Lab Assignment - Final

CB.EN.U4CSE20138

A. Data Manipulation-Pandas

Dataset - Birthrate data

In [1]:

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

In [2]:

```
df = pd.read_csv('https://raw.githubusercontent.com/jakevdp/data-CDCbirths/master/births.cs
```

In [3]:

```
df
```

Out[3]:

	year	month	day	gender	births
0	1969	1	1.0	F	4046
1	1969	1	1.0	M	4440
2	1969	1	2.0	F	4454
3	1969	1	2.0	M	4548
4	1969	1	3.0	F	4548
...	...	...	...	...	...
15542	2008	10	NaN	M	183219
15543	2008	11	NaN	F	158939
15544	2008	11	NaN	M	165468
15545	2008	12	NaN	F	173215
15546	2008	12	NaN	M	181235

15547 rows × 5 columns

Indexing

In [4]:

```
index = [i for i in range(1,15548)]
df1 = pd.DataFrame(df,index=index)
```

In [5]:

```
df1
```

Out[5]:

	year	month	day	gender	births
1	1969.0	1.0	1.0	M	4440.0
2	1969.0	1.0	2.0	F	4454.0
3	1969.0	1.0	2.0	M	4548.0
4	1969.0	1.0	3.0	F	4548.0
5	1969.0	1.0	3.0	M	4994.0
...	...	...	...	...	...
15543	2008.0	11.0	NaN	F	158939.0
15544	2008.0	11.0	NaN	M	165468.0
15545	2008.0	12.0	NaN	F	173215.0
15546	2008.0	12.0	NaN	M	181235.0
15547	NaN	NaN	NaN	NaN	NaN

15547 rows × 5 columns

Missing values

In [6]:

```
df1.columns
```

Out[6]:

```
Index(['year', 'month', 'day', 'gender', 'births'], dtype='object')
```

In [7]:

```
for i in df1.columns:
    print(df1[i].isnull().sum())
```

```
1
1
481
1
1
```

In [8]:

```
for i in df1.columns:
    if i!='gender':
        df1[i].fillna(np.mean(df1[i]),inplace=True)
```

In [9]:

```
df1.isna().sum()
```

Out[9]:

```
year      0
month     0
day       0
gender    1
births    0
dtype: int64
```

In [10]:

```
x = df1['gender'].mode()
df1['gender'].fillna(x[0],inplace=True)
```

In [11]:

```
df1.isna().sum()
```

Out[11]:

```
year      0
month     0
day       0
gender    0
births    0
dtype: int64
```

concat

In [12]:

```
grid = [[1,2,3],[4,5,6]]
print(len(grid[0]))
```

```
3
```

In [13]:

```
import math
l = len(df1)
l=math.ceil(l/2)
df3 = df1[:l]
df4 = df1[l:]
df5 = pd.concat([df3,df4])
df5
```

Out[13]:

	year	month	day	gender	births
1	1969.000000	1.000000	1.000000	M	4440.000000
2	1969.000000	1.000000	2.000000	F	4454.000000
3	1969.000000	1.000000	2.000000	M	4548.000000
4	1969.000000	1.000000	3.000000	F	4548.000000
5	1969.000000	1.000000	3.000000	M	4994.000000
...	...	...	...	...	...
15543	2008.000000	11.000000	17.771008	F	158939.000000
15544	2008.000000	11.000000	17.771008	M	165468.000000
15545	2008.000000	12.000000	17.771008	F	173215.000000
15546	2008.000000	12.000000	17.771008	M	181235.000000
15547	1979.038081	6.516274	17.771008	F	9762.661263

15547 rows × 5 columns

Append

In [14]:

```
df6 = df3.append(df4)
df6
```

```
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_18064\565437931.py:1: FutureWarn
ing: The frame.append method is deprecated and will be removed from pandas i
n a future version. Use pandas.concat instead.
  df6 = df3.append(df4)
```

Out[14]:

	year	month	day	gender	births
1	1969.000000	1.000000	1.000000	M	4440.000000
2	1969.000000	1.000000	2.000000	F	4454.000000
3	1969.000000	1.000000	2.000000	M	4548.000000
4	1969.000000	1.000000	3.000000	F	4548.000000
5	1969.000000	1.000000	3.000000	M	4994.000000
...	...	...	...	...	...
15543	2008.000000	11.000000	17.771008	F	158939.000000
15544	2008.000000	11.000000	17.771008	M	165468.000000
15545	2008.000000	12.000000	17.771008	F	173215.000000
15546	2008.000000	12.000000	17.771008	M	181235.000000
15547	1979.038081	6.516274	17.771008	F	9762.661263

15547 rows × 5 columns

merge and join

In [15]:

```
df7 = pd.merge(df3,df4,how='inner')
df7
```

Out[15]:

year	month	day	gender	births

In [16]:

```
print(pd.concat((df1.iloc[:,0:3],df1.iloc[:,2:5]),join="inner").head())
```

```
   day
1  1.0
2  2.0
3  2.0
4  3.0
5  3.0
```

In [17]:

```
print("Concatenated result (using Outer Join) :")
print(pd.concat((df1,df1.iloc[:,0:3]),join="outer").head())
```

```
Concatenated result (using Outer Join) :
     year  month  day gender  births
1  1969.0    1.0  1.0      M  4440.0
2  1969.0    1.0  2.0      F  4454.0
3  1969.0    1.0  2.0      M  4548.0
4  1969.0    1.0  3.0      F  4548.0
5  1969.0    1.0  3.0      M  4994.0
```

Aggregation

In [18]:

```
df1.sum()
```

Out[18]:

```
year                                           30768105.038081
month                                            101308.516274
day                                               276285.85464
gender    MFMFMFMFMFMFMFMFMFMFMFMFMFMFMFMFMFMFMFMFMFMFMFMF...
births                                        151780094.661263
dtype: object
```

In [19]:

```
df1.mean()
```

```
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_18064\2053335143.py:1: FutureWar
ning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_on
ly=None') is deprecated; in a future version this will raise TypeError.  Sel
ect only valid columns before calling the reduction.
  df1.mean()
```

Out[19]:

```
year      1979.038081
month        6.516274
day         17.771008
births    9762.661263
dtype: float64
```

In [20]:

```
df1.min()
```

Out[20]:

```
year      1969.0
month        1.0
day          1.0
gender         F
births       1.0
dtype: object
```

In [21]:

```
df1.max()
```

Out[21]:

```
year        2008.0
month         12.0
day           99.0
gender           M
births    199622.0
dtype: object
```

In [22]:

```
df1.median()
```

```
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_18064\2279417019.py:1: FutureWar
ning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_on
ly=None') is deprecated; in a future version this will raise TypeError.  Sel
ect only valid columns before calling the reduction.
  df1.median()
```

Out[22]:

```
year      1979.0
month        7.0
day         17.0
births    4814.0
dtype: float64
```

In [23]:

```
df1.std()
```

```
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_18064\3039516898.py:1: FutureWar
ning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_on
ly=None') is deprecated; in a future version this will raise TypeError.  Sel
ect only valid columns before calling the reduction.
  df1.std()
```

Out[23]:

```
year          6.727859
month         3.449348
day          15.045627
births    28552.429000
dtype: float64
```

In [24]:

```
df1.prod()
```

```
D:\Application\Anaconda\lib\site-packages\numpy\core\_methods.py:52: Runtime
Warning: overflow encountered in reduce
  return umr_prod(a, axis, dtype, out, keepdims, initial, where)
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_18064\1211784430.py:1: FutureWar
ning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_on
ly=None') is deprecated; in a future version this will raise TypeError.  Sel
ect only valid columns before calling the reduction.
  df1.prod()
```

Out[24]:

```
year      inf
month     inf
day       inf
births    inf
dtype: float64
```

In [25]:

```
df1.mad()
```

Out[25]:

```
year         5.452924
month        2.995740
day          9.204946
births    9853.394172
dtype: float64
```

Transform

In [26]:

```
df8 = df1.groupby('year').transform(lambda x: x - x.mean())
df8
```

```
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_18064\1067088748.py:1: FutureWar
ning: Dropping invalid columns in DataFrameGroupBy.transform is deprecated.
In a future version, a TypeError will be raised. Before calling .transform,
select only columns which should be valid for the function.
  df8 = df1.groupby('year').transform(lambda x: x - x.mean())
```

Out[26]:

	month	day	births
1	-5.507171	-17.616688	-248.604954
2	-5.507171	-16.616688	-234.604954
3	-5.507171	-16.616688	-140.604954
4	-5.507171	-15.616688	-140.604954
5	-5.507171	-15.616688	305.395046
...	...	...	...
15543	4.500000	0.000000	-18359.166667
15544	4.500000	0.000000	-11830.166667
15545	5.500000	0.000000	-4083.166667
15546	5.500000	0.000000	3936.833333
15547	0.000000	0.000000	0.000000

15547 rows × 3 columns

In [27]:

```
def norm_by_data2(x):
 # x is a DataFrame of group values
 x['month'].mean()
 return x
print(df1);
print(df1.groupby('month').apply(norm_by_data2))
df1.groupby('month').apply(norm_by_data2)
```

```
              year      month        day gender         births
1      1969.000000   1.000000   1.000000      M    4440.000000
2      1969.000000   1.000000   2.000000      F    4454.000000
3      1969.000000   1.000000   2.000000      M    4548.000000
4      1969.000000   1.000000   3.000000      F    4548.000000
5      1969.000000   1.000000   3.000000      M    4994.000000
...            ...        ...        ...    ...            ...
15543  2008.000000  11.000000  17.771008      F  158939.000000
15544  2008.000000  11.000000  17.771008      M  165468.000000
15545  2008.000000  12.000000  17.771008      F  173215.000000
15546  2008.000000  12.000000  17.771008      M  181235.000000
15547  1979.038081   6.516274  17.771008      F    9762.661263

[15547 rows x 5 columns]
              year      month        day gender         births
1      1969.000000   1.000000   1.000000      M    4440.000000
2      1969.000000   1.000000   2.000000      F    4454.000000
3      1969.000000   1.000000   2.000000      M    4548.000000
4      1969.000000   1.000000   3.000000      F    4548.000000
5      1969.000000   1.000000   3.000000      M    4994.000000
...            ...        ...        ...    ...            ...
15543  2008.000000  11.000000  17.771008      F  158939.000000
15544  2008.000000  11.000000  17.771008      M  165468.000000
15545  2008.000000  12.000000  17.771008      F  173215.000000
15546  2008.000000  12.000000  17.771008      M  181235.000000
15547  1979.038081   6.516274  17.771008      F    9762.661263

[15547 rows x 5 columns]
```

Out[27]:

	year	month	day	gender	births
1	1969.000000	1.000000	1.000000	M	4440.000000
2	1969.000000	1.000000	2.000000	F	4454.000000
3	1969.000000	1.000000	2.000000	M	4548.000000
4	1969.000000	1.000000	3.000000	F	4548.000000
5	1969.000000	1.000000	3.000000	M	4994.000000
...	...	...	...	...	...
15543	2008.000000	11.000000	17.771008	F	158939.000000
15544	2008.000000	11.000000	17.771008	M	165468.000000
15545	2008.000000	12.000000	17.771008	F	173215.000000
15546	2008.000000	12.000000	17.771008	M	181235.000000
15547	1979.038081	6.516274	17.771008	F	9762.661263

