Impact of Alcoholism on workplace Absenteeism

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Final Project

Abstract

Employee absenteeism from work due to a factor of different reseaons such as health problem , alcoholism , age and the absenteeism type can be white or gray. This work analysis factors that affect the employee absenteeism , based on the survey (dataset) created by Andrea Martiniano , Ricardo Pinto Ferreira , and Renato Jose Sassi from July 2007 to July 2010 at a courier company in Brazil. The research project has leveraged the dataset to explore the main absenteeism reasons , the average absenteeism time for social alcoholic and non-alcoholic employees, the most absent group in age, whether the main absent reason falls to white or black absent type , and finally test the machine classification model to prediction black absent type. Quantitative research method was employed to achieve the research objective. Data clearing and transforming were employed to prepared for data analysis .

The data analysis result indicated the top ten(10) reason for absenteeism were dental consultation , medical consultation, physiotherapy ,diseases of the musculoskeletal system and connective tissue ,no reason, Injury, poisoning and certain other consequences of external causes ,patient follow-up, unjustified absence ,diseases of the respiratory system, diseases of the genitourinary system respectively. The average employees absent time in hour was 6.9 hours , 5.9 hours by non-social drinkers and 7.7 hours by social drinkers. The employees at age 28 has contributed negatively the company productivity as they were recorded the most. Whereas an employee at age 58 was the highest absence rate about 33 hours. The accuracy score to predict the classification model into white or gray absent type was 66.12%.

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Motivation

•Alcoholism is a sensitive topic on employee productivity.
•Alcoholism is a high financial impact on employee productivity leads to absenteeism . According to Carol Galbicsek written on alcohol rehan guide, “companies across the nation spend anywhere between 33billion and 68 billion annually due to employee alcohol abuse. ” absenteeism due to alcoholism greater than normal, she added.
•"About 17.6 million adults in the U.S. currently suffer from alcohol abuse or dependence. Several million more people engage in risky, binge drinking patterns that can lead to alcohol addiction" said , (Brian Hughes). https://www.huffingtonpost.com/brian-hughes/the-negative-impact-of-alcohol_b_12039814.html
•According to different researchers a new study indicates they may be facing an even greater threat to productivity from "social drinkers" who have too much to drink the night before work or during the day. Getting high or drunk the night before will exacerbate work performance problems the next day — a "hangover" effect.
•"You can get increased absenteeism due to health problems [caused by too much drinking] or plain hangovers — particularly concentrated on Mondays or holidays," says Laura Schneider, LCSW, EAP coordinator for the Van Nuys, CA, office of PacifiCare Behavioral Health.
•Exploring the employee absenteeism per age group , Alcoholism impact, absenteeism category(white or Gray&black type)
•Compare the absenteeism time of the social drinkers with other non drinker employees
•According to the theoretical literature about machine learning “the predicted value for the outcome can differ from the actual value of the outcome because a classification model is almost never perfect ”.

Dataset(s)

- The database was created with records of absenteeism at work from July 2007 to July 2010 at a courier company in Brazil.
- Creators original owner and donors are Andrea Martiniano , Ricardo Pinto Ferreira , and Renato Jose Sassi available at UCI's Machine Learning Repository - UC Irvine maintains a fantastic collection of datasets for machine learning, tagged by machine learning task (among other things). It was used in academic research at the Universidade Nove de Julho - Postgraduate Program in Informatics and Knowledge Management.
- The dataset was consists of 740 records. Every records of was attributed with 21 factors such as individual identification reason for absence , month of absence , day of the week , seasons, transportation expense , distance from residence to work, service time , age, work load average per day, hit target, disciplinary failure, education , son, social drinker, social smoker , pet, weight , height , body mass index against to absenteeism time in hours(target).

Data Preparation and Cleaning

Perform the data munging , wrangling and preprocessing to address a data quality issue.

Cleaning any missing or uncomplete employee absenteeism record has been performed . The following tasks were employed to clean and prepare the original data.

- ❖ Explored the nature of the dataset and conducted preliminary analysis such as size of data , type of data, attributes and descriptive statistics of absenteeism time in hour.

- ❖ Check if there was missing or NULL data across the row and column.

- ❖ Clean and transform any missing record, invalid or uncompleted attribute

- ❖ Feature selection to organize only social drinkers data , describe the average the absenteeism hours , and to test the accuracy score level of predicting the black or gray type absenteeism.

Research Question(s)

- What were the main absenteeism reasons?
- Is the reason of the social drinkers are fall to black or gray absenteeism?
- Were/was the cause of absenteeism related with alcoholic impact ?
- which age group was the most absent from work?
- Whose employee's age has the most absenteeism rate?
- What was the average absenteeism time in hours of each group (social drinkers and non social drinkers against the total average)?
- What was the accuracy score level of the classification model to predict black or gray absenteeism category?

Methods

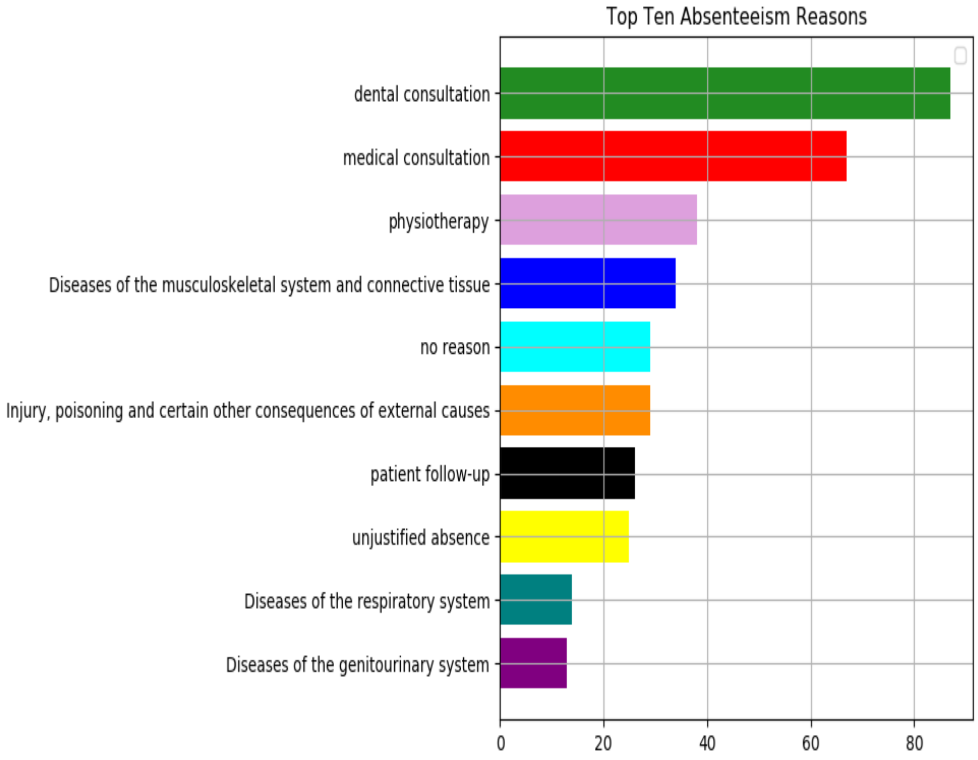
The binary classification technic was employed to predict the absenteeism category (white or black type) from other attributes as the classification was supervised task and required categorical target.

