Diabetes_R

February 8, 2024

1 Machine Learning - Linear Regression

1.1 Import Libraries

[ ]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns

from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import StandardScaler

import warnings
warnings.filterwarnings('ignore')
```

1.2 Load Diabetes Dataset

age age in years

sex

bmi body mass index

bp average blood pressure

s1 tc, total serum cholesterol

s2 ldl, low-density lipoproteins

s3 hdl, high-density lipoproteins

s4 tch, total cholesterol / HDL

s5 ltg, possibly log of serum triglycerides level

s6 glu, blood sugar level

442 instances. 11 columns. Target: quantitative measure of disease progression one year after baseline

[ ]:
```python
# Convert sklearn diabetes dataset to dataframe

def sklearn_to_df(sklearn_dataset):
    df = pd.DataFrame(sklearn_dataset.data, columns=sklearn_dataset.
 ↪feature_names)
    df['target'] = pd.Series(sklearn_dataset.target)
    return df

df_diabetes = sklearn_to_df(datasets.load_diabetes())
```

1.3 Exploratory Data Analysis

[ ]:
```python
# Dimensions of dataframe
df_diabetes.shape

# (rows, columns)
```

[ ]:
```
(442, 11)
```

[ ]:
```python
# Summary of dataframe structure and information
df_diabetes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 442 entries, 0 to 441
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   age     442 non-null    float64
 1   sex     442 non-null    float64
 2   bmi     442 non-null    float64
 3   bp      442 non-null    float64
 4   s1      442 non-null    float64
 5   s2      442 non-null    float64
 6   s3      442 non-null    float64
 7   s4      442 non-null    float64
 8   s5      442 non-null    float64
 9   s6      442 non-null    float64
 10  target  442 non-null    float64
dtypes: float64(11)
memory usage: 38.1 KB
```

[ ]:
```python
# Basic statistics
df_diabetes.describe().transpose()
```

[ ]:
```
        count          mean       std       min       25%       50%  \
age     442.0 -2.511817e-19  0.047619 -0.107226 -0.037299  0.005383
sex     442.0  1.230790e-17  0.047619 -0.044642 -0.044642 -0.044642
```

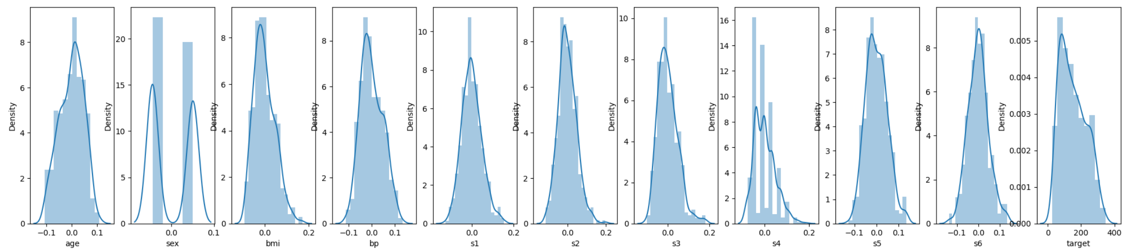
```
bmi     442.0 -2.245564e-16   0.047619  -0.090275  -0.034229   -0.007284
bp      442.0 -4.797570e-17   0.047619  -0.112399  -0.036656   -0.005670
s1      442.0 -1.381499e-17   0.047619  -0.126781  -0.034248   -0.004321
s2      442.0  3.918434e-17   0.047619  -0.115613  -0.030358   -0.003819
s3      442.0 -5.777179e-18   0.047619  -0.102307  -0.035117   -0.006584
s4      442.0 -9.042540e-18   0.047619  -0.076395  -0.039493   -0.002592
s5      442.0  9.293722e-17   0.047619  -0.126097  -0.033246   -0.001947
s6      442.0  1.130318e-17   0.047619  -0.137767  -0.033179   -0.001078
target  442.0  1.521335e+02  77.093005  25.000000  87.000000  140.500000

