1 Aim : Demostrate Data Imputation with satistical techniques on numerical values and write down the conclusion about the assumption.

In [1]:

```
import pandas as pd
import numpy as np
```

In [2]:

```
df = pd.read_csv("titanic_toy - titanic_toy.csv")
```

In [3]:

```
df.head()
```

Out[3]:

	Age	Fare	Family	Survived
0	22.0	7.2500	1	0
1	38.0	71.2833	1	1
2	26.0	7.9250	0	1
3	35.0	53.1000	1	1
4	35.0	8.0500	0	0

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Age       714 non-null    float64
 1   Fare      846 non-null    float64
 2   Family    891 non-null    int64  
 3   Survived  891 non-null    int64  
dtypes: float64(2), int64(2)
memory usage: 28.0 KB
```

In [6]:

```
df.isnull().sum()
```

Out[6]:

```
Age         177
Fare         45
Family        0
Survived      0
dtype: int64
```

In [9]:

```
df.isnull().mean()*100
```

Out[9]:

```
Age         19.865320
Fare         5.050505
Family       0.000000
Survived     0.000000
dtype: float64
```

In [10]:

```
x = df.drop(columns = ['Survived']) # independent Columns
```

In [11]:

```
y = df['Survived'] #dependent columns
```

In [12]:

```
y
```

Out[12]:

```
0      0
1      1
2      1
3      1
4      0
      ..
886    0
887    1
888    0
889    1
890    0
Name: Survived, Length: 891, dtype: int64
```

In [13]:

```
df.shape
```

Out[13]:

```
(891, 4)
```

In [21]:

```
from sklearn.model_selection import train_test_split
```

In [22]:

```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_state=2)
```

In [23]:

```
x_train.shape
```

Out[23]:

```
(712, 3)
```

In [32]:

```
x_test.shape
```

Out[32]:

```
(179, 3)
```

In [35]:

```
mean_age = x_train["Age"].mean()
```

In [36]:

```
mean_age
```

Out[36]:

```
29.78590425531915
```

In [28]:

```
df.describe()
```

Out[28]:

	Age	Fare	Family	Survived
count	714.000000	846.000000	891.000000	891.000000
mean	29.699118	32.279338	0.904602	0.383838
std	14.526497	50.305796	1.613459	0.486592
min	0.420000	0.000000	0.000000	0.000000
25%	20.125000	7.895800	0.000000	0.000000
50%	28.000000	14.454200	0.000000	0.000000
75%	38.000000	31.206250	1.000000	1.000000
max	80.000000	512.329200	10.000000	1.000000

In [37]:

```
median_age  = x_train["Age"].median()
```

In [38]:

```
median_age
```

Out[38]:

28.75

In [40]:

```
mean_fare = x_train['Fare'].mean()
mean_fare
```

Out[40]:

32.617596893491076

In [42]:

```
median_fare = x_train['Fare'].median()
median_fare
```

Out[42]:

14.4583

In [46]:

```
#imputation


x_train['Age_mean']=x_train['Age'].fillna(mean_age)
x_train['Age_median']=x_train['Age'].fillna(median_age)
```

In [48]:

```
x_train
```

Out[48]:

	Age	Fare	Family	Age_mean	Age_median
30	40.0	27.7208	0	40.000000	40.00
10	4.0	16.7000	2	4.000000	4.00
873	47.0	9.0000	0	47.000000	47.00
182	9.0	31.3875	6	9.000000	9.00
876	20.0	9.8458	0	20.000000	20.00
...	...	...	...	...	...
534	30.0	8.6625	0	30.000000	30.00
584	NaN	8.7125	0	29.785904	28.75
493	71.0	49.5042	0	71.000000	71.00
527	NaN	221.7792	0	29.785904	28.75
168	NaN	25.9250	0	29.785904	28.75

712 rows × 5 columns

In [50]:

```
x_train['Fare_mean']=x_train['Fare'].fillna(mean_age)
x_train['Fare_median']=x_train['Fare'].fillna(median_age)
```

In [51]:

```
x_train
```

Out[51]:

	Age	Fare	Family	Age_mean	Age_median	Fare_mean	Fare_median
30	40.0	27.7208	0	40.000000	40.00	27.7208	27.7208
10	4.0	16.7000	2	4.000000	4.00	16.7000	16.7000
873	47.0	9.0000	0	47.000000	47.00	9.0000	9.0000
182	9.0	31.3875	6	9.000000	9.00	31.3875	31.3875
876	20.0	9.8458	0	20.000000	20.00	9.8458	9.8458
...	...	...	...	...	...	...	...
534	30.0	8.6625	0	30.000000	30.00	8.6625	8.6625
584	NaN	8.7125	0	29.785904	28.75	8.7125	8.7125
493	71.0	49.5042	0	71.000000	71.00	49.5042	49.5042
527	NaN	221.7792	0	29.785904	28.75	221.7792	221.7792
168	NaN	25.9250	0	29.785904	28.75	25.9250	25.9250

712 rows × 7 columns

In [63]:

```
print('Original age variance',x_train["Age"].var())
```

```
Original age variance 204.3495133904614
```

In [64]:

```
print("After imputation age variance of age",x_train['Age_mean'].var())
print("After imputation age variance of age",x_train['Age_median'].var())
```

```
After imputation age variance of age 161.81262452718673
After imputation age variance of age 161.9895663346054
```

In [65]:

```
print('Original age variance',x_train["Fare"].var())
```

```
Original age variance 2448.197913706318
```

In [66]:

