Name: Jonathan Ogden

Course: CS 5402

Assignment: Programming Assignment 3

Date: 07/07/2020

In [1]:

```
### IMPORTS ###
# For managing data
import pandas as pd
# For frequency counts
import collections
# For plotting data
import matplotlib.pyplot as plt
# For model training
from sklearn.neighbors import KNeighborsClassifier
# For splitting data into test/train sets
from sklearn.model_selection import train_test_split
# For confusion matricies and other statistics
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
# for Graphing
import seaborn
# For Regression
import statsmodels.api as sm
# for math
import numpy as np
```

Concept Description:

Analyze the provided data to determine any connections between certain given biological metrics and Chronic Hear Disease.

Data Collection:

Data was provided by the instructor, Perry Koob.

Example Description:

age

The person's age (*Int - interval*)

cigsPerDay

The count of the person's Cigarettes per Day (*Int - ratio*)

totChol

The person's total cholesterol (*Int - interval*)

sysBP

The person's systolic blood pressure (*Float - interval*)

diaBP

The person's diastolic blood pressure (*Float - interval*)

BMI

The person's body mass index (*Float - interval*)

heartRate

The person's heart rate (*Int - interval*)

glucose

The person's blood glucose level (*Int - interval*)

CHD

Where or not the person has Chronic Heart Disease - *CHD* (*Boolean - Binary, Nominal*)

Data Import and Wrangling:

The data is imported from a csv format to a dataframe format to make working with it in python easier. Care is taken to ensure the data is read as a string of characters.

In [2]:

```
df = pd.read_csv("../src-data/heart-disease.csv", dtype=str)
# make all data numeric instead of sting
df = df.apply(pd.to_numeric)
df
```

Out[2]:

	age	cigsPerDay	totChol	sysBP	diaBP	BMI	heartRate	glucose	CHD
0	39	0.0	195.0	106.0	70.0	26.97	80.0	77.0	0
1	46	0.0	250.0	121.0	81.0	28.73	95.0	76.0	0
2	48	20.0	245.0	127.5	80.0	25.34	75.0	70.0	0
3	61	30.0	225.0	150.0	95.0	28.58	65.0	103.0	1
4	46	23.0	285.0	130.0	84.0	23.10	85.0	85.0	0
...	...	...	...	...	...	...	...	...	...
4233	50	1.0	313.0	179.0	92.0	25.97	66.0	86.0	1
4234	51	43.0	207.0	126.5	80.0	19.71	65.0	68.0	0
4235	48	20.0	248.0	131.0	72.0	22.00	84.0	86.0	0
4236	44	15.0	210.0	126.5	87.0	19.16	86.0	NaN	0
4237	52	0.0	269.0	133.5	83.0	21.47	80.0	107.0	0

4238 rows × 9 columns

Mining or Analytics:

cigsPerDay, totChol, BMI, heartRate, and glucose all have missing values, so we deterine the correlation between the values to find a value that can predict each.

In [3]:

```
df.corr()
```

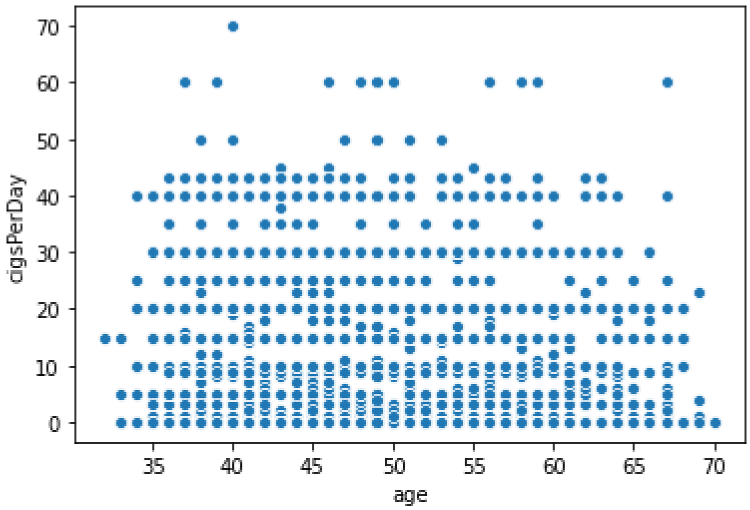
Out[3]:

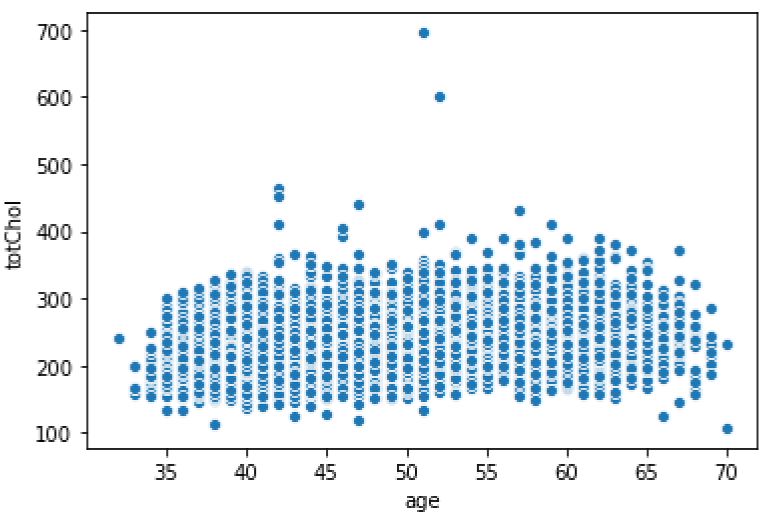
	age	cigsPerDay	totChol	sysBP	diaBP	BMI	heartRate	gluco
age	1.000000	-0.192791	0.262131	0.394302	0.206104	0.135800	-0.012823	0.1222
cigsPerDay	-0.192791	1.000000	-0.026320	-0.088780	-0.056632	-0.092856	0.075157	-0.058
totChol	0.262131	-0.026320	1.000000	0.208908	0.165182	0.115767	0.091125	0.0464
sysBP	0.394302	-0.088780	0.208908	1.000000	0.784002	0.326981	0.182246	0.1406
diaBP	0.206104	-0.056632	0.165182	0.784002	1.000000	0.377588	0.181255	0.0612
BMI	0.135800	-0.092856	0.115767	0.326981	0.377588	1.000000	0.067678	0.087
heartRate	-0.012823	0.075157	0.091125	0.182246	0.181255	0.067678	1.000000	0.094
glucose	0.122256	-0.058960	0.046408	0.140621	0.061231	0.087377	0.094500	1.000
CHD	0.225256	0.057884	0.082184	0.216429	0.145299	0.075192	0.022913	0.125

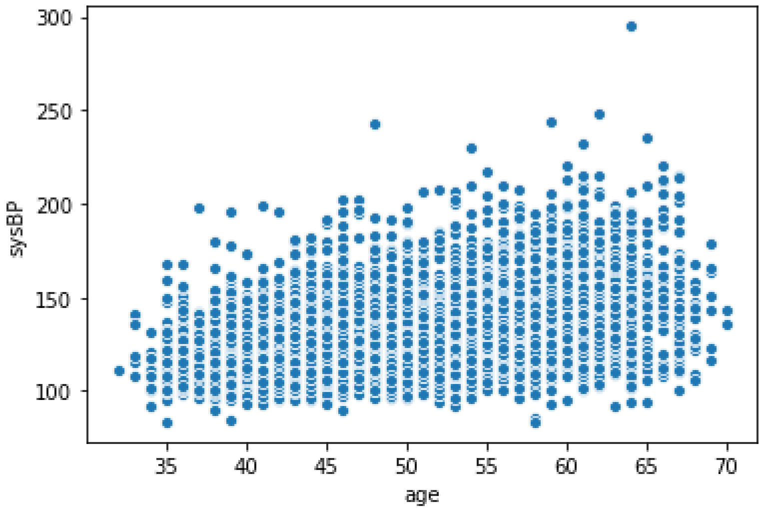
In [4]:

```
#Plotting all combinations
graphs = []
# remove the CHD column for comparisons
temp_df = df.drop(['CHD'], axis=1)
for x in temp_df:
    for y in temp_df:
        # Remove comparing it to itself (1)
        if x != y:
            plt.figure()
            seaborn.scatterplot(x=x,y=y,data=df)
```

```
c:\users\jon\appdata\local\programs\python\python36-32\lib\site-packages\ipyk
ernel_launcher.py:9: RuntimeWarning: More than 20 figures have been opened. F
igures created through the pyplot interface (`matplotlib.pyplot.figure`) are
retained until explicitly closed and may consume too much memory. (To control
this warning, see the rcParam `figure.max_open_warning`).
  if __name__ == '__main__':
```



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sysBP
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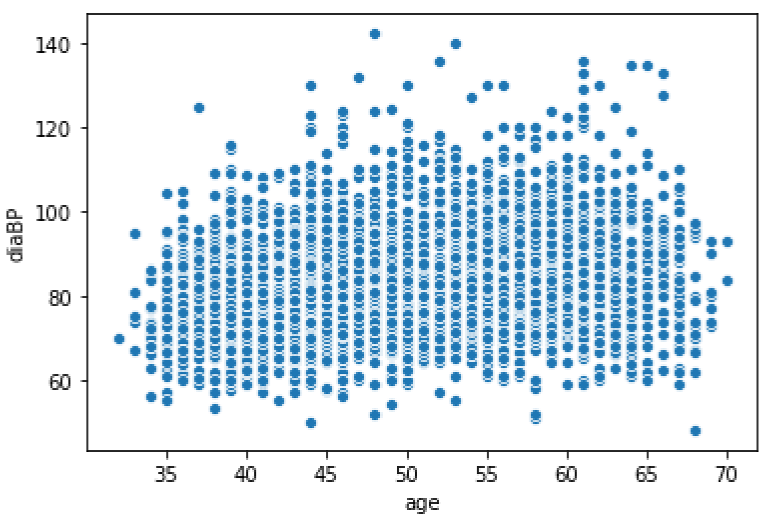
age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diaBP
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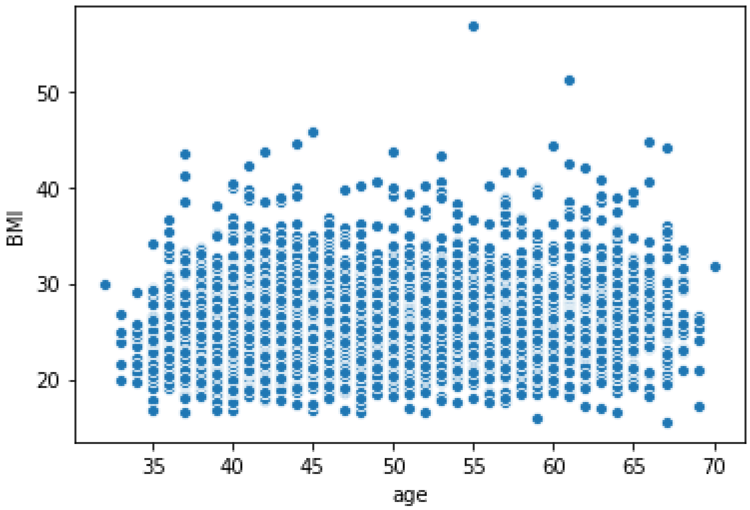
70
age