               75%         max
age       0.038076    0.110727
sex       0.050680    0.050680
bmi       0.031248    0.170555
bp        0.035644    0.132044
s1        0.028358    0.153914
s2        0.029844    0.198788
s3        0.029312    0.181179
s4        0.034309    0.185234
s5        0.032432    0.133597
s6        0.027917    0.135612
target  211.500000  346.000000
```

[ ]:
```
# Display first 5 rows
df_diabetes.head()
```

[ ]:
```
        age       sex       bmi        bp        s1        s2        s3  \
0  0.038076  0.050680  0.061696  0.021872 -0.044223 -0.034821 -0.043401
1 -0.001882 -0.044642 -0.051474 -0.026328 -0.008449 -0.019163  0.074412
2  0.085299  0.050680  0.044451 -0.005670 -0.045599 -0.034194 -0.032356
3 -0.089063 -0.044642 -0.011595 -0.036656  0.012191  0.024991 -0.036038
4  0.005383 -0.044642 -0.036385  0.021872  0.003935  0.015596  0.008142

         s4        s5        s6  target
0 -0.002592  0.019907 -0.017646   151.0
1 -0.039493 -0.068332 -0.092204    75.0
2 -0.002592  0.002861 -0.025930   141.0
3  0.034309  0.022688 -0.009362   206.0
4 -0.002592 -0.031988 -0.046641   135.0
```

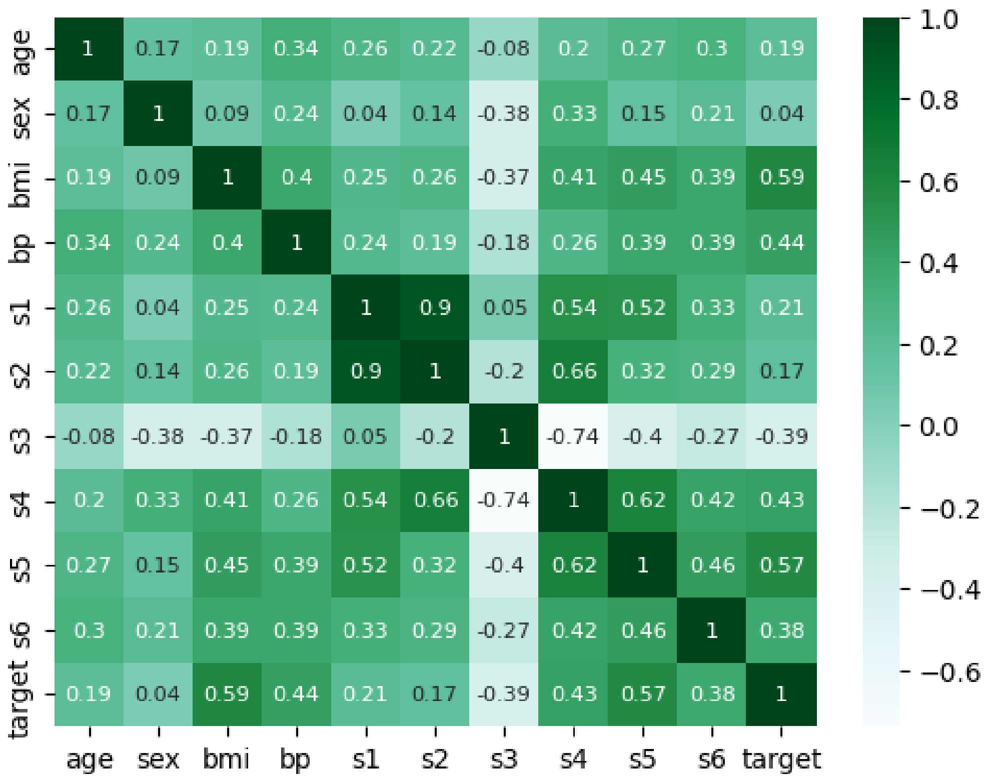
[ ]:
```
# Assign column names to a variable
columns = df_diabetes.columns