- Model was built using the sklearn.model_selection
- Sklearn algorithm was employed to model during training.
- Decision tree algorithm was employed for classification
- Model was tested using sklearn metrics such as accuracy score .

Findings

Research Question:

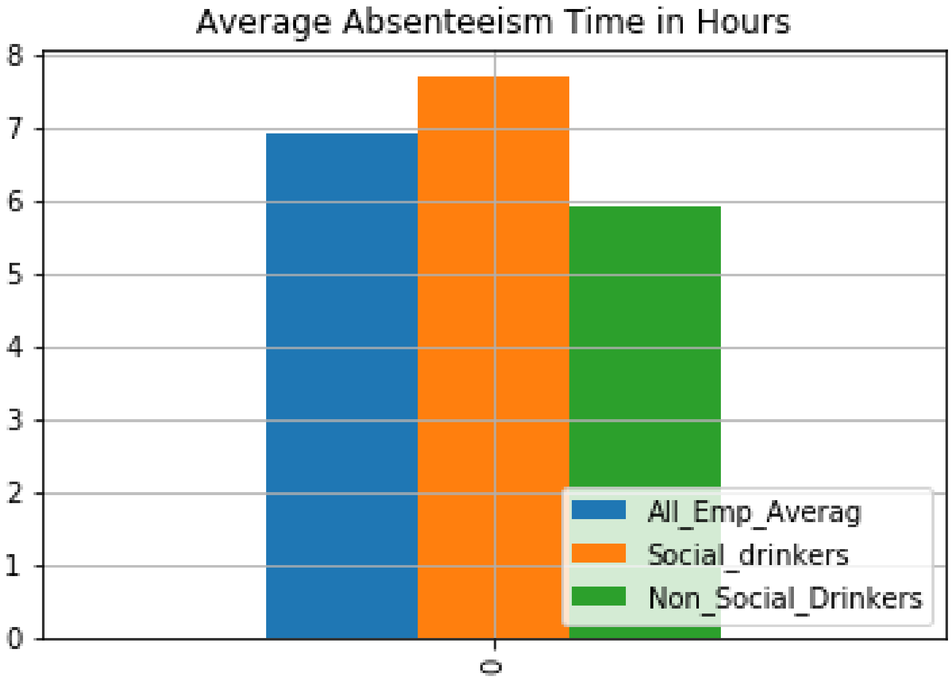
-What were the main absenteeism reasons?
-Is the reason of the social drinkers are fall to black or gray absenteeism?



- Among Top 3 reasons were dental consultation, medical consultation and physiotherapy
- The Above top 3 cause of absenteeism were not fall to International Code of diseases (ICD) which are the black absenteeism category.
- The fist 8 cause of absenteeism were related to external causes or mayn’t lead to absenteeism.

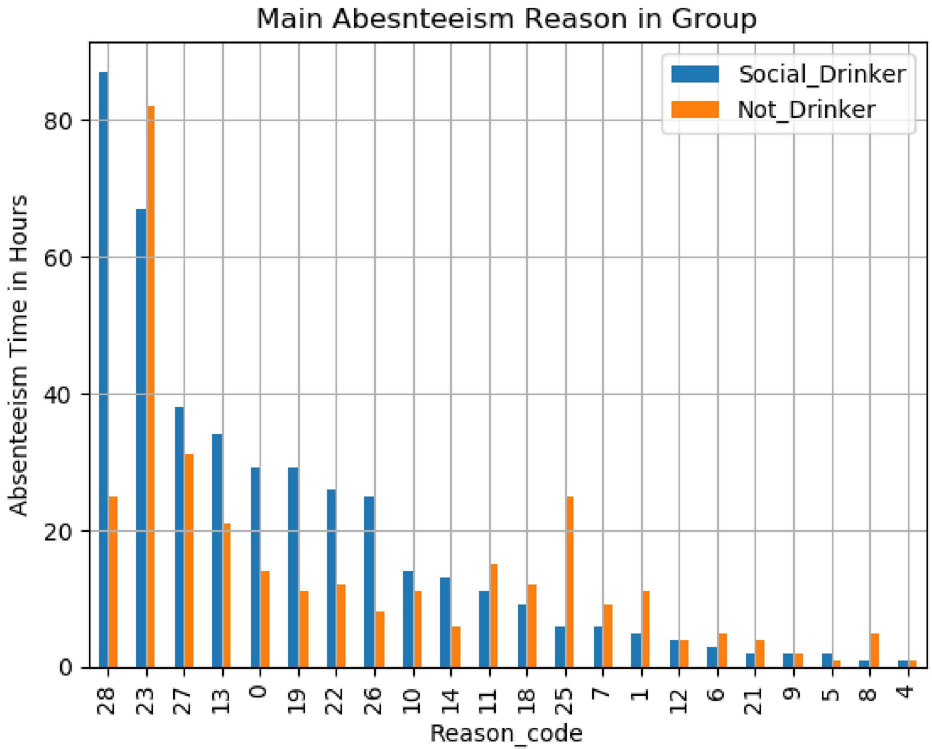
Research Question:

-What was the average absenteeism time in hours of each group (social drinkers and non social drinkers against the total average)?



- The Average absenteeism hours of social drinkers was 7.7 hours which was higher than the average employee absenteeism (6.9 hours) and non social drinkers (5.9 hours).
- This result shows that the alcoholism a negative impact on employee productivity which leads to absenteeism from work.

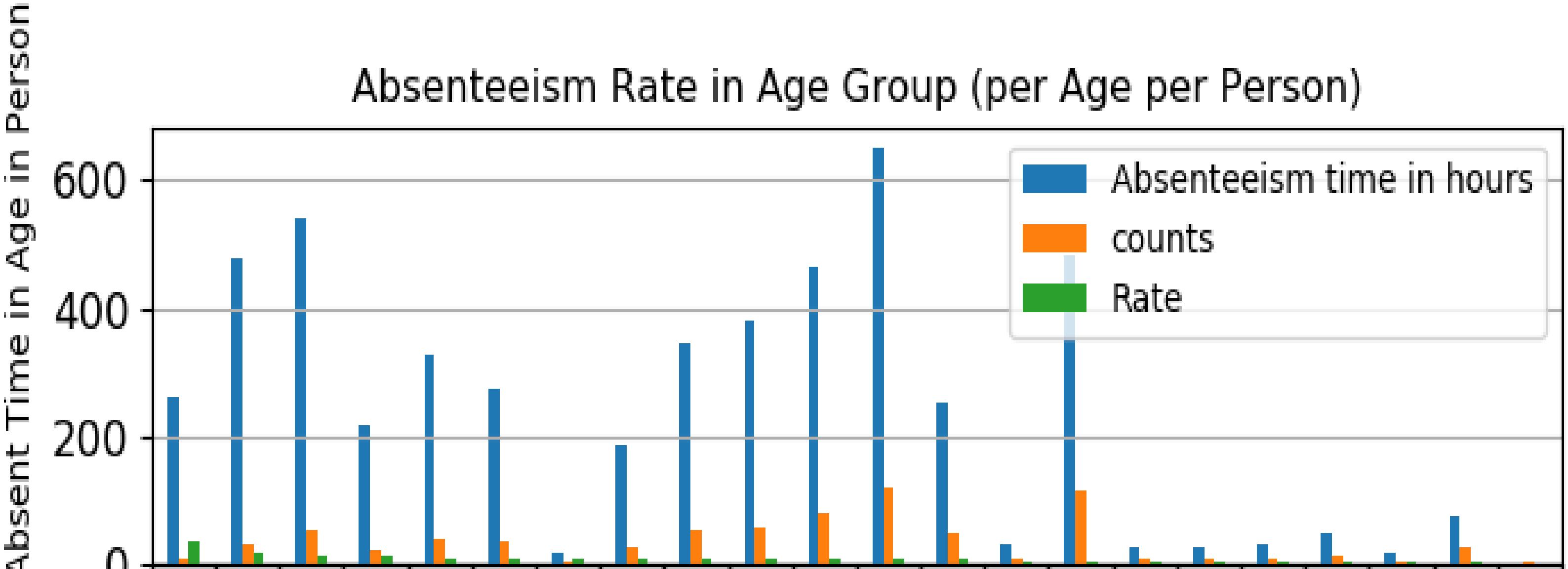
Research question: Were/was the cause of absenteeism related with alcoholic impact ?



- Among the top ten cause of the absenteeism 9 or 90% of the causes were related to social drinkers.
- As we have seen in the previous question , the causes were related with external or disease of respiratory system .
- The social drinkers have more absenteeism than the normal employees.
- The answer to the research question is because this result supports that the conclusion of the literature shows employee having drinking will lead to absenteeism from work.

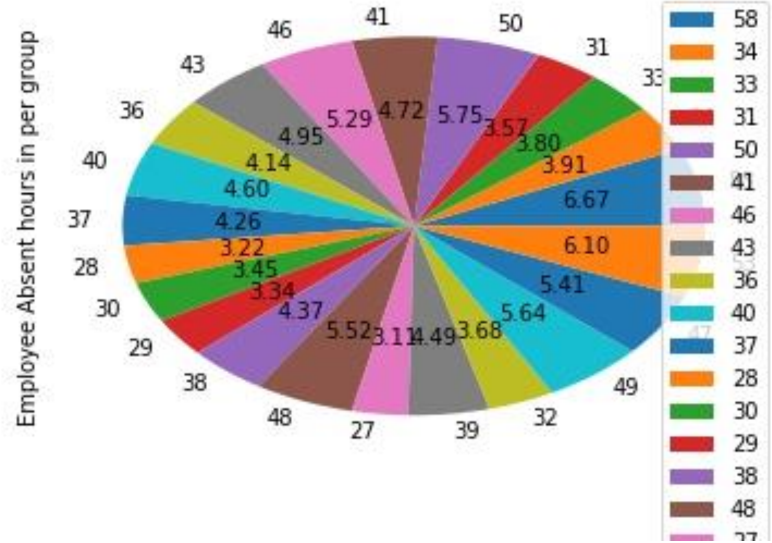
Research questions:

- which age group was the most absent from work?



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Age	58.0	34.0	33.0	31.0	50.0	41.0	46.0	43.0	36.0	40.0	37.0	28.0	30.0	29.0	38.0	48.0	27.0	39.0	32.0	49.0	47.0	53.0
Absenteeism time in hours	262.0	476.0	538.0	217.0	327.0	275.0	16.0	187.0	346.0	379.0	465.0	651.0	253.0	31.0	482.0	25.0	27.0	30.0	48.0	16.0	73.0	0.0
counts	8.0	29.0	51.0	22.0	37.0	34.0	2.0	24.0	50.0	58.0	78.0	117.0	46.0	7.0	113.0	6.0	7.0	8.0	13.0	5.0	24.0	1.0
Rate	32.75	16.41	10.55	9.86	8.84	8.09	8.0	7.79	6.92	6.53	5.96	5.56	5.5	4.43	4.27	4.17	3.86	3.75	3.69	3.2	3.04	0.0

Research question: Whose employee's age has the most absenteeism rate?



- The person at age 58 had the highest absenteeism rate in the group next to the person at age 34 and 33.

Limitations

The finding and conclusion of this research is true for tourism courier company in Brazil but may not be applicable to other company because of the source data was collected in this company .

Conclusions

Report your overall conclusions, preferably a conclusion per research question

- About 57%(420) employes were social drinkers .This result indicates that alcholism has a negative impact on employee productivity that leads them to absent from work.

- The Average absenteeism hours of social drinkers were above the average absent hours of total employees.

- The main absenteeism causes from work in the company were gray or black type absent which were not supposed to force employee to leave from work. The alcoholism may be the main impact the employee absenteeism.

- The classification model has been tested . The result shows that the prediction level of the decision tree classifiers model was about 66.12%.

Acknowledgements

First of all I would like to achknowldge the owner of the dataset Andrea Martiniano , Ricardo Pinto Ferreira , and Renato Jose Sassi . Different reports that shows about the negative impact of alcoholism on employee productivity by Carol Galbicsek , Brian Hughes and finally Laura Schneider, LCSW, EAP coordinator for the Van Nuys, CA, office of PacifiCare Behavioral Health.

References

If applicable, report any references you used in your work. For example, you may have used a research paper from X to help guide your analysis. You should cite that work here. If you did all the work on your own, please state this.

1. Martiniano, A., Ferreira, R. P., Sassi, R. J., & Affonso, C. (2012). Application of a neuro fuzzy network in prediction of absenteeism at work. In Information Systems and Technologies (CISTI), 7th Iberian Conference on (pp. 1-4). IEEE.

2. https://www.huffingtonpost.com/brian-hughes/the-negative-impact-of-alcohol_b_12039814.html.

Final_Project_Notebook

December 5, 2018

Data Analaysis

1 Preparing and importing the mandatory librareis for data analaysis

The researcher has performed the follwing tasks the prepare to data for further analysis. * Exploring : conduct a prelimunary analasys and understand the nature of the data * Pre-processing: cleaning ,integrate , and packaging

1.1 Importing the Necessary Libraries

```
In [1]: import pandas as pd
        from sklearn.tree import DecisionTreeRegressor
        from sklearn.linear_model import LinearRegression
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import mean_squared_error
        from math import sqrt
        import matplotlib.pyplot as plt
        import numpy as np
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.metrics import accuracy_score
```

1.2 Data Engineering

1.2.1 Acquire The Dataset :Identify , Retrieve and Query Data

- Identify database was created with records of absenteeism at work from July 2007 to July 2010 at a courier company in Brazil.
- Retrieve query All The attributes

```
In [2]: df=pd.read_excel("./Absenteeism_at_work.xls")
```

1.2.2 Prepare The Dataset

Exploring Dataset (Data Ingestion)

```
In [3]: df.head()
```

```
Out[3]:    ID  Reason for absence  Month of absence  Day of the week  Seasons  \
        0  11                  26                 7                3        1
        1  36                   0                 7                3        1
        2   3                  23                 7                4        1
        3   7                   7                 7                5        1
        4  11                  23                 7                5        1

           Transportation expense  Distance from Residence to Work  Service time  Age  \
        0                     289                               36            13   33
        1                     118                               13            18   50
        2                     179                               51            18   38
        3                     279                                5            14   39
        4                     289                               36            13   33

           Work_load_ Average_day            ...             Disciplinary failure  \
        0                 239554            ...                                 0
        1                 239554            ...                                 1
        2                 239554            ...                                 0
        3                 239554            ...                                 0
        4                 239554            ...                                 0

           Education  Son  Social drinker  Social smoker  Pet  Weight  Height  \
        0          1    2               1              0    1      90     172
        1          1    1               1              0    0      98     178
        2          1    0               1              0    0      89     170
        3          1    2               1              1    0      68     168
        4          1    2               1              0    1      90     172

           Body mass index  Absenteeism time in hours
        0               30                          4
        1               31                          0
        2               31                          2
        3               24                          4
        4               30                          2

        [5 rows x 21 columns]
```

Explore The Attributes of the dataset

```
In [4]: df.columns
```

```
Out[4]: Index(['ID', 'Reason for absence', 'Month of absence', 'Day of the week',
               'Seasons', 'Transportation expense', 'Distance from Residence to Work',
               'Service time', 'Age', 'Work_load_ Average_day', 'Hit target',
               'Disciplinary failure', 'Education', 'Son', 'Social drinker',
               'Social smoker', 'Pet', 'Weight', 'Height', 'Body mass index',
               'Absenteeism time in hours'],
              dtype='object')
```

Explore The Size of The Dataset

```
In [5]: df.shape
```

```
Out[5]: (740, 21)
```

1.2.3 Preprocessing Data: Cleaning and Transform

Data Munging , Data Wrangling and prepprocessing

- Cleaning any empty or uncomplete emplyee absenteeism record
- clear any empty or uncomplte attribute
- orginize only social drinkers data
- Filtering and classify required attribute to study the absenteeism hours of social drinkers

Check if there is any null value in the dataset

```
In [7]: df.isnull().any().any()
```

```
Out[7]: False
```

The About result indicated that there is null or empty record within the dataset.

```
In [10]: df['Absenteeism time in hours'].describe()
```

```
Out[10]: count    740.000000
         mean       6.924324
         std       13.330998
         min        0.000000
         25%        2.000000
         50%        3.000000
         75%        8.000000
         max      120.000000
         Name: Absenteeism time in hours, dtype: float64
```

```
In [4]: Total_mean=df['Absenteeism time in hours'].mean()
        Total_mean
```

```
Out[4]: 6.924324324324324
```

Classfiyy the only social drinkers

```
In [11]: Social_drinkers_data=df[df['Social drinker']==1]
```

Classfiyy the non social drinkers

```
In [13]: Non_Social_drinker=df[df['Social drinker']==0]
```

Explore The Socail Drinkers Dataset

```
In [9]: Social_drinkers_data.shape
```

```
Out[9]: (420, 21)
```

