In [3]:

```
# You can import data from various sources into your Pandas
# dataframe.
# A CSV file is a type of file where each line contains a single
# record, and all the columns are separated from each other via
# a comma.
# You can read CSV files using the read_csv() function of the
# Pandas dataframe, as shown below.

import pandas as pd
titanic_data = pd.read_csv("titanic.csv")
titanic_data.head()

# If you print the dataframe header, you should see that the
# header contains first five rows
```

Out[3]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck
0	NaN	0	3	male	22.0	1	0	7.2500	S	Third	man	True
1	NaN	1	1	female	38.0	1	0	71.2833	C	First	woman	False
2	NaN	1	3	female	26.0	0	0	7.9250	S	Third	woman	False
3	NaN	1	1	female	35.0	1	0	53.1000	S	First	woman	False
4	NaN	0	3	male	35.0	0	0	8.0500	S	Third	man	True

In [4]:

```
import pandas as pd
titanic_data = pd.read_csv("titanic.csv")
titanic_data.tail()

# If you print the dataframe tail, you should see that the
# tail contains last five rows
```

Out[4]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	
886	NaN	0	2	male	27.0	0	0	13.00	S	Second	man	
887	NaN	1	1	female	19.0	0	0	30.00	S	First	woman	F
888	NaN	0	3	female	NaN	1	2	23.45	S	Third	woman	F
889	NaN	1	1	male	26.0	0	0	30.00	C	First	man	
890	NaN	0	3	male	32.0	0	0	7.75	Q	Third	man	

In [5]:

```
# To handle missing numerical data, we can use statistical
# techniques. The use of statistical techniques or algorithms to
# replace missing values with statistically generated values is
# called imputation.

import matplotlib.pyplot as plt
import seaborn as sns
plt.rcParams["figure.figsize"] = [8,6]
sns.set_style("darkgrid")
titanic_data = sns.load_dataset('titanic')
titanic_data.head()
```

Out[5]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True

In [6]:

```
# Let’s filter some of the numeric columns from the dataset and
# see if they contain any missing values.

titanic_data = titanic_data[["survived", "pclass", "age", "fare"]]
titanic_data.head()
```

Out[6]:

	survived	pclass	age	fare
0	0	3	22.0	7.2500
1	1	1	38.0	71.2833
2	1	3	26.0	7.9250
3	1	1	35.0	53.1000
4	0	3	35.0	8.0500

In [7]:

```
# To find missing values from the aforementioned columns, you
# need to first call the isnull() method on the titanic_data
# dataframe, and then you need to call the mean() method, as
# shown below.

titanic_data.isnull().mean()

# The output shows that only the age column contains
# missing values. And the ratio of missing values is around 19.86
# percent.
```

Out[7]:

```
survived    0.000000
pclass      0.000000
age         0.198653
fare        0.000000
dtype: float64
```

In [8]:

```
# Let’s now find out the median and mean values for all the nonmissing
# values in the age column.

median = titanic_data.age.median()
print(median)
mean = titanic_data.age.mean()
print(mean)

# The age column has a median value of 28 and a mean value of
# 29.6991.
```

```
28.0
29.69911764705882
```

In [9]:

```
# To plot the kernel density plots for the actual age and median
# and mean age, we will add columns to the Pandas dataframe.

import numpy as np
titanic_data['Median_Age'] = titanic_data.age.fillna(median)
titanic_data['Mean_Age'] = titanic_data.age.fillna(mean)
titanic_data['Mean_Age'] = np.round(titanic_data['Mean_Age'], 1)
titanic_data.head(20)

# The above script adds Median_Age and Mean_Age columns
# to the titanic_data dataframe and prints the first 20 records.
# Here is the output of the above script:
```

