Loading the required Libraries

In [78]:

```
#General Libraries
import warnings
warnings.filterwarnings("ignore")

#Data preprocessing & Visualization
%matplotlib inline
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Statistics
import statistics
from statsmodels.stats.outliers_influence import variance_inflation_factor
from scipy import stats
import math

# Sampling for train - test
from sklearn.model_selection import train_test_split

# ML Algorithms
from sklearn.linear_model import LinearRegression,Ridge,Lasso
import statsmodels.api as sm
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor


# Metrics
from sklearn import metrics
from sklearn.metrics import mean_squared_error
```

Setting the working path

In [6]:

```
os.chdir(r"C:\Users\1198472\Desktop")
os.getcwd()
```

Out[6]:

```
'C:\\Users\\1198472\\Desktop'
```

Loading the data to dataframe

In [7]:

```
## Load Data
df = pd.read_excel("Absenteeism_at_work_Project.xls")
```

In [8]:

```
## Check data in the dataset abesnteeism_data
df.head()
```

Out[8]:

	ID	Reason for absence	Month of absence	Day of the week	Seasons	Transportation expense	Distance from Residence to Work	Service time	Age	Work loa Average/da
0	11	26.0	7.0	3	1	289.0	36.0	13.0	33.0	239554
1	36	0.0	7.0	3	1	118.0	13.0	18.0	50.0	239554
2	3	23.0	7.0	4	1	179.0	51.0	18.0	38.0	239554
3	7	7.0	7.0	5	1	279.0	5.0	14.0	39.0	239554
4	11	23.0	7.0	5	1	289.0	36.0	13.0	33.0	239554

5 rows × 21 columns

In [9]:

```
df.shape
```

Out[9]:

```
(740, 21)
```

In [10]:

```
##Check datatypes of columns
df.dtypes
```

Out[10]:

```
ID                                  int64
Reason for absence                float64
Month of absence                  float64
Day of the week                     int64
Seasons                             int64
Transportation expense            float64
Distance from Residence to Work   float64
Service time                      float64
Age                               float64
Work load Average/day             float64
Hit target                        float64
Disciplinary failure              float64
Education                         float64
Son                               float64
Social drinker                    float64
Social smoker                     float64
Pet                               float64
Weight                            float64
Height                            float64
Body mass index                   float64
Absenteeism time in hours         float64
dtype: object
```

In [11]:

```
##Check summary of the data
df.describe()
```

Out[11]:

	ID	Reason for absence	Month of absence	Day of the week	Seasons	Transportation expense	Distance from Residence to Work
count	740.000000	737.000000	739.000000	740.000000	740.000000	733.000000	737.000000
mean	18.017568	19.188602	6.319350	3.914865	2.544595	221.035471	29.667571
std	11.021247	8.437493	3.435948	1.421675	1.111831	66.954179	14.848124
min	1.000000	0.000000	0.000000	2.000000	1.000000	118.000000	5.000000
25%	9.000000	13.000000	3.000000	3.000000	2.000000	179.000000	16.000000
50%	18.000000	23.000000	6.000000	4.000000	3.000000	225.000000	26.000000
75%	28.000000	26.000000	9.000000	5.000000	4.000000	260.000000	50.000000
max	36.000000	28.000000	12.000000	6.000000	4.000000	388.000000	52.000000

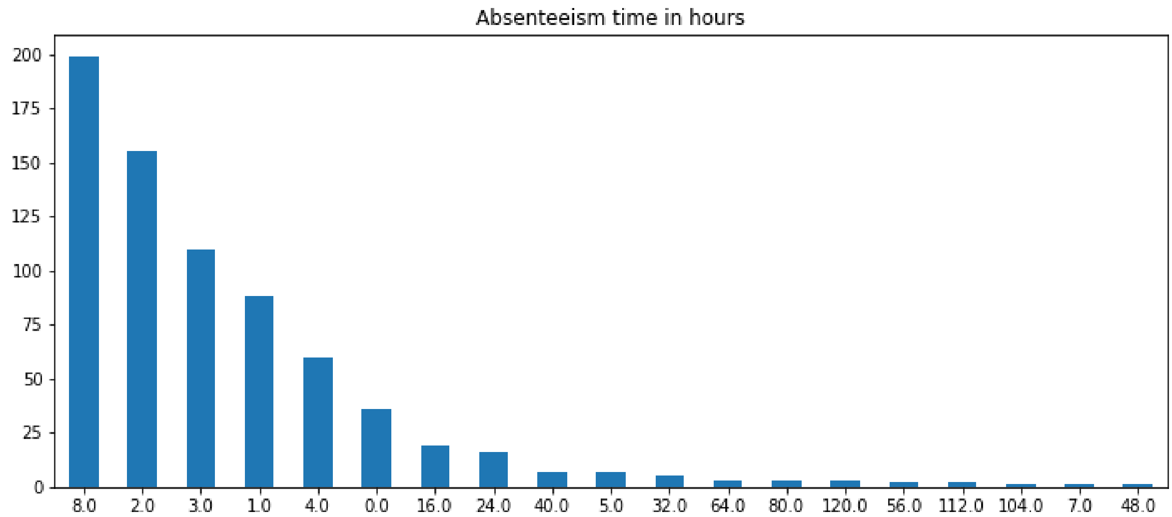
8 rows × 21 columns

In [12]:

```
(df["Absenteeism time in hours"].value_counts().
 plot(kind='bar', title= "Absenteeism time in hours" , rot = 'horizontal', figsize = (12,5)
```

Out[12]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x294183ff748>
```



Summary

1. More no.of persons (~200) are absent for 8 hours.
2. Less no.of persons (~10) are absent for 48 hours.
3. Highest no.of hours a few persons are absent from work is 120 hours.

In [13]:

```
## Separate features into categorical and numerical data set

categorical_set = ["Reason for absence","Month of absence","Day of the week","Seasons","Dis
numerical_set = ["ID","Transportation expense","Distance from Residence to Work","Service t
## Converting categorical_set data into category types from int/float
for i in categorical_set :
    df[i] = df[i].astype("category")
```

In [14]:

```
##Check datatypes of columns
df.dtypes
```

Out[14]:

```
ID                                int64
Reason for absence             category
Month of absence               category
Day of the week                category
Seasons                        category
Transportation expense          float64
Distance from Residence to Work float64
Service time                    float64
Age                             float64
Work load Average/day           float64
Hit target                      float64
Disciplinary failure           category
Education                      category
Son                             float64
Social drinker                 category
Social smoker                  category
Pet                             float64
Weight                          float64
Height                          float64
Body mass index                 float64
Absenteeism time in hours       float64
dtype: object
```

In [15]:

```
## In our data set if the below features has 0 as the value ,since it is  practically not
for i in ["Reason for absence","Month of absence","Day of the week","Seasons","Education","
        df[i] = df[i].replace(0,np.nan)
```

Summary:

1. Convert the datatypes to required datatypes
2. Replaced the illegal 0 values to NaN on certain columns where 0's are not acceptable
3. Identified the target variable and its type.
4. Target variable is a continous variable, So regression problem.
5. Models used for regression problems

```
a. Linear regression
b. Decision tree
c. Random forests
d. XGboost etc..
```

6. Metrics used for regression problems

```
a. RMSE
b. MSE
c. R-squared etc...
```

Missing Value Analysis

In [16]:

```
#Create dataframe with missing percentage
missing_val = pd.DataFrame(df.isnull().sum()).reset_index()
missing_val = missing_val.rename(columns = {'index': 'Variables', 0: 'Missing_percentage'})
missing_val['Missing_percentage'] = (missing_val['Missing_percentage']/len(df))*100
missing_val = missing_val.sort_values('Missing_percentage', ascending = False).reset_index(
print(missing_val)
```

```
                         Variables  Missing_percentage
0                Reason for absence            6.216216
1                   Body mass index            4.189189
2          Absenteeism time in hours           2.972973
3                            Height            1.891892
4             Work load Average/day            1.351351
5                         Education            1.351351
6            Transportation expense            0.945946
7                               Son            0.810811
8              Disciplinary failure            0.810811
9                        Hit target            0.810811
10                    Social smoker            0.540541
11                 Month of absence            0.540541
12                              Age            0.405405
13                     Service time            0.405405
14  Distance from Residence to Work            0.405405
15                   Social drinker            0.405405
16                              Pet            0.270270
17                           Weight            0.135135
18                          Seasons            0.000000
19                  Day of the week            0.000000
20                               ID            0.000000
```

In [17]:

```
##If any feature has more than 30% of missing data then drop that column else perform missi
for i in range(0,len(missing_val)):
    if(missing_val['Missing_percentage'][i]>=30):
        df.drop([i],axis = 1)
```

In [18]:

```
# Manual checking of best method for imputation.

data = df.copy()
column = 'Body mass index'
row = 122
print(f"Selected column : {column}\nSelected row no. : {row}")

x = data[column].loc[row]
print("Actual value : ",x)
data[column].loc[row] = np.nan

#Mean Imputation
data[column] = data[column].fillna(data[column].mean())
print("Mean Imputation : ",data[column].loc[row])
data[column].loc[row] = np.nan

#Median Imputation
data[column] = data[column].fillna(data[column].median())
print("Median Imputation : ",data[column].loc[row])
data[column].loc[row] = np.nan


#KNN imputation - Got some error while installing the "pip install fancyimpute".
#df = pd.DataFrame(KNN(k = 1).fit_transform(data), columns = data.columns)
#print("KNN imputation : ",data[column].loc[row])
#data[column].loc[row]  = x
```

```
Selected column : Body mass index
Selected row no. : 122
Actual value :  24.0
Mean Imputation :  26.687853107344633
Median Imputation :  25.0
```

In [19]:

```
#### Missing value analysis
## Mean mode median method
## Mean for numerical features
##Mode for categorical features
def Null_value_impute(data_set, method):
    for i in data_set.columns.values:
        # mean method of imputing
        if (data_set.loc[:,i].dtypes.name == 'int64'or data_set.loc[:,i].dtypes.name == 'fl
            data_set[i] = round(data_set[i].fillna(data_set[i].mean()))