1.3 Describe The main reason for absenteeism in work for All type of Employees

```
In [14]: Reason_absences=Non_Social_drinker['Reason for absence'].value_counts()
         Reason_absences=Reason_absences.to_frame(name='counts_non')
         Reason_absences.reset_index(inplace=True)
         Reason_absences.rename(columns={'index':'Reason_code'}, inplace=True)
         Reason_absences.head(10)
```

Out[14]:

	Reason_code	counts_non
0	23	82
1	27	31
2	28	25
3	25	25
4	13	21
5	11	15
6	0	14
7	18	12
8	22	12
9	19	11

Reason Code Descrption : The above result indicated the top ten(10) reason for absencenteeism dental consultation (28), medical consultation (23), physiotherapy (27),XIII Diseases of the musculoskeletal system and connective tissue (13),no reason(0),XIX Injury, poisoning and certain other consequences of external causes ,patient follow-up (22), unjustified absence (26), X Diseases of the respiratory system,XIV Diseases of the genitourinary system

1.3.1 Basic Statstics of employee Absenteeism using .describe() method.

- **count:** The number of rows in the dataset, which were filtered to only Social drinkers/Non Drinkers and Total employees.
- **mean:** the average absent time in hour.
- **std:** the standard deviation.
- **min:** the shortest absent hour in the dataset.
- **25%:** the 25th percentile. 25% of absent hours were lower than .
- **50%:** the 50th percentile, or the median. 50% of absent hours were lower than .
- **75%:** the 75th percentile. 75% of absent hours were lower than .
- **max:** the longest hours in the absenteeism dataset:

```
In [23]: Non_Social_drinker['Absenteeism time in hours'].describe()
```

```
Out[23]: count    320.000000
         mean       5.931250
         std       12.736353
         min        0.000000
         25%        2.000000
         50%        3.000000
         75%        8.000000
         max      120.000000
         Name: Absenteeism time in hours, dtype: float64
```

In [8]:
```
Non_Social_mean=Non_Social_drinker['Absenteeism time in hours'].mean()
Non_Social_mean
```

Out[8]: 5.93125

In [24]:
```
Social_drinkers_data['Absenteeism time in hours'].describe()
```

Out[24]:
```
count    420.000000
mean       7.680952
std       13.733680
min        0.000000
25%        2.000000
50%        4.000000
75%        8.000000
max      120.000000
Name: Absenteeism time in hours, dtype: float64
```

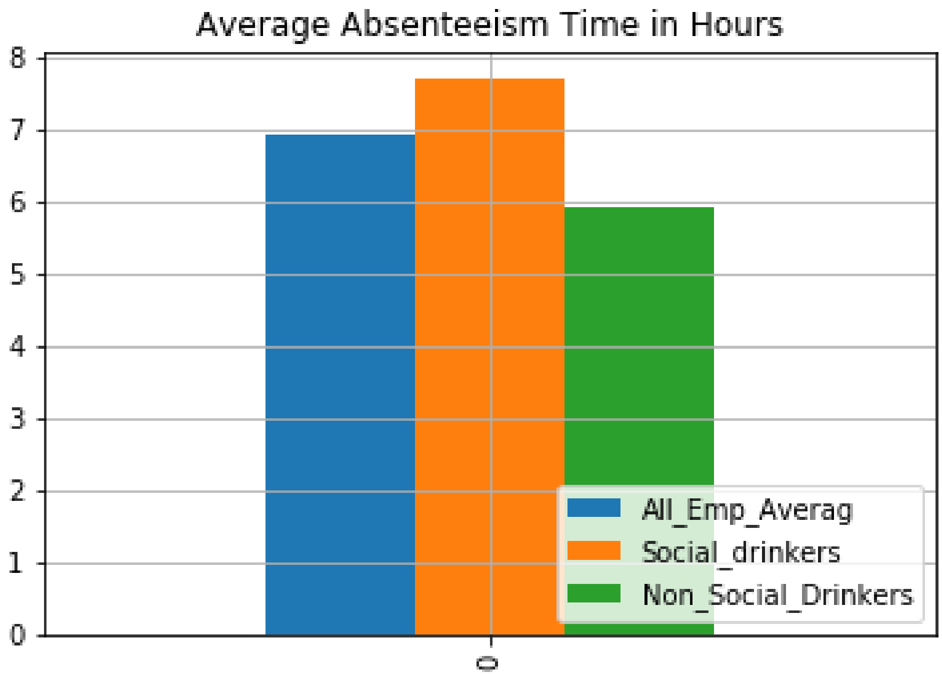
In [11]:
```
Socail_Dr_mean=Social_drinkers_data['Absenteeism time in hours'].mean()
Socail_Dr_mean
```

Out[11]: 7.680952380952381

1.4 Visualization

In [165]:
```
d={'All_Emp_Averag':[Total_mean],'Social_drinkers':[Socail_Dr_mean],'Non_Social_Drink
Average_df=pd.DataFrame(data=d)
plt.figure(figsize=(8,8))
Average_df.plot(kind='bar')
plt.title('Average Absenteeism Time in Hours')
plt.grid(True)
plt.legend(loc='lower right')
plt.savefig('C:/DataScienceUCSD/Projects/Final_Project/Average_Abs.png',bbox_inches=
```

<Figure size 576x576 with 0 Axes>




```
In [9]: Top_Reasons=['dental consultation','medical consultation','physiotherapy','Diseases of

In [10]: Fabs_R['Description']=Top_Reasons
         Fabs_R
```