15547 rows × 5 columns

Pivot table

In [28]:

```
df1.pivot_table(index='gender')
```

Out[28]:

gender	births	day	month	year
F	9521.802940	17.784698	6.514084	1979.038714
M	10003.674559	17.757308	6.518466	1979.037447

B. Time Series

In [29]:

```
ts = pd.read_csv('Fremont_Bridge_Bicycle_Counter.csv',index_col='Date',parse_dates=True)
```

In [30]:

```
ts
```

Out[30]:

Date	Fremont Bridge Total	Fremont Bridge East Sidewalk	Fremont Bridge West Sidewalk
2012-10-03 00:00:00	13.0	4.0	9.0
2012-10-03 01:00:00	10.0	4.0	6.0
2012-10-03 02:00:00	2.0	1.0	1.0
2012-10-03 03:00:00	5.0	2.0	3.0
2012-10-03 04:00:00	7.0	6.0	1.0
...	...	...	...
2022-09-30 19:00:00	168.0	57.0	111.0
2022-09-30 20:00:00	73.0	33.0	40.0
2022-09-30 21:00:00	69.0	30.0	39.0
2022-09-30 22:00:00	51.0	10.0	41.0
2022-09-30 23:00:00	59.0	22.0	37.0

87600 rows × 3 columns

In [31]:

```
ts.columns = ['Total','West', 'East']
```

In [32]:

```
ts
```

Out[32]:

	Total	West	East
Date			
2012-10-03 00:00:00	13.0	4.0	9.0
2012-10-03 01:00:00	10.0	4.0	6.0
2012-10-03 02:00:00	2.0	1.0	1.0
2012-10-03 03:00:00	5.0	2.0	3.0
2012-10-03 04:00:00	7.0	6.0	1.0
...	...	...	...
2022-09-30 19:00:00	168.0	57.0	111.0
2022-09-30 20:00:00	73.0	33.0	40.0
2022-09-30 21:00:00	69.0	30.0	39.0
2022-09-30 22:00:00	51.0	10.0	41.0
2022-09-30 23:00:00	59.0	22.0	37.0

87600 rows × 3 columns

In [33]:

```
ts.dropna().describe()
```

Out[33]:

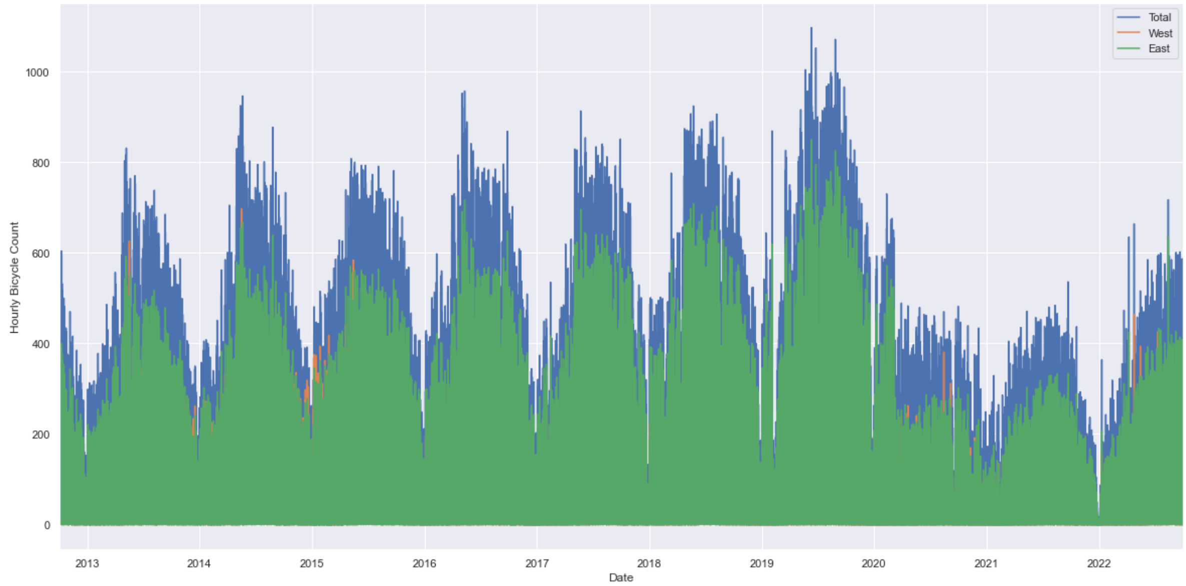
	Total	West	East
count	87586.000000	87586.000000	87586.000000
mean	107.240849	48.086623	59.154226
std	134.790561	61.573965	83.567491
min	0.000000	0.000000	0.000000
25%	13.000000	6.000000	7.000000
50%	60.000000	27.000000	30.000000
75%	144.000000	66.000000	75.000000
max	1097.000000	698.000000	850.000000

In [34]:

```
import seaborn as sns
import matplotlib.pyplot as plt
sns.set(rc={"figure.figsize":(20, 10)})
#plt.figure(figsize=(20,20))
ts.plot()
plt.ylabel('Hourly Bicycle Count')
```

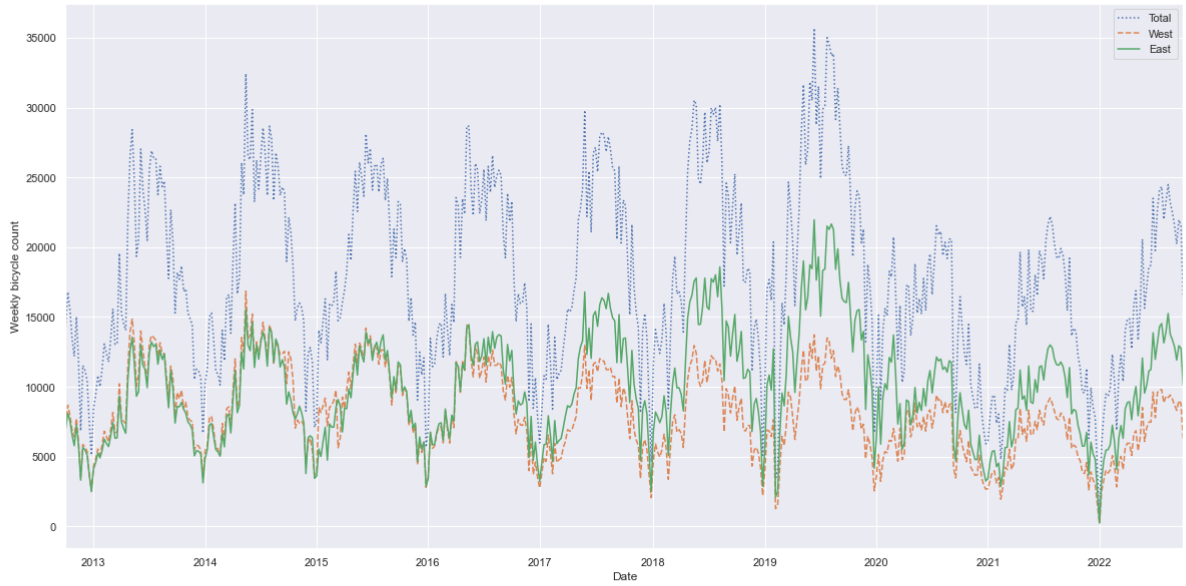
Out[34]:

```
Text(0, 0.5, 'Hourly Bicycle Count')
```



In [35]:

```
weekly = ts.resample('W').sum()
weekly.plot(style=[':', '--', '-'])
plt.ylabel('Weekly bicycle count');
```

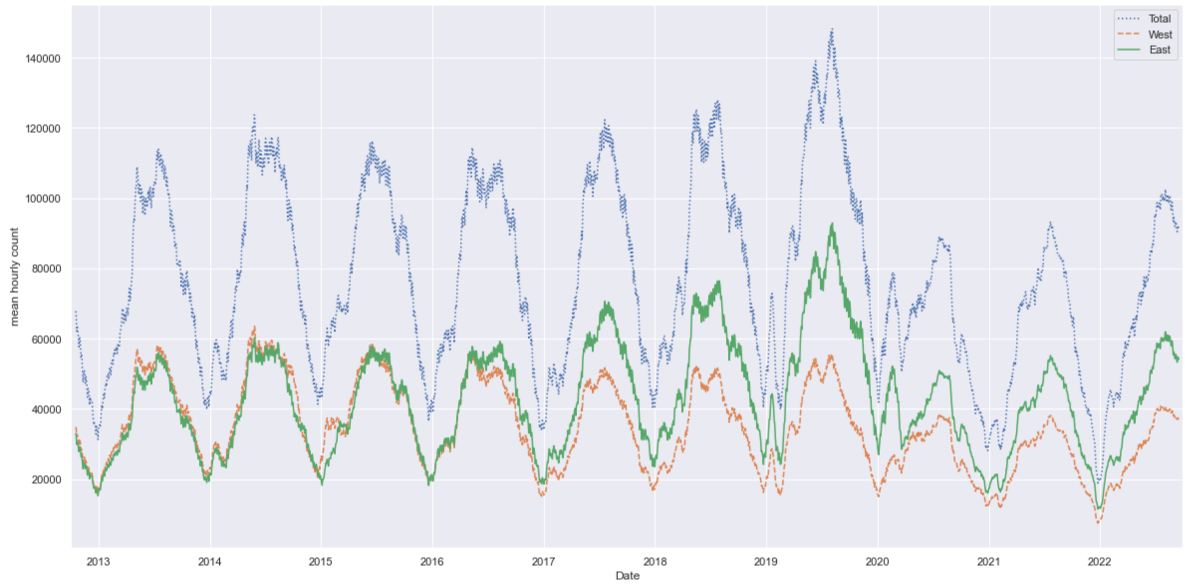


In [36]:

```
daily = ts.resample('D').sum()
daily.rolling(30, center=True).sum().plot(style=[':', '--', '-'])
plt.ylabel('mean hourly count')
```

Out[36]:

```
Text(0, 0.5, 'mean hourly count')
```

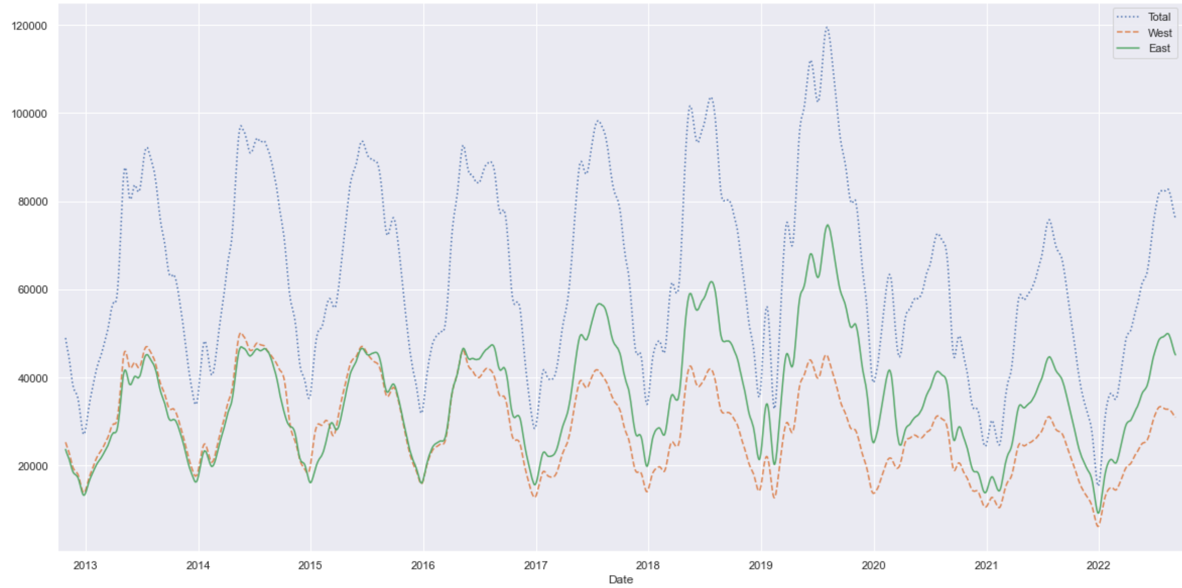


In [37]:

```
daily.rolling(50, center=True,win_type='gaussian').sum(std=10).plot(style=[':', '--', '-'])
```