Out[9]:

	survived	pclass	age	fare	Median_Age	Mean_Age
0	0	3	22.0	7.2500	22.0	22.0
1	1	1	38.0	71.2833	38.0	38.0
2	1	3	26.0	7.9250	26.0	26.0
3	1	1	35.0	53.1000	35.0	35.0
4	0	3	35.0	8.0500	35.0	35.0
5	0	3	NaN	8.4583	28.0	29.7
6	0	1	54.0	51.8625	54.0	54.0
7	0	3	2.0	21.0750	2.0	2.0
8	1	3	27.0	11.1333	27.0	27.0
9	1	2	14.0	30.0708	14.0	14.0
10	1	3	4.0	16.7000	4.0	4.0
11	1	1	58.0	26.5500	58.0	58.0
12	0	3	20.0	8.0500	20.0	20.0
13	0	3	39.0	31.2750	39.0	39.0
14	0	3	14.0	7.8542	14.0	14.0
15	1	2	55.0	16.0000	55.0	55.0
16	0	3	2.0	29.1250	2.0	2.0
17	1	2	NaN	13.0000	28.0	29.7
18	0	3	31.0	18.0000	31.0	31.0
19	1	3	NaN	7.2250	28.0	29.7

In [10]:

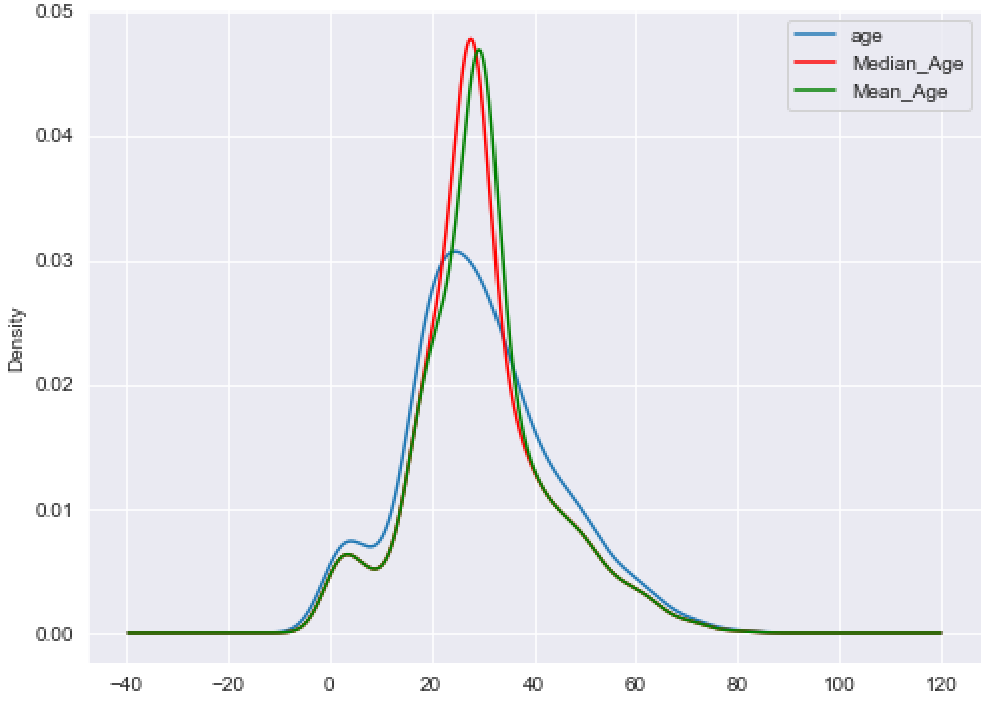
```
# Some rows in the above output show that NaN, i.e.,
# null values in the age column, have been replaced by the
# median values in the Median_Age column and by mean values
# in the Mean_Age column.
# The mean and median imputation can affect the data
# distribution for the columns containing the missing values.
# Specifically, the variance of the column is decreased by mean
# and median imputation now since more values are added to
# the center of the distribution. The following script plots the
# distribution of data for the age, Median_Age, and Mean_Age
# columns.

fig = plt.figure()
ax = fig.add_subplot(111)
titanic_data['age'] .plot(kind='kde', ax=ax)
titanic_data['Median_Age'] .plot(kind='kde', ax=ax, color='red')
titanic_data['Mean_Age'] .plot(kind='kde', ax=ax, color='green')
lines, labels = ax.get_legend_handles_labels()
ax.legend(lines, labels, loc='best')

# Here is the output of the script above:
```

Out[10]:

```
<matplotlib.legend.Legend at 0x6121ef3cd0>
```



In [11]:

```
# You can see that the default values in the age columns have
# been distorted by the mean and median imputation, and the
# overall variance of the dataset has also been decreased.

#Recommendation

# Mean and Median imputation could be used for the missing
# numerical data in case the data is missing at random. If the
# data is normally distributed, mean imputation is better, or else,
# median imputation is preferred in case of skewed
# distributions.
```

In [12]:

```
# One of the most common ways of handling missing values in a
# categorical column is to replace the missing values with the
# most frequently occurring values, i.e., the mode of the column.
# It is for this reason, frequent category imputation is also
# known as mode imputation. Let’s see a real-world example of
# the frequent category imputation.
# We will again use the Titanic dataset. We will first try to find
# the percentage of missing values in the age, fare, and
# embarked_ town columns.
```

In [13]:

```
import matplotlib.pyplot as plt
import seaborn as sns
plt.rcParams["figure.figsize"] = [8,6]
sns.set_style("darkgrid")
titanic_data = sns.load_dataset('titanic')
titanic_data = titanic_data[["embark_town", "age", "fare"]]
titanic_data.head()
titanic_data.isnull().mean()
```

Out[13]:

```
embark_town    0.002245
age            0.198653
fare           0.000000
dtype: float64
```

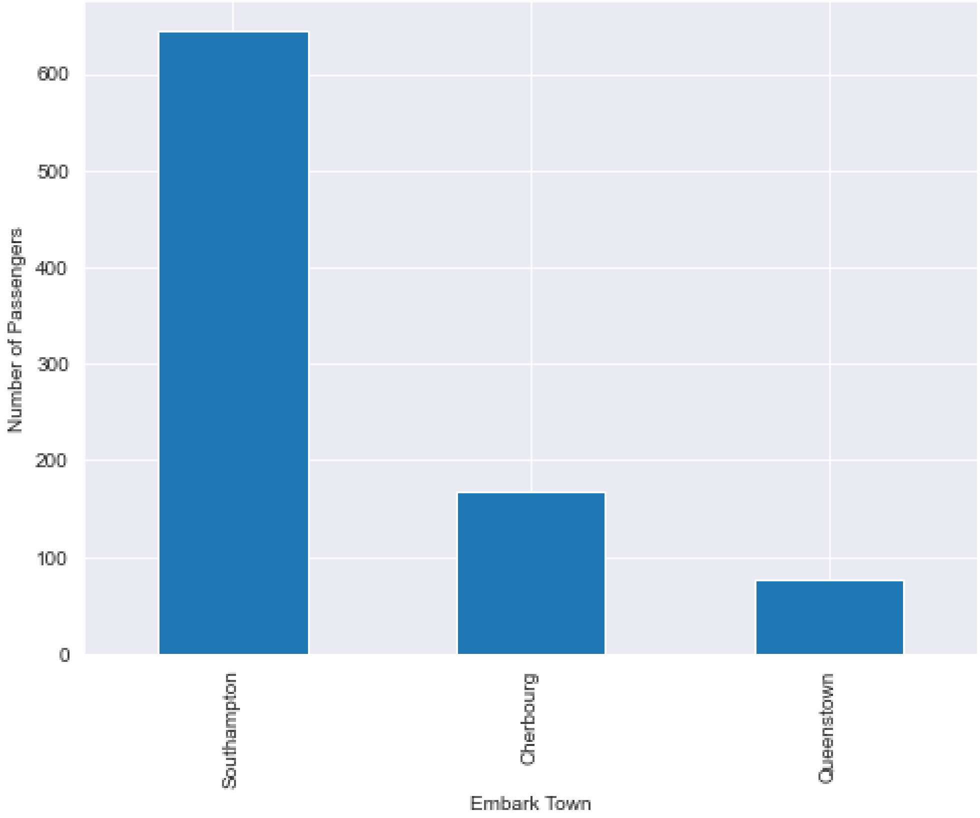
In [14]:

```
# The output shows that embark_town and age columns have
# missing values. The ratio of missing values for the embark_
# town column is very less.
# Let’s plot the bar plot that shows each category in the
# embark_town column against the number of passengers.

titanic_data.embark_town.value_counts().sort_values(ascending=False).plot.bar()
plt.xlabel('Embark Town')
plt.ylabel('Number of Passengers')
```

Out[14]:

```
Text(0, 0.5, 'Number of Passengers')
```



In [15]:

```
# The output below clearly shows that most of the passengers
# embarked from Southampton.
# Let’s make sure if Southampton is the mode value for the
# embark_town column.

titanic_data.embark_town.mode()
```