```
print("After imputation age variance of age",x_train['Fare_mean'].var())
print("After imputation age variance of age",x_train['Fare_median'].var())
```

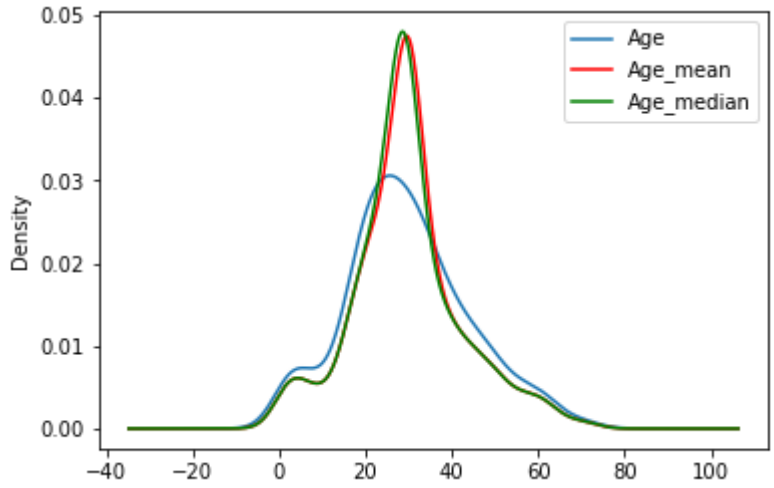
```
After imputation age variance of age 2324.623996772905
After imputation age variance of age 2324.9576136149317
```

In [73]:

```
import matplotlib.pyplot as plt
fig = plt.figure()
ax = fig.add_subplot(111)
x_train['Age'].plot(kind='kde' ,ax=ax) #original Distribution
#After imputaion with mean
x_train['Age_mean'].plot(kind='kde', ax=ax,color='red')
#After imputation with median
x_train['Age_median'].plot(kind='kde' ,ax=ax,color='green')
#Adding legends
lines,labels = ax.get_legend_handles_labels()
ax.legend(lines,labels,loc='best')
```

Out[73]:

```
<matplotlib.legend.Legend at 0x259614b3be0>
```

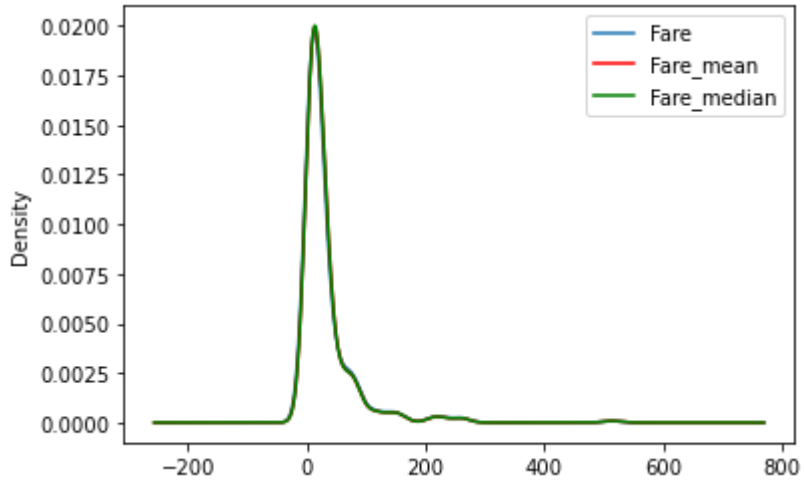


In [74]:

```
import matplotlib.pyplot as plt
fig = plt.figure()
ax = fig.add_subplot(111)
x_train['Fare'].plot(kind='kde' ,ax=ax) #original Distribution
#After imputaion with mean
x_train['Fare_mean'].plot(kind='kde', ax=ax,color='red')
#After imputation with median
x_train['Fare_median'].plot(kind='kde' ,ax=ax,color='green')
#Adding legends
lines,labels = ax.get_legend_handles_labels()
ax.legend(lines,labels,loc='best')
```

Out[74]:

```
<matplotlib.legend.Legend at 0x259614b6910>
```



In [80]:

```
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
```

In [81]:

```
imputer1= SimpleImputer(strategy='mean')
imputer2= SimpleImputer(strategy='median')
```

In [82]:

```
trf =ColumnTransformer([
    ('imputer1',imputer1,['Age']),
    ('imputer2',imputer2,['Age']),
],remainder='passthrough')
```

In [83]:

```
trf.fit(df)
```

Out[83]:

```
ColumnTransformer(remainder='passthrough',
                  transformers=[('imputer1', SimpleImputer(), ['Age']),
                                ('imputer2', SimpleImputer(strategy='media
n'),
                                 ['Age'])])
```

In [84]:

```
trf.named_transformers_['imputer1'].statistics_
```

Out[84]:

```
array([29.69911765])
```

In [85]:

```
trf.named_transformers_['imputer2'].statistics_
```

Out[85]:

```
array([28.])
```

In [87]:

```
sm = trf.transform(df)
sm
```

Out[87]:

```
array([[22.        , 22.        ,  7.25      ,  1.        ,  0.        ],
       [38.        , 38.        , 71.2833    ,  1.        ,  1.        ],
       [26.        , 26.        ,  7.925     ,  0.        ,  1.        ],
       ...,
       [29.69911765, 28.        , 23.45      ,  3.        ,  0.        ],
       [26.        , 26.        ,         nan,  0.        ,  1.        ],
       [32.        , 32.        ,  7.75      ,  0.        ,  0.        ]])
```

2 Conclusion:

We have observed while finding the mean and median of Age and Fare columns,replacing nulls values of both the columns are highly affected the data distribution while the replacing the null values with median are less afftected compare to mean. Also, if nulls values are less than 5% in the column, the data distribtuion is not affected after replacing the values by mean/median.

In [ ]: