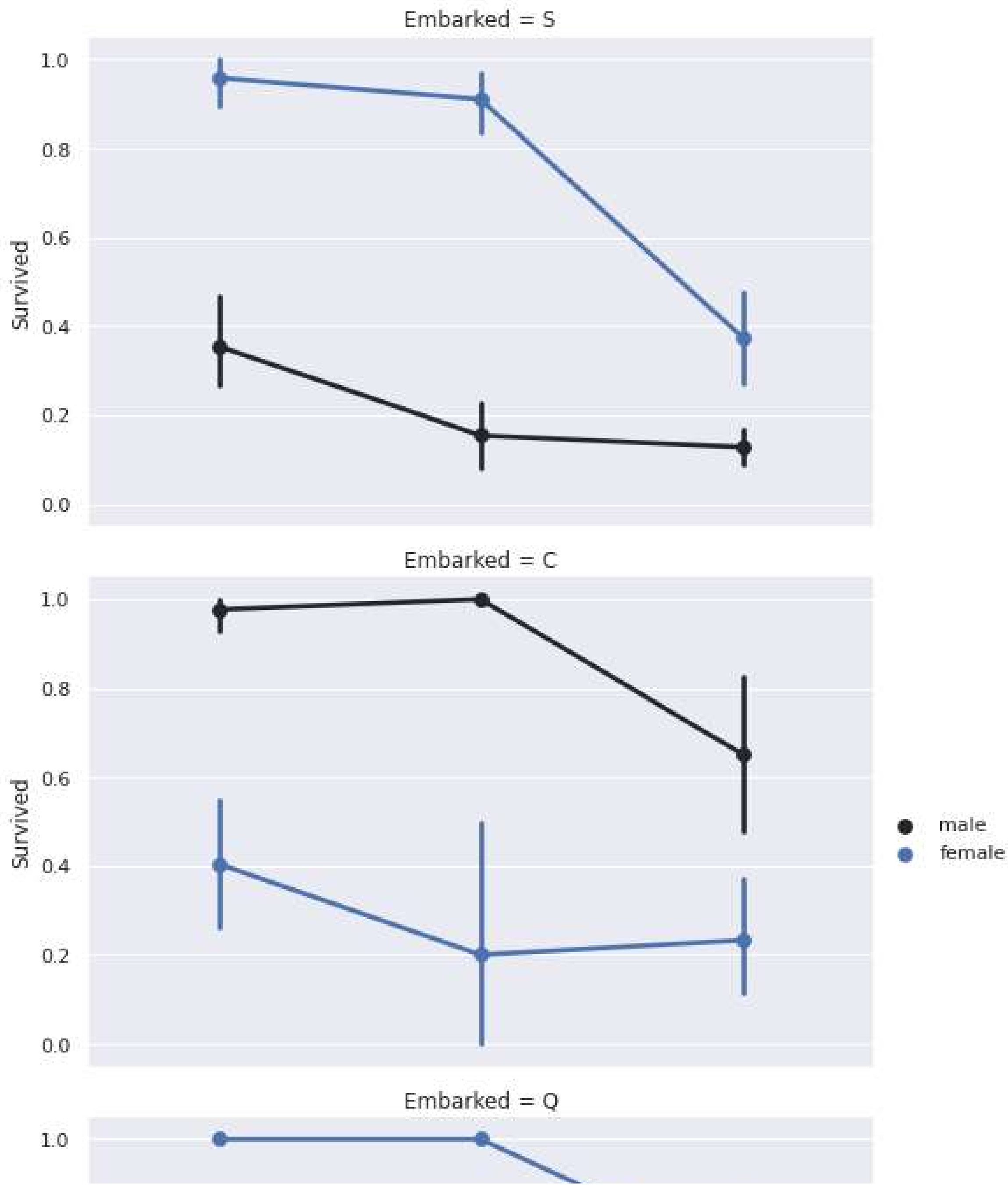
observation: Through this plots we can clearly say that people belonging to female categories have higher chances of survival then male