Out[37]:

<AxesSubplot:xlabel='Date'>

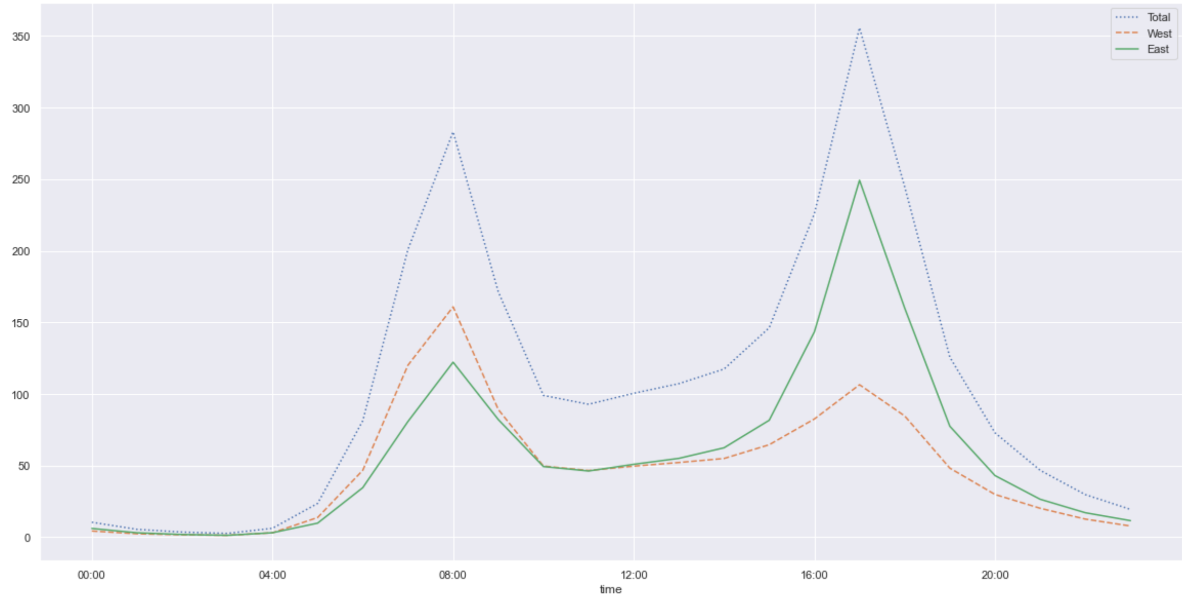


In [38]:

```
by_time = ts.groupby(ts.index.time).mean()
hourly_ticks = 4 * 60 * 60 * np.arange(6)
by_time.plot(xticks=hourly_ticks, style=[':', '--', '-'])
```

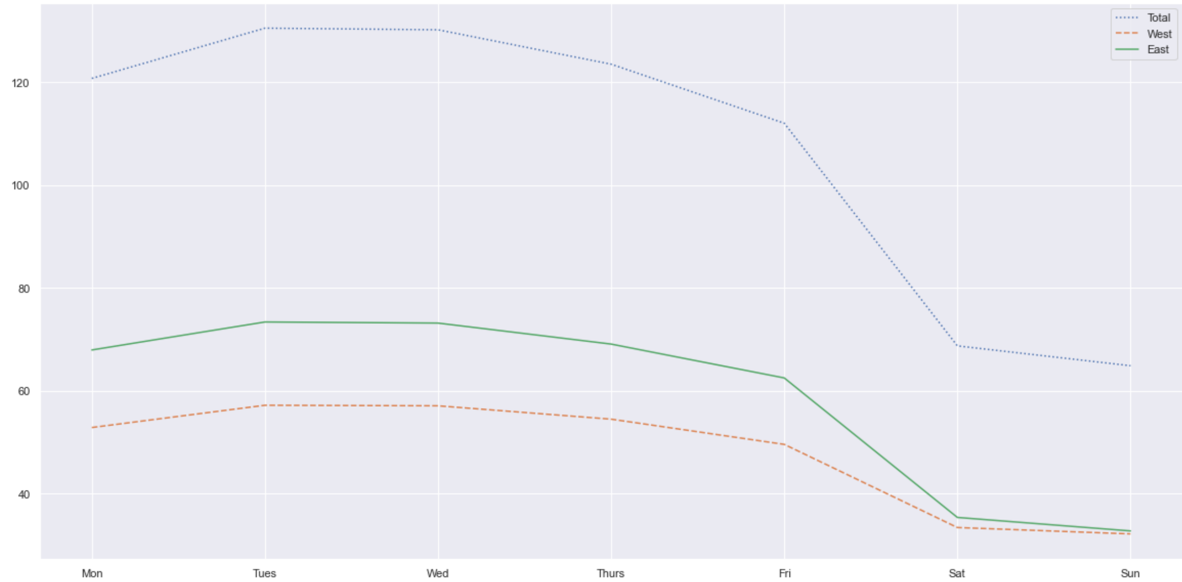
Out[38]:

<AxesSubplot:xlabel='time'>



In [39]:

```
by_weekday = ts.groupby(ts.index.dayofweek).mean()
by_weekday.index = ['Mon', 'Tues', 'Wed', 'Thurs', 'Fri', 'Sat', 'Sun']
by_weekday.plot(style=[':', '--', '-']);
```



In [40]:

```
weekend = np.where(ts.index.weekday < 5, 'Weekday', 'Weekend')
by_time = ts.groupby([weekend, ts.index.time]).mean()
# weekday = np.where(ts.index.weekday >= 5, 'Weekday', 'Weekend')
# by_time = ts.groupby([weekday, ts.index.time]).mean()
```

Time shifts

In [41]:

```
fig, ax = plt.subplots(3, sharey=True)
ts = ts.asfreq('D', method='pad')
ts.plot(ax=ax[0])
ts.shift(300).plot(ax=ax[1])
ts.tshift(300).plot(ax=ax[2])
local_max = pd.to_datetime('2006-10-03')
offset = pd.Timedelta(300, 'D')
ax[0].legend(['input'], loc=2)
ax[0].get_xticklabels()[2].set(color='red')
ax[0].axvline(local_max, alpha=0.3, color='red')
ax[1].legend(['shift(300)'], loc=2)
ax[1].get_xticklabels()[2].set(color='red')
ax[1].axvline(local_max + offset, alpha=0.3, color='red')
ax[2].legend(['tshift(300)'], loc=2)
ax[2].get_xticklabels()[1].set( color='red')
ax[2].axvline(local_max + offset, alpha=0.3, color='red')
```

```
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_18064\3600603100.py:5: FutureWar
ning: tshift is deprecated and will be removed in a future version. Please u
se shift instead.
  ts.tshift(300).plot(ax=ax[2])
```

Out[41]:

```
<matplotlib.lines.Line2D at 0x1eb4aa648b0>
```

Q3 - Stocks dataset

In [42]:

```
sd=pd.read_csv("stock_px_2.csv")
```

In [43]:

```
sd
```

Out[43]:

	Unnamed: 0	AAPL	MSFT	XOM	SPX
0	2003-01-02 00:00:00	7.40	21.11	29.22	909.03
1	2003-01-03 00:00:00	7.45	21.14	29.24	908.59
2	2003-01-06 00:00:00	7.45	21.52	29.96	929.01
3	2003-01-07 00:00:00	7.43	21.93	28.95	922.93
4	2003-01-08 00:00:00	7.28	21.31	28.83	909.93
...	...	...	...	...	...
2209	2011-10-10 00:00:00	388.81	26.94	76.28	1194.89
2210	2011-10-11 00:00:00	400.29	27.00	76.27	1195.54
2211	2011-10-12 00:00:00	402.19	26.96	77.16	1207.25
2212	2011-10-13 00:00:00	408.43	27.18	76.37	1203.66
2213	2011-10-14 00:00:00	422.00	27.27	78.11	1224.58

2214 rows × 5 columns

In [44]:

```
sd.set_index("Unnamed: 0",inplace=True)
sd
```

Out[44]:

	AAPL	MSFT	XOM	SPX
Unnamed: 0				
2003-01-02 00:00:00	7.40	21.11	29.22	909.03
2003-01-03 00:00:00	7.45	21.14	29.24	908.59
2003-01-06 00:00:00	7.45	21.52	29.96	929.01
2003-01-07 00:00:00	7.43	21.93	28.95	922.93
2003-01-08 00:00:00	7.28	21.31	28.83	909.93
...	...	...	...	...
2011-10-10 00:00:00	388.81	26.94	76.28	1194.89
2011-10-11 00:00:00	400.29	27.00	76.27	1195.54
2011-10-12 00:00:00	402.19	26.96	77.16	1207.25
2011-10-13 00:00:00	408.43	27.18	76.37	1203.66
2011-10-14 00:00:00	422.00	27.27	78.11	1224.58

2214 rows × 4 columns

Indexing, selecting and subsetting

In [45]:

```
#by columns
sd.loc[:,['XOM']]
```

Out[45]:

	XOM
Unnamed: 0	
2003-01-02 00:00:00	29.22
2003-01-03 00:00:00	29.24
2003-01-06 00:00:00	29.96
2003-01-07 00:00:00	28.95
2003-01-08 00:00:00	28.83
...	...
2011-10-10 00:00:00	76.28
2011-10-11 00:00:00	76.27
2011-10-12 00:00:00	77.16
2011-10-13 00:00:00	76.37
2011-10-14 00:00:00	78.11

2214 rows × 1 columns

In [46]:

```
sd.loc[:,['AAPL']]
```

Out[46]:

	AAPL
Unnamed: 0	
2003-01-02 00:00:00	7.40
2003-01-03 00:00:00	7.45
2003-01-06 00:00:00	7.45
2003-01-07 00:00:00	7.43
2003-01-08 00:00:00	7.28
...	...
2011-10-10 00:00:00	388.81
2011-10-11 00:00:00	400.29
2011-10-12 00:00:00	402.19
2011-10-13 00:00:00	408.43
2011-10-14 00:00:00	422.00

2214 rows × 1 columns

In [47]:

```
#selection example
sd['AAPL'][sd['AAPL']>100]
```

Out[47]:

```
Unnamed: 0
2007-05-02 00:00:00    100.39
2007-05-03 00:00:00    100.40
2007-05-04 00:00:00    100.81
2007-05-07 00:00:00    103.92
2007-05-08 00:00:00    105.06
                        ...
2011-10-10 00:00:00    388.81
2011-10-11 00:00:00    400.29
2011-10-12 00:00:00    402.19
2011-10-13 00:00:00    408.43
2011-10-14 00:00:00    422.00
Name: AAPL, Length: 1023, dtype: float64
```