# Distplot
#for i in columns:
#    plt.figure(figsize=(4,4))
#    (sns.distplot(df_diabetes[i]))
```

```
plt.figure(figsize=(25,5))
for indx, cols in enumerate(columns):
    plt.subplot(1,len(columns), indx+1)
    sns.distplot(df_diabetes[cols])
```

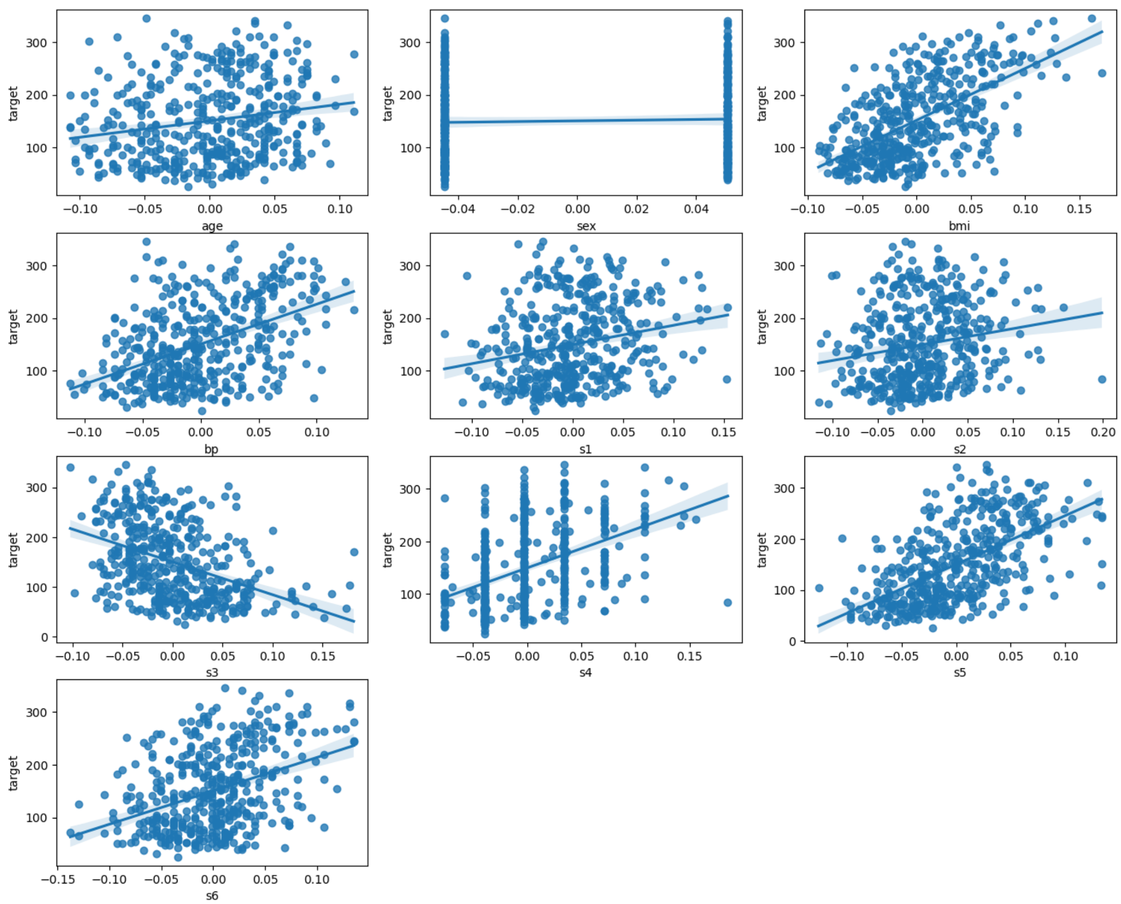