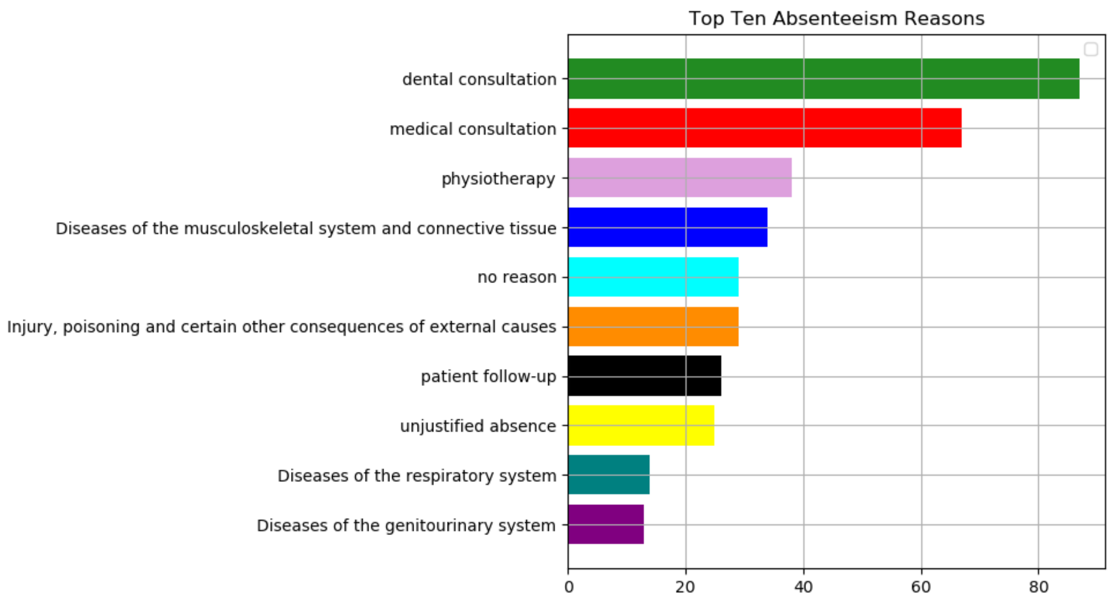
```
C:\Users\asfetu\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """Entry point for launching an IPython kernel.
```

Out[10]:

	Reason_code	counts	Description
0	28	87	dental consultation
1	23	67	medical consultation
2	27	38	physiotherapy
3	13	34	Diseases of the musculoskeletal system and con...
4	0	29	no reason
5	19	29	Injury, poisoning and certain other consequenc...
6	22	26	patient follow-up
7	26	25	unjustified absence
8	10	14	Diseases of the respiratory system
9	14	13	Diseases of the genitourinary system

In [74]:
```
fig=plt.figure(figsize=(6,6))
plt.barh(Fabs_R['Description'],Fabs_R['counts'],color=['forestgreen', 'red', 'plum',
plt.title('Top Ten Absenteeism Reasons')
plt.gca().invert_yaxis()
plt.legend()
plt.grid(True)
fig.show()
plt.savefig('C:/DataScienceUCSD/Projects/Final_Project/Top_Reason.png',bbox_inches='t
```

```
No handles with labels found to put in legend.
C:\Users\asfetu\Anaconda3\lib\site-packages\matplotlib\figure.py:459: UserWarning: matplotlib i
  "matplotlib is currently using a non-GUI backend, "
```



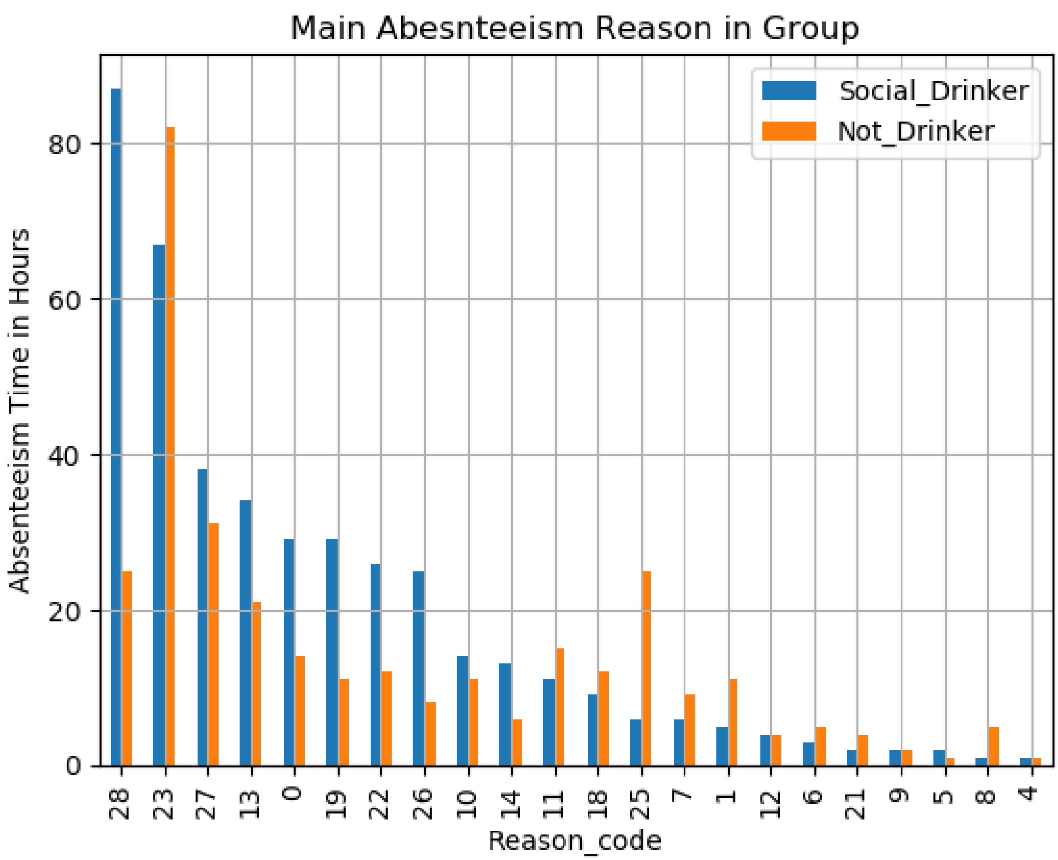
In [11]:
```
both_table=Reason_absence.merge(Reason_absences,on='Reason_code')
both_table.rename(columns={'counts':'Social_Drinker','counts_non':'Not_Drinker'}, inpl
both_table[:3]
```

Out[11]:

	Reason_code	Social_Drinker	Not_Drinker
0	28	87	25
1	23	67	82
2	27	38	31

In [75]:
```
both_table.plot(x='Reason_code', kind='bar')
plt.title('Main Abesnteeism Reason in Group')
plt.ylabel('Absenteeism Time in Hours')
plt.grid(True)
fig.show()
plt.savefig('C:/DataScienceUCSD/Projects/Final_Project/Groupcomparison.png',bbox_inche
```

```
C:\Users\asfetu\Anaconda3\lib\site-packages\matplotlib\figure.py:459: UserWarning: matplotlib i
  "matplotlib is currently using a non-GUI backend, "
```