50
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BMI
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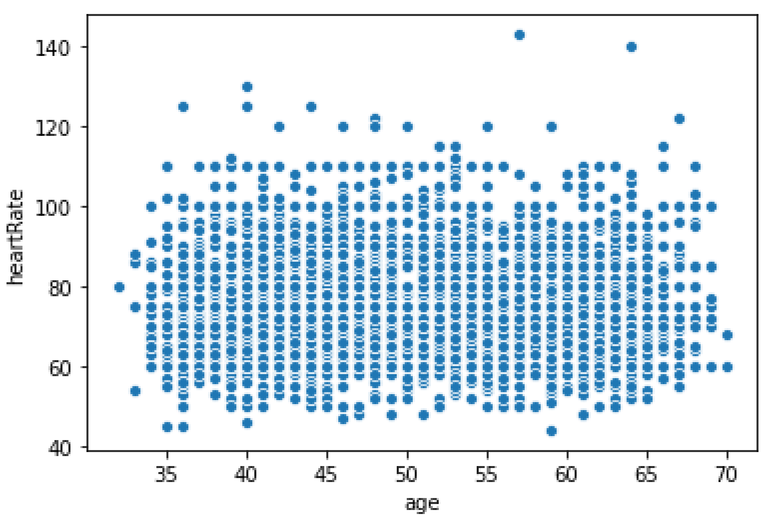
65
70
age


140
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heartRate
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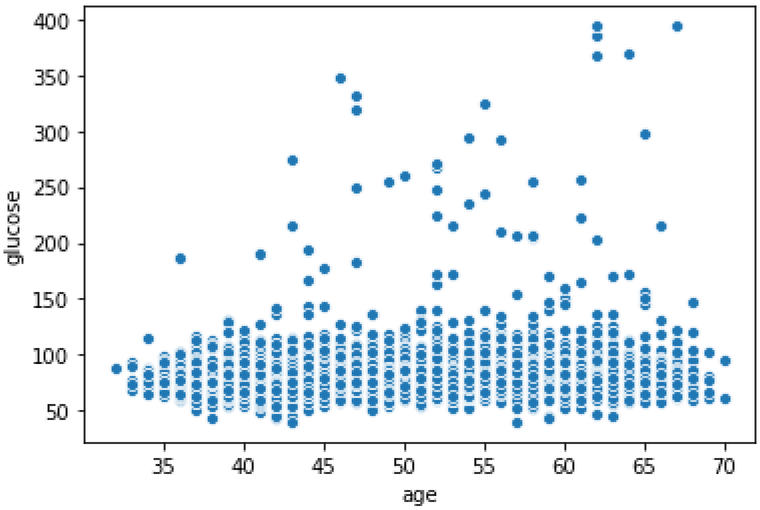
70
age


glucose
age
400
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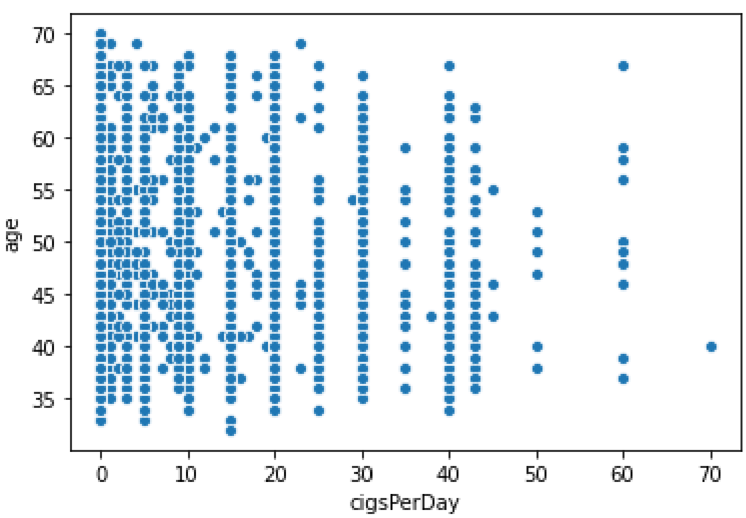
age
cigsPerDay
70
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35
0
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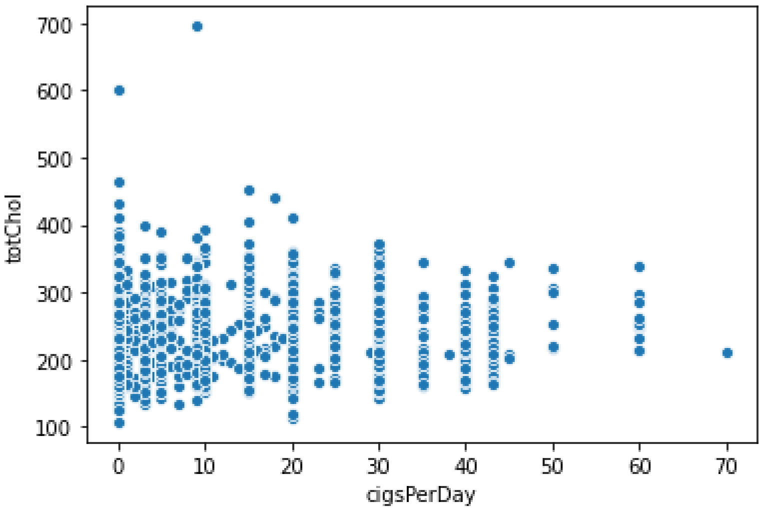
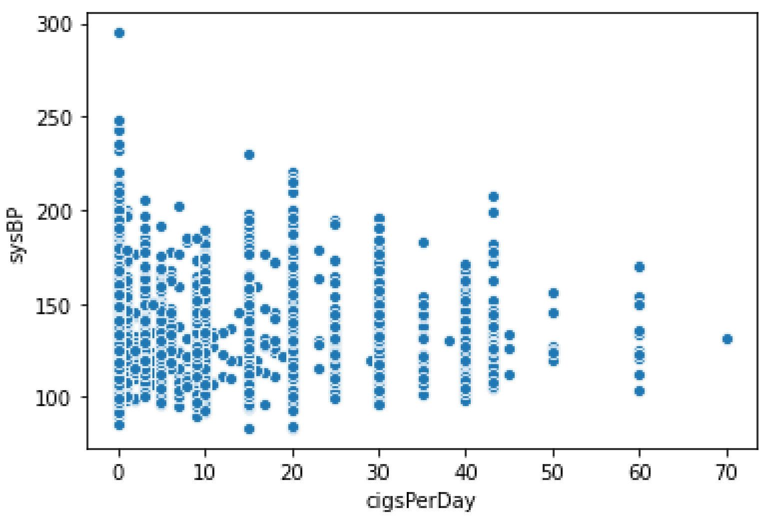
70


700
600
500
400
300
200
100
totChol
0
10
20
30
40
50
60
70
cigsPerDay


300
250
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100
sysBP
0
10
20
30
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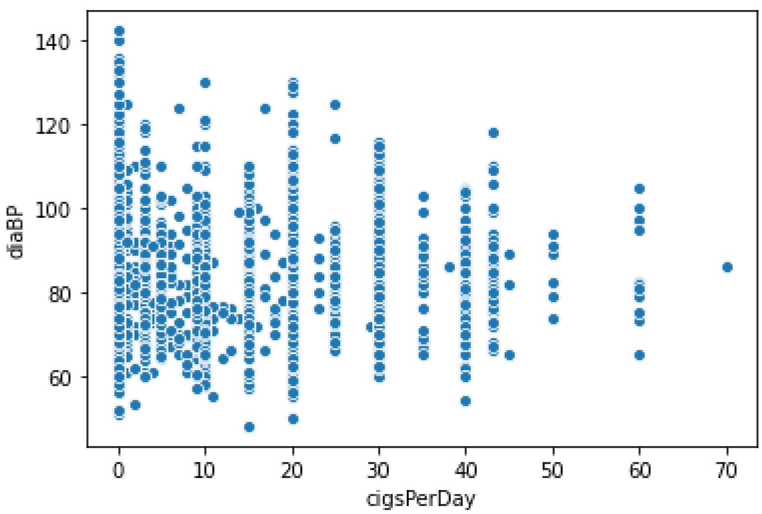
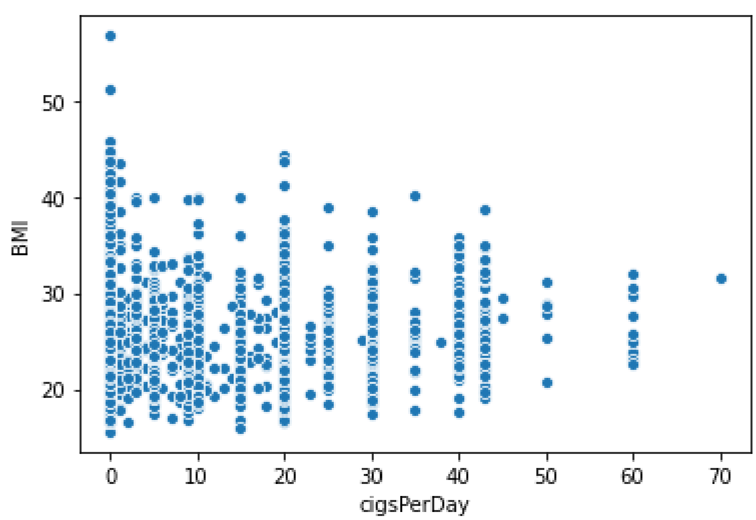
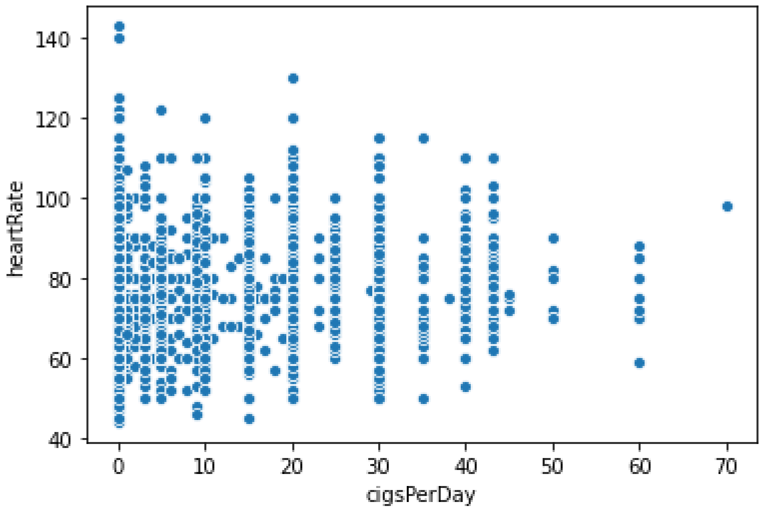
50
60
70
cigsPerDay



diaBP
cigsPerDay



BMI
cigsPerDay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cigsPerDay
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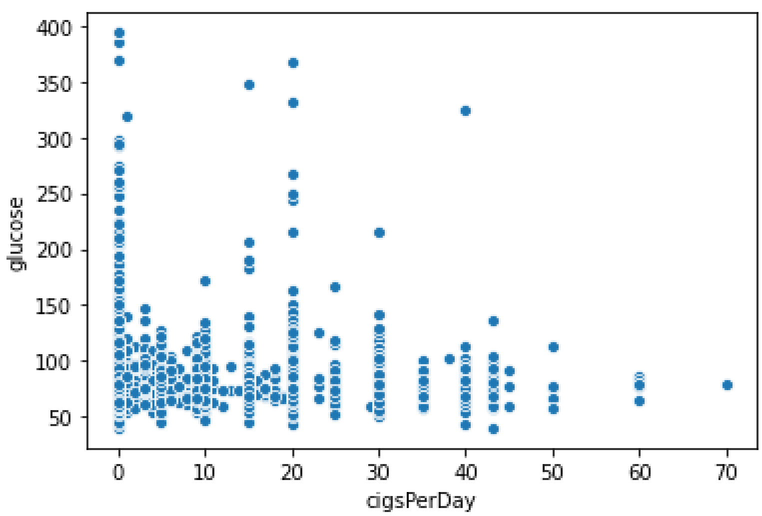
70