```
[ ]: # Correlation between features and outcome
sns.heatmap(round(df_diabetes.corr(numeric_only=True),2), annot=True,␣
↪cmap="BuGn", annot_kws={'size': 8})
```

[ ]: <Axes: >

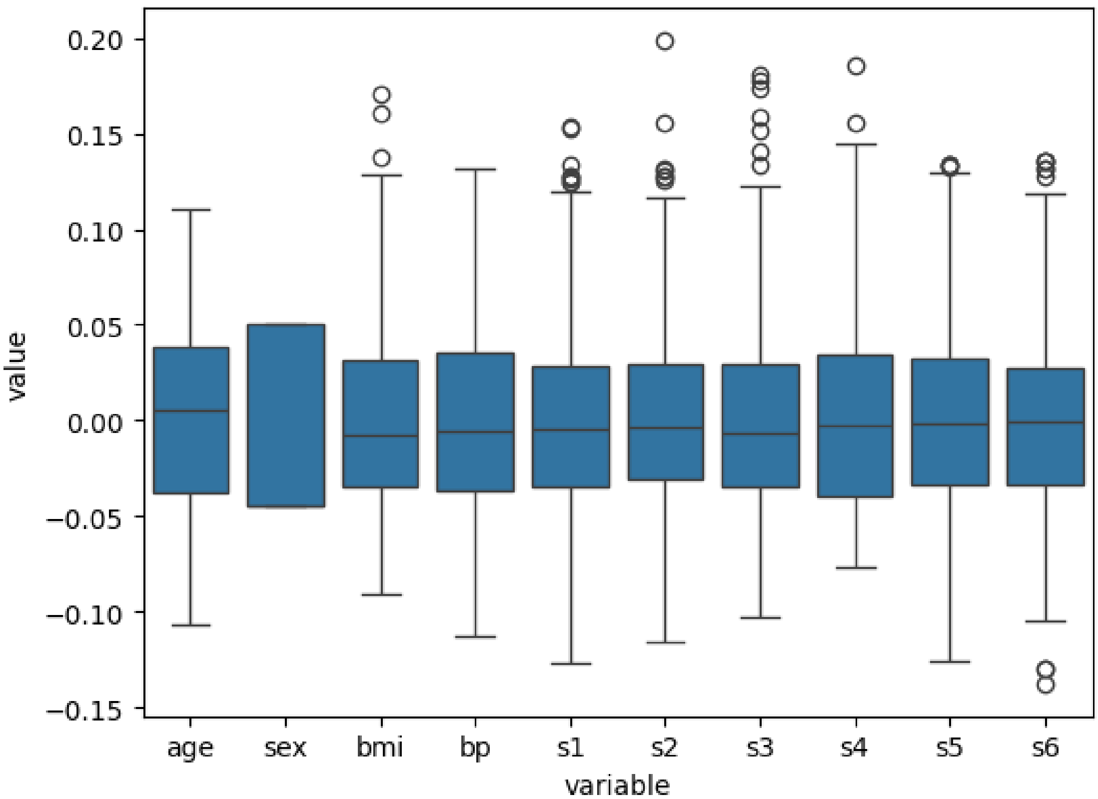


```
[ ]: # Regplot
plt.figure(figsize=(16,13))
cols = ['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6']


for i, feat in enumerate(cols):
    plt.subplot(4,3,i+1)
    sns.regplot(data=df_diabetes, x = df_diabetes[feat], y = 'target',␣
 ↪robust=True)

plt.show()
```




```
[ ]: # Boxplot
df_diabetes_g = df_diabetes[cols]
sns.boxplot(x="variable", y = "value", data=pd.melt(df_diabetes_g))
```

```
[ ]: <Axes: xlabel='variable', ylabel='value'>
```



1.4 Separate Features from Outcome

[ ]:
```python
# Define X.  Features
X = df_diabetes.drop('target', axis=1)
X
```

[ ]:
```
          age       sex       bmi        bp        s1        s2        s3  \
0    0.038076  0.050680  0.061696  0.021872 -0.044223 -0.034821 -0.043401
1   -0.001882 -0.044642 -0.051474 -0.026328 -0.008449 -0.019163  0.074412
2    0.085299  0.050680  0.044451 -0.005670 -0.045599 -0.034194 -0.032356
3   -0.089063 -0.044642 -0.011595 -0.036656  0.012191  0.024991 -0.036038
4    0.005383 -0.044642 -0.036385  0.021872  0.003935  0.015596  0.008142
..        …         …         …         …         …         …         …
437  0.041708  0.050680  0.019662  0.059744 -0.005697 -0.002566 -0.028674
438 -0.005515  0.050680 -0.015906 -0.067642  0.049341  0.079165 -0.028674
439  0.041708  0.050680 -0.015906  0.017293 -0.037344 -0.013840 -0.024993
440 -0.045472 -0.044642  0.039062  0.001215  0.016318  0.015283 -0.028674
441 -0.045472 -0.044642 -0.073030 -0.081413  0.083740  0.027809  0.173816

           s4        s5        s6
0   -0.002592  0.019907 -0.017646
```

```
1   -0.039493 -0.068332 -0.092204
2   -0.002592  0.002861 -0.025930
3    0.034309  0.022688 -0.009362
4   -0.002592 -0.031988 -0.046641
..        …        …        …
437 -0.002592  0.031193  0.007207
438  0.034309 -0.018114  0.044485
439 -0.011080 -0.046883  0.015491
440  0.026560  0.044529 -0.025930
441 -0.039493 -0.004222  0.003064