1.5 Absenteeism Rate in Age Group (per Age per Person)

In [15]:
```
#Age_Group_total_hours
Age_count=df.Age.value_counts()
Age_count=Age_count.to_frame(name='counts').reset_index().rename(columns={'index':'Age
Age_Absent_Rate=Age_Group_total_hours.merge(Age_count,on='Age')
Age_Absent_Rate['Rate']=Age_Absent_Rate['Absenteeism time in hours']/Age_Absent_Rate[
Age_Absent_Rate.sort_values(by='Rate', ascending=False, inplace=True)
Age_Absent_Rate=Age_Absent_Rate.reset_index()
Age_Absent_Rate.index+=1
del Age_Absent_Rate['index']
Age_Absent_Rate
```

Out[15]:

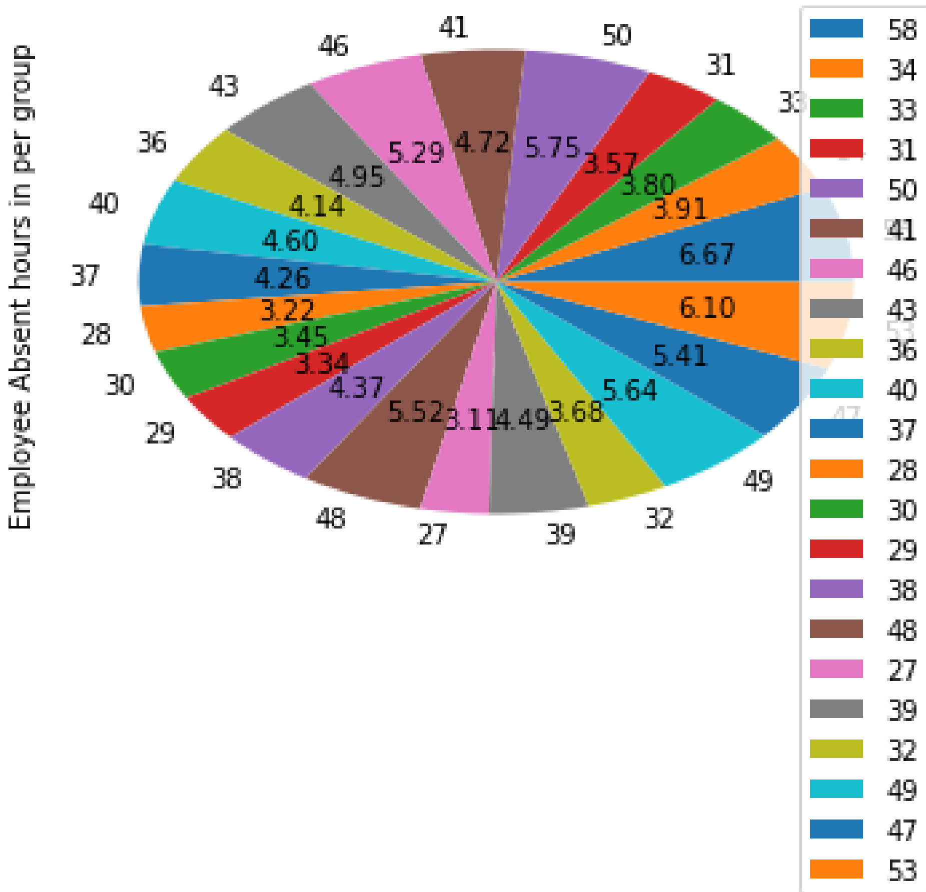
	Age	Absenteeism time in hours	counts	Rate
1	58	262	8	32.750000
2	34	476	29	16.413793

3	33	538	51	10.549020
4	31	217	22	9.863636
5	50	327	37	8.837838
6	41	275	34	8.088235
7	46	16	2	8.000000
8	43	187	24	7.791667
9	36	346	50	6.920000
10	40	379	58	6.534483
11	37	465	78	5.961538
12	28	651	117	5.564103
13	30	253	46	5.500000
14	29	31	7	4.428571
15	38	482	113	4.265487
16	48	25	6	4.166667
17	27	27	7	3.857143
18	39	30	8	3.750000
19	32	48	13	3.692308
20	49	16	5	3.200000
21	47	73	24	3.041667
22	53	0	1	0.000000

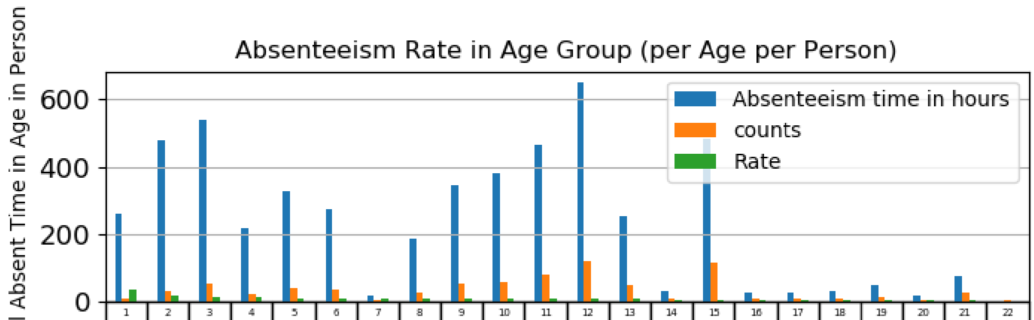
Discussion: The Above data shows that the absenteeism per employee per age .An emplyee at age 58 has most records. Almost an employee at age 58 was absent for 33 hours becuase of the above reasons.

```
In [17]: fig=plt.figure()
         Display= pd.Series(Age_Absent_Rate['Age'], index=Age_Absent_Rate.index, name='Employe
         Display.plot.pie(labels=Age_Absent_Rate['Age'],legend=True, autopct='%.2f', subplots=
         fig.show()
         plt.savefig('C:/DataScienceUCSD/Projects/Final_Project/rating_per_age.jpg')
```

```
C:\Users\asfetu\Anaconda3\lib\site-packages\matplotlib\figure.py:459: UserWarning: matplotlib 
  "matplotlib is currently using a non-GUI backend, "
```




```
In [88]: fig, ax = plt.subplots(1, 1)
         ax.get_xaxis().set_visible(False)
         Age_Absent_Rate.plot(x='Age',kind='bar',table=np.round(Age_Absent_Rate.T, 2), ax=ax, 
         plt.title('Absenteeism Rate in Age Group (per Age per Person)')
         plt.ylabel('Total Absent Time in Age in Person')
         plt.grid(True)
         plt.savefig('C:/DataScienceUCSD/Projects/Final_Project/Abs_Age_group.png',bbox_inches=
```