glucose
cigsPerDay
400
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0
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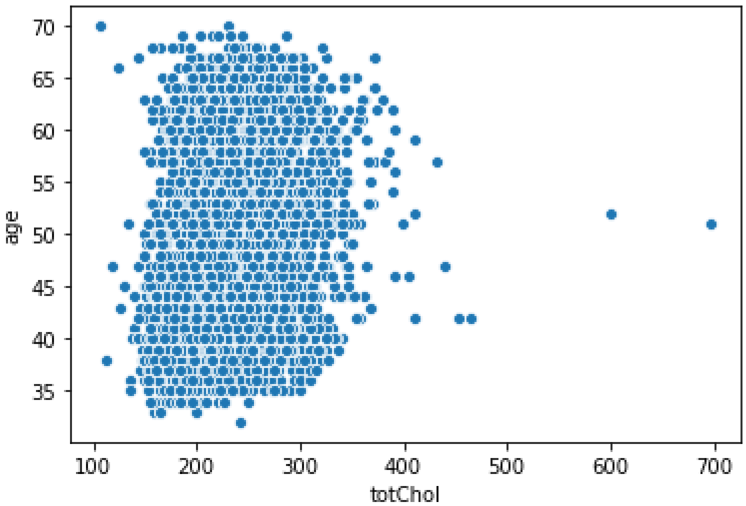
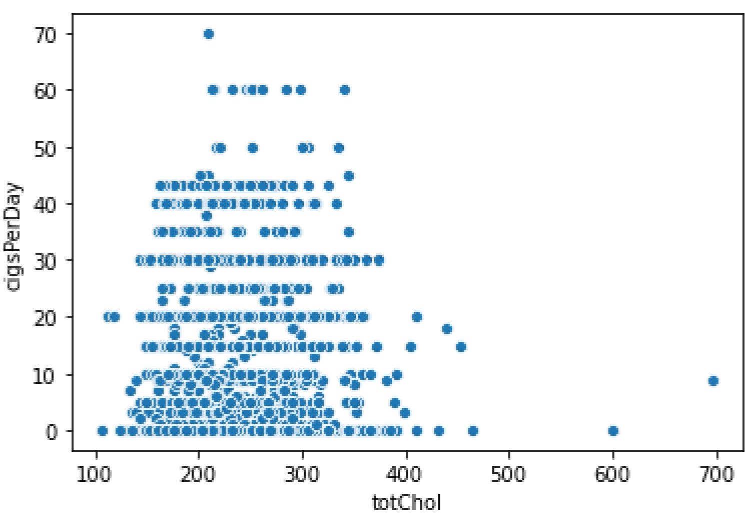
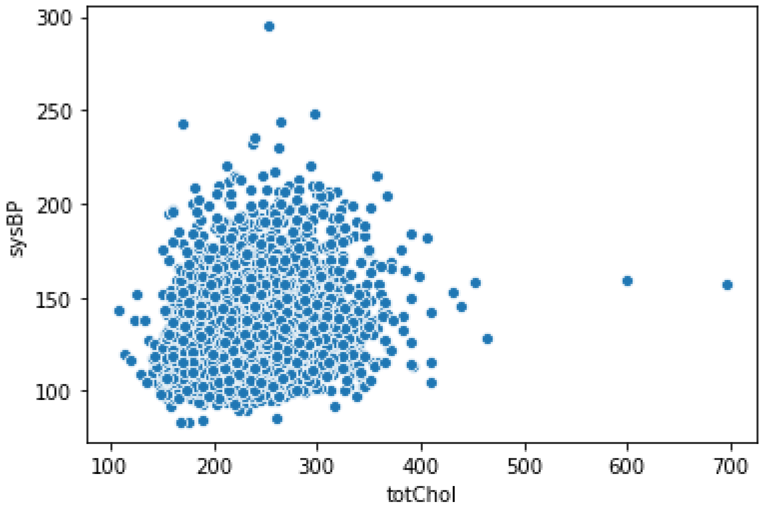
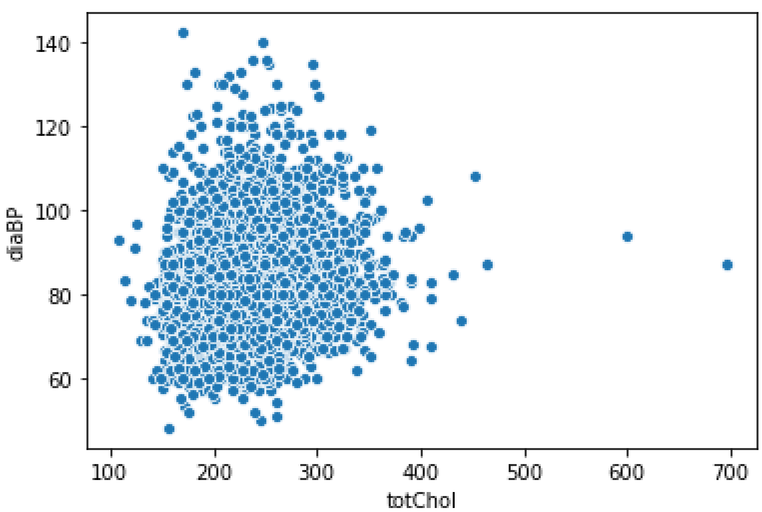
70


age
totChol

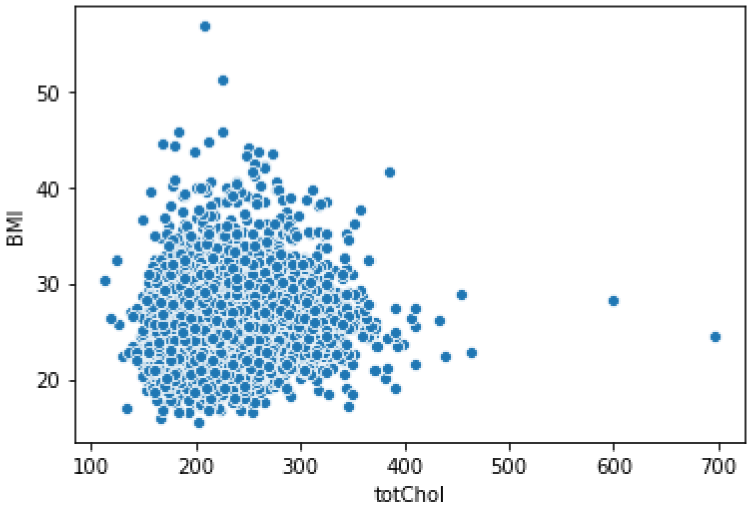

cigsPerDay
totChol



sysBP
totChol



diaBP
totChol


BMI
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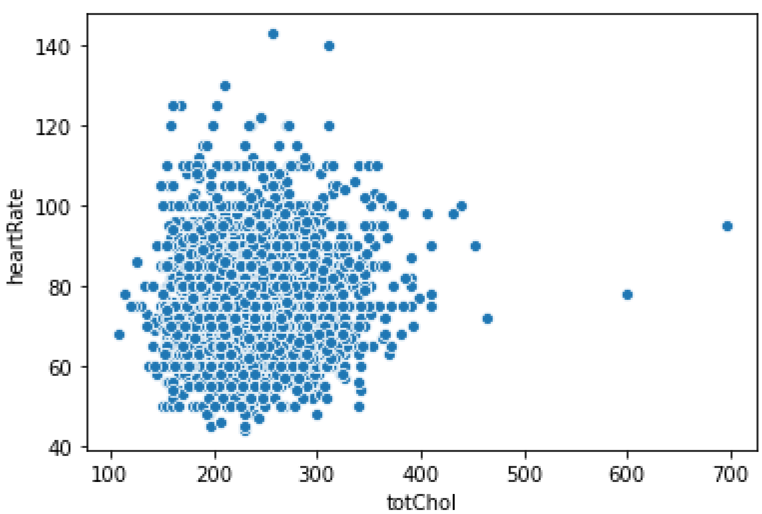
100 200 300 400 500 600 700
totChol


heartRate
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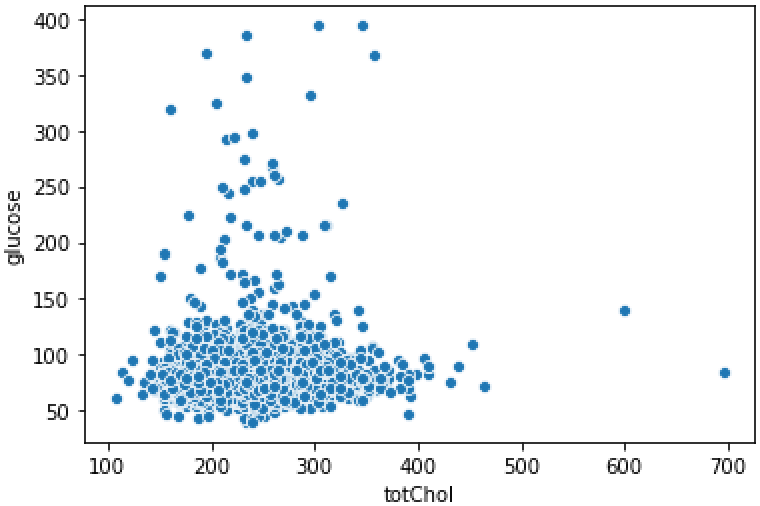
totChol