Embarked vs Pclass vs Sex

“FacetGrid class helps in visualizing distribution of one variable as well as the relationship between multiple variables separately within subsets of your dataset using multiple panels.”

```
FacetGrid = sns.FacetGrid(train_df, row='Embarked', size=4.5, aspect=1.6)

FacetGrid.map(sns.pointplot, 'Pclass', 'Survived', 'Sex', palette=None,order=None, hue_order=
FacetGrid.add_legend()
```

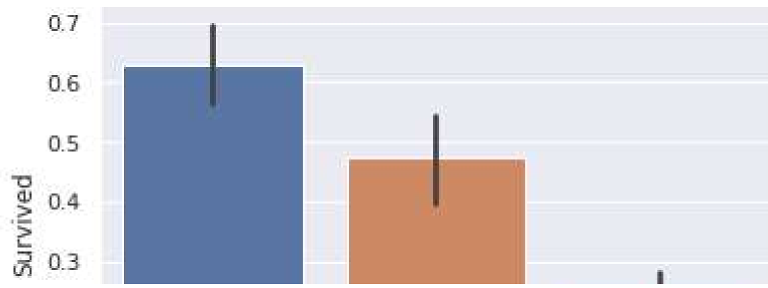
```
/usr/local/lib/python3.6/dist-packages/seaborn/axisgrid.py:316: UserWarning: The `size`
  warnings.warn(msg, UserWarning)
<seaborn.axisgrid.FacetGrid at 0x7fe9f3e7a748>
```



Pclass

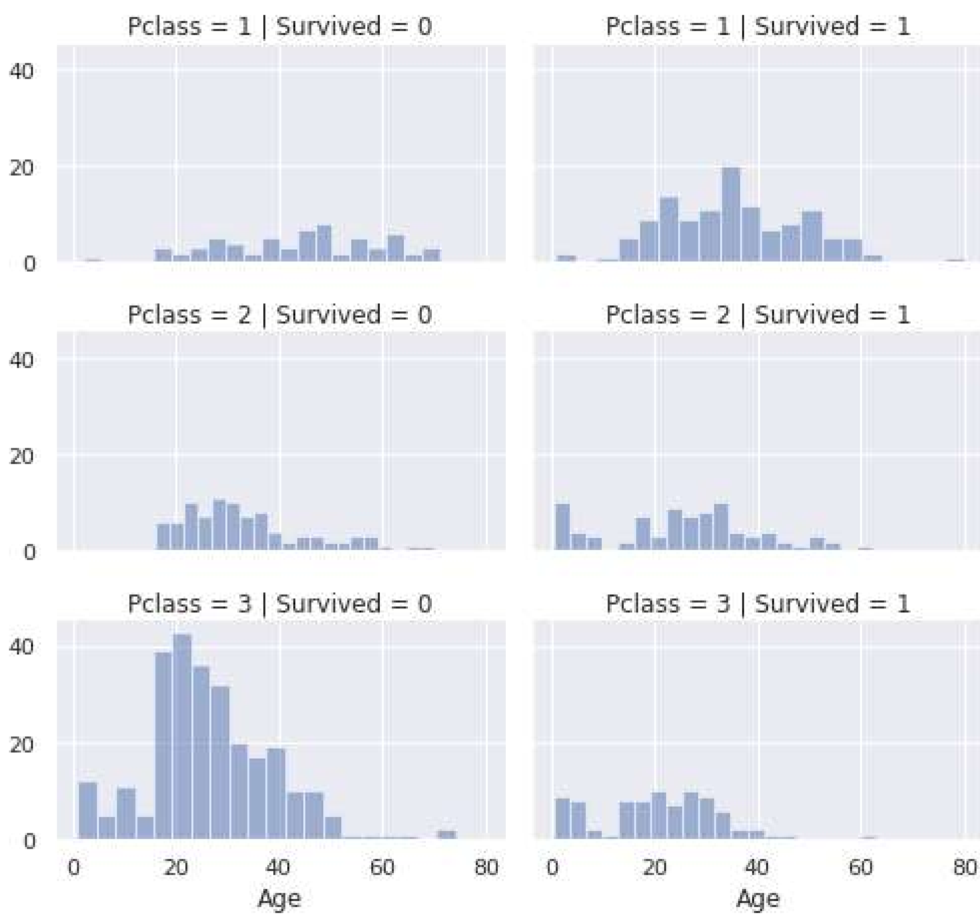

```
sns.barplot(x='Pclass', y='Survived', data=train_df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe9f2ba9630>
```




```
grid = sns.FacetGrid(train_df, col='Survived', row='Pclass', size=2.2, aspect=1.6)

grid.map(plt.hist, 'Age', alpha=.5, bins=20)

grid.add_legend();
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/axisgrid.py:316: UserWarning: The `size`
  warnings.warn(msg, UserWarning)
```