	1	2	3	4	5	6	7	8	9	10	11
Age	58.0	34.0	33.0	31.0	50.0	41.0	46.0	43.0	36.0	40.0	37.0
Absenteeism time in hours	262.0	476.0	538.0	217.0	327.0	275.0	16.0	187.0	346.0	379.0	465.0
counts	8.0	29.0	51.0	22.0	37.0	34.0	2.0	24.0	50.0	58.0	78.0
Rate	32.75	16.41	10.55	9.86	8.84	8.09	8.0	7.79	6.92	6.53	5.96

	12	13	14	15	16	17	18	19	20	21	22
Age	28.0	30.0	29.0	38.0	48.0	27.0	39.0	32.0	49.0	47.0	53.0
Absenteeism time in hours	651.0	253.0	31.0	482.0	25.0	27.0	30.0	48.0	16.0	73.0	0.0
counts	117.0	46.0	7.0	113.0	6.0	7.0	8.0	13.0	5.0	24.0	1.0
Rate	5.56	5.5	4.43	4.27	4.17	3.86	3.75	3.69	3.2	3.04	0.0

2 Test The Accuracy level of Classificatio Model: Decision Tree Classification Model

2.1 Check whether there is Null Value

```
In [16]: df.isnull().any().any()
```

```
Out[16]: False
```

2.2 Convert to Classification Task

According to The catagory classified in the orginal Data source .

Catagory 1 White Absenteeism: Based on ICD * 21 type of Absenteeism Reason **Catagory 2** Black Absenteeism: 7 categories without (CID) * patient follow-up (22), * medical consultation (23), * blood donation (24), * laboratory examination (25), * unjustified absence (26), * physiotherapy (27), * dental consultation (28).

```
In [17]: df['Non_ICD']=((df['Reason for absence']==22)*1 )| ((df['Reason for absence']==23)*1)
         #df['Non_ICD']=((df['Reason for absence']==22) | (df['Reason for absence']==23))*1
         df.head()
```

```
Out[17]:    ID  Reason for absence  Month of absence  Day of the week  Seasons  \
         0  11                  26                 7                3        1
         1  36                   0                 7                3        1
         2   3                  23                 7                4        1
         3   7                   7                 7                5        1
         4  11                  23                 7                5        1

            Transportation expense  Distance from Residence to Work  Service time  Age  \
         0                     289                               36            13   33
         1                     118                               13            18   50
         2                     179                               51            18   38
```

```
3                   279                               5         14   39
4                   289                              36         13   33

   Work_load_ Average_day   ...     Education  Son  Social drinker  \
0                  239554   ...             1    2               1
1                  239554   ...             1    1               1
2                  239554   ...             1    0               1
3                  239554   ...             1    2               1
4                  239554   ...             1    2               1

   Social smoker  Pet  Weight  Height  Body mass index  \
0              0    1      90     172               30
1              0    0      98     178               31
2              0    0      89     170               31
3              1    0      68     168               24
4              0    1      90     172               30

   Absenteeism time in hours  Non_ICD
0                          4        1
1                          0        0
2                          2        1
3                          4        0
4                          2        1

[5 rows x 22 columns]
```

In [21]:
```
Final_data=df.copy()
type(Final_data)
```

Out[21]: `pandas.core.frame.DataFrame`

2.3 Attributes (Features and Target) are saved in X and Y respectively

2.3.1 Target saved in y

In [22]:
```
y=Final_data[['Non_ICD']].copy()
```

In [23]:
```
type(y)
```

Out[23]: `pandas.core.frame.DataFrame`

2.3.2 Features are saved in X to predict the Black or Grey abesenteeism

In [24]:
```
Features=['Month of absence','Day of the week',
         'Seasons','Transportation expense','Distance from Residence to Work',
         'Service time','Age','Work_load_ Average_day','Hit target',
         'Disciplinary failure', 'Education','Son','Social drinker',
         'Social smoker','Pet','Weight','Height','Body mass index']
```

In [25]:
```
X=Final_data[Features].copy()
```

```
In [26]: type(X)
```

```
Out[26]: pandas.core.frame.DataFrame
```

2.4 Perform Test and Train Split

```
In [27]: X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=0.33, random_state=
```

```
In [31]: Black_Absenteeism_Classifier=DecisionTreeClassifier(max_leaf_nodes=20, random_state=0)
         Black_Absenteeism_Classifier.fit(X_train, y_train)
```

```
Out[31]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                     max_features=None, max_leaf_nodes=20,
                     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=0,
                     splitter='best')
```

2.4.1 Fit on Train Set

```
In [30]: type(Black_Absenteeism_Classifier)
```

```
Out[30]: sklearn.tree.tree.DecisionTreeClassifier
```

2.4.2 Predict on Test Set

```
In [29]: Black_Absent_Prediction=Black_Absenteeism_Classifier.predict(X_test)
```

```
In [32]: Black_Absent_Prediction[:10]
```

```
Out[32]: array([1, 1, 1, 1, 1, 0, 1, 1, 1, 0], dtype=int32)
```

```
In [33]: y_test.columns
```

```
Out[33]: Index(['Non_ICD'], dtype='object')
```

2.5 Measure The Accuracy of The Classifier

```
In [34]: accuracy_score(y_true=y_test, y_pred=Black_Absent_Prediction)
```

```
Out[34]: 0.6612244897959184
```