glucose
totChol
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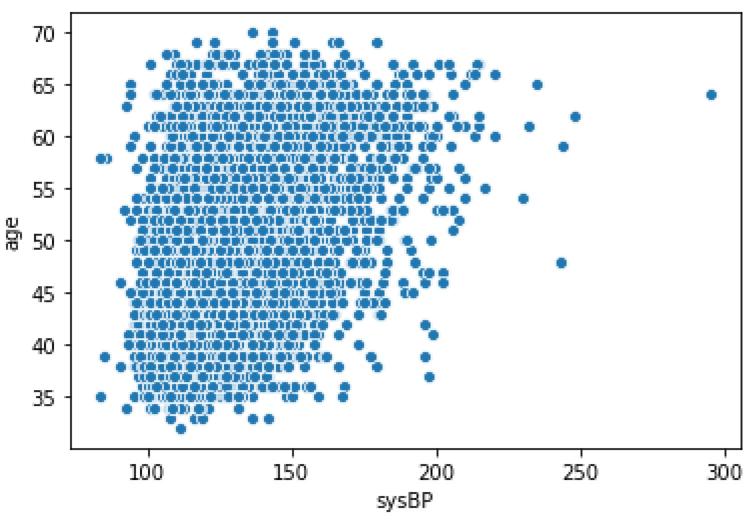
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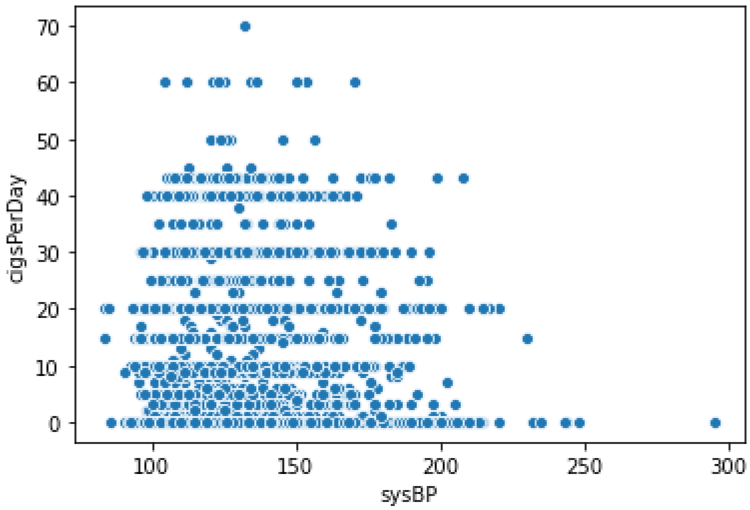
cigsPerDay
sysBP
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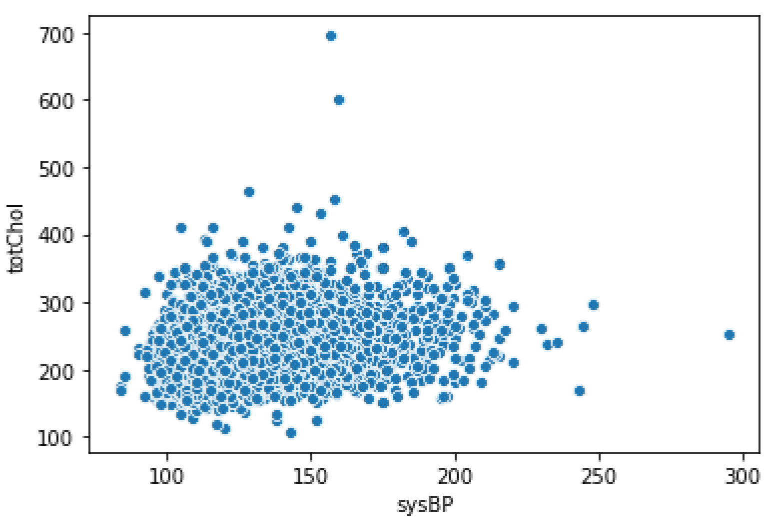
totChol
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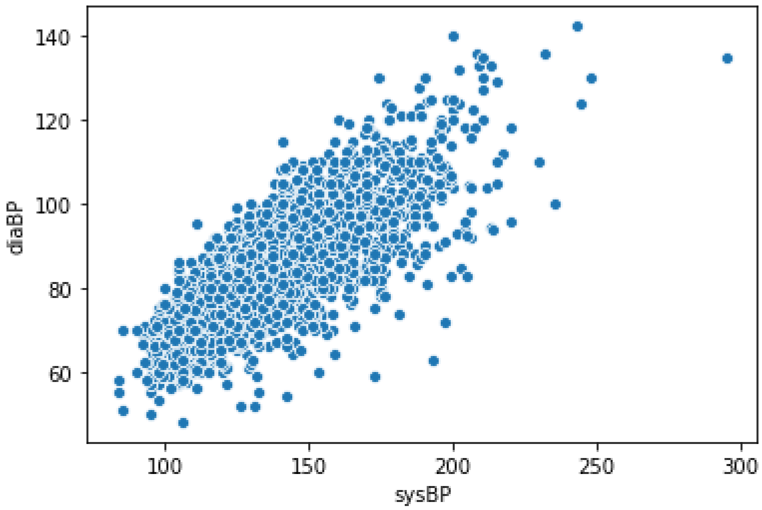
140
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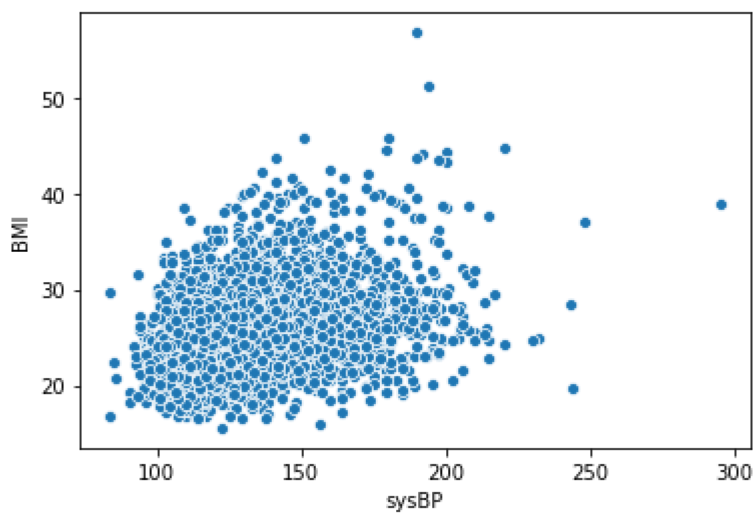
sysBP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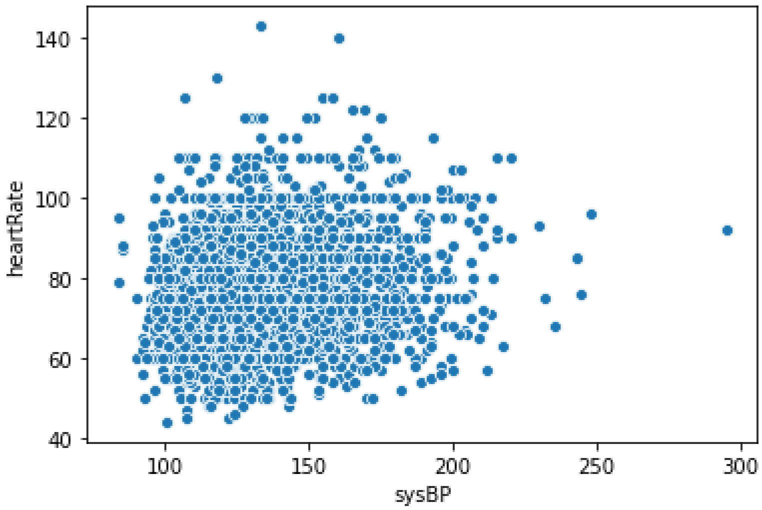
sysBP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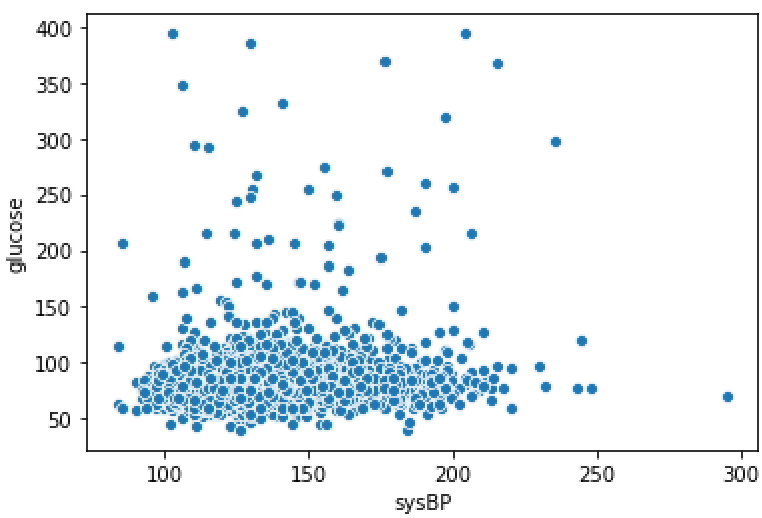
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glucose
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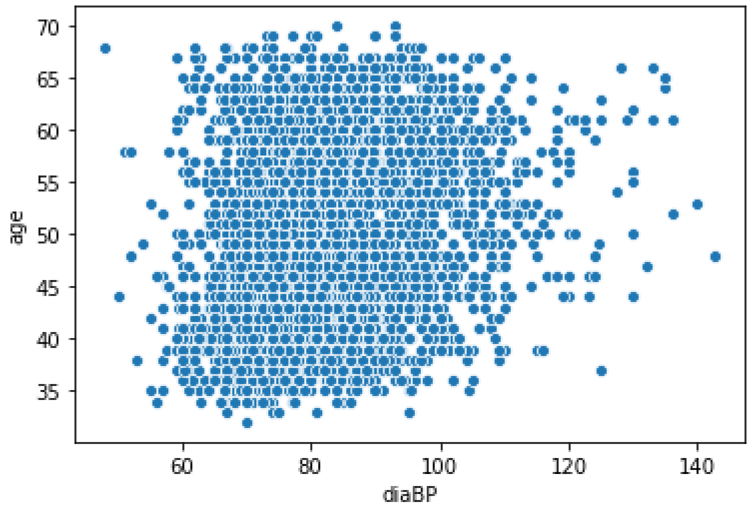
sysBP



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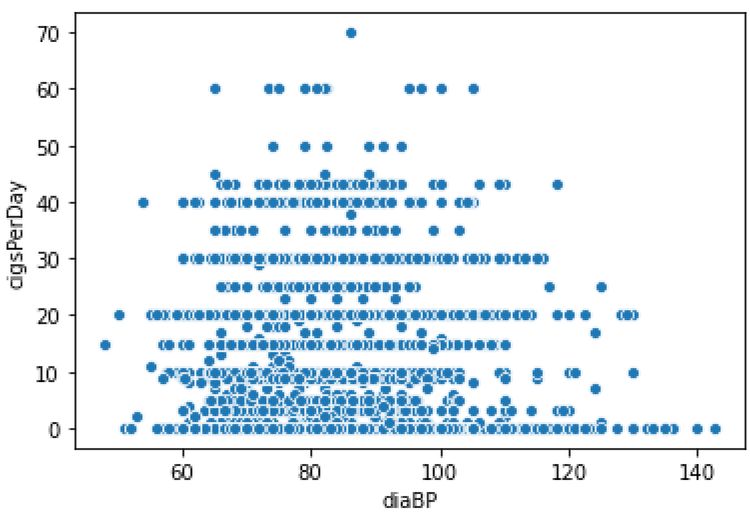
diaBP