observation: Through this plots we can clearly say that people belonging to 1st class have been given priority then 2nd or 3rd class and also people which belong to 20-30 years of age have higher chances of survival then others.

SibSp and Parch (also some feature engg)

sibsp: # no. of siblings / spouses aboard the Titanic parch: # of parents / children aboard the Titanic

```
data = [train_df, test_df]

for dataset in data:
    dataset['relatives'] = dataset['SibSp'] + dataset['Parch']
    dataset.loc[dataset['relatives'] > 0, 'not_alone'] = 0
    dataset.loc[dataset['relatives'] == 0, 'not_alone'] = 1
    dataset['not_alone'] = dataset['not_alone'].astype(int)
```

```
train_df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.250
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs	female	38.0	1	0	PC 17599	71.283

No of people alone or not

```
train_df['not_alone'].value_counts()
```

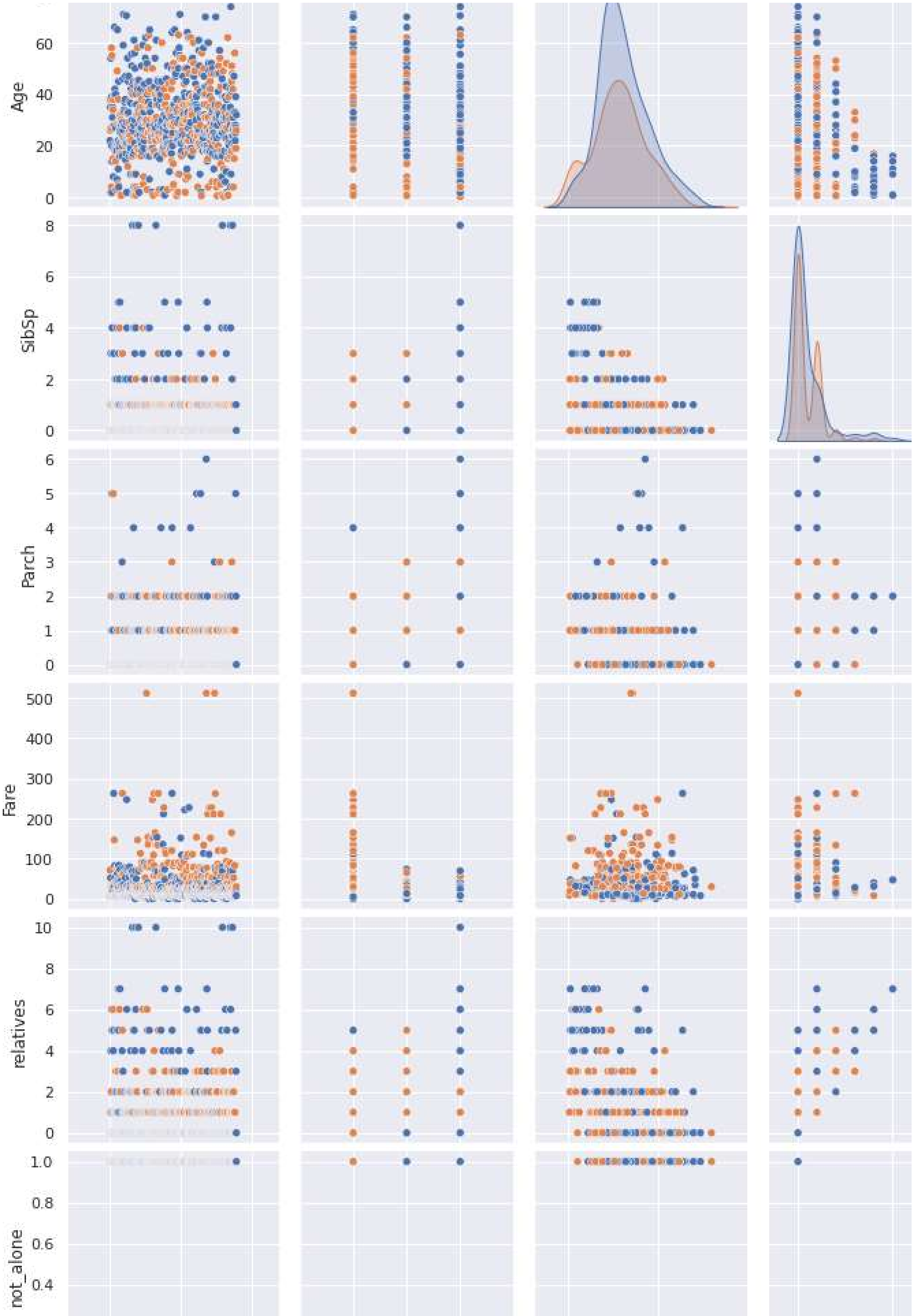
```
1    537
0    354
Name: not_alone, dtype: int64
```