Out[15]:

```
0    Southampton
dtype: object
```

In [16]:

```
# Next, we can simply replace the missing values in the embark
# town column by Southampton.

titanic_data.embark_town.fillna('Southampton', inplace=True)
```

In [17]:

```
# Let’s now find the mode of the age column and use it to
# replace the missing values in the age column.

titanic_data.age.mode()
```

Out[17]:

```
0    24.0
dtype: float64
```

In [18]:

```
# The output shows that the mode of the age column is 24.
# Therefore, we can use this value to replace the missing values
# in the age column.

import numpy as np
titanic_data['age_mode'] = titanic_data.age.fillna(24)
titanic_data.head(20)
```

Out[18]:

	embark_town	age	fare	age_mode
0	Southampton	22.0	7.2500	22.0
1	Cherbourg	38.0	71.2833	38.0
2	Southampton	26.0	7.9250	26.0
3	Southampton	35.0	53.1000	35.0
4	Southampton	35.0	8.0500	35.0
5	Queenstown	NaN	8.4583	24.0
6	Southampton	54.0	51.8625	54.0
7	Southampton	2.0	21.0750	2.0
8	Southampton	27.0	11.1333	27.0
9	Cherbourg	14.0	30.0708	14.0
10	Southampton	4.0	16.7000	4.0
11	Southampton	58.0	26.5500	58.0
12	Southampton	20.0	8.0500	20.0
13	Southampton	39.0	31.2750	39.0
14	Southampton	14.0	7.8542	14.0
15	Southampton	55.0	16.0000	55.0
16	Queenstown	2.0	29.1250	2.0
17	Southampton	NaN	13.0000	24.0
18	Southampton	31.0	18.0000	31.0
19	Cherbourg	NaN	7.2250	24.0

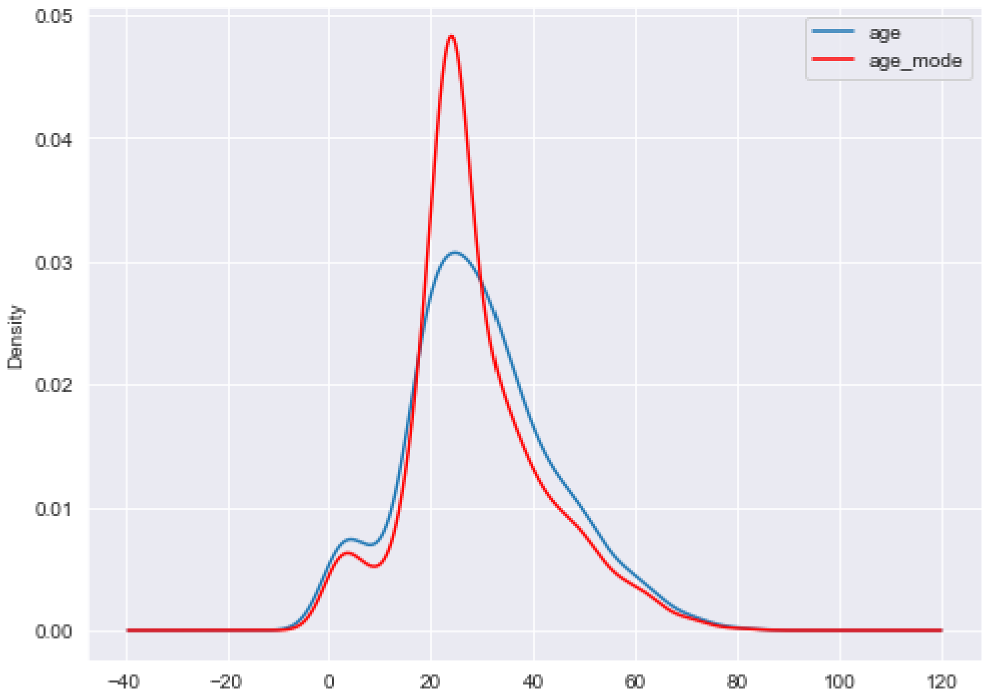
In [19]:

```
# Finally, let’s plot the kernel density estimation plot for the
# original age column and the age column that contains the
# mode of the values in place of the missing values.

plt.rcParams["figure.figsize"] = [8,6]
fig = plt.figure()
ax = fig.add_subplot(111)
titanic_data['age'] .plot(kind='kde', ax=ax)
titanic_data['age_mode'] .plot(kind='kde', ax=ax, color='red')
lines, labels = ax.get_legend_handles_labels()
ax.legend(lines, labels, loc='best')
```