70
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cigsPerDay
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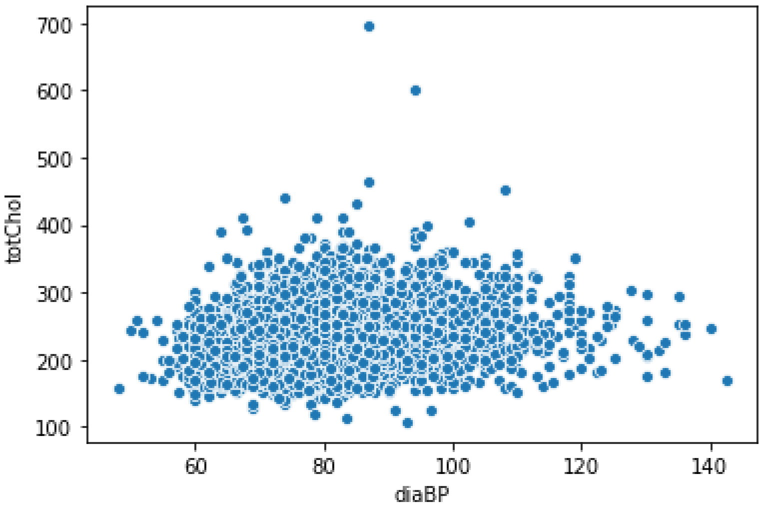
diaBP


totChol
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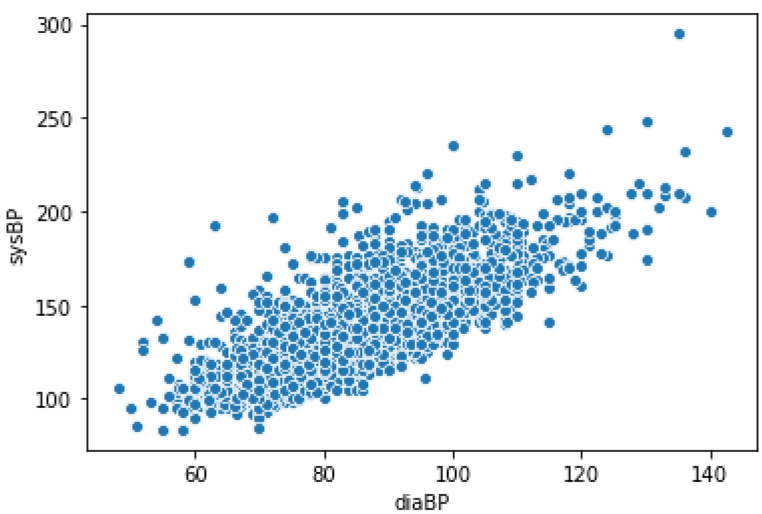
sysBP
diaBP
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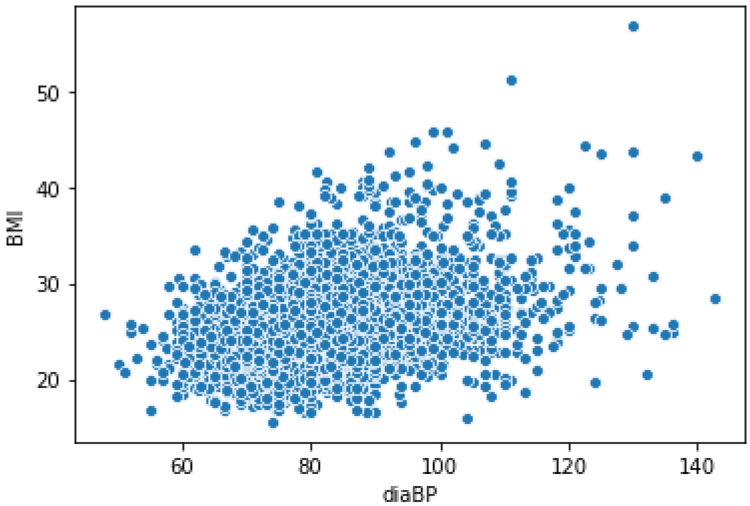
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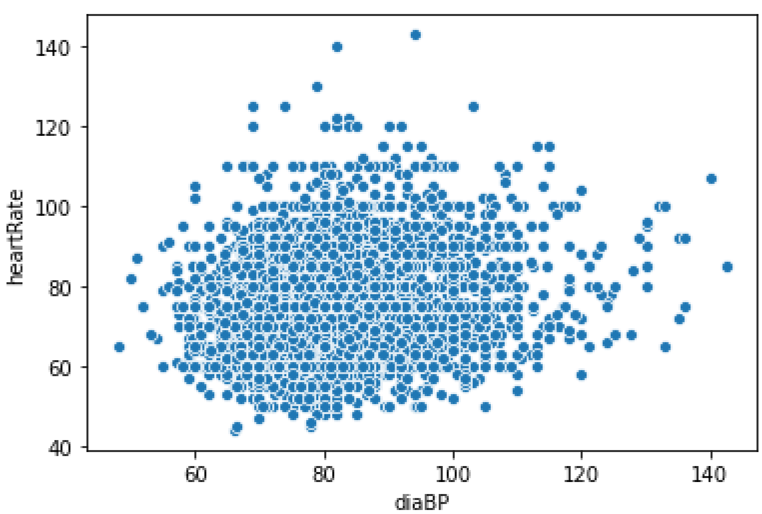
diaBP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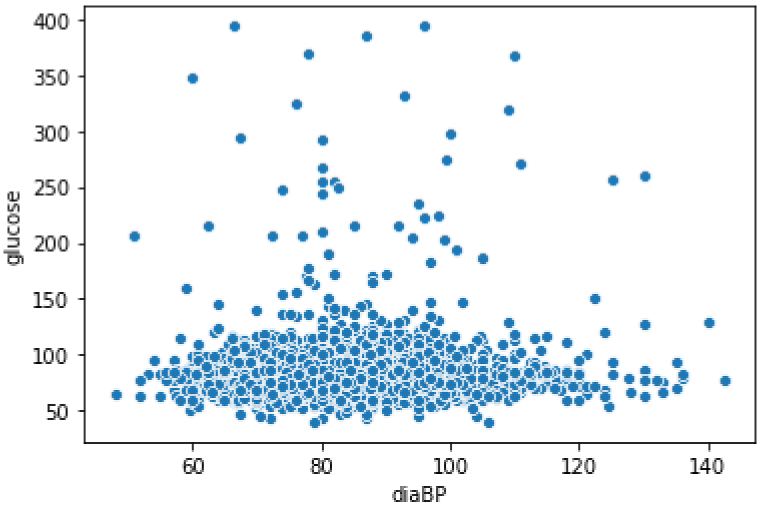
diaBP


glucose
diaBP
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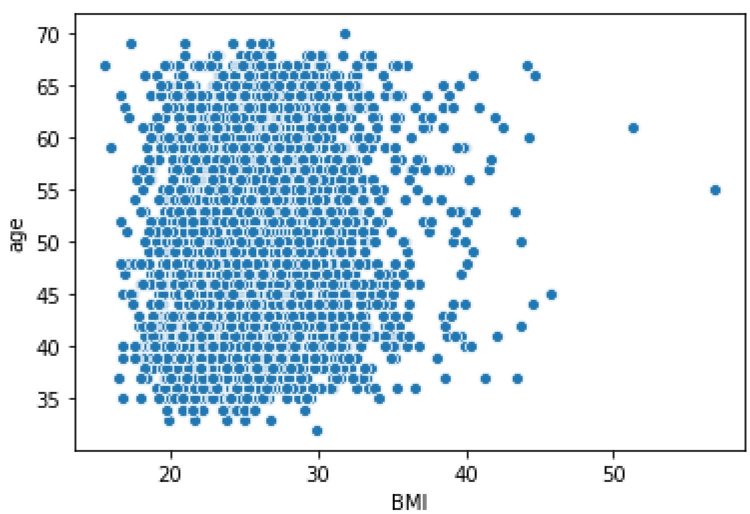
age
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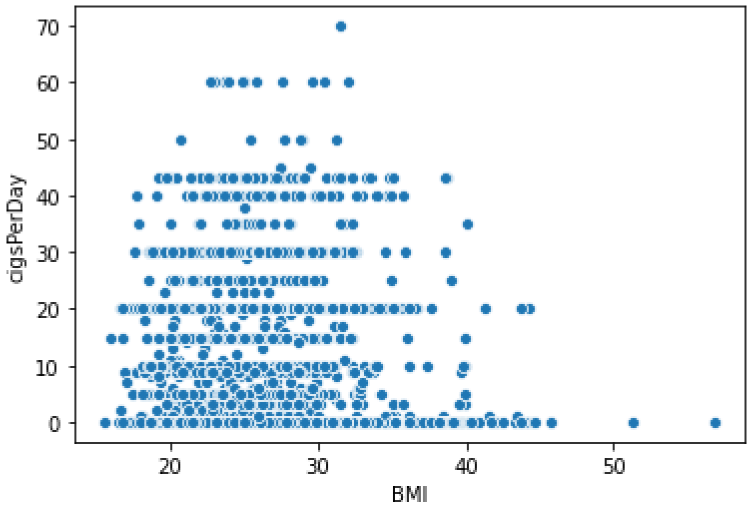
cigsPerDay
BMI
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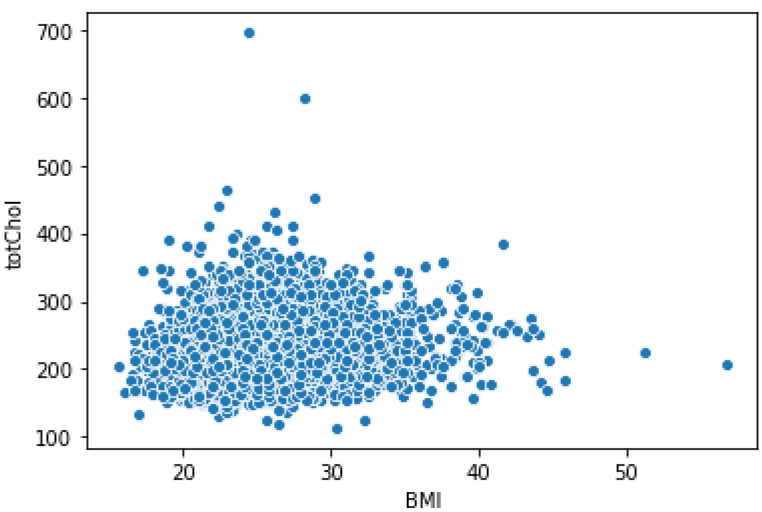
totChol
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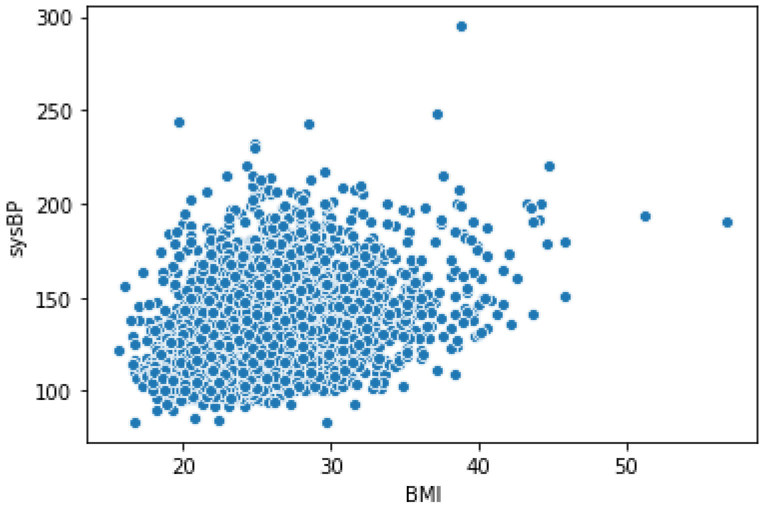
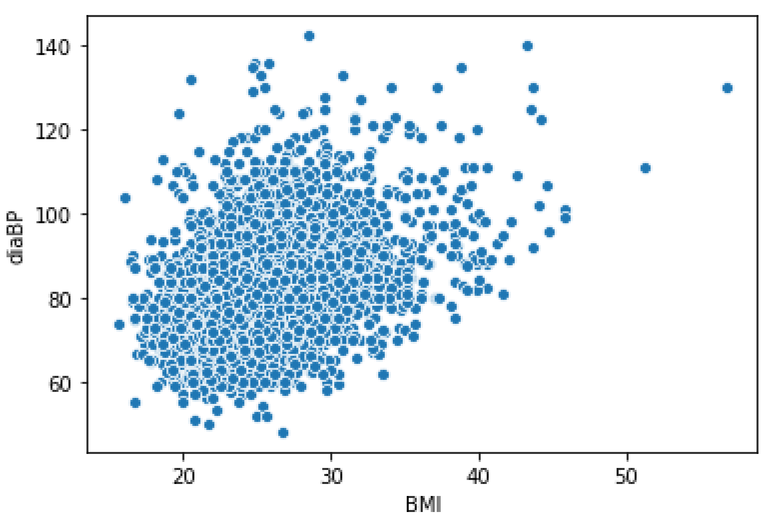
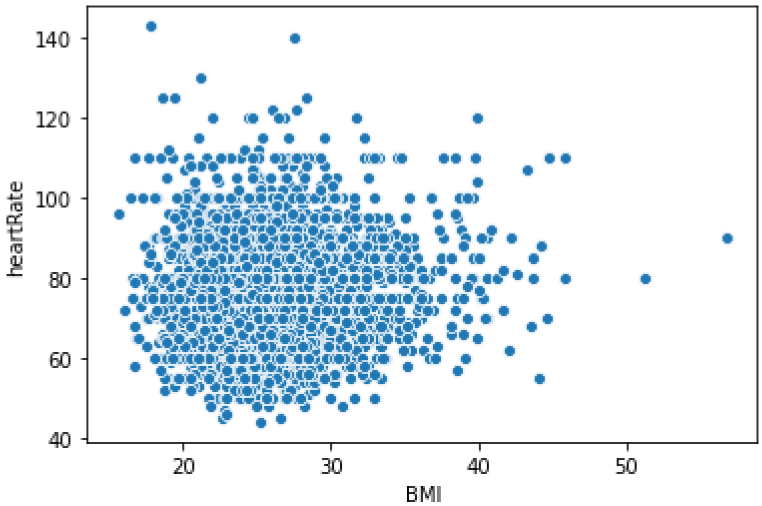


sysBP
BMI



diaBP
BMI


heartRate
BMI
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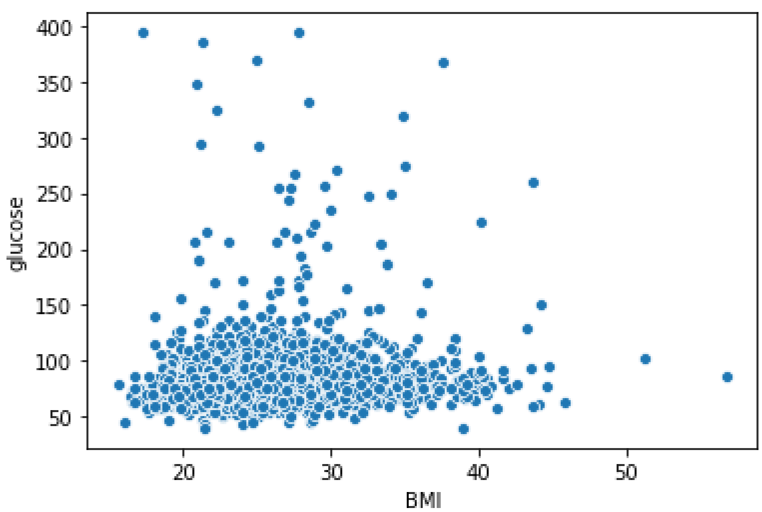
glucose
BMI
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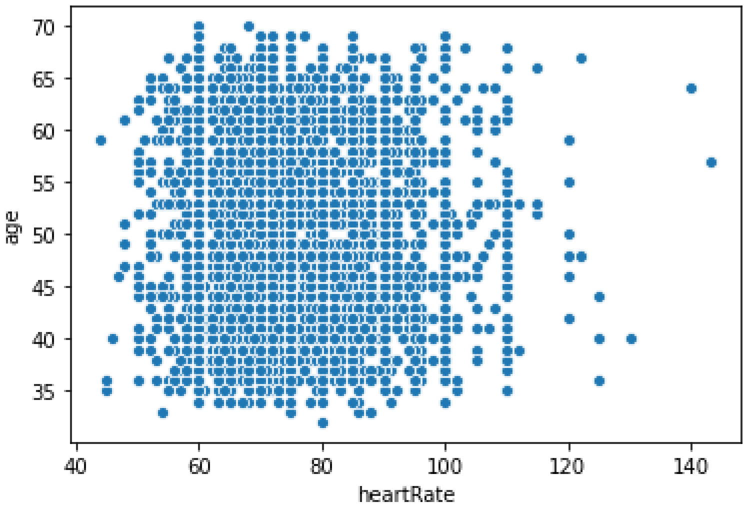
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age
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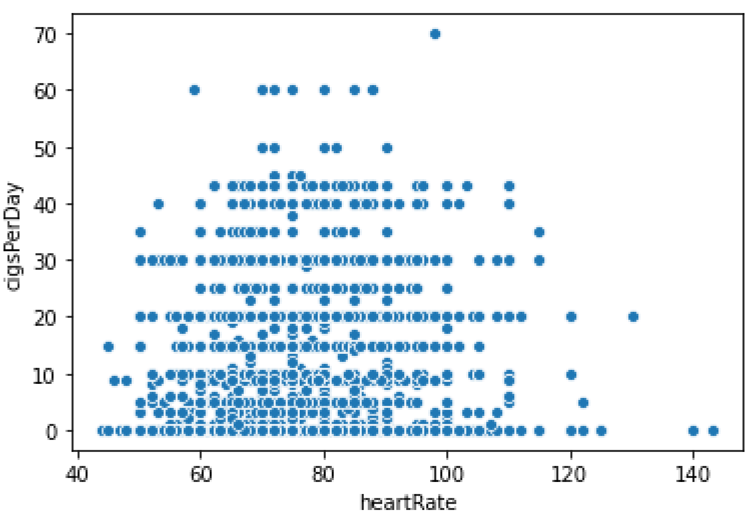
120
140
heartRate


70
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cigsPerDay
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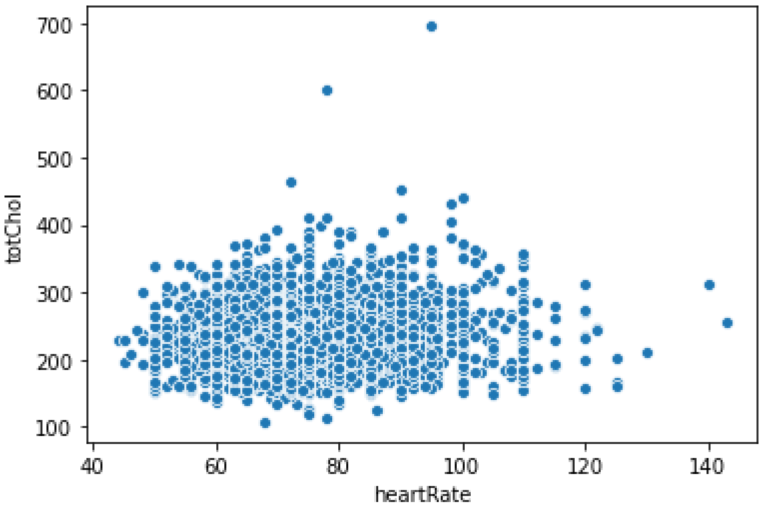
heartRate


totChol
heartRate
700
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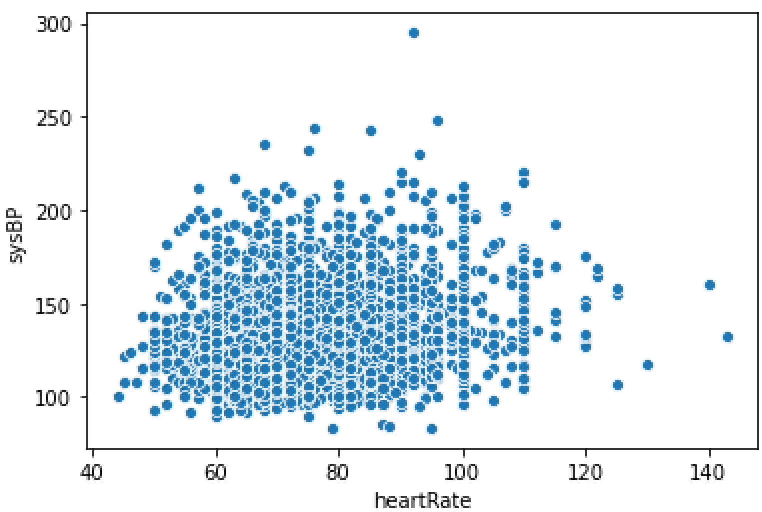
140