```
axes = sns.factorplot('relatives','Survived',
                      data=train_df, aspect = 2.5, )
```

```
;r/local/lib/python3.6/dist-packages/seaborn/categorical.py:3714: UserWarning: The `facto
varnings.warn(msg)
;r/local/lib/python3.6/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the f
FutureWarning
```

observation: If there are 2 to 3 number of people are more belonging to same family , then they have higher chances of survival. As size increases the chance of survial is decreased.

```
# df_train_drop = train_df.dropna()

# sns.pairplot(df_train_drop, hue='Survived');

sns.pairplot(train_df, hue='Survived');
```


Age
60
40
20
0
SibSp
8
6
4
2
0
Parch
6
5
4
3
2
1
0
Fare
500
400
300
200
100
0
relatives
10
8
6
4
2
0
not_alone
1.0
0.8
0.6
0.4
0.2

observation: All the attributes are plotted, we can see that passenger_id having values between 0-700 where the passenger are survived, pclass=1 people are survived, higher the fair more the survival chance.

5 Data preprocessing and Feature Engg

Drop passenger ID

```
train_df = train_df.drop(['PassengerId'], axis=1)
```

```
train_df
```

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

Fix cabin

```
train_df['Cabin'].describe()
```

```
count             204
unique            147
top       C23 C25 C27
freq                4
Name: Cabin, dtype: object
```

```
train_df['Cabin']
```

```
#looks like the cabin number - lets convert to deck
```

```
0       NaN
1       C85
2       NaN
3      C123
4       NaN
       ...
886     NaN
887     B42
888     NaN
889    C148
890     NaN
Name: Cabin, Length: 891, dtype: object
```

```
import re

deck = {"A": 1, "B": 2, "C": 3, "D": 4, "E": 5, "F": 6, "G": 7, "U": 8}
data = [train_df, test_df]

for dataset in data:
    dataset['Cabin'] = dataset['Cabin'].fillna("U0")
    dataset['Deck'] = dataset['Cabin'].map(lambda x: re.compile("([a-zA-Z]+)").search(x).grou
    dataset['Deck'] = dataset['Deck'].map(deck)
    dataset['Deck'] = dataset['Deck'].fillna(0)
    dataset['Deck'] = dataset['Deck'].astype(int)

# we can now drop the cabin feature
train_df = train_df.drop(['Cabin'], axis=1)
test_df = test_df.drop(['Cabin'], axis=1)
```

```
train_df.head()
```

	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	1	1	Cumings, Mrs. John Bradley (Florence Briggs	female	38.0	1	0	PC 17599	71.2833	C

Fix Age

Lets get the mean,std of age and creat random ages in the range

```
train_df["Age"]
```

```
0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
       ...
886    27.0
887    19.0
888     NaN
889    26.0
890    32.0
Name: Age, Length: 891, dtype: float64
```

```
# Fill the null values


data = [train_df, test_df]

for dataset in data:
    mean = train_df["Age"].mean()
    std = test_df["Age"].std()
    is_null = dataset["Age"].isnull().sum()

    # compute random numbers between the mean, std and is_null
    rand_age = np.random.randint(mean - std, mean + std, size = is_null)

    # fill NaN values in Age column with random values generated
    age_slice = dataset["Age"].copy()
    age_slice[np.isnan(age_slice)] = rand_age
    dataset["Age"] = age_slice
    dataset["Age"] = train_df["Age"].astype(int)
train_df["Age"].isnull().sum()
```

```
0
```

```
train_df.head()
```

	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7.2500	S
1	1	1	Cumings, Mrs. John Bradley (Florence Briggs	female	38	1	0	PC 17599	71.2833	C

Fix Embarked -

```
train_df['Embarked'].describe()
```

```
count     889
unique      3
top         S
freq      644
Name: Embarked, dtype: object
```

```
# only 3 missing so lets do most common

common_value = 'S'
data = [train_df, test_df]

for dataset in data:
    dataset['Embarked'] = dataset['Embarked'].fillna(common_value)
```

5.1 Converting Features

Fare - convert to int

```
dataset['Fare']
```

```
0        7.8292
1        7.0000
2        9.6875
3        8.6625
4       12.2875
         ...
413      8.0500
414    108.9000
415      7.2500
416      8.0500
417     22.3583
Name: Fare, Length: 418, dtype: float64
```

```
data = [train_df, test_df]

for dataset in data:
    dataset['Fare'] = dataset['Fare'].fillna(0)
    dataset['Fare'] = dataset['Fare'].astype(int)
```

```
dataset['Fare']
```

```
0        7
1        7
2        9
3        8
4       12
      ...
```

```
413      8
414    108
415      7
416      8
417     22
Name: Fare, Length: 418, dtype: int64
```

Name - Extract Titles from name

```
data = [train_df, test_df]
titles = {"Mr": 1, "Miss": 2, "Mrs": 3, "Master": 4, "Rare": 5}

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

    # replace titles with a more common title or as Rare
    dataset['Title'] = dataset['Title'].replace(['Lady', 'Countess','Capt','Col','Don', 'Dr',
                        'Major', 'Rev', 'Sir', 'Jonkheer','Dona'], 'Rare')
    dataset['Title'] = dataset['Title'].replace('Mlle', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Ms', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Mme', 'Mrs')

    # convert titles into numbers
    dataset['Title'] = dataset['Title'].map(titles)

    # filling NaN with 0, to get safe
    dataset['Title'] = dataset['Title'].fillna(0)

train_df = train_df.drop(['Name'], axis=1)
test_df = test_df.drop(['Name'], axis=1)
```

```
dataset['Title']
```

```
0      1
1      3
2      1
3      1
4      3
      ..
413    1
414    5
415    1
416    1
417    4
Name: Title, Length: 418, dtype: int64
```

```
train_df.head()
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	relatives	not
0	0	3	male	22	1	0	A/5 21171	7	S	1	
1	1	1	female	38	1	0	PC 17599	71	C	1	
2	1	3	female	26	0	0	STON/O2. 3101282	7	S	0	
3	1	1	female	35	1	0	113803	53	S	1	

Sex to numeric

```
genders = {"male": 0, "female": 1}
data = [train_df, test_df]

for dataset in data:
    dataset['Sex'] = dataset['Sex'].map(genders)
```

Ticket

```
train_df['Ticket'].describe()
```

```
count        891
unique       681
top       347082
freq           7
Name: Ticket, dtype: object
```

too many unique values...lets drop it

```
train_df = train_df.drop(['Ticket'], axis=1)

test_df = test_df.drop(['Ticket'], axis=1)
```

Embarked

```
ports = {"S": 0, "C": 1, "Q": 2}
data = [train_df, test_df]

for dataset in data:
    dataset['Embarked'] = dataset['Embarked'].map(ports)
```

5.2 Creating Categories

Age - convert into buckets... be carefull that number of samples in each class should be kinda equal

```
data = [train_df, test_df]

for dataset in data:
    dataset['Age'] = dataset['Age'].astype(int)
    dataset.loc[ dataset['Age'] <= 11, 'Age'] = 0
    dataset.loc[(dataset['Age'] > 11) & (dataset['Age'] <= 18), 'Age'] = 1
    dataset.loc[(dataset['Age'] > 18) & (dataset['Age'] <= 22), 'Age'] = 2
    dataset.loc[(dataset['Age'] > 22) & (dataset['Age'] <= 27), 'Age'] = 3
    dataset.loc[(dataset['Age'] > 27) & (dataset['Age'] <= 33), 'Age'] = 4
    dataset.loc[(dataset['Age'] > 33) & (dataset['Age'] <= 40), 'Age'] = 5
    dataset.loc[(dataset['Age'] > 40) & (dataset['Age'] <= 66), 'Age'] = 6
    dataset.loc[ dataset['Age'] > 66, 'Age'] = 7
```

```
train_df
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	relatives	not_alone	Dec
0	0	3	0	2	1	0	7	0	1	0	
1	1	1	1	5	1	0	71	1	1	0	
2	1	3	1	3	0	0	7	0	0	1	
3	1	1	1	5	1	0	53	0	1	0	
4	0	3	0	5	0	0	8	0	0	1	
...	...	...	...	...	...	...	...	...	...	...	
886	0	2	0	3	0	0	13	0	0	1	
887	1	1	1	2	0	0	30	0	0	1	
888	0	3	1	2	1	2	23	0	3	0	
889	1	1	0	3	0	0	30	1	0	1	
890	0	3	0	4	0	0	7	2	0	1	

891 rows × 12 columns

```
train_df['Age'].value_counts()
```

```
4    163
6    153
5    150
3    141
2    112
1     97
0     68
7      7
Name: Age, dtype: int64
```

Fare

```
data = [train_df, test_df]
for dataset in data:
    dataset.loc[ dataset['Fare'] <= 7.91, 'Fare'] = 0
    dataset.loc[(dataset['Fare'] > 7.91) & (dataset['Fare'] <= 14.454), 'Fare'] = 1
    dataset.loc[(dataset['Fare'] > 14.454) & (dataset['Fare'] <= 31), 'Fare'] = 2
    dataset.loc[(dataset['Fare'] > 31) & (dataset['Fare'] <= 99), 'Fare'] = 3
    dataset.loc[(dataset['Fare'] > 99) & (dataset['Fare'] <= 250), 'Fare'] = 4
    dataset.loc[ dataset['Fare'] > 250, 'Fare'] = 5
    dataset['Fare'] = dataset['Fare'].astype(int)
```

5.3 Creating new features

Age time class since we saw a affect of both on surviving

```
data = [train_df, test_df]

for dataset in data:
    dataset['Age_Class']= dataset['Age']* dataset['Pclass']
```

Fare per person in family - is a indication of number of people and which class

```
for dataset in data:
    dataset['Fare_Per_Person'] = dataset['Fare']/(dataset['relatives']+1)
    dataset['Fare_Per_Person'] = dataset['Fare_Per_Person'].astype(int)
```

6 Building ML models

```
## Create Train, and Test

X_train = train_df.drop("Survived", axis=1)
Y_train = train_df["Survived"]
X_test = test_df.drop("PassengerId", axis=1).copy()
```