[442 rows x 10 columns]
```

[ ]:
```python
# Define y. Outcome
y = df_diabetes['target']
y
```

[ ]:
```
0      151.0
1       75.0
2      141.0
3      206.0
4      135.0
       …
437    178.0
438    104.0
439    132.0
440    220.0
441     57.0
Name: target, Length: 442, dtype: float64
```

[ ]:
```python
# Dimensions of X and y.  Features and Outcome
print(X.shape, y.shape)
```

```
(442, 10) (442,)
```

1.5 OLS Regression

1.5.1 OLS Regression 1

[ ]:
```python
import statsmodels.api as sm

# STATSMODELS

# Add intercept
X = sm.add_constant(X)

# create model
lml = sm.OLS(y,X)
```

```python
# fit model
results = lml.fit()

# print regression results
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 target   R-squared:                       0.518
Model:                            OLS   Adj. R-squared:                  0.507
Method:                 Least Squares   F-statistic:                     46.27
Date:                Wed, 07 Feb 2024   Prob (F-statistic):           3.83e-62
Time:                        22:21:14   Log-Likelihood:                -2386.0
No. Observations:                 442   AIC:                             4794.
Df Residuals:                     431   BIC:                             4839.
Df Model:                          10
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        152.1335      2.576     59.061      0.000     147.071     157.196
age          -10.0099     59.749     -0.168      0.867    -127.446     107.426
sex         -239.8156     61.222     -3.917      0.000    -360.147    -119.484
bmi          519.8459     66.533      7.813      0.000     389.076     650.616
bp           324.3846     65.422      4.958      0.000     195.799     452.970
s1          -792.1756    416.680     -1.901      0.058   -1611.153      26.802
s2           476.7390    339.030      1.406      0.160    -189.620    1143.098
s3           101.0433    212.531      0.475      0.635    -316.684     518.770
s4           177.0632    161.476      1.097      0.273    -140.315     494.441
s5           751.2737    171.900      4.370      0.000     413.407    1089.140
s6            67.6267     65.984      1.025      0.306     -62.064     197.318
==============================================================================
Omnibus:                        1.506   Durbin-Watson:                   2.029
Prob(Omnibus):                  0.471   Jarque-Bera (JB):                1.404
Skew:                           0.017   Prob(JB):                        0.496
Kurtosis:                       2.726   Cond. No.                         227.
==============================================================================

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

The above summary provides the following information.

R-squared: the model only explains 51% of the data.

The F-statistic probability is less than 0.05 indicating the model is statistically significant and the selected features are useful for explaining the variation in the target.

The probability for the t-test of four features (sex, bmi, bp, and s5) have a value less than 0.05 indicating the features have a relationship with the target.

```
[ ]: # Calculate the Root Mean Squared Error for the last run of the OLS model

from statsmodels.tools.eval_measures import rmse
# Predict
ypred = results.predict(X)

# calc rmse
rmse = rmse(y, ypred)
print("OLS RMSE:  ", rmse)
```

```
OLS RMSE:   53.47612876402657
```

1.5.2 OLS Regression 2

```
[ ]: # Run OLS again with the features that have a relationship with the target

# Select features that have a relationship with target
SX = df_diabetes[['sex', 'bmi', 'bp', 's5']]

# Add intercept
SX = sm.add_constant(SX)

# Create model
lml2 = sm.OLS(y,SX)

# Fit model
results2 = lml2.fit()

# Print regression results
print(results2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 target   R-squared:                       0.487
Model:                            OLS   Adj. R-squared:                  0.482
Method:                 Least Squares   F-statistic:                     103.6
Date:                Wed, 07 Feb 2024   Prob (F-statistic):           5.42e-62
Time:                        22:21:57   Log-Likelihood:                -2399.8
No. Observations:                 442   AIC:                             4810.
Df Residuals:                     437   BIC:                             4830.
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
```

```
const        152.1335      2.639     57.648      0.000     146.947     157.320
sex         -136.7580     57.304     -2.387      0.017    -249.383     -24.132
bmi          598.2839     64.365      9.295      0.000     471.781     724.786
bp           292.9722     63.935      4.582      0.000     167.314     418.630
s5           554.4326     64.427      8.606      0.000     427.807     681.059
==============================================================================
Omnibus:                        5.261   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.072   Jarque-Bera (JB):                4.282
Skew:                           0.145   Prob(JB):                        0.118
Kurtosis:                       2.614   Cond. No.                         28.5
==============================================================================

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

[ ]:
```
# Calculate the Root Mean Squared Error for the last run of the OLS model

from statsmodels.tools.eval_measures import rmse
# Predict
ypred = results2.predict(SX)