sysBP
heartRate
300
250
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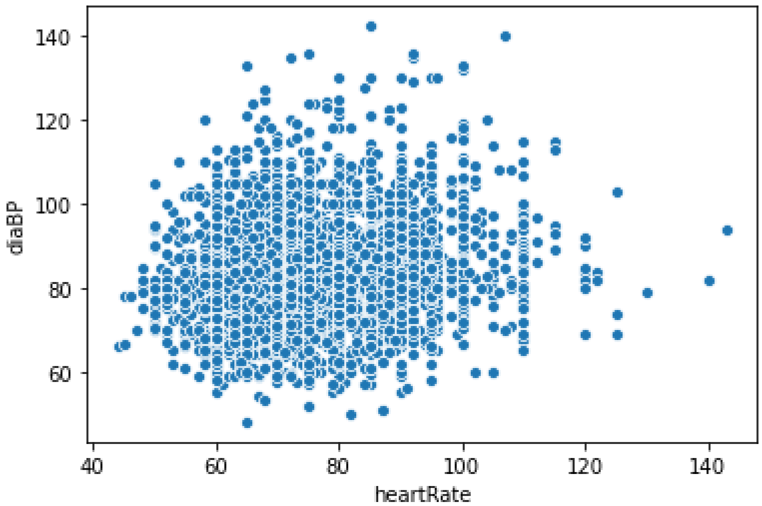
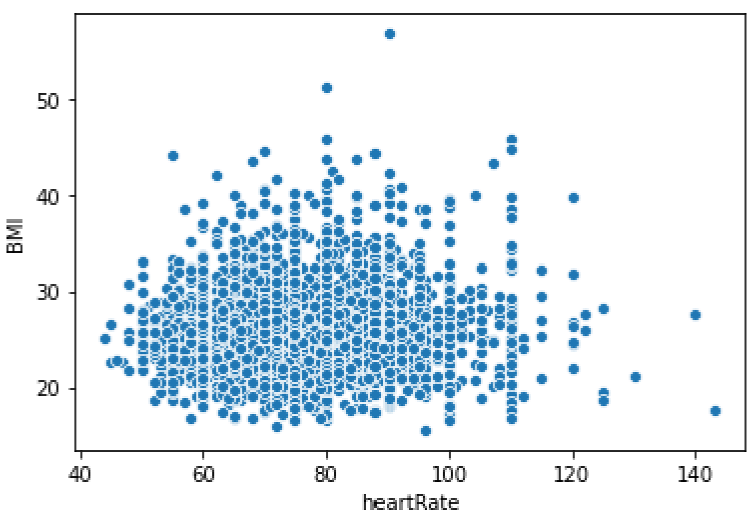
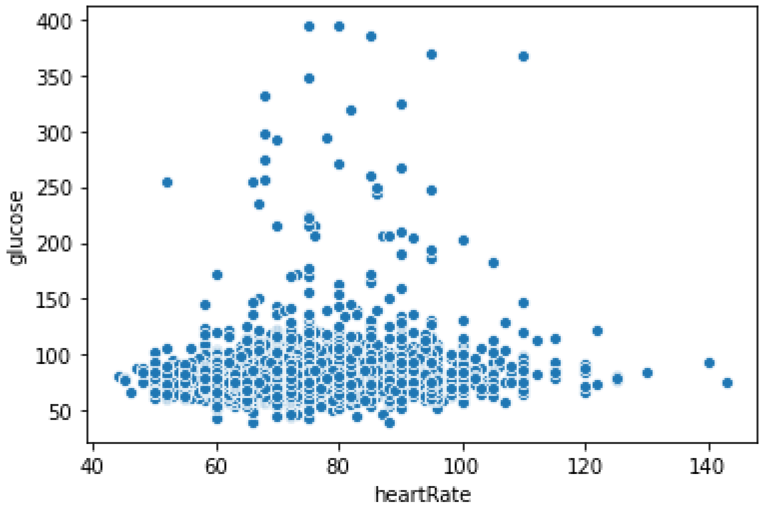
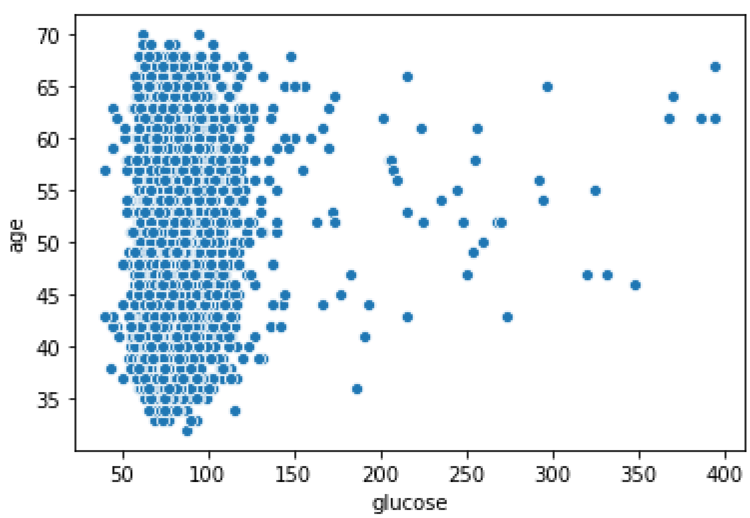
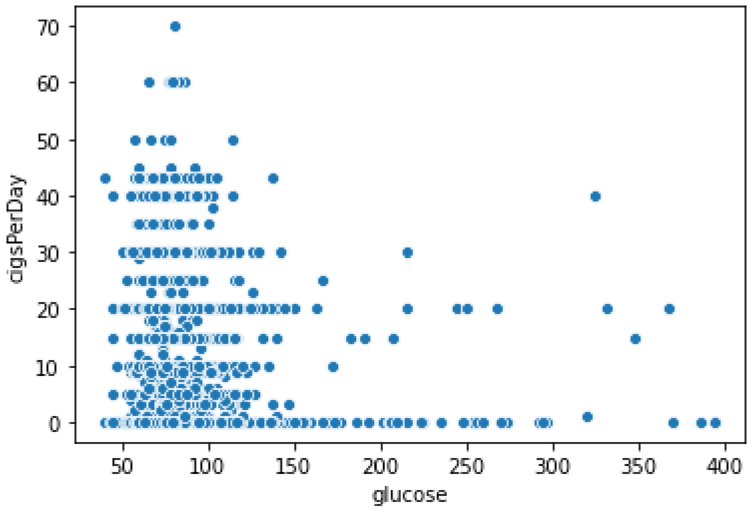
100
120
140

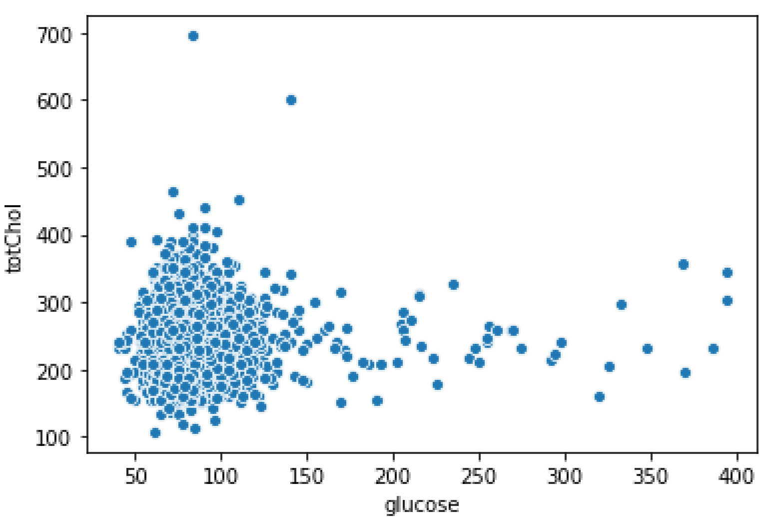

diaBP
heartRate
140
120
100
80
60
40
60
80
100
120
140

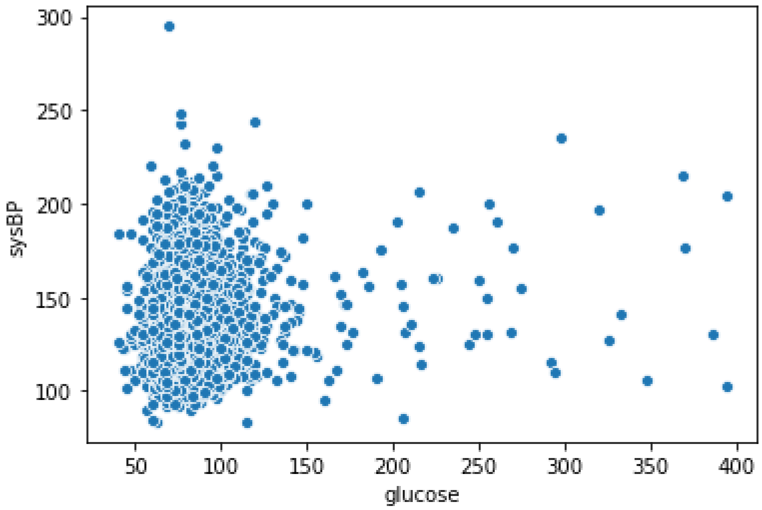

BMI
heartRate
50
40
30
20
40
60
80
100
120
140

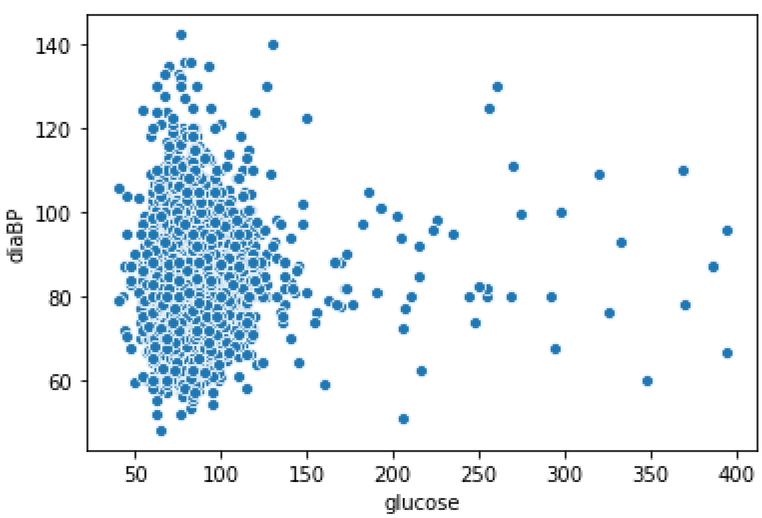

glucose
heartRate
400
350
300
250
200
150
100
50
40
60
80
100
120
140

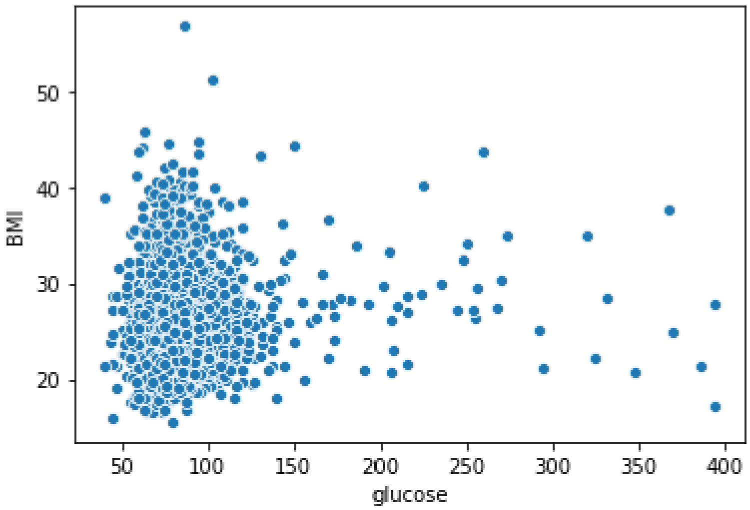

age
glucose
70
65
60
55
50
45
40
35
50
100
150
200
250
300
350
400

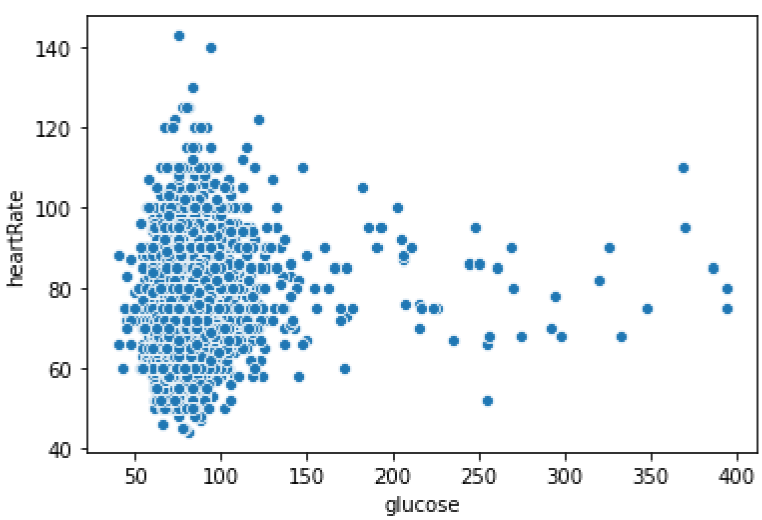

cigsPerDay
glucose
0
10
20
30
40
50
60
70
50
100
150
200
250
300
350
400


totChol
glucose
100
200
300
400
500
600
700
50
100
150
200
250
300
350
400


sysBP
glucose
300
250
200
150
100
50
100
150
200
250
300
350
400


diaBP
glucose
140
120
100
80
60
50
100
150
200
250
300
350
400





After the calculation and graphs above, the best correlated attributes are:
cigPerDay <- Age,
totChol <- Age,
BMI <- diaBP,
heartRate <- sysBP,
glucose <- sysBP
We then fill in the missing values with our estimates:

In [5]:

```
## cigsPerDay
temp_df = df[df['cigsPerDay'].notna()]
x = temp_df["age"]
x = sm.add_constant(x)
y = temp_df["cigsPerDay"]

model = sm.OLS(y,x).fit()
model.summary()
```