        ## mode method for categorical features
        elif data_set.loc[:,i].dtypes.name == 'category':
            data_set[i] = data_set[i].fillna(statistics.mode(data_set[i]))

        # median method of imputing
        elif data_set.loc[:,i].dtypes.name == 'int64'or data_set.loc[:,i].dtypes.name == 'f
            data_set[i] = data_set[i].fillna(data_set[i].median())

        # KNN method of imputing
        else:
            data_set = pd.DataFrame(KNN(k=3).complete(data_set),columns = data_set.columns)

    return data_set[0:5]
```

In [20]:

```
Null_value_impute(df, method = 'median')
```

Out[20]:

	ID	Reason for absence	Month of absence	Day of the week	Seasons	Transportation expense	Distance from Residence to Work	Service time	Age	Work loa Average/da
0	11	26.0	7.0	3	1	289.0	36.0	13.0	33.0	239554
1	36	23.0	7.0	3	1	118.0	13.0	18.0	50.0	239554
2	3	23.0	7.0	4	1	179.0	51.0	18.0	38.0	239554
3	7	7.0	7.0	5	1	279.0	5.0	14.0	39.0	239554
4	11	23.0	7.0	5	1	289.0	36.0	13.0	33.0	239554

5 rows × 21 columns

In [21]:

```
if df.isnull().sum().all() == 0:
    print("There are No Null values")
else:
    print("Still there are Null values")
```

```
There are No Null values
```

Data Visualisation

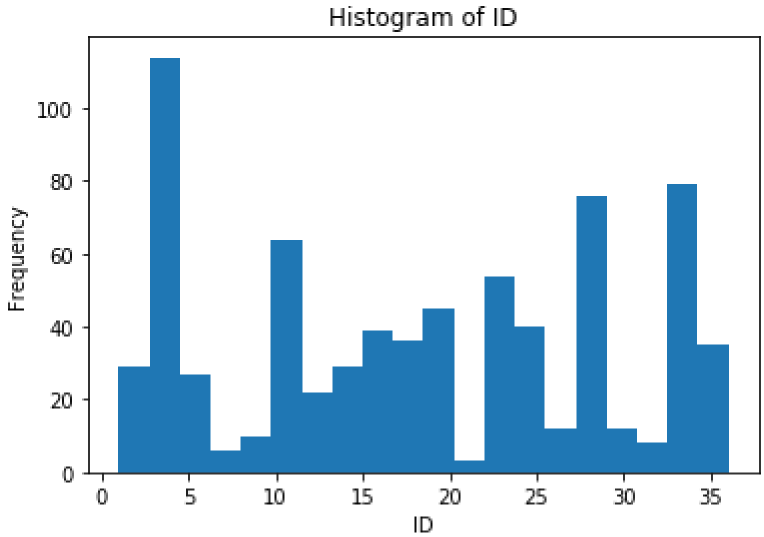
Numerical set

In [22]:

```
%matplotlib inline
plt.hist(df['ID'],bins = 20)
plt.xlabel("ID")
plt.ylabel("Frequency")
plt.title("Histogram of ID")
```

Out[22]:

```
Text(0.5, 1.0, 'Histogram of ID')
```

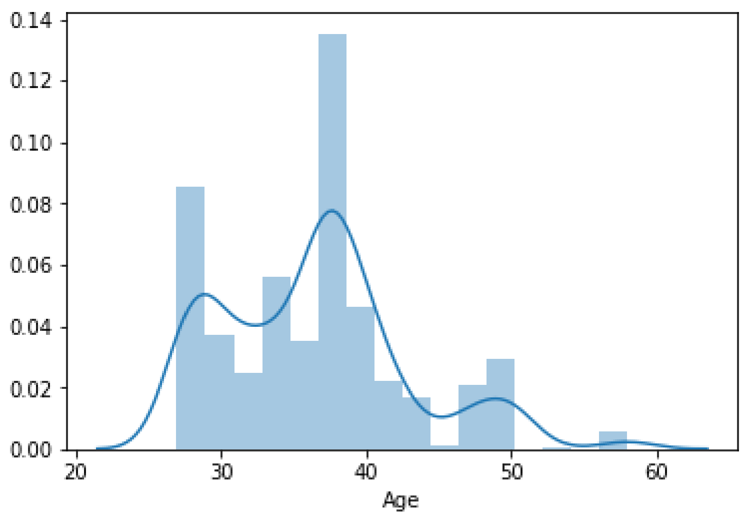


In [23]:

```
sns.distplot(df['Age'])
```

Out[23]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29418633208>
```

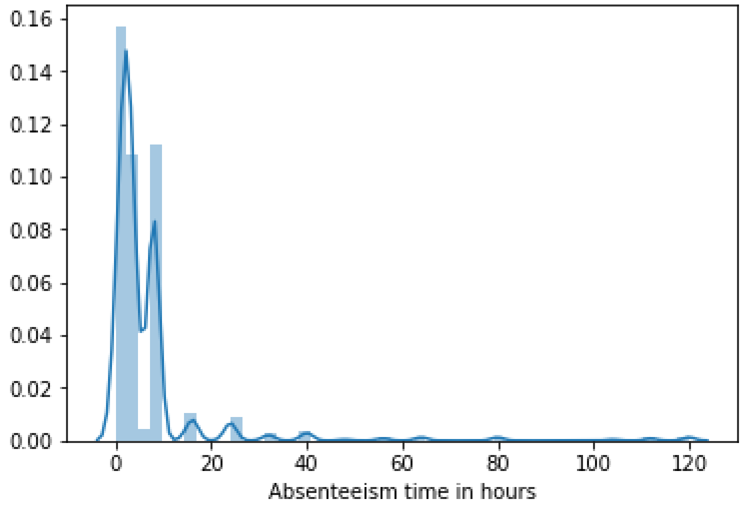


In [24]:

```
sns.distplot(df['Absenteeism time in hours'])
```

Out[24]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29418712d68>
```

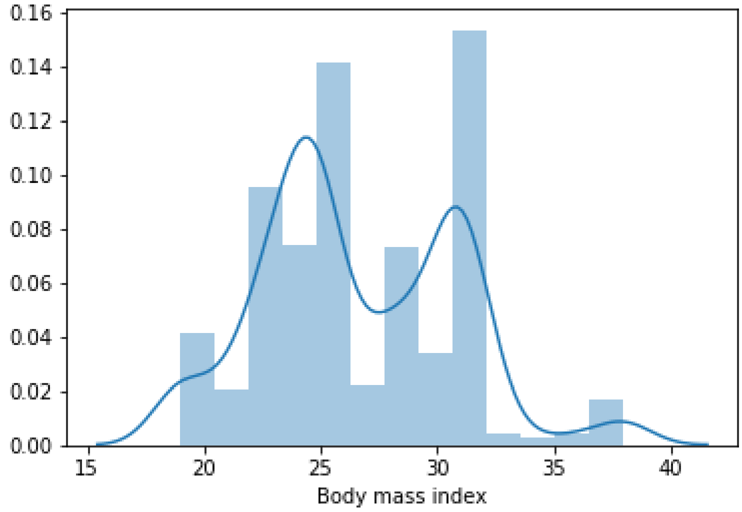


In [25]:

```
sns.distplot(df['Body mass index'])
```

Out[25]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29418a6a588>
```

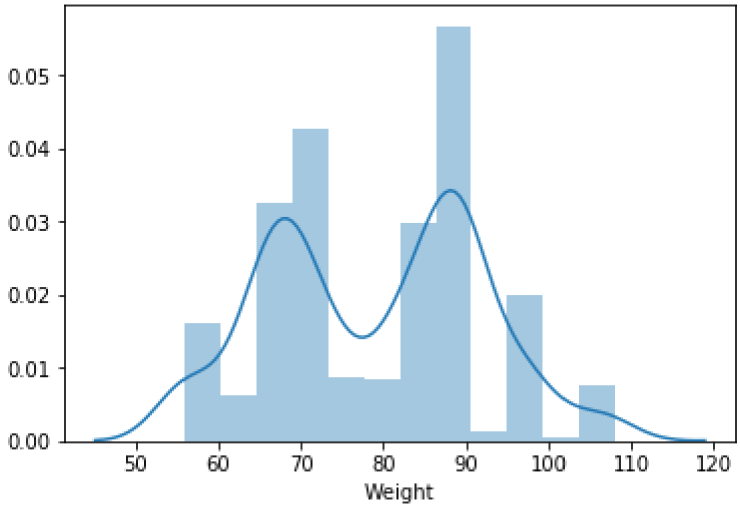


In [26]:

```
sns.distplot(df['Weight'])
```

Out[26]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29418b21cc0>
```

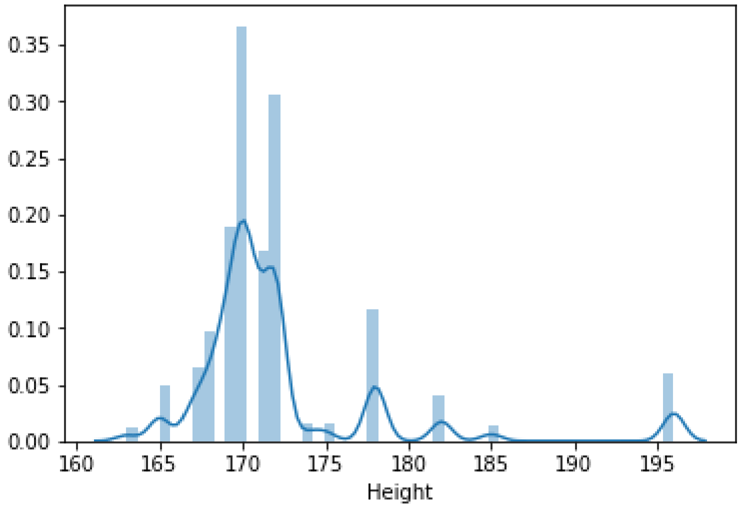


In [27]:

```
sns.distplot(df['Height'])
```

Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29418b92e10>
```

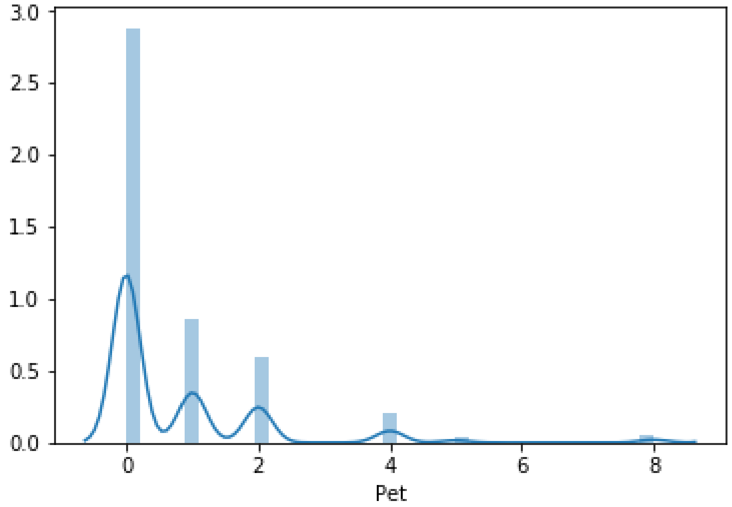


In [28]:

```
sns.distplot(df['Pet'])
```

Out[28]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29418a940b8>
```

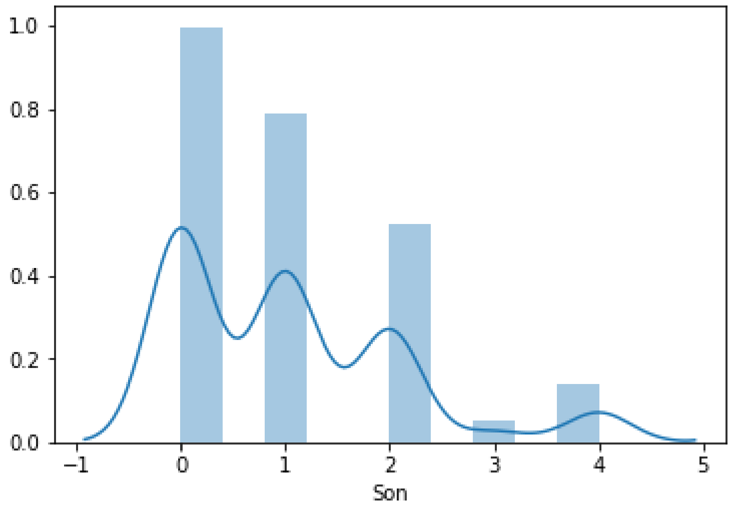


In [29]:

```
sns.distplot(df['Son'])
```

Out[29]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29419cf3390>
```

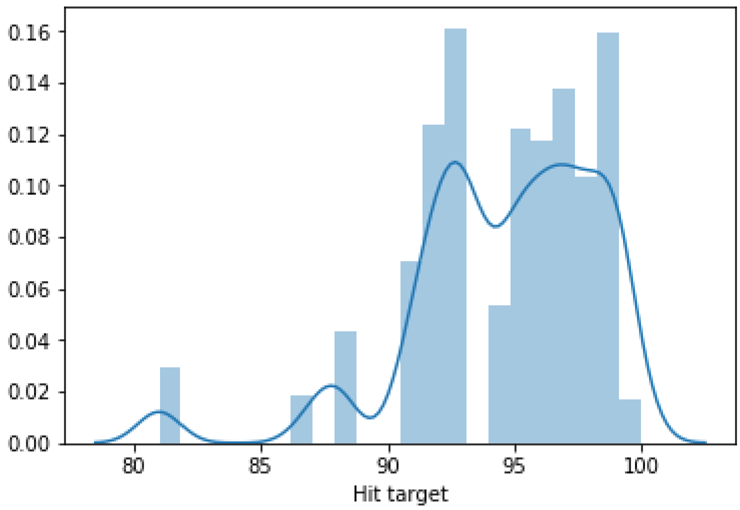


In [30]:

```
sns.distplot(df['Hit target'])
```

Out[30]:

<matplotlib.axes._subplots.AxesSubplot at 0x29419d69b00>

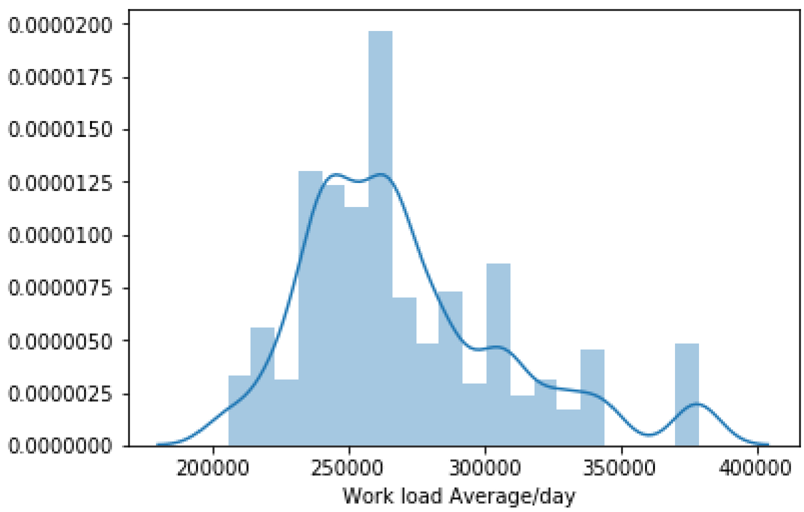


In [31]:

```
sns.distplot(df['Work load Average/day '])
```

Out[31]:

<matplotlib.axes._subplots.AxesSubplot at 0x29419df36a0>

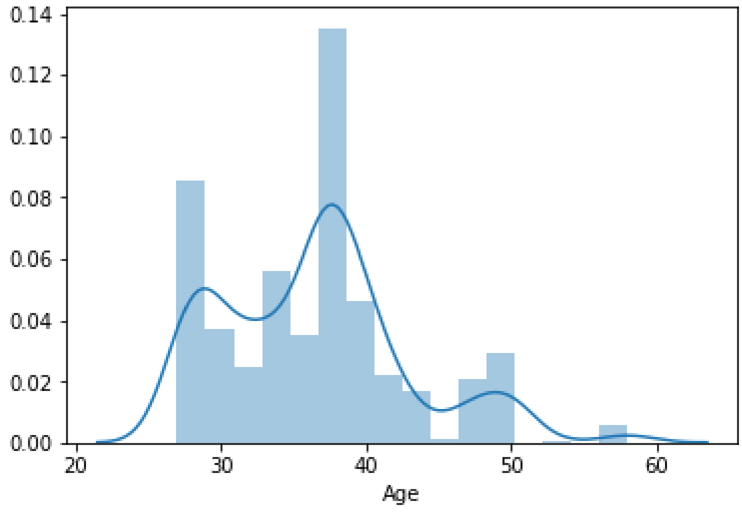


In [32]:

```
sns.distplot(df['Age'])
```

Out[32]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29419e8e978>
```

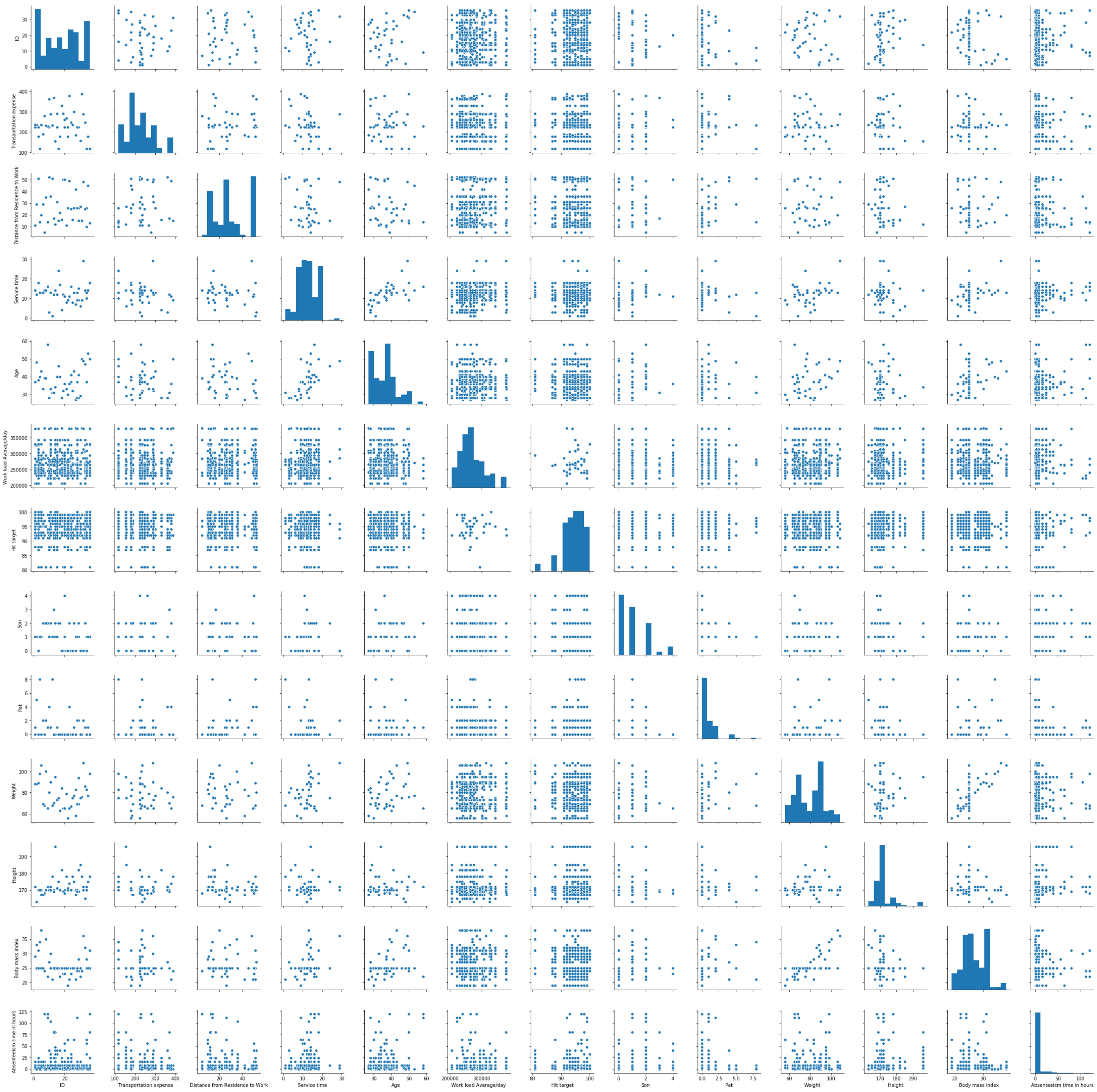


In [33]:

```
%matplotlib inline
sns.pairplot(df[numerical_set[0:13]])
```

Out[33]:

```
<seaborn.axisgrid.PairGrid at 0x29419e5ed68>
```



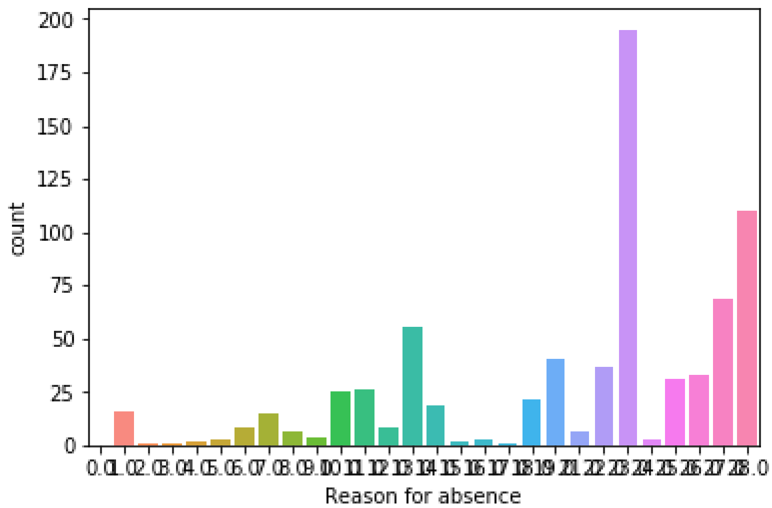
Summary:

1. Most of the people are in the age of 30-40 years with workload average of 250000/day and 95-100% succesful delivery rate
2. Most people are in the height range of 170 CM, weight ranges of 60-70 & 80-90KG's with BMI ranges 20 - 30

Categorical feature set

In [34]:

```
ax = sns.countplot(df["Reason for absence"],saturation=1)
```

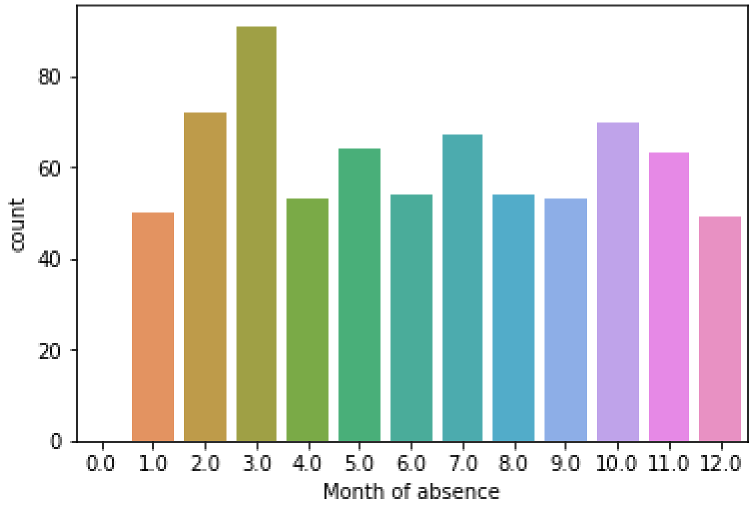


In [35]:

```
sns.countplot(df["Month of absence"])
```

Out[35]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29421dd0828>
```

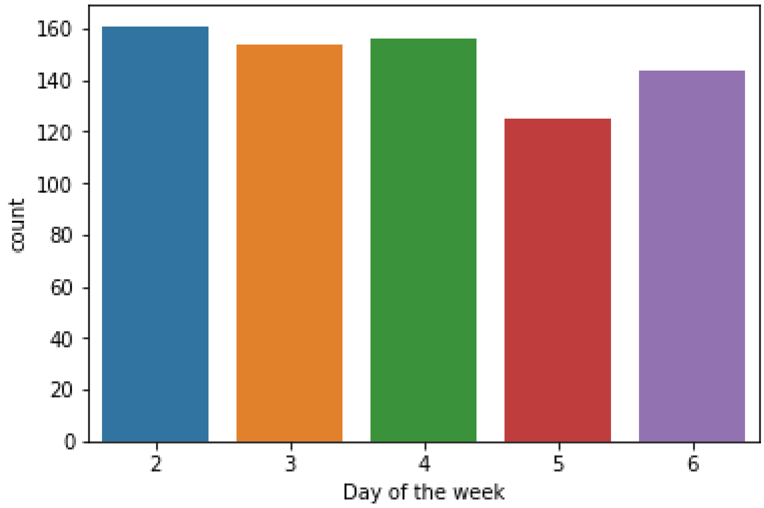


In [36]:

```
sns.countplot(df["Day of the week"])
```

Out[36]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29421dcb198>
```

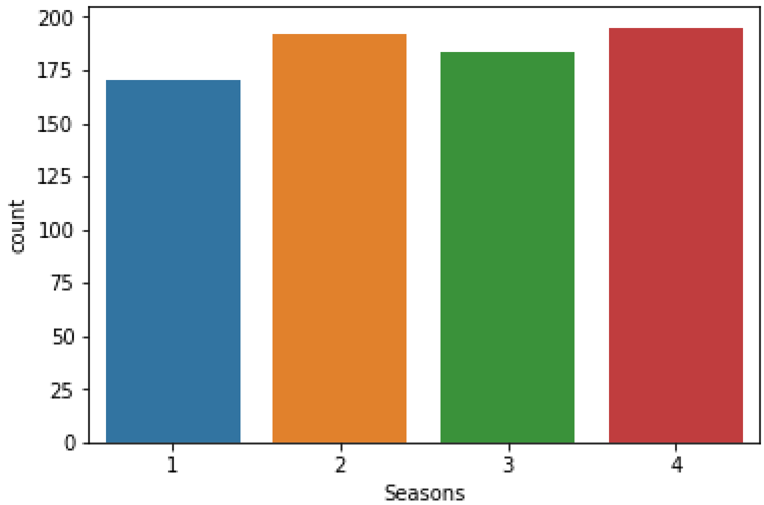


In [37]:

```
sns.countplot(df["Seasons"])
```

Out[37]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29421e90438>
```

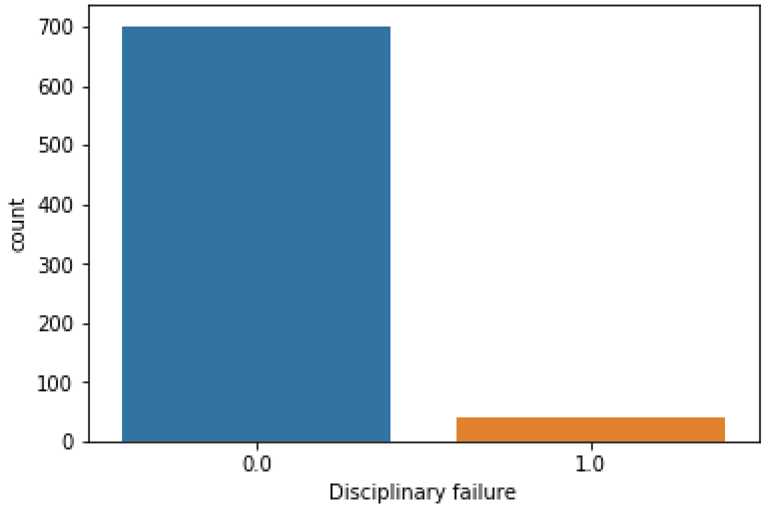


In [38]:

```
sns.countplot(df["Disciplinary failure"])
```

Out[38]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29421e85c18>
```

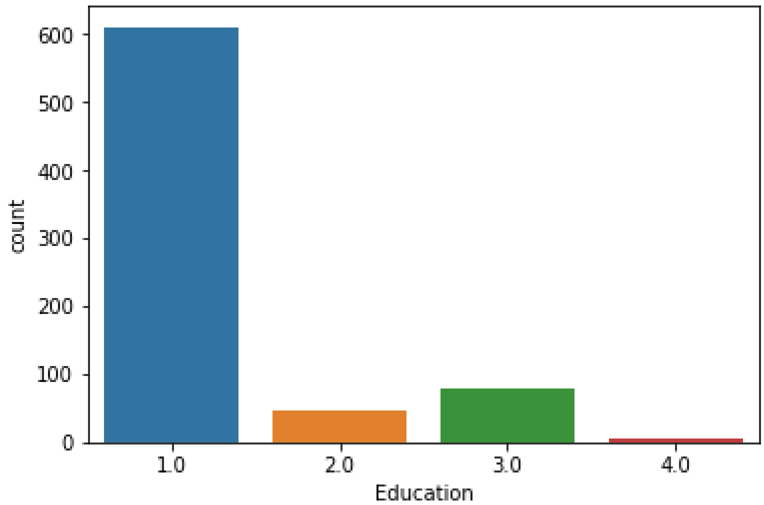


In [39]:

```
sns.countplot(df["Education"])
```

Out[39]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29421f50668>
```

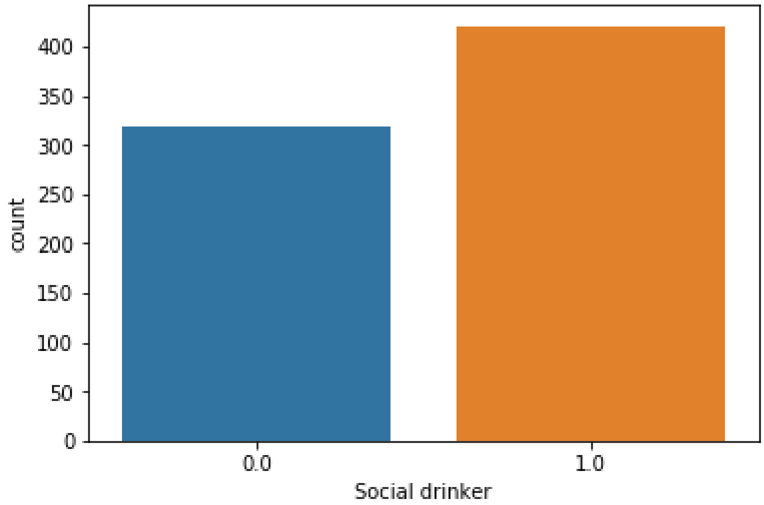


In [40]:

```
sns.countplot(df["Social drinker"])
```

Out[40]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29421f9afd0>
```

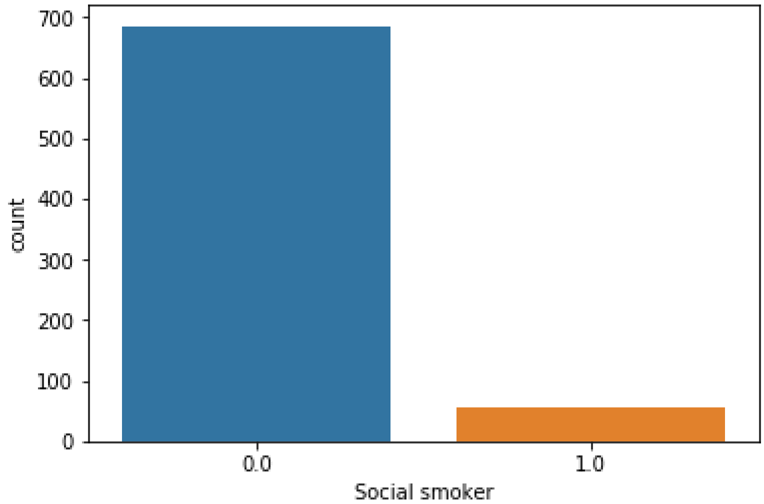


In [41]:

```
sns.countplot(df["Social smoker"])
```

Out[41]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29422007080>
```



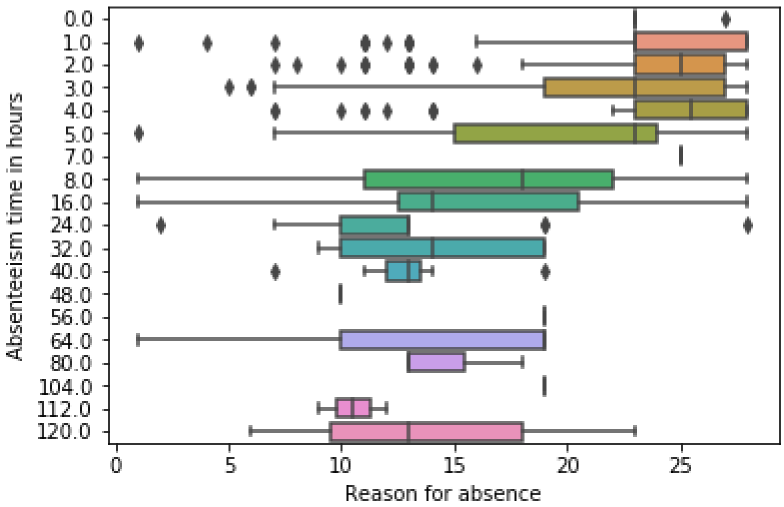
Categorical feature set vs Target variable

In [42]:

```
sns.boxplot(df['Reason for absence'],df['Absenteeism time in hours'], orient="h")
```

Out[42]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2942204ccc0>
```

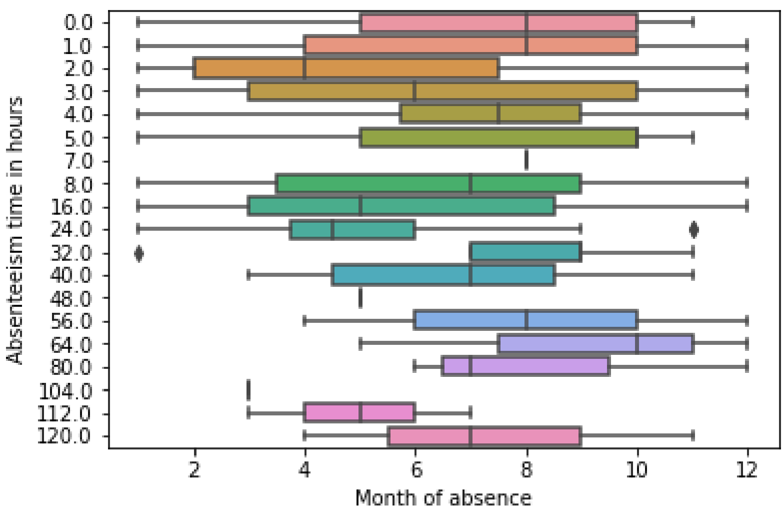


In [43]:

```
%matplotlib inline
sns.boxplot(df['Month of absence'],df['Absenteeism time in hours'], orient="h")
```

Out[43]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29423180588>
```

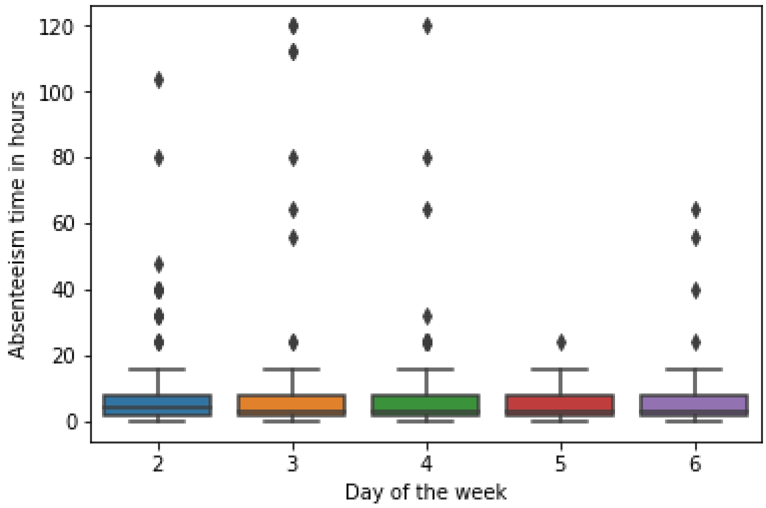


In [44]:

```
sns.boxplot(df['Day of the week'],df['Absenteeism time in hours'])
```

Out[44]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x294233442b0>
```

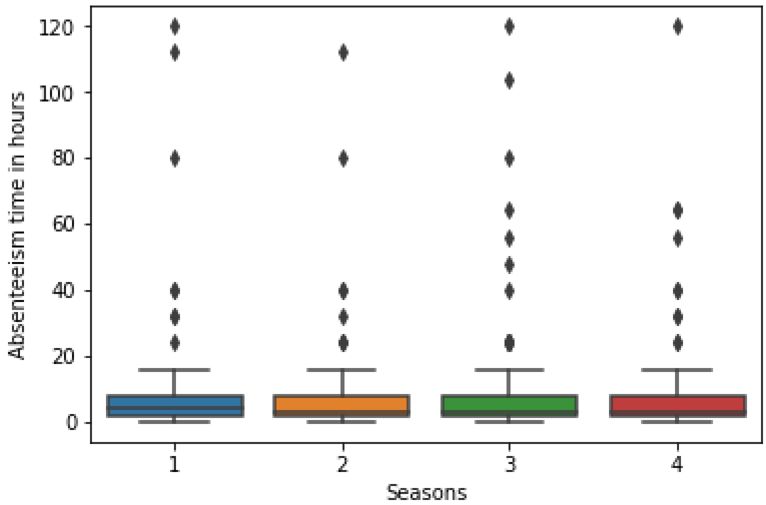


In [45]:

```
sns.boxplot(df['Seasons'],df['Absenteeism time in hours'])
```

Out[45]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29423416780>
```

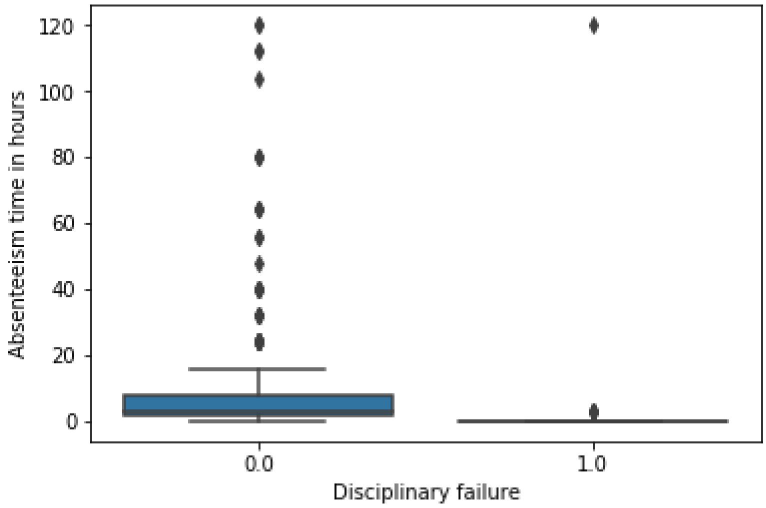


In [46]:

```
%matplotlib inline
sns.boxplot(df['Disciplinary failure'],df['Absenteeism time in hours'])
```

Out[46]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29423492b70>
```

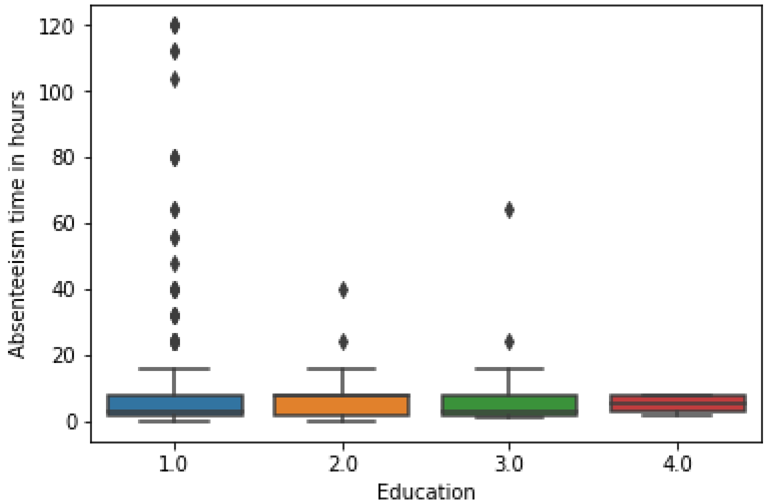


In [47]:

```
sns.boxplot(df['Education'],df['Absenteeism time in hours'])
```

Out[47]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2942350dba8>
```

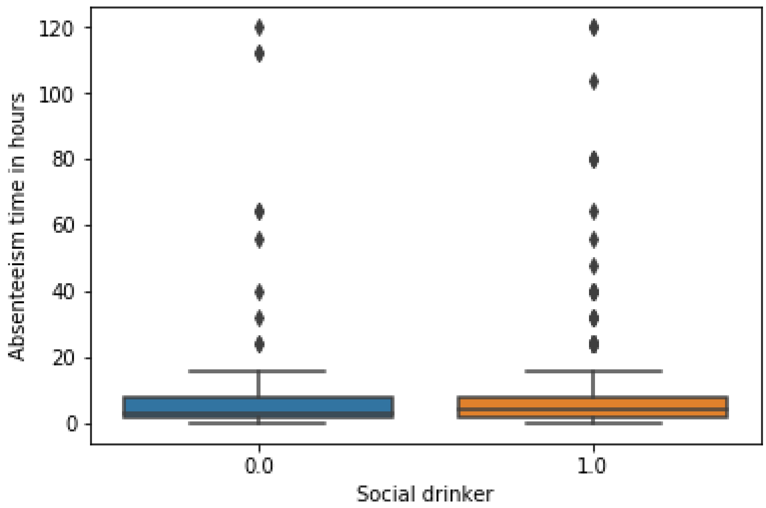


In [48]:

```
sns.boxplot(df['Social drinker'],df['Absenteeism time in hours'])
```

Out[48]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29423599eb8>
```

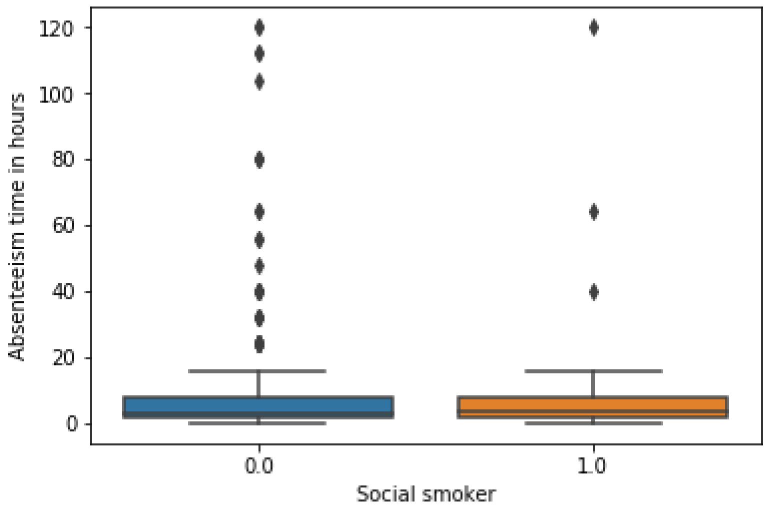


In [49]:

```
sns.boxplot(df['Social smoker'],df['Absenteeism time in hours'])
```

Out[49]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2942360cb70>
```



Summary:

1. What changes company should bring to reduce the number of absenteeism?

Company should bring a good medical plan for their employess, reduce the workload on each employees by recruting the people and motivate the people towards work by providing rewards or

incentives on timely basis.

Summary from the visualization:

Absenteeism time in hours:

```
More no.of persons (200) are absent for 8 hours.
Less no.of persons (~10) are absent for 48 hours.
Highest no.of hours a few persons are absent from work is 120 hours.
```

Numerical data sumary:

```
Most of the people are in the age of 30-40 years with workload average of 250000/d
ay and 95-100% succesful delivery rate
Most people are in the height range of 170 CM, weight ranges of 60-70 & 80-90KG's
 with BMI ranges 20 - 30
```

Categorical data summary:

```
Most no of people said the reason as medical consultation (23) for their absent.
We can see more no of absents in the march month.
Almost everyday, there are 140-160 are getting absent to work. This is same for ev
ery season
Most of the people who work are from high school education and there are very less
no of persons from master graduate & doctor's
There are more drinkers than smokers.
We cann see lot of outliers in the data that should be cleaned are modified.
```

Outlier Analysis

In [50]:

```
##Outlier analysis
## Replace outliers with NaN
for i in numerical_set:
    q75,q25 = np.percentile(df[i],[75,25])
    iqr = q75-q25
    min_bar = (q25-(1.5*iqr))
    max_bar = (q75+(1.5*iqr))
    print(f"{i} : min({min_bar}), max({max_bar})")
    print("-"*50)
    df.loc[df[i]<min_bar,i] = np.nan
    df.loc[df[i]>max_bar,i] = np.nan
```

```
ID : min(-19.5), max(56.5)
--------------------------------------------------
Transportation expense : min(57.5), max(381.5)
--------------------------------------------------
Distance from Residence to Work : min(-35.0), max(101.0)
--------------------------------------------------
Service time : min(-1.5), max(26.5)
--------------------------------------------------
Age : min(17.5), max(53.5)
--------------------------------------------------
Work load Average/day  : min(183688.0), max(345552.0)
--------------------------------------------------
Hit target : min(87.0), max(103.0)
--------------------------------------------------
Son : min(-3.0), max(5.0)
--------------------------------------------------
Pet : min(-1.5), max(2.5)
--------------------------------------------------
Weight : min(39.0), max(119.0)
--------------------------------------------------
Height : min(164.5), max(176.5)
--------------------------------------------------
Body mass index : min(13.5), max(41.5)
--------------------------------------------------
Absenteeism time in hours : min(-7.0), max(17.0)
--------------------------------------------------
```

In [51]:

```
#impute NaN with median mode
## median mode method for imputation
Null_value_impute(df, method = 'median')
#df
```

Out[51]:

	ID	Reason for absence	Month of absence	Day of the week	Seasons	Transportation expense	Distance from Residence to Work	Service time	Age	Work l Average/
0	11.0	26.0	7.0	3	1	289.0	36.0	13.0	33.0	2395!
1	36.0	23.0	7.0	3	1	118.0	13.0	18.0	50.0	2395!
2	3.0	23.0	7.0	4	1	179.0	51.0	18.0	38.0	2395!
3	7.0	7.0	7.0	5	1	279.0	5.0	14.0	39.0	2395!
4	11.0	23.0	7.0	5	1	289.0	36.0	13.0	33.0	2395!

5 rows × 21 columns

Feature Selection

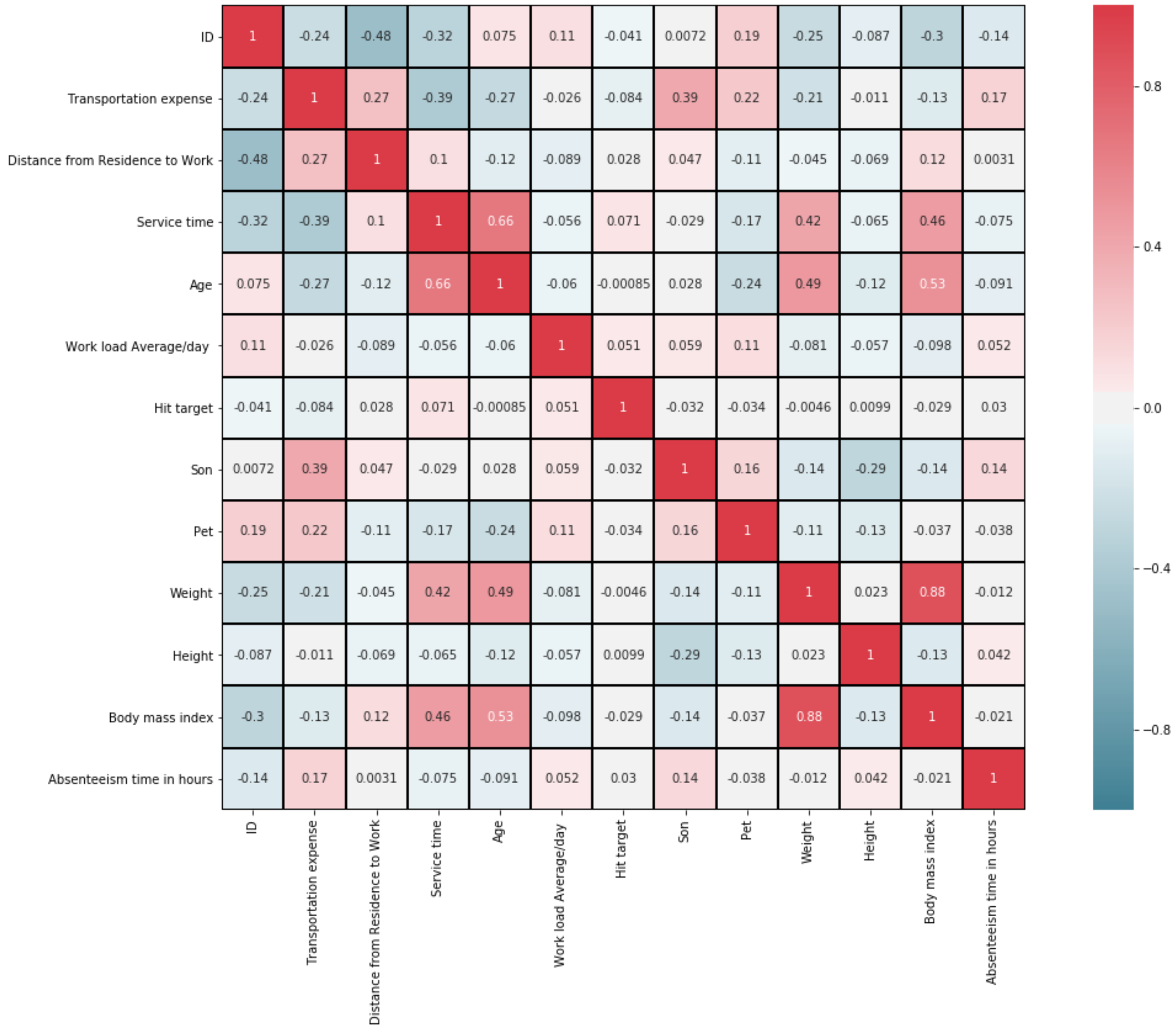
Correlation Analysis

In [52]:

```
#let us see the correlation
data_corr=df.loc[:,numerical_set]

#generating correlation matrix
corr=data_corr.corr()

#Setting up the pane or matrix size
f, ax = plt.subplots(figsize=(20,12))

#Plot using Seaborn library
sns.heatmap(corr,mask=np.zeros_like(corr, dtype=np.bool), cmap=sns.diverging_palette(220,10
            square=True, ax=ax,annot=True,linewidths=1 , linecolor= 'black',vmin = -1, vmax
```

Out[52]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2942366dd30>
```



	ID	Transportation expense	Distance from Residence to Work	Service time	Age	Work load Average/day	Hit target	Son	Pet	Weight	Height	Body mass index	Absenteeism time in hours
ID	1	-0.24	-0.48	-0.32	0.075	0.11	-0.041	0.0072	0.19	-0.25	-0.087	-0.3	-0.14
Transportation expense	-0.24	1	0.27	-0.39	-0.27	-0.026	-0.084	0.39	0.22	-0.21	-0.011	-0.13	0.17
Distance from Residence to Work	-0.48	0.27	1	0.1	-0.12	-0.089	0.028	0.047	-0.11	-0.045	-0.069	0.12	0.0031
Service time	-0.32	-0.39	0.1	1	0.66	-0.056	0.071	-0.029	-0.17	0.42	-0.065	0.46	-0.075
Age	0.075	-0.27	-0.12	0.66	1	-0.06	-0.00085	0.028	-0.24	0.49	-0.12	0.53	-0.091
Work load Average/day	0.11	-0.026	-0.089	-0.056	-0.06	1	0.051	0.059	0.11	-0.081	-0.057	-0.098	0.052
Hit target	-0.041	-0.084	0.028	0.071	-0.00085	0.051	1	-0.032	-0.034	-0.0046	0.0099	-0.029	0.03
Son	0.0072	0.39	0.047	-0.029	0.028	0.059	-0.032	1	0.16	-0.14	-0.29	-0.14	0.14
Pet	0.19	0.22	-0.11	-0.17	-0.24	0.11	-0.034	0.16	1	-0.11	-0.13	-0.037	-0.038
Weight	-0.25	-0.21	-0.045	0.42	0.49	-0.081	-0.0046	-0.14	-0.11	1	0.023	0.88	-0.012
Height	-0.087	-0.011	-0.069	-0.065	-0.12	-0.057	0.0099	-0.29	-0.13	0.023	1	-0.13	0.042
Body mass index	-0.3	-0.13	0.12	0.46	0.53	-0.098	-0.029	-0.14	-0.037	0.88	-0.13	1	-0.021
Absenteeism time in hours	-0.14	0.17	0.0031	-0.075	-0.091	0.052	0.03	0.14	-0.038	-0.012	0.042	-0.021	1

VIF(Variance Inflation Factor)

In [53]:

```
#Multicollinearity check - VIF
X = df[numerical_set].assign(const = 1)
pd.Series([variance_inflation_factor(X.values,i) for i in range(X.shape[1])],index=X.column
#only Weight and Body mass index has VIF >5 .Thus we will remove one of them
```

Out[53]:

```
ID                                     2.555528
Transportation expense                 2.199472
Distance from Residence to Work        1.593952
Service time                           3.443374
Age                                    3.501619
Work load Average/day                  1.042375
Hit target                             1.024523
Son                                    1.532156
Pet                                    1.458590
Weight                                 6.039502
Height                                 1.328574
Body mass index                        7.227522
Absenteeism time in hours              1.082891
const                              14722.123211
dtype: float64
```

In [54]:

```
## Performing one way ANOVA on categorical dataset
for i in categorical_set:
    print(i)
    print(stats.f_oneway(df[i],df['Absenteeism time in hours']))
    print("="*50)
```

```
Reason for absence
F_onewayResult(statistic=3326.088836175677, pvalue=0.0)
==================================================
Month of absence
F_onewayResult(statistic=149.391598795114, pvalue=8.502044431590593e-33)
==================================================
Day of the week
F_onewayResult(statistic=4.344633101981018, pvalue=0.03729711354406971)
==================================================
Seasons
F_onewayResult(statistic=164.8759113241966, pvalue=7.43274223297258e-36)
==================================================
Disciplinary failure
F_onewayResult(statistic=1154.6532791575944, pvalue=1.6372426248884337e-187)
==================================================
Education
F_onewayResult(statistic=546.5398916261591, pvalue=4.1194026059897665e-103)
==================================================
Social drinker
F_onewayResult(statistic=869.0362524023035, pvalue=1.2809993353034328e-150)
==================================================
Social smoker
F_onewayResult(statistic=1141.5220610928714, pvalue=6.6118550765910436e-186)
==================================================
```

Dimension reduction

Chi square test

from scipy.stats import ttest_1samp import numpy as np

print(df['passenger_count'].head()) passenger_count_mean = np.mean(df['passenger_count'].values) print(passenger_count_mean) tset, pval = ttest_1samp(passenger_count_mean, 4) print('p-values',pval) if pval < 0.05: # alpha value is 0.05 or 5% print(" we are rejecting null hypothesis") else: print("we are accepting null hypothesis")

In [55]:

```
## Dimension reduction
df = df.drop(["Weight","Day of the week","Seasons","Education","Social smoker","Social drin
df.head()
```

Out[55]:

	ID	Reason for absence	Month of absence	Transportation expense	Distance from Residence to Work	Service time	Age	Work load Average/day	Hit target	Disc
0	11.0	26.0	7.0	289.0	36.0	13.0	33.0	239554.0	97.0	
1	36.0	23.0	7.0	118.0	13.0	18.0	50.0	239554.0	97.0	
2	3.0	23.0	7.0	179.0	51.0	18.0	38.0	239554.0	97.0	
3	7.0	7.0	7.0	279.0	5.0	14.0	39.0	239554.0	97.0	
4	11.0	23.0	7.0	289.0	36.0	13.0	33.0	239554.0	97.0	

Metrics in Crossvalidation: https://scikit-learn.org/stable/modules/model_evaluation.html#scoring (https://scikit-learn.org/stable/modules/model_evaluation.html#scoring)

Sampling or Train- test split

In [56]:

```
df.dtypes
```

Out[56]:

```
ID                                 float64
Reason for absence                category
Month of absence                  category
Transportation expense             float64
Distance from Residence to Work    float64
Service time                       float64
Age                                float64
Work load Average/day              float64
Hit target                         float64
Disciplinary failure              category
Son                                float64
Pet                                float64
Height                             float64
Body mass index                    float64
Absenteeism time in hours          float64
dtype: object
```

In [57]:

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

Out[57]:

```
ID                                0
Reason for absence                0
Month of absence                  0
Transportation expense            0
Distance from Residence to Work   0
Service time                      0
Age                               0
Work load Average/day             0
Hit target                        0
Disciplinary failure              0
Son                               0
Pet                               0
Height                            0
Body mass index                   0
Absenteeism time in hours         0
dtype: int64
```

In [58]:

```
for i in df.columns.values:
    df[i] = df[i].astype('float')

df.dtypes
```

Out[58]:

```
ID                                float64
Reason for absence                float64
Month of absence                  float64
Transportation expense            float64
Distance from Residence to Work   float64
Service time                      float64
Age                               float64
Work load Average/day             float64
Hit target                        float64
Disciplinary failure              float64
Son                               float64
Pet                               float64
Height                            float64
Body mass index                   float64
Absenteeism time in hours         float64
dtype: object
```

In [59]:

```
df_final = df.copy()
Y = df_final['Absenteeism time in hours'].values
df_final.drop('Absenteeism time in hours', axis=1, inplace=True)
X = df_final

# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_spli
from sklearn.model_selection import train_test_split

# Splitting train & test data.

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33, random_state=42)

# this is Stratified splitting
print('Train shape:',X_train.shape, y_train.shape)
print('Test Shape:',X_test.shape, y_test.shape)
print("="*100)
```

```
Train shape: (495, 14) (495,)
Test Shape: (245, 14) (245,)
============================================================================
========================
```

Model Development

In [60]:

```
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression,Ridge,Lasso
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor
import xgboost as xgb

from sklearn.metrics import mean_squared_error
from sklearn import metrics
```

In [61]:

```
X_train = X_train
y_train = y_train
X_test = X_test
y_test = y_test
```

In [62]:

```
def model_and_metrics(X_train, y_train, X_test, y_test, model):

    """ Common function for Model BuildUP & metrics """

    print("===================Building the model... ===========================")
    model = model
    #Train the algorithm
    model.fit(X_train, y_train)
    # predict the response
    y_pred = model.predict(X_test)
    print("Model {} ran successfully..".format(model))
    print('\n')

    print("======================== Score's ===================================")
    print('r square : ', metrics.r2_score(y_test, y_pred))
    print('Adjusted r square : {}'.format(1 - (1-metrics.r2_score(y_test, y_pred))*
                                          (len(y_test)-1)/(len(y_test)-X_train.shape[1]-1))
    print('MSE :', metrics.mean_squared_error(y_test, y_pred))
    print('RMSE :', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

LinearRegression

In [63]:

```
model = LinearRegression()
model_and_metrics(X_train, y_train, X_test, y_test, model)
```

```
===================Building the model... ===========================
Model LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False) ran successfully..


======================== Score's ===================================
r square :  0.1619149462136349
Adjusted r square : 0.11090107337446486
MSE : 7.563276053740129
RMSE : 2.7501410970603177
```

LinearRegression with statsmodels

In [64]:

```
import statsmodels.api as sm
modelLR = sm.OLS(y_train,X_train,data = df_final).fit()
print(modelLR.summary())
## Predict
predictLR = modelLR.predict(X_test)
#RMSE
print(f"RMSE value : {math.sqrt(mean_squared_error(y_test,predictLR))}")
```

```
                            OLS Regression Results
=============================================================================
==
Dep. Variable:                      y   R-squared:                       0.7
11
Model:                            OLS   Adj. R-squared:                  0.7
03
Method:                 Least Squares   F-statistic:                     84.
70
Date:                Thu, 13 Feb 2020   Prob (F-statistic):          5.93e-1
20
Time:                        17:27:27   Log-Likelihood:                -123
7.9
No. Observations:                 495   AIC:                             250
4.
Df Residuals:                     481   BIC:                             256
3.
Df Model:                          14
Covariance Type:            nonrobust
=============================================================================
=======================
                                      coef    std err          t      P>|t|
[0.025      0.975]
-----------------------------------------------------------------------------
-----------------------
ID                                 -0.0540      0.020     -2.713      0.007
-0.093      -0.015
Reason for absence                 -0.1626      0.020     -7.963      0.000
-0.203      -0.122
Month of absence                   -0.0218      0.045     -0.483      0.630
-0.111       0.067
Transportation expense              0.0060      0.003      1.986      0.048
6.34e-05       0.012
Distance from Residence to Work    -0.0251      0.011     -2.311      0.021
-0.046      -0.004
Service time                       -0.0614      0.061     -1.007      0.314
-0.181       0.058
Age                                -0.0239      0.043     -0.562      0.574
-0.108       0.060
Work load Average/day            6.835e-06   4.31e-06      1.586      0.113
-1.63e-06    1.53e-05
Hit target                          0.0115      0.047      0.243      0.808
-0.081       0.104
Disciplinary failure               -4.0336      0.638     -6.323      0.000
-5.287      -2.780
Son                                 0.4247      0.141      3.012      0.003
0.148       0.702
Pet                                -0.5629      0.228     -2.471      0.014
-1.011      -0.115
Height                              0.0362      0.029      1.236      0.217
-0.021       0.094
```

```
Body mass index                    0.0275      0.044      0.628      0.530
-0.058       0.113
============================================================================
==
Omnibus:                        147.752   Durbin-Watson:                  1.8
49
Prob(Omnibus):                    0.000   Jarque-Bera (JB):             423.6
74
Skew:                             1.433   Prob(JB):                    1.00e-
92
Kurtosis:                         6.511   Cond. No.                    1.28e+
06
============================================================================
==

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
[2] The condition number is large, 1.28e+06. This might indicate that there
are
strong multicollinearity or other numerical problems.
RMSE value : 2.749753681856593
```

Ridge

In [65]:

```
model = Ridge()
model_and_metrics(X_train, y_train, X_test, y_test, model)
```

```
===================Building the model... ===========================
Model Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001) ran success
fully..


======================== Score's ===================================
r square :  0.16290132541040903
Adjusted r square : 0.11194749304408602
MSE : 7.55437450117674
RMSE : 2.7485222395274045
```

Lasso

In [66]:

```
model = Lasso()
model_and_metrics(X_train, y_train, X_test, y_test, model)
```

```
===================Building the model... ===========================
Model Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False) ran successfully..


======================== Score's ===================================
r square :  0.10909471500822399
Adjusted r square : 0.05486569766089855
MSE : 8.039950811300876
RMSE : 2.8354807019799795
```

KNeighborsRegressor

In [67]:

```
model = KNeighborsRegressor()
model_and_metrics(X_train, y_train, X_test, y_test, model)
```

```
===================Building the model... ===========================
Model KNeighborsRegressor(algorithm='auto', leaf_size=30, metric='minkowsk
i',
          metric_params=None, n_jobs=None, n_neighbors=5, p=2,
          weights='uniform') ran successfully..


======================== Score's ===================================
r square :  -0.19719804908306182
Adjusted r square : -0.270070973809857
MSE : 10.80408163265306
RMSE : 3.286956287000644
```

DecisionTreeRegressor

In [68]:

```
model = DecisionTreeRegressor()
model_and_metrics(X_train, y_train, X_test, y_test, model)
```

```
===================Building the model... ===========================
Model DecisionTreeRegressor(criterion='mse', max_depth=None, max_features=No
ne,
           max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           presort=False, random_state=None, splitter='best') ran successful
ly..


======================== Score's ===================================
r square :  -0.6504395413528308
Adjusted r square : -0.7509010786525685
MSE : 14.894347303849734
RMSE : 3.859319538966647
```

RandomForestRegressor

In [69]:

```
model = RandomForestRegressor(max_depth=2,n_estimators=10,random_state=0,max_features=10)
model_and_metrics(X_train, y_train, X_test, y_test, model)
```

```
===================Building the model... ===========================
Model RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=2,
           max_features=10, max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           n_estimators=10, n_jobs=None, oob_score=False, random_state=0,
           verbose=0, warm_start=False) ran successfully..


======================== Score's ===================================
r square :  0.21175865984268571
Adjusted r square : 0.16377875218093607
MSE : 7.1134627990866495
RMSE : 2.667107571712594
```

XGBRegressor

In [70]:

```
model = XGBRegressor()
model_and_metrics(X_train, y_train, X_test, y_test, model)
```

```
===================Building the model... ===========================
[17:28:03] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/obje
ctive/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:sq
uarederror.
Model XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bynode=1, colsample_bytree=1, gamma=0,
       importance_type='gain', learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=None, subsample=1, verbosity=1) ran successfully..


======================== Score's ===================================
r square :  0.2517689470391494
Adjusted r square : 0.20622444816327157
MSE : 6.752391037110787
RMSE : 2.5985363259171086
```

Chossing the best model and Deployment:

XGBRegressor

In [71]:

```
model = XGBRegressor()
model_and_metrics(X_train, y_train, X_test, y_test, model)
```

```
===================Building the model... ===========================
[17:28:08] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/obje
ctive/regression_obj.cu:152: reg:linear is now deprecated in favor of reg:sq
uarederror.
Model XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bynode=1, colsample_bytree=1, gamma=0,
       importance_type='gain', learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=None, subsample=1, verbosity=1) ran successfully..


======================== Score's ===================================
r square :  0.2517689470391494
Adjusted r square : 0.20622444816327157
MSE : 6.752391037110787
RMSE : 2.5985363259171086
```

In [72]:

```
import pickle

# Save the model as a pickle in a file
model_file = open('Absent_model.pkl', 'ab')
pickle.dump(model, model_file)
model_file.close()

# # Load the model from the file
# model_from_pickle = pickle.load('cab_fare_model.pkl')
```

Summary:

Out of all the models, XGBoost gave the best results with an RMSE value of 2.59. So we can use XGboost for this problem.

2. How much losses every month can we project in 2011 if same trend of absenteeism continues?

Considering

work loss in Hours = (Work load Average/day/Service time)*Absenteeism time in hours

In [73]:

```
#df.columns.values
loss_data = df[["Month of absence","Work load Average/day ","Service time","Absenteeism tim
```

In [74]:

```
loss_data["Work Loss"]=(df["Work load Average/day "]/df["Service time"])*df["Absenteeism ti
loss_data.head()
```

Out[74]:

	Month of absence	Work load Average/day	Service time	Absenteeism time in hours	Work Loss
0	7.0	239554.0	13.0	4.0	73708.923077
1	7.0	239554.0	18.0	0.0	0.000000
2	7.0	239554.0	18.0	2.0	26617.111111
3	7.0	239554.0	14.0	4.0	68444.000000
4	7.0	239554.0	13.0	2.0	36854.461538

In [75]:

```
monthly_loss = loss_data[["Month of absence","Work Loss"]]
```

In [76]:

```
monthly_loss = monthly_loss.groupby("Month of absence").sum()
monthly_loss
```

Out[76]:

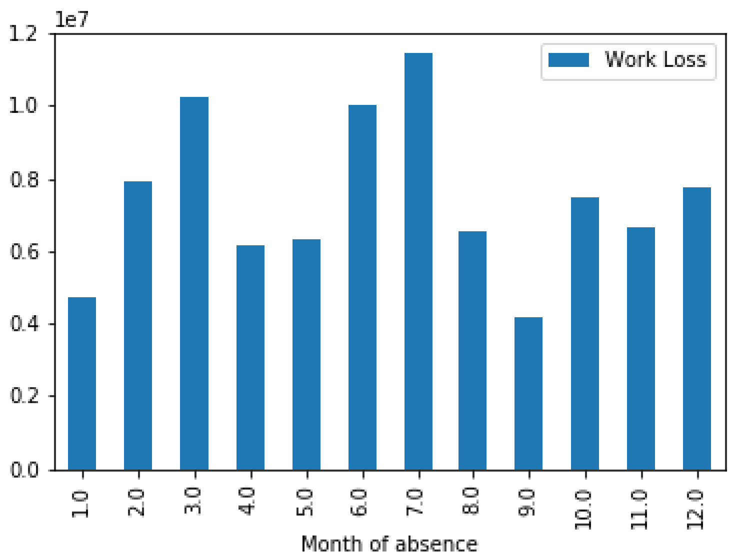
Month of absence	Work Loss
1.0	4.730330e+06
2.0	7.938029e+06
3.0	1.023768e+07
4.0	6.140413e+06
5.0	6.341453e+06
6.0	1.003318e+07
7.0	1.143110e+07
8.0	6.520187e+06
9.0	4.159296e+06
10.0	7.494952e+06
11.0	6.674416e+06
12.0	7.742550e+06

In [77]:

```
monthly_loss.plot(kind='bar')
```

Out[77]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x29421db6a20>
```



Final Summary:

Work loss for 2011 ,considering the same trend in the absenteeism pattern is shown above

Below are the absent no.of hours for all the employees.
We can see july month has more no.of absent hours.

In [ ]:

```

```