Out[19]:

```
<matplotlib.legend.Legend at 0x610d9cc040>
```



In [20]:

```
# Missing value imputation adds an arbitrary category, e.g.,
# missing in place of the missing values. Take a look at an
# example of missing value imputation.
# Let’s load the Titanic dataset and see if any categorical
# column contains missing values.

import matplotlib.pyplot as plt
import seaborn as sns
plt.rcParams["figure.figsize"] = [8,6]
sns.set_style("darkgrid")
titanic_data = sns.load_dataset('titanic')
titanic_data = titanic_data[["embark_town", "age", "fare"]]
titanic_data.head()
titanic_data.isnull().mean()
```

Out[20]:

```
embark_town    0.002245
age            0.198653
fare           0.000000
dtype: float64
```

In [21]:

```
# The output shows that the embark_town column is a
# categorical column that contains some missing values too. We
# will apply the missing value imputation to this column.

titanic_data.embark_town.fillna('Missing', inplace=True)
```

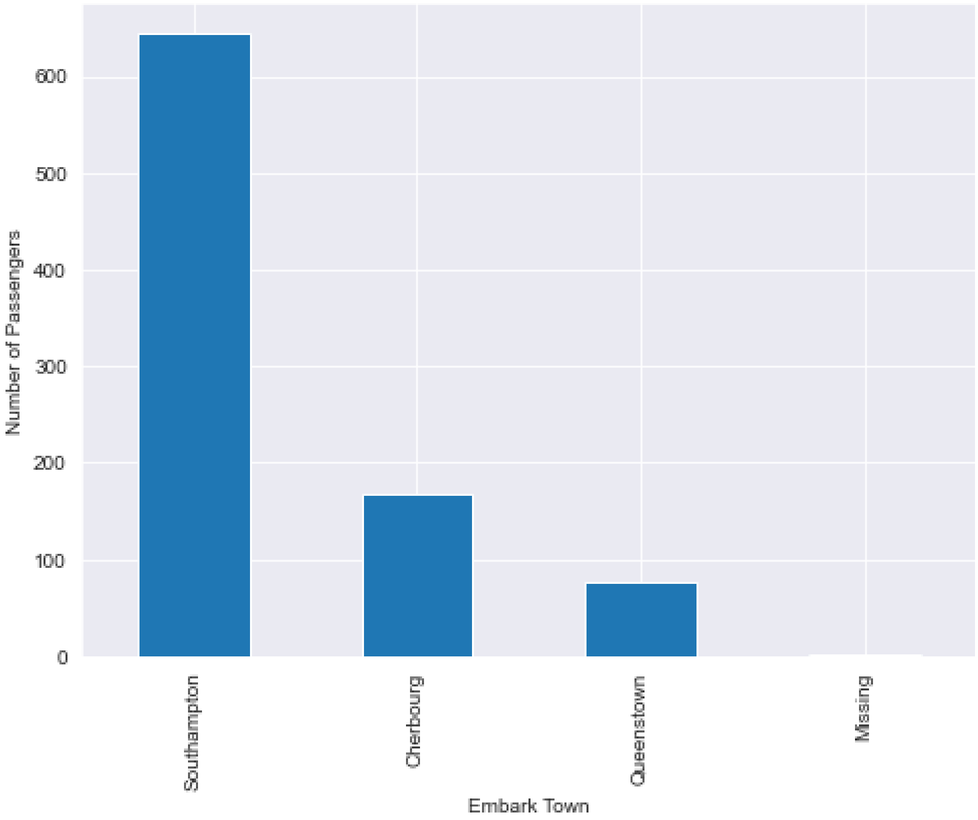
In [22]:

```
# After applying missing value imputation, plot the bar plot for
# the embark_town column. You can see that we have a very
# small, almost negligible plot for the missing column.

titanic_data.embark_town.value_counts().sort_values(ascending=False).plot.bar()
plt.xlabel('Embark Town')
plt.ylabel('Number of Passengers')
```

Out[22]:

```
Text(0, 0.5, 'Number of Passengers')
```


Number of Passengers
Southampton
Cherbourg
Queenstown
Missing
Embark Town