# calc rmse
rmse = rmse(y, ypred)
print("OLS RMSE:  ", rmse)
```

```
OLS RMSE:   55.166891255875804
```

1.5.3 OLS Regression 3

The above summary provides the following information.

R-squared: the model only explains 49% of the data.

The F-statistic increased from 46.27 to 103.60. The F-statistic probability is less than 0.05 indicating the model is statistically significant and the selected features are useful for explaining the variation in the target.

The probability for the t-test of four features (sex, bmi, bp, and s5) have a value less than 0.05 indicating the features have a relationship with the target. Three features have a probability of 0.

[ ]:
```
# Run the model again.  This time drop feature: sex.

# Select features
SX = df_diabetes[['bmi', 'bp', 's5']]

# Add intercept
SX = sm.add_constant(SX)

# Create model
```

```python
lml3 = sm.OLS(y,SX)

# Fit model
results3 = lml3.fit()

# Print regression results
print(results3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 target   R-squared:                       0.480
Model:                            OLS   Adj. R-squared:                  0.477
Method:                 Least Squares   F-statistic:                     134.8
Date:                Wed, 07 Feb 2024   Prob (F-statistic):           7.16e-62
Time:                        22:23:19   Log-Likelihood:                -2402.6
No. Observations:                 442   AIC:                             4813.
Df Residuals:                     438   BIC:                             4830.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        152.1335      2.653     57.342      0.000     146.919     157.348
bmi          603.0784     64.677      9.324      0.000     475.962     730.194
bp           262.2720     62.962      4.166      0.000     138.527     386.017
s5           543.8712     64.619      8.417      0.000     416.870     670.873
==============================================================================
Omnibus:                        9.591   Durbin-Watson:                   1.971
Prob(Omnibus):                  0.008   Jarque-Bera (JB):                6.859
Skew:                           0.183   Prob(JB):                       0.0324
Kurtosis:                       2.511   Cond. No.                         28.3
==============================================================================

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

The above summary provides the following information.

R-squared: the model only explains 48% of the data.

The F-statistic increased from 103.60 to 134.8. The F-statistic probability is less than 0.05 indicating the model is statistically significant and the selected features are useful for explaining the variation in the target.

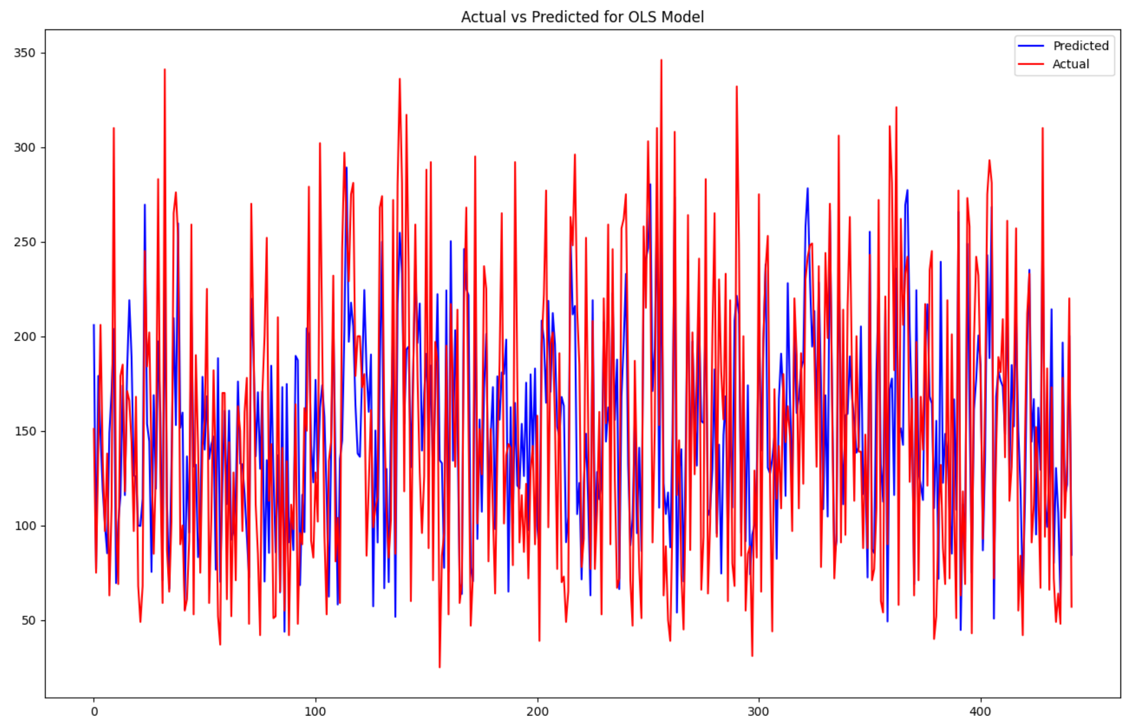
The probability for the t-test of three features (bmi, bp, and s5) have a value less than 0.05 indicating the features have a relationship with the target.