In [48]:

```
sd['Sum']=sd['AAPL']+sd['SPX']+sd['MSFT']+sd['XOM']
sd
```

Out[48]:

	AAPL	MSFT	XOM	SPX	Sum
Unnamed: 0					
2003-01-02 00:00:00	7.40	21.11	29.22	909.03	966.76
2003-01-03 00:00:00	7.45	21.14	29.24	908.59	966.42
2003-01-06 00:00:00	7.45	21.52	29.96	929.01	987.94
2003-01-07 00:00:00	7.43	21.93	28.95	922.93	981.24
2003-01-08 00:00:00	7.28	21.31	28.83	909.93	967.35
...	...	...	...	...	...
2011-10-10 00:00:00	388.81	26.94	76.28	1194.89	1686.92
2011-10-11 00:00:00	400.29	27.00	76.27	1195.54	1699.10
2011-10-12 00:00:00	402.19	26.96	77.16	1207.25	1713.56
2011-10-13 00:00:00	408.43	27.18	76.37	1203.66	1715.64
2011-10-14 00:00:00	422.00	27.27	78.11	1224.58	1751.96

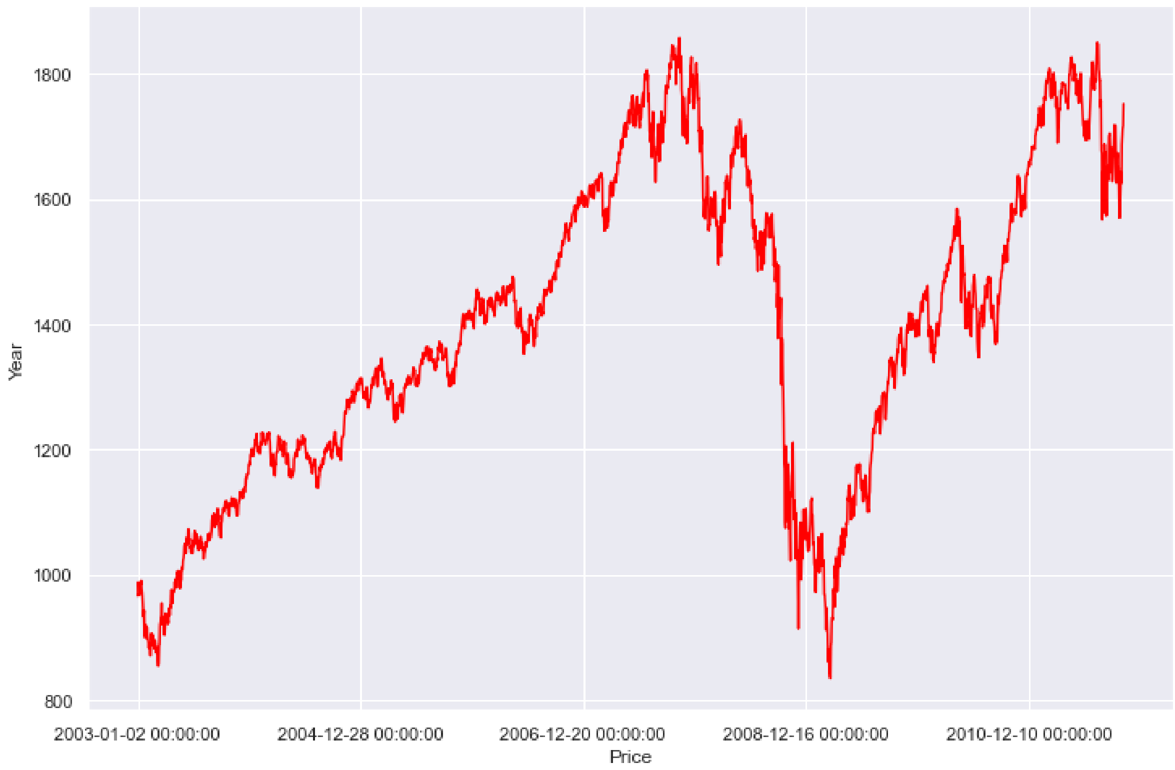
2214 rows × 5 columns

In [49]:

```
sd.iloc[:,4].plot(figsize=(12,8),color='red')
plt.xlabel('Price')
plt.ylabel('Year')
```

Out[49]:

```
Text(0, 0.5, 'Year')
```



In [50]:

```
sd.rolling(50, center=True,win_type='gaussian').sum(std=10).plot(style= '--',figsize=(12,6)
plt.xlabel("year")
plt.ylabel("stock price")
```

Out[50]:

```
Text(0, 0.5, 'stock price')
```

Date Ranges, Frequencies, and Shifting (Leading and Lagging) Data

In [51]:

```
from datetime import datetime
now = datetime.now().time()
print("now =", now)
```

```
now = 19:09:09.712081
```

In [52]:

```
stock=sd
```

In [53]:

```
import datetime
datetime.datetime.combine(datetime.date(2011, 1, 1), datetime.time(10, 23))
```

Out[53]:

```
datetime.datetime(2011, 1, 1, 10, 23)
```

In [54]:

```
pd.date_range(start='2012-04-01', periods=20)
```

Out[54]:

```
DatetimeIndex(['2012-04-01', '2012-04-02', '2012-04-03', '2012-04-04',
               '2012-04-05', '2012-04-06', '2012-04-07', '2012-04-08',
               '2012-04-09', '2012-04-10', '2012-04-11', '2012-04-12',
               '2012-04-13', '2012-04-14', '2012-04-15', '2012-04-16',
               '2012-04-17', '2012-04-18', '2012-04-19', '2012-04-20'],
              dtype='datetime64[ns]', freq='D')
```

In [55]:

```
shift1=stock.shift(1, axis = 1)
shift1.head()
```

Out[55]:

	AAPL	MSFT	XOM	SPX	Sum
Unnamed: 0					
2003-01-02 00:00:00	NaN	7.40	21.11	29.22	909.03
2003-01-03 00:00:00	NaN	7.45	21.14	29.24	908.59
2003-01-06 00:00:00	NaN	7.45	21.52	29.96	929.01
2003-01-07 00:00:00	NaN	7.43	21.93	28.95	922.93
2003-01-08 00:00:00	NaN	7.28	21.31	28.83	909.93

In [56]:

```
shift1=stock.shift(-2, axis = 0)
shift1.tail()
```

Out[56]:

	AAPL	MSFT	XOM	SPX	Sum
Unnamed: 0					
2011-10-10 00:00:00	402.19	26.96	77.16	1207.25	1713.56
2011-10-11 00:00:00	408.43	27.18	76.37	1203.66	1715.64
2011-10-12 00:00:00	422.00	27.27	78.11	1224.58	1751.96
2011-10-13 00:00:00	NaN	NaN	NaN	NaN	NaN
2011-10-14 00:00:00	NaN	NaN	NaN	NaN	NaN

Time localisation

In [57]:

```
import pytz
pytz.common_timezones[-5:]
```

Out[57]:

```
['US/Eastern', 'US/Hawaii', 'US/Mountain', 'US/Pacific', 'UTC']
```

In [58]:

```
tz = pytz.timezone('America/New_York')
tz
```

Out[58]:

```
<DstTzInfo 'America/New_York' LMT-1 day, 19:04:00 STD>
```

In [59]:

```
pd.date_range('3/9/2012 9:30', periods=10, freq='D', tz='UTC')
```

Out[59]:

```
DatetimeIndex(['2012-03-09 09:30:00+00:00', '2012-03-10 09:30:00+00:00',
               '2012-03-11 09:30:00+00:00', '2012-03-12 09:30:00+00:00',
               '2012-03-13 09:30:00+00:00', '2012-03-14 09:30:00+00:00',
               '2012-03-15 09:30:00+00:00', '2012-03-16 09:30:00+00:00',
               '2012-03-17 09:30:00+00:00', '2012-03-18 09:30:00+00:00'],
              dtype='datetime64[ns, UTC]', freq='D')
```

In [60]:

```
import numpy as np
rng = pd.date_range('3/9/2012 9:30', periods=6, freq='D')
ts = pd.Series(np.random.randn(len(rng)), index=rng)
ts
```

Out[60]:

```
2012-03-09 09:30:00   -2.044955
2012-03-10 09:30:00   -0.881985
2012-03-11 09:30:00    0.672232
2012-03-12 09:30:00    0.414242
2012-03-13 09:30:00   -0.821002
2012-03-14 09:30:00   -0.115646
Freq: D, dtype: float64
```

In [61]:

```
ts_utc = ts.tz_localize('UTC')
ts_utc
```

Out[61]:

```
2012-03-09 09:30:00+00:00   -2.044955
2012-03-10 09:30:00+00:00   -0.881985
2012-03-11 09:30:00+00:00    0.672232
2012-03-12 09:30:00+00:00    0.414242
2012-03-13 09:30:00+00:00   -0.821002
2012-03-14 09:30:00+00:00   -0.115646
Freq: D, dtype: float64
```

In [62]:

```
ts_utc.index
```

Out[62]:

```
DatetimeIndex(['2012-03-09 09:30:00+00:00', '2012-03-10 09:30:00+00:00',
               '2012-03-11 09:30:00+00:00', '2012-03-12 09:30:00+00:00',
               '2012-03-13 09:30:00+00:00', '2012-03-14 09:30:00+00:00'],
              dtype='datetime64[ns, UTC]', freq='D')
```

In [63]:

```
ts_eastern = ts.tz_localize('America/New_York')
ts_eastern
```

Out[63]:

```
2012-03-09 09:30:00-05:00   -2.044955
2012-03-10 09:30:00-05:00   -0.881985
2012-03-11 09:30:00-04:00    0.672232
2012-03-12 09:30:00-04:00    0.414242
2012-03-13 09:30:00-04:00   -0.821002
2012-03-14 09:30:00-04:00   -0.115646
dtype: float64
```

In [64]:

```
ts_eastern.tz_convert('UTC')
```

Out[64]:

```
2012-03-09 14:30:00+00:00   -2.044955
2012-03-10 14:30:00+00:00   -0.881985
2012-03-11 13:30:00+00:00    0.672232
2012-03-12 13:30:00+00:00    0.414242
2012-03-13 13:30:00+00:00   -0.821002
2012-03-14 13:30:00+00:00   -0.115646
dtype: float64
```

Periods and Period Arithmetic and Period Frequency Conversion

In [65]:

```
prd = pd.Period(2010, freq='A-DEC')
prd
```

Out[65]:

```
Period('2010', 'A-DEC')
```

In [66]:

```
rng = pd.period_range('2000-01-01', '2000-06-30', freq='M')
rng
```

Out[66]:

```
PeriodIndex(['2000-01', '2000-02', '2000-03', '2000-04', '2000-05', '2000-0
6'], dtype='period[M]')
```

In [67]:

```
prd = pd.Period('2012Q4', freq='Q-JAN')
prd
```

Out[67]:

```
Period('2012Q4', 'Q-JAN')
```

In [68]:

```
 rng = pd.date_range('2000-01-01', periods=3, freq='M')
```

In [69]:

```
pts=ts.to_period()
pts
```

Out[69]:

```
2012-03-09   -2.044955
2012-03-10   -0.881985
2012-03-11    0.672232
2012-03-12    0.414242
2012-03-13   -0.821002
2012-03-14   -0.115646
Freq: D, dtype: float64
```

C. Classifier

Q4

In [70]:

```
kd=pd.read_csv("ckd.csv")
```

In [71]:

```
kd
```

Out[71]:

	Age	Blood Pressure	Specific Gravity	Albumin	Sugar	Red Blood Cells	Pus Cell	Pus Cell clumps	Bacteria	Blc Gluc Rand
0	48	70	1.005	4	0	normal	abnormal	present	notpresent	
1	53	90	1.020	2	0	abnormal	abnormal	present	notpresent	
2	63	70	1.010	3	0	abnormal	abnormal	present	notpresent	
3	68	80	1.010	3	2	normal	abnormal	present	present	
4	61	80	1.015	2	0	abnormal	abnormal	notpresent	notpresent	
...	...	...	...	...	...	...	...	...	...	
153	55	80	1.020	0	0	normal	normal	notpresent	notpresent	
154	42	70	1.025	0	0	normal	normal	notpresent	notpresent	
155	12	80	1.020	0	0	normal	normal	notpresent	notpresent	
156	17	60	1.025	0	0	normal	normal	notpresent	notpresent	
157	58	80	1.025	0	0	normal	normal	notpresent	notpresent	

158 rows × 25 columns

In [72]:

```
kd.isna().sum()
```

Out[72]:

```
Age                        0
Blood Pressure             0
Specific Gravity           0
Albumin                    0
Sugar                      0
Red Blood Cells            0
Pus Cell                   0
Pus Cell clumps            0
Bacteria                   0
Blood Glucose Random       0
Blood Urea                 0
Serum Creatinine           0
Sodium                     0
Potassium                  0
Hemoglobin                 0
Packed Cell Volume         0
White Blood Cell Count     0
Red Blood Cell Count       0
Hypertension               0
Diabetes Mellitus          0
Coronary Artery Disease    0
Appetite                   0
Pedal Edema                0
Anemia                     0
Class                      0
dtype: int64
```

In [73]:

```
len(kd.columns)
```

Out[73]:

```
25
```

In [74]:

```
# let us take only few featue and extract them
```

In [75]:

```
kd=kd[["Hemoglobin","Blood Glucose Random","Class"]]
```

In [76]:

```
print("Number of samples in class 1 (With Chronic Kidney Disease) : ",len(kd[kd.Class==1]))
```

```
Number of samples in class 1 (With Chronic Kidney Disease) :  43
```

In [77]:

```
print("Number of samples in class 0 (Without Chronic Kidney Disease) : ",len(kd[kd.Class==0
```

```
Number of samples in class 0 (Without Chronic Kidney Disease) :  115
```

In [78]:

```
to_predict_Hemoglobin = 0
to_predict_Glucose_Level = (1.1 * kd["Blood Glucose Random"].describe()["std"] + kd["Blood
```

In [79]:

```
print("We need to predict whether Alice has CKD")
print("From the question : - ")
print("Alice's Hemoglobin : ",to_predict_Hemoglobin)
print("Alice's Glucose Level : ",to_predict_Glucose_Level)
```

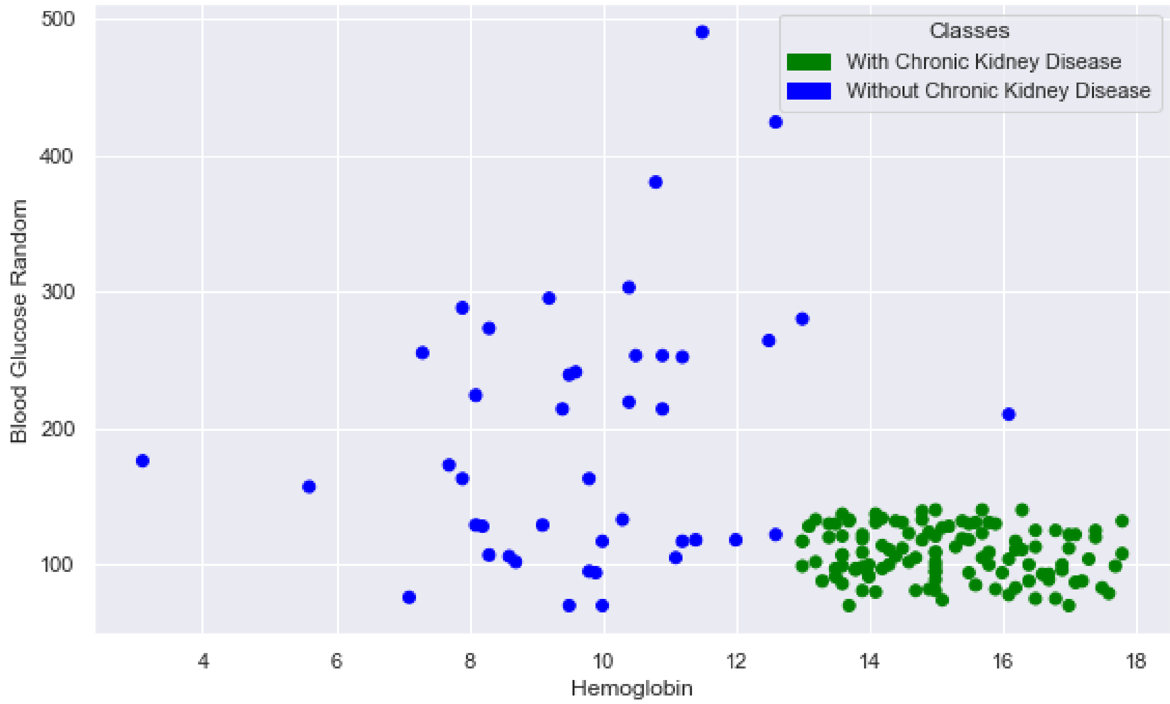
```
We need to predict whether Alice has CKD
From the question : -
Alice's Hemoglobin :  0
Alice's Glucose Level :  202.7755876116037
```

In [80]:

```
import matplotlib
from matplotlib.patches import Patch
x_feature = kd.Hemoglobin
y_feature = kd["Blood Glucose Random"]
plt.figure(figsize=(10, 6))
colors=["green","blue"]
plt.scatter(x_feature, y_feature, c=[colors[label] for label in kd.Class])
plt.xlabel("Hemoglobin")
plt.ylabel("Blood Glucose Random")
class_labels = ['With Chronic Kidney Disease', 'Without Chronic Kidney Disease']
patches = [Patch(color=color, label=label) for color, label in zip(colors, class_labels)]
plt.legend(title='Classes', handles=patches)
```

Out[80]:

```
<matplotlib.legend.Legend at 0x1eb44a34070>
```

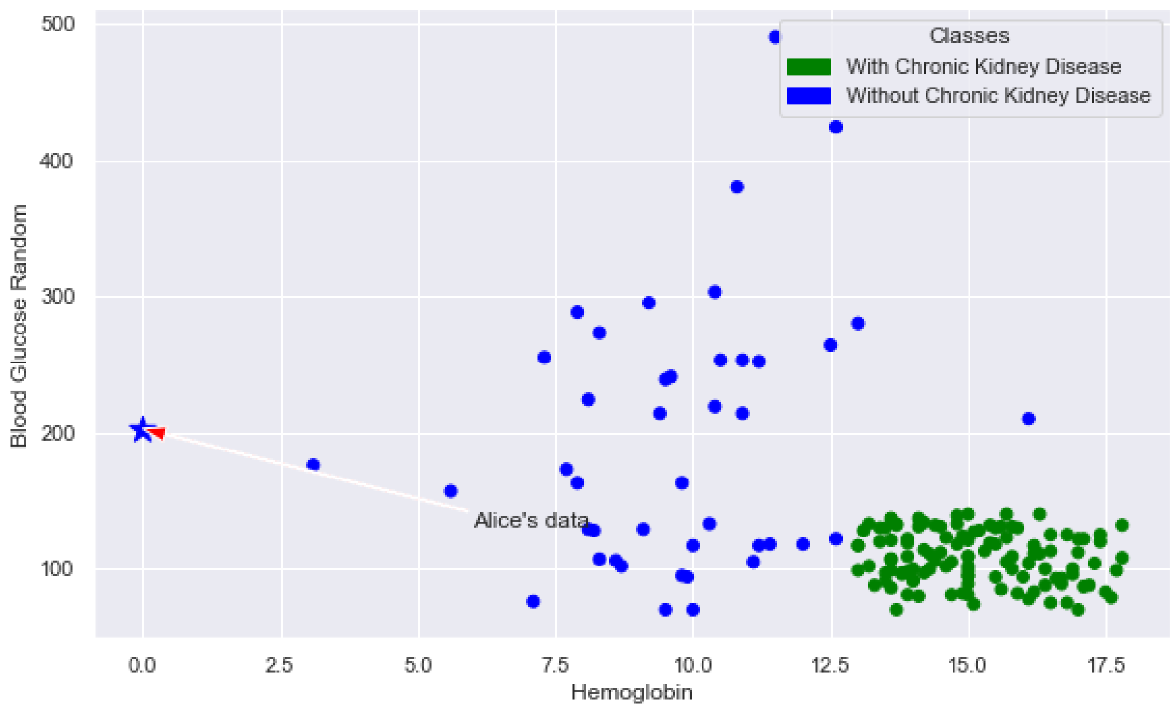


In [81]:

```
x_feature = kd.Hemoglobin
y_feature = kd["Blood Glucose Random"]
plt.figure(figsize=(10, 6))
colors=["green","blue"]
plt.scatter(x_feature, y_feature, c=[colors[label] for label in kd.Class])
new_point = (to_predict_Hemoglobin, to_predict_Glucose_Level)
plt.scatter(new_point[0], new_point[1], c='blue', marker='*', s=200)
plt.annotate("Alice's data", xy=new_point, xytext=(6, 130), arrowprops=dict(facecolor='red'
plt.xlabel("Hemoglobin")
plt.ylabel("Blood Glucose Random")
class_labels = ['With Chronic Kidney Disease', 'Without Chronic Kidney Disease']
patches = [Patch(color=color, label=label) for color, label in zip(colors, class_labels)]
plt.legend(title='Classes', handles=patches)
```

Out[81]:

```
<matplotlib.legend.Legend at 0x1eb4ffbb5b0>
```



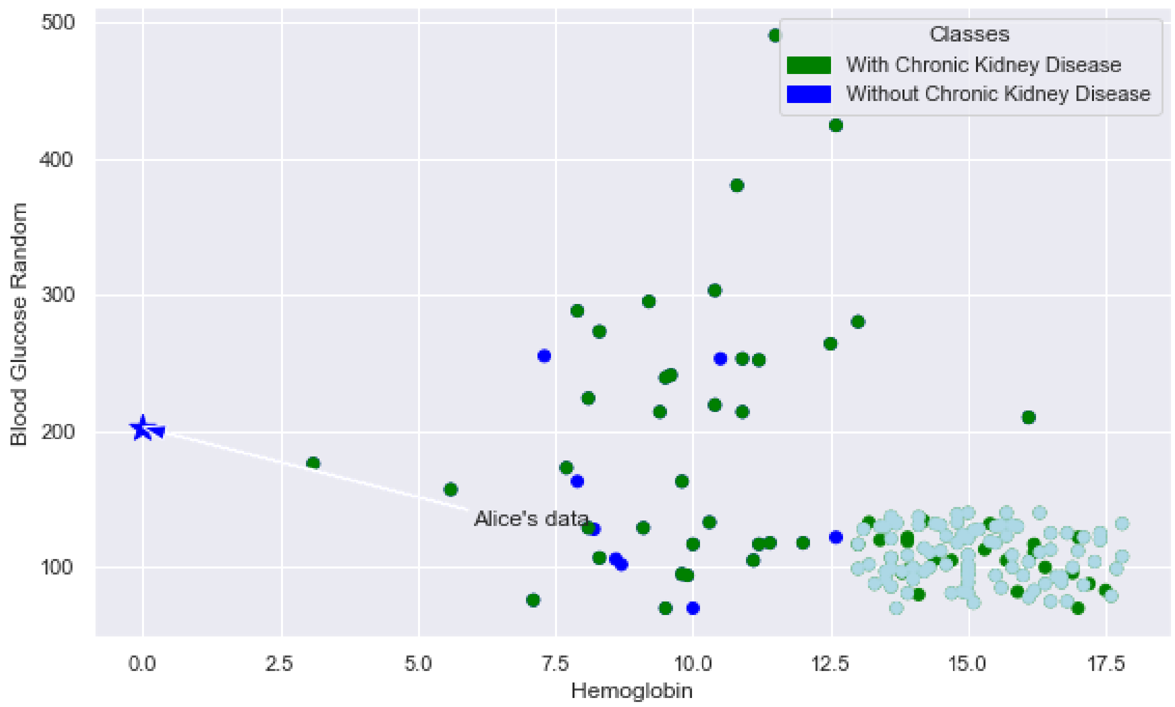
In [82]:

```
n.model_selection import train_test_split
test, y_train, y_test = train_test_split(kd[["Hemoglobin","Blood Glucose Random"]], kd["Clas
```

In [83]:

```
x_feature = kd.Hemoglobin
y_feature = kd["Blood Glucose Random"]
plt.figure(figsize=(10, 6))
colors=["green","blue"]
plt.scatter(x_feature, y_feature, c=[colors[label] for label in kd.Class])
new_point = (to_predict_Hemoglobin, to_predict_Glucose_Level)
plt.scatter(new_point[0], new_point[1], c='blue', marker='*', s=200)
plt.annotate("Alice's data", xy=new_point, xytext=(6, 130), arrowprops=dict(facecolor='blue
plt.xlabel("Hemoglobin")
plt.ylabel("Blood Glucose Random")
train_features_x=X_train.Hemoglobin
train_features_y=X_train["Blood Glucose Random"]
colors_train=["lightblue","green"]
plt.scatter(train_features_x,train_features_y, c=[colors_train[label] for label in y_train]
class_labels = ['With Chronic Kidney Disease', 'Without Chronic Kidney Disease']
patches = [Patch(color=color, label=label) for color, label in zip(colors, class_labels)]
plt.legend(title='Classes', handles=patches)
print("Light blue and Green color data represents the samples chosen for training")
```

Light blue and Green color data represents the samples chosen for training



In [84]:

```
#KNN
```

In [85]:

```
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=3)
```

In [86]:

```
classifier.fit(X_train,y_train)
```

Out[86]:

```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

In [87]:

```
predictions=classifier.predict(X_test)
```

In [88]:

```
predictions
```

Out[88]:

```
array([0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 1, 1, 1, 0, 1, 0, 0, 0, 0], dtype=int64)
```

In [89]:

```
# validation
```

In [90]:

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
```

In [91]:

```
acc = accuracy_score(y_test, predictions)
print("Accuracy : ",acc)
```

```
Accuracy :  0.90625
```

In [92]:

```
confusion_matrix_ = confusion_matrix(y_test, predictions)
print("Confusion Matrix : ")
print(confusion_matrix_)
```

```
Confusion Matrix :
[[23  1]
 [ 2  6]]
```

In [93]:

```
report = classification_report(y_test, predictions)
print("Overall Report")
print(report)
```

```
Overall Report
              precision    recall  f1-score   support

           0       0.92      0.96      0.94        24
           1       0.86      0.75      0.80         8

    accuracy                           0.91        32
   macro avg       0.89      0.85      0.87        32
weighted avg       0.90      0.91      0.90        32
```

In [94]:

```
# Alice
```

In [95]:

```
class_Alice = classifier.predict([[to_predict_Hemoglobin, to_predict_Glucose_Level]])
```

```
D:\Application\Anaconda\lib\site-packages\sklearn\base.py:450: UserWarning:
X does not have valid feature names, but KNeighborsClassifier was fitted wit
h feature names
  warnings.warn(
```

In [96]:

```
print("Alice doesn't have CKD")
```

```
Alice doesn't have CKD
```

In [97]:

```
from sklearn import tree
```

In [98]:

```
classifier = tree.DecisionTreeClassifier()
```

In [99]:

```
classifier.fit(X_train,y_train)
```

Out[99]:

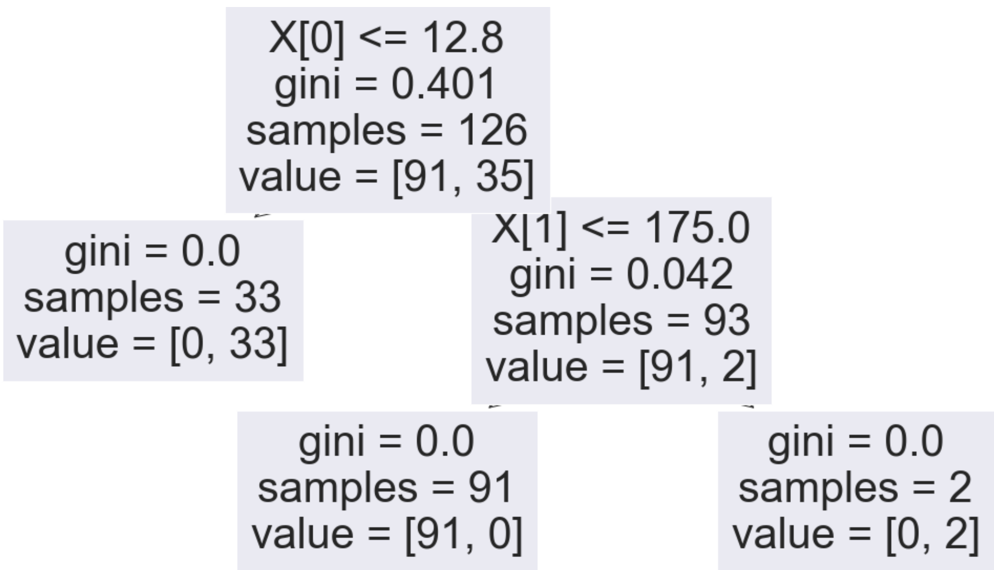
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [100]:

```
tree.plot_tree(classifier)
```

Out[100]:

```
[Text(0.4, 0.8333333333333334, 'X[0] <= 12.8\ngini = 0.401\nsamples = 126\nv
alue = [91, 35]'),
 Text(0.2, 0.5, 'gini = 0.0\nsamples = 33\nvalue = [0, 33]'),
 Text(0.6, 0.5, 'X[1] <= 175.0\ngini = 0.042\nsamples = 93\nvalue = [91,
2]'),
 Text(0.4, 0.16666666666666666, 'gini = 0.0\nsamples = 91\nvalue = [91,
0]'),
 Text(0.8, 0.16666666666666666, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]')]
```



In [101]:

```
predictions=classifier.predict(X_test)
```

In [102]:

```
confusion_matrix_ = confusion_matrix(y_test, predictions)
print("Confusion Matrix : ")
print(confusion_matrix_)
```

```
Confusion Matrix :
[[24  0]
 [ 0  8]]
```

In [103]:

```
report = classification_report(y_test, predictions)
print("Overall Report")
print(report)
```

```
Overall Report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        24
           1       1.00      1.00      1.00         8

    accuracy                           1.00        32
   macro avg       1.00      1.00      1.00        32
weighted avg       1.00      1.00      1.00        32
```

In [104]:

```
from sklearn.linear_model import LogisticRegression
```

In [105]:

```
classifier = LogisticRegression()
```

In [106]:

```
classifier.fit(X_train,y_train)
```

Out[106]:

```
▾ LogisticRegression
LogisticRegression()
```

In [107]:

```
predictions=classifier.predict(X_test)
```

In [108]:

```
confusion_matrix_ = confusion_matrix(y_test, predictions)
print("Confusion Matrix : ")
print(confusion_matrix_)
```

```
Confusion Matrix :
[[24  0]
 [ 1  7]]
```

In [109]:

```
report = classification_report(y_test, predictions)
print("Overall Report")
print(report)
```

```
Overall Report
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        24
           1       1.00      0.88      0.93         8

    accuracy                           0.97        32
   macro avg       0.98      0.94      0.96        32
weighted avg       0.97      0.97      0.97        32
```

In [ ]:

```

```

Q5

In [110]:

```
x = pd.read_csv('wine.csv')
```

In [111]:

```
x
```

Out[111]:

	Wine	Alcohol	Malic.acid	Ash	Acl	Mg	Phenols	Flavanoids	Nonflavanoid.phenols	Pr
0	1	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	
1	1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	
2	1	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	
3	1	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	
4	1	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	
...	...	...	...	...	...	...	...	...	...	
173	3	13.71	5.65	2.45	20.5	95	1.68	0.61	0.52	
174	3	13.40	3.91	2.48	23.0	102	1.80	0.75	0.43	
175	3	13.27	4.28	2.26	20.0	120	1.59	0.69	0.43	
176	3	13.17	2.59	2.37	20.0	120	1.65	0.68	0.53	
177	3	14.13	4.10	2.74	24.5	96	2.05	0.76	0.56	

178 rows × 14 columns

In [112]:

```
x.isna().sum()
```

Out[112]:

```
Wine                    0
Alcohol                 0
Malic.acid              0
Ash                     0
Acl                     0
Mg                      0
Phenols                 0
Flavanoids              0
Nonflavanoid.phenols    0
Proanth                 0
Color.int               0
Hue                     0
OD                      0
Proline                 0
dtype: int64
```

In [113]:

```
from sklearn.neighbors import KNeighborsClassifier
```

In [114]:

```
from sklearn.model_selection import train_test_split
X = x.drop(['Wine'],axis='columns')
y = x['Wine']
X_train, X_test, y_train, y_test= train_test_split(X, y, test_size=0.2, random_state=50)
```

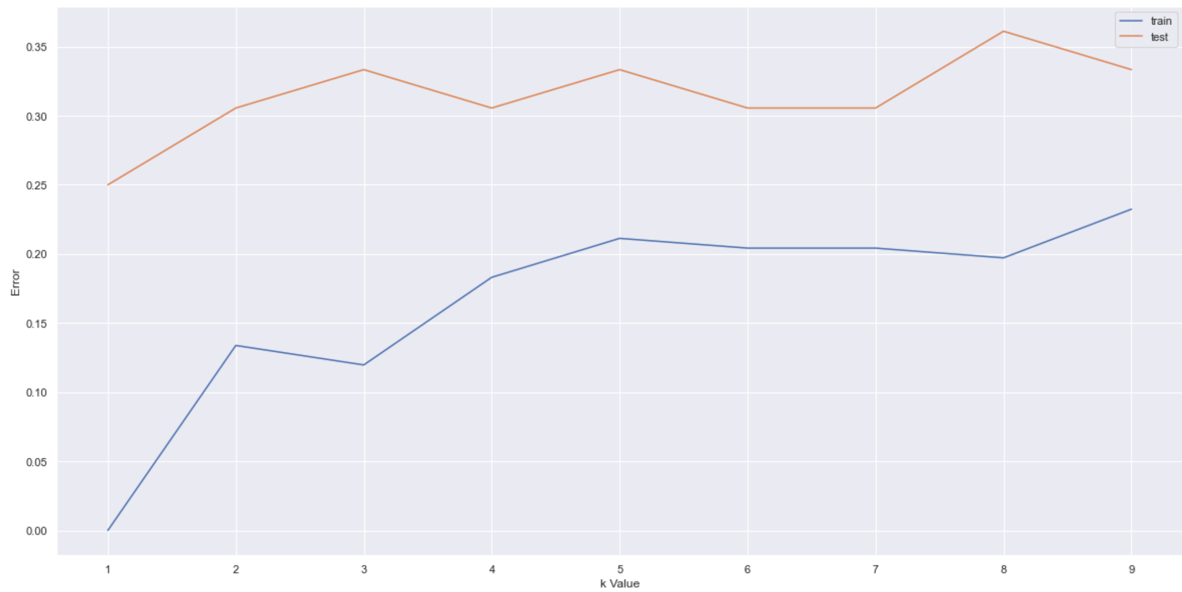
In [115]:

```
error1= []
error2= []
for k in range(1,10):
    knn= KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train,y_train)
    y_pred1= knn.predict(X_train)
    error1.append(np.mean(y_train!= y_pred1))
    y_pred2= knn.predict(X_test)
    error2.append(np.mean(y_test!= y_pred2))

plt.plot(range(1,10),error1,label="train")
plt.plot(range(1,10),error2,label="test")
plt.xlabel('k Value')
plt.ylabel('Error')
plt.legend()
```

Out[115]:

```
<matplotlib.legend.Legend at 0x1eb539c09d0>
```



In [116]:

```
knn = KNeighborsClassifier(n_neighbors=1)
```

In [117]:

```
knn.fit(X_train, y_train)
```

Out[117]:

```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=1)
```

In [118]:

```
knn.score(X_test, y_test)
```

Out[118]:

```
0.75
```

In [119]:

```
from sklearn.metrics import confusion_matrix
y_pred = knn.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
cm
```

Out[119]:

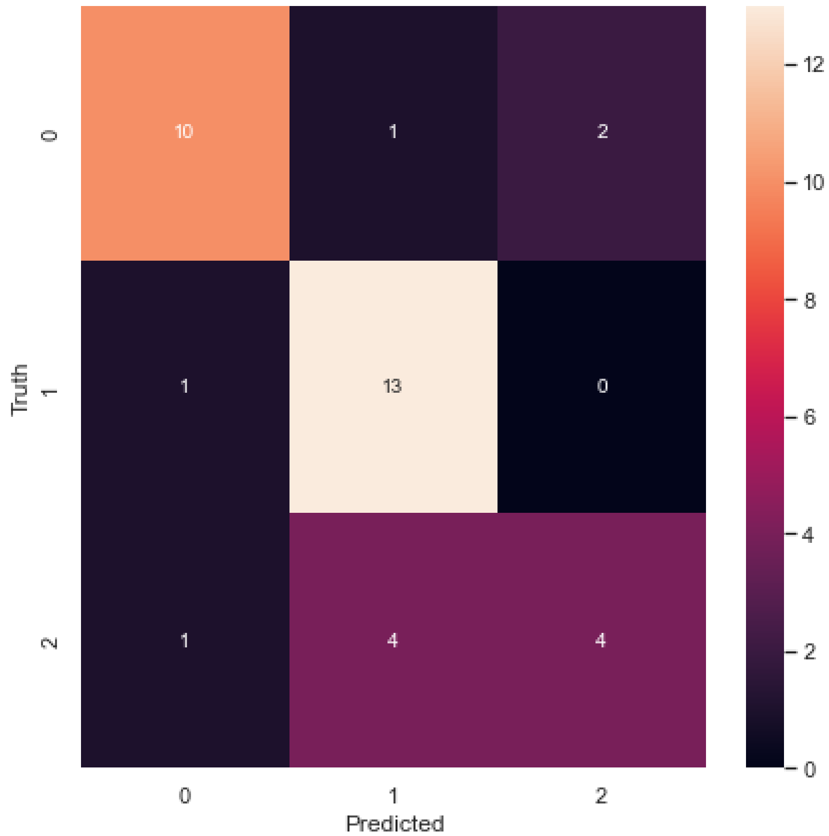
```
array([[10,  1,  2],
       [ 1, 13,  0],
       [ 1,  4,  4]], dtype=int64)
```

In [120]:

```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sn
plt.figure(figsize=(7,7))
sn.heatmap(cm, annot=True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[120]:

```
Text(39.5, 0.5, 'Truth')
```



In [121]:

```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           1       0.83      0.77      0.80        13
           2       0.72      0.93      0.81        14
           3       0.67      0.44      0.53         9

    accuracy                           0.75        36
   macro avg       0.74      0.71      0.72        36
weighted avg       0.75      0.75      0.74        36
```

In [122]:

```
#other classifier
```

In [123]:

```
from sklearn.ensemble import RandomForestRegressor
```

In [124]:

```
rf = RandomForestRegressor(random_state =1, max_features=4)
```

In [125]:

```
X_train, X_test, y_train, y_test= train_test_split(X, y, test_size=0.2, random_state=50)
```

In [126]:

```
rf.fit(X_train,y_train)
```

Out[126]:

```
▾ RandomForestRegressor
RandomForestRegressor(max_features=4, random_state=1)
```

In [127]:

```
y_pred = rf.predict(X_test)
```

In [128]:

```
rf.score(X_test, y_test)
```

Out[128]:

```
0.9208835051546392
```

In [129]:

```
from sklearn.metrics import confusion_matrix
y_pred = knn.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
cm
```

Out[129]:

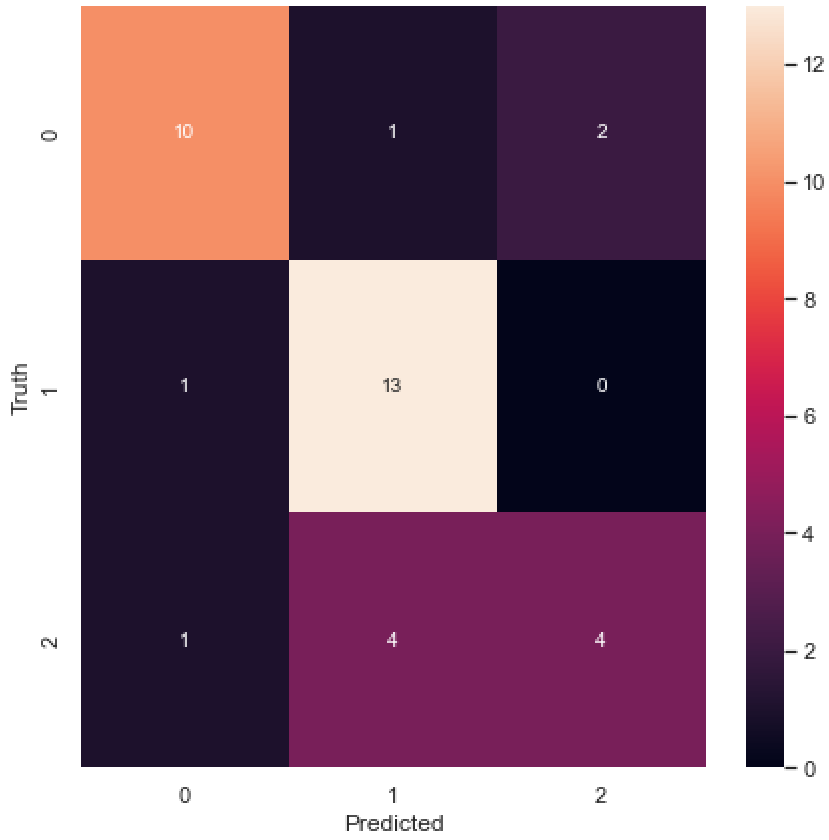
```
array([[10,  1,  2],
       [ 1, 13,  0],
       [ 1,  4,  4]], dtype=int64)
```

In [130]:

```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sn
plt.figure(figsize=(7,7))
sn.heatmap(cm, annot=True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[130]:

```
Text(39.5, 0.5, 'Truth')
```



In [131]:

```
#other classifier
```

In [132]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33)
```

In [133]:

```
from sklearn.svm import SVC
svm = SVC(C=10000,gamma=0.00001)
svm.fit(X_train,y_train)
```

Out[133]:

```
▾ SVC
SVC(C=10000, gamma=1e-05)
```

In [134]:

```
svm.score(X_test, y_test)
```

Out[134]:

```
0.9322033898305084
```

Regression

Q7

In [135]:

```
df=pd.read_csv("Housing.csv")
```

In [136]:

```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
le.fit(df.mainroad)
df.mainroad=le.transform(df.mainroad)
le.fit(df.guestroom)
df.guestroom=le.transform(df.guestroom)
le.fit(df.basement)
df.basement=le.transform(df.basement)
le.fit(df.hotwaterheating)
df.hotwaterheating=le.transform(df.hotwaterheating)
le.fit(df.airconditioning)
df.airconditioning=le.transform(df.airconditioning)
le.fit(df.prefarea)
df.prefarea=le.transform(df.prefarea)
le.fit(df.furnishingstatus)
df.furnishingstatus=le.transform(df.furnishingstatus)
```

In [137]:

```
corr_matrix = df.corr()
print(corr_matrix["price"])
```

```
price               1.000000
area                0.535997
bedrooms            0.366494
bathrooms           0.517545
stories             0.420712
mainroad            0.296898
guestroom           0.255517
basement            0.187057
hotwaterheating     0.093073
airconditioning     0.452954
parking             0.384394
prefarea            0.329777
furnishingstatus   -0.304721
Name: price, dtype: float64
```

In [138]:

```
print("Area is highly correlated to price compared to others : So we shall use area for vis
```

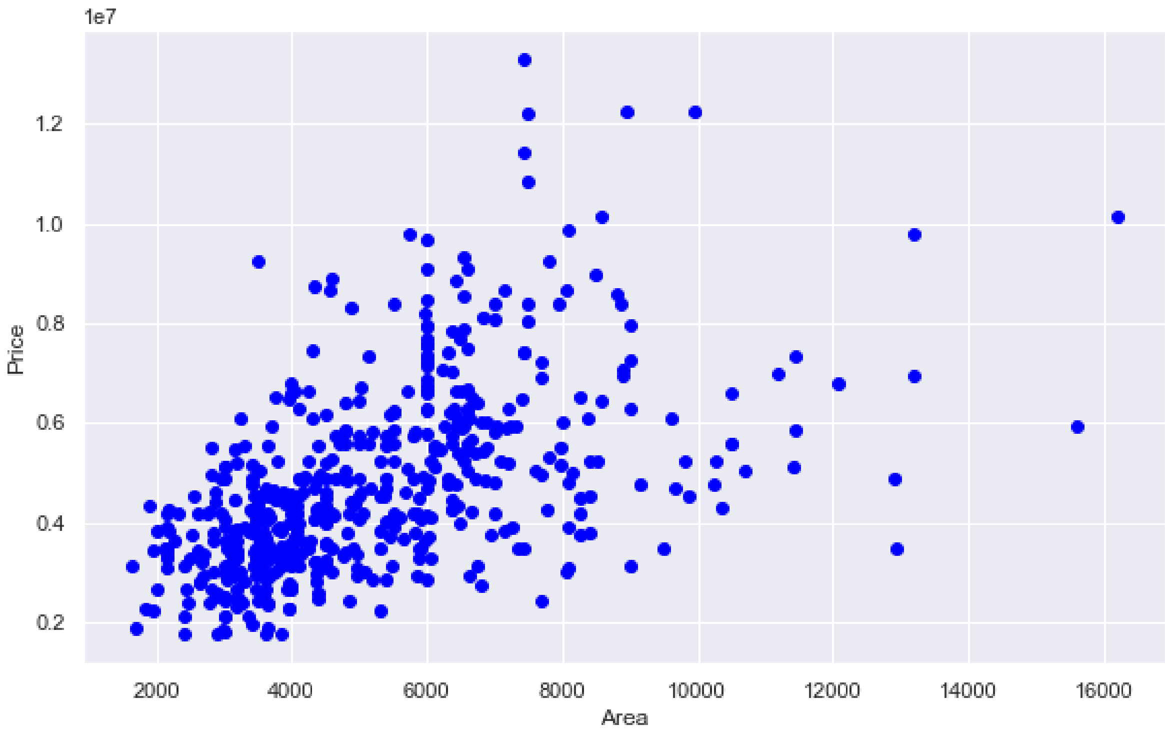
```
Area is highly correlated to price compared to others : So we shall use area
for visualizations
```

In [139]:

```
x_feature = df.area
y_feature = df.price
plt.figure(figsize=(10, 6))
plt.scatter(x_feature, y_feature,c="blue")
plt.xlabel("Area")
plt.ylabel("Price")
```

Out[139]:

```
Text(0, 0.5, 'Price')
```



In [140]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df.drop(columns="area"), df["area"], te
```

In [141]:

```
#KNN
```

In [142]:

```
from sklearn.neighbors import KNeighborsRegressor
```

In [143]:

```
regressor = KNeighborsRegressor(n_neighbors=3)
```

In [144]:

```
regressor.fit(X_train, y_train)
```

Out[144]:

```
▾ KNeighborsRegressor
KNeighborsRegressor(n_neighbors=3)
```

In [145]:

```
predictions=regressor.predict(X_test)
```

In [146]:

```
# Validation
```

In [147]:

```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
```

In [148]:

```
mse = mean_squared_error(y_test, predictions)
print("Mean squared Error:", mse)
```

```
Mean squared Error: 4793420.15188583
```

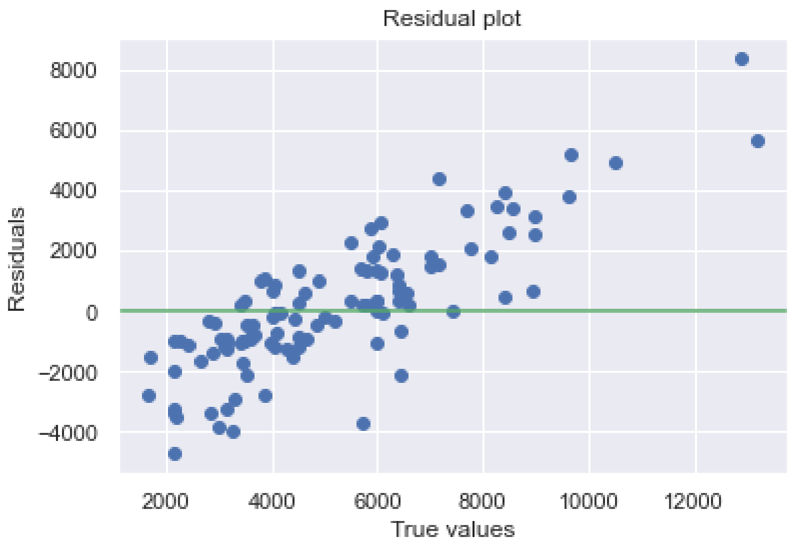
In [149]:

```
mae = mean_absolute_error(y_test, predictions)
print("Mean Absolute Error:", mae)
```

```
Mean Absolute Error: 1641.4220183486236
```

In [150]:

```
residuals = y_test - predictions
plt.scatter(y_test, residuals)
plt.axhline(y=0, color='g')
plt.xlabel("True values")
plt.ylabel("Residuals")
plt.title("Residual plot")
plt.show()
```



In [151]:

```
#Residuals are randomly distributed around the horizontal axis,
#it suggests that the model is a decent fit for the data. "Decent" not "good" because the m
```

Q8

In [152]:

```
df_train=pd.read_csv("train.csv")
```

In [153]:

```
df_test=pd.read_csv("test.csv")
```

In [154]:

```
df_train.dropna(inplace=True)
```

In [155]:

```
df_train.isna().sum()
```

Out[155]:

```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Cabin          0
Embarked       0
dtype: int64
```

In [156]:

```
df_train.drop(columns=["Name","PassengerId"],inplace=True)
```

In [157]:

```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
le.fit(df_train.Embarked)
df_train.Embarked=le.transform(df_train.Embarked)
le.fit(df_train.Cabin)
df_train.Cabin=le.transform(df_train.Cabin)
le.fit(df_train.Ticket)
df_train.Ticket=le.transform(df_train.Ticket)
le.fit(df_train.Sex)
df_train.Sex=le.transform(df_train.Sex)
```

In [158]:

```
corr_matrix = df_train.corr()
print(corr_matrix["Survived"])
```

```
Survived    1.000000
Pclass     -0.034542
Sex        -0.532418
Age        -0.254085
SibSp       0.106346
Parch       0.023582
Ticket      0.022768
Fare        0.134241
Cabin      -0.010664
Embarked   -0.100943
Name: Survived, dtype: float64
```

In [159]:

```
print("Area is highly correlated to Fare,SibSp compared to others : So we shall use area fo
```

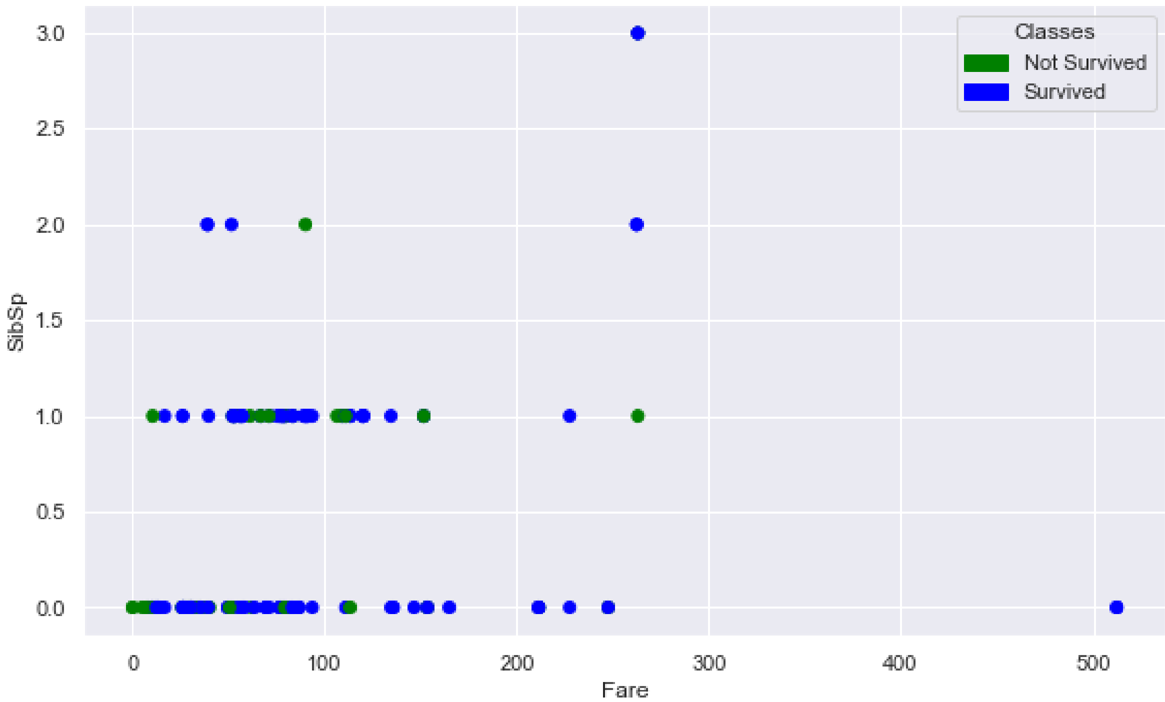
```
Area is highly correlated to Fare,SibSp compared to others : So we shall use
area for visualizations
```

In [160]:

```
x_feature = df_train.Fare
y_feature = df_train.SibSp
plt.figure(figsize=(10, 6))
colors=["green","blue"]
plt.scatter(x_feature, y_feature, c=[colors[label] for label in df_train.Survived])
plt.xlabel("Fare")
plt.ylabel("SibSp")
class_labels = ['Not Survived', 'Survived']
patches = [Patch(color=color, label=label) for color, label in zip(colors, class_labels)]
plt.legend(title='Classes', handles=patches)
```

Out[160]:

```
<matplotlib.legend.Legend at 0x1eb5460afa0>
```



In [161]:

```
df_test.dropna(inplace=True)
```

In [162]:

```
df_test.drop(columns=["Name","PassengerId"],inplace=True)
```

In [163]:

```
le = preprocessing.LabelEncoder()
le.fit(df_test.Embarked)
df_test.Embarked=le.transform(df_test.Embarked)
le.fit(df_test.Cabin)
df_test.Cabin=le.transform(df_test.Cabin)
le.fit(df_test.Ticket)
df_test.Ticket=le.transform(df_test.Ticket)
le.fit(df_test.Sex)
df_test.Sex=le.transform(df_test.Sex)
```

In [164]:

```
X=df_train.drop(columns="Survived")
```

In [165]:

```
Y=df_train.Survived
```

In [166]:

```
# Logistic Regression
```

In [167]:

```
from sklearn.linear_model import LogisticRegression
```

In [168]:

```
classifier = LogisticRegression()
```

In [169]:

```
classifier.fit(X,Y)
```

```
D:\Application\Anaconda\lib\site-packages\sklearn\linear_model\_logistic.py:
444: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scik
it-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)
  n_iter_i = _check_optimize_result(
```

Out[169]:

```
▾ LogisticRegression
LogisticRegression()
```

In [170]:

```
#Train-test split within df_train to carry out validations
```

In [171]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2,random_state=0)
```

In [172]:

```
classifier = LogisticRegression()
```

In [173]:

```
classifier.fit(X_train,y_train)
```

```
D:\Application\Anaconda\lib\site-packages\sklearn\linear_model\_logistic.py:
444: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scik
it-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)
  n_iter_i = _check_optimize_result(
```

Out[173]:

```
▾ LogisticRegression
LogisticRegression()
```

In [174]:

```
predictions=classifier.predict(X_test)
```

In [175]:

```
confusion_matrix_ = confusion_matrix(y_test, predictions)
print("Confusion Matrix : ")
print(confusion_matrix_)
```

```
Confusion Matrix :
[[ 4  3]
 [ 4 26]]
```

In [176]:

```
report = classification_report(y_test, predictions)
print("Overall Report")
print(report)
```

```
Overall Report
              precision    recall  f1-score   support

           0       0.50      0.57      0.53         7
           1       0.90      0.87      0.88        30

    accuracy                           0.81        37
   macro avg       0.70      0.72      0.71        37
weighted avg       0.82      0.81      0.82        37
```

In [ ]:

```

```