Out[5]:

OLS Regression Results

Dep. Variable:	cigsPerDay	**R-squared:**	0.037
Model:	OLS	**Adj. R-squared:**	0.037
Method:	Least Squares	**F-statistic:**	162.4
Date:	Tue, 07 Jul 2020	**Prob (F-statistic):**	1.59e-36
Time:	19:31:37	**Log-Likelihood:**	-16323.
No. Observations:	4209	**AIC:**	3.265e+04
Df Residuals:	4207	**BIC:**	3.266e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	22.2803	1.057	21.072	0.000	20.207	24.353
age	-0.2678	0.021	-12.744	0.000	-0.309	-0.227

Omnibus:	785.277	**Durbin-Watson:**	1.978
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1322.127
Skew:	1.236	**Prob(JB):**	8.01e-288
Kurtosis:	4.194	**Cond. No.**	295.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [6]:

```
## totChol
temp_df = df[df['totChol'].notna()]
x = temp_df["age"]
x = sm.add_constant(x)
y = temp_df["totChol"]

model = sm.OLS(y,x).fit()
model.summary()
```

Out[6]:

OLS Regression Results

Dep. Variable:	totChol	**R-squared:**	0.069
Model:	OLS	**Adj. R-squared:**	0.068
Method:	Least Squares	**F-statistic:**	308.9
Date:	Tue, 07 Jul 2020	**Prob (F-statistic):**	9.19e-67
Time:	19:31:37	**Log-Likelihood:**	-21697.
No. Observations:	4188	**AIC:**	4.340e+04
Df Residuals:	4186	**BIC:**	4.341e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	169.0609	3.907	43.271	0.000	161.401	176.721
age	1.3652	0.078	17.574	0.000	1.213	1.517

Omnibus:	909.943	**Durbin-Watson:**	2.020
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	4685.659
Skew:	0.944	**Prob(JB):**	0.00
Kurtosis:	7.825	**Cond. No.**	296.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [7]:

```
## BMI
temp_df = df[df['BMI'].notna()]
x = temp_df["diaBP"]
x = sm.add_constant(x)
y = temp_df["BMI"]

model = sm.OLS(y,x).fit()
model.summary()
```

Out[7]:

OLS Regression Results

Dep. Variable:	BMI	**R-squared:**	0.143
Model:	OLS	**Adj. R-squared:**	0.142
Method:	Least Squares	**F-statistic:**	701.2
Date:	Tue, 07 Jul 2020	**Prob (F-statistic):**	4.56e-143
Time:	19:31:37	**Log-Likelihood:**	-11594.
No. Observations:	4219	**AIC:**	2.319e+04
Df Residuals:	4217	**BIC:**	2.320e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	15.0733	0.409	36.826	0.000	14.271	15.876
diaBP	0.1294	0.005	26.480	0.000	0.120	0.139

Omnibus:	525.294	**Durbin-Watson:**	1.992
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1094.179
Skew:	0.767	**Prob(JB):**	2.52e-238
Kurtosis:	4.968	**Cond. No.**	589.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [8]:

```
## heartRate
temp_df = df[df['heartRate'].notna()]
x = temp_df["sysBP"]
x = sm.add_constant(x)
y = temp_df["heartRate"]

model = sm.OLS(y,x).fit()
model.summary()
```

Out[8]:

OLS Regression Results

Dep. Variable:	heartRate	**R-squared:**	0.033
Model:	OLS	**Adj. R-squared:**	0.033
Method:	Least Squares	**F-statistic:**	145.5
Date:	Tue, 07 Jul 2020	**Prob (F-statistic):**	5.79e-33
Time:	19:31:37	**Log-Likelihood:**	-16478.
No. Observations:	4237	**AIC:**	3.296e+04
Df Residuals:	4235	**BIC:**	3.297e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	62.7132	1.107	56.676	0.000	60.544	64.883
sysBP	0.0995	0.008	12.062	0.000	0.083	0.116

Omnibus:	287.739	**Durbin-Watson:**	2.008
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	388.903
Skew:	0.598	**Prob(JB):**	3.55e-85
Kurtosis:	3.878	**Cond. No.**	817.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [9]:

```
## glucose
temp_df = df[df['glucose'].notna()]
x = temp_df["sysBP"]
x = sm.add_constant(x)
y = temp_df["glucose"]

model = sm.OLS(y,x).fit()
model.summary()
```

Out[9]:

OLS Regression Results

Dep. Variable:	glucose	**R-squared:**	0.020
Model:	OLS	**Adj. R-squared:**	0.020
Method:	Least Squares	**F-statistic:**	77.63
Date:	Tue, 07 Jul 2020	**Prob (F-statistic):**	1.85e-18
Time:	19:31:37	**Log-Likelihood:**	-17653.
No. Observations:	3850	**AIC:**	3.531e+04
Df Residuals:	3848	**BIC:**	3.532e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	61.8044	2.320	26.638	0.000	57.256	66.353
sysBP	0.1522	0.017	8.811	0.000	0.118	0.186

Omnibus:	4515.241	**Durbin-Watson:**	2.035
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	560136.877
Skew:	6.113	**Prob(JB):**	0.00
Kurtosis:	60.812	**Cond. No.**	815.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Based on the simple linear regressions above we can get the following equations for the missing values:
cigsPerDay = 22.2803 - 0.2678(age)
totChol = 169.0609 + 1.3652(age)
BMI = 15.0733 + 0.1294(diaBP)
heartRate = 62.7312 + 0.0775(sysBP) glucose = 61.8044 + 0.1522(sysBP)
Filling in the missing values with those equations:

In [10]:

```
# cigsPerDay
df['cigsPerDay'] = df.apply(
    lambda row: 22.2803 - (0.2678*row['age']) if np.isnan(row['cigsPerDay']) else row['cig
sPerDay'],
    axis=1
)
```

In [11]:

```
# totChol
df['totChol'] = df.apply(
    lambda row: 169.0609 + (1.365*row['age']) if np.isnan(row['totChol']) else row['totCho
l'],
    axis=1
)
```

In [12]:

```
# BMI
df['BMI'] = df.apply(
    lambda row: 15.0733 + (0.1294*row['diaBP']) if np.isnan(row['BMI']) else row['BMI'],
    axis=1
)
```

In [13]:

```
# heartRate
df['heartRate'] = df.apply(
    lambda row: 15.0733 + (0.1294*row['sysBP']) if np.isnan(row['heartRate']) else row['he
artRate'],
    axis=1
)
```

In [14]:

```
# glucose
df['glucose'] = df.apply(
    lambda row: 61.8044 + (0.1522*row['sysBP']) if np.isnan(row['glucose']) else row['gluc
ose'],
    axis=1
)
df.isnull().sum(axis = 0)
```

Out[14]:

```
age           0
cigsPerDay    0
totChol       0
sysBP         0
diaBP         0
BMI           0
heartRate     0
glucose       0
CHD           0
dtype: int64
```

Exploratory Data Analysis:

The data is split into a training and testing set with an 80/20 split. Seed = 8675309 (Jenny's Number)

In [15]:

```
X = df.drop(['CHD'], axis=1)
Y = df[['CHD']]
X_Train, X_Test, Y_Train, Y_Test = train_test_split(X, Y, train_size = 0.80, random_state
= 8675309)
```

In [16]:

```
# Training k=3
model = KNeighborsClassifier(n_neighbors=3)

model.fit(X_Train, Y_Train['CHD'])
y_pred = model.predict(X_Test)
pred = pd.DataFrame(y_pred, )
pred.rename(columns = {0:"Pred"}, inplace = True)
results = pd.concat([pred, Y_Test.reset_index(drop=True)], axis = 1)
x = confusion_matrix(results['CHD'], results["Pred"])
y = accuracy_score(results['CHD'], results["Pred"])
print("Matrix: ")
print(x)
print("Accuracy: ", y)
print("Error_rate:", 1 - y)
```

```
Matrix:
[[665  45]
 [123  15]]
Accuracy:  0.8018867924528302
Error_rate: 0.19811320754716977
```

In [17]:

```
# Training k=5
model = KNeighborsClassifier(n_neighbors=5)

model.fit(X_Train, Y_Train['CHD'])
y_pred = model.predict(X_Test)
pred = pd.DataFrame(y_pred, )
pred.rename(columns = {0:"Pred"}, inplace = True)
results = pd.concat([pred, Y_Test.reset_index(drop=True)], axis = 1)
x = confusion_matrix(results['CHD'], results["Pred"])
y = accuracy_score(results['CHD'], results["Pred"])
print("Matrix: ")
print(x)
print("Accuracy: ", y)
print("Error_rate:", 1 - y)
```

```
Matrix:
[[676  34]
 [125  13]]
Accuracy:  0.8125
Error_rate: 0.1875
```

In [18]:

```
# Training k=7
model = KNeighborsClassifier(n_neighbors=7)

model.fit(X_Train, Y_Train['CHD'])
y_pred = model.predict(X_Test)
pred = pd.DataFrame(y_pred, )
pred.rename(columns = {0:"Pred"}, inplace = True)
results = pd.concat([pred, Y_Test.reset_index(drop=True)], axis = 1)
x = confusion_matrix(results['CHD'], results["Pred"])
y = accuracy_score(results['CHD'], results["Pred"])
print("Matrix: ")
print(x)
print("Accuracy: ", y)
print("Error_rate:", 1 - y)
```

```
Matrix:
[[687  23]
 [128  10]]
Accuracy:  0.8219339622641509
Error_rate: 0.17806603773584906
```

Evaluation:

Comparing the error rates of the 3 k-values, the highest k that was tested, k=7, had the highest accuracy rate, leading to the lowest error rate, making it the best overall option for predicting the CHD diagnosis. Although the other 2 models using lower k's never fell below 0.8 accuracy, they still were worse than k=7. My suggestion to the client would be KNeighbors k = 7 for the highest chance of being right overall.

Results:

Using k=7 or higher would yield the best results for the tests, and it would be smart to not rely on the glucose to predict the CHD, as alot of those data points themselves were predicted, which could lead to the data become skewed and becoming less accurate. Further testing could reveal a better k value which would raise the accuracy, more than likely that k-value would be larger than 7.

Reference:

SeanLaw (2015). Convert a Pandas DataFrame to Numeric. Retrieved (2020, July 7) from http://seanlaw.github.io/2015/12/15/convert-pandas-dataframe-to-numeric/ (http://seanlaw.github.io/2015/12/15/convert-pandas-dataframe-to-numeric/)
Pandas Documentation (2014). pandas.DataFrame.drop. Retrieved (2020, July 7) from https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.drop.html (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.drop.html)
Stack Exchange (2019). How to fill missing value based on othercolumns in Pandas dataframe?. Retrieved (2020, July 7) from https://datascience.stackexchange.com/questions/17769/how-to-fill-missing-value-based-on-other-columns-in-pandas-dataframe (https://datascience.stackexchange.com/questions/17769/how-to-fill-missing-value-based-on-other-columns-in-pandas-dataframe)
Stack Overflow (2020). How to count the NaN values in a column in pandas DataFrame. Retrieved (2020, July 7) from https://stackoverflow.com/questions/26266362/how-to-count-the-nan-values-in-a-column-in-pandas-dataframe (https://stackoverflow.com/questions/26266362/how-to-count-the-nan-values-in-a-column-in-pandas-dataframe)