[ ]:
```python
# Calculate the Root Mean Squared Error for the last run of the OLS model

from statsmodels.tools.eval_measures import rmse
# Predict
ypred = results3.predict(SX)

# calc rmse
rmse = rmse(y, ypred)
print("OLS RMSE:  ", rmse)
```

```
OLS RMSE:   55.52523159092378
```

[ ]:
```python
# Plot Actual vs Predicted for OLS Model

plt.figure(figsize=(16, 10))
plt.plot(range(len(ypred)), ypred, color= "blue", label = "Predicted")
plt.plot(range(len(y)),y, color = "red", label = "Actual")
plt.legend(loc="upper right")
plt.title("Actual vs Predicted for OLS Model")
```

[ ]: Text(0.5, 1.0, 'Actual vs Predicted for OLS Model')



1.6 Ridge () Linear Regression

1.6.1 Hyperparameter Optimization for Regression using RandomSearch

What are the best parameters for the Ridge Regression model based on this data?

```
[ ]: # Load libraries for Hyperparameter Optimization
from sklearn.linear_model import Ridge
from sklearn.model_selection import RepeatedKFold
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import loguniform
```

```
[ ]: # Define model
model = Ridge(random_state = 1)
```

```
[ ]: # Define cross-validation object
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
```

```
[ ]: # Define hyperparameter search space
space = dict()
space['solver'] = ['svd', 'cholesky', 'lsqr', 'sag']
space['alpha'] = loguniform(1e-5, 100)
space['fit_intercept'] = [True, False]
```

```
[ ]: # Define hyperparameter search
search = RandomizedSearchCV(model,space, n_iter=500,␣
 ↪scoring='neg_mean_absolute_error', n_jobs=-1, cv=cv, random_state=1)
```

```
[ ]: feature_cols = ['bmi', 'bp', 's5']
X = df_diabetes[feature_cols]
y = df_diabetes['target']
print(X.shape, y.shape)
```

```
(442, 3) (442,)
```

```
[ ]: # Execute hyperparameter search
Result = search.fit(X,y)
```

```
[ ]: # Summarize result. Print optimal parameters for the model with score
print('Best Score: %s'% Result.best_score_)
print('Best Hyperparameters: %s'% Result.best_params_)
```

```
Best Score: -46.320330017086306
Best Hyperparameters: {'alpha': 1.1549780125663173e-05, 'fit_intercept': True,
'solver': 'sag'}
```

1.6.2 Ridge() Linear Regression - Split into Train and Test datasets

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,␣
↪random_state=42)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(309, 3)
(133, 3)
(309,)
(133,)
```

1.6.3 Ridge() Linear Regression - Define, Fit, Predict, Metrics

[ ]:
```
# Define model using best hyperparameters
r_model = Ridge(alpha= 1.1549780125663173e-05, fit_intercept= True, solver=␣
↪'sag')
```

[ ]:
```
# Fit model
r_model.fit(X_train,y_train)
```

[ ]:
```
Ridge(alpha=1.1549780125663173e-05, solver='sag')
```

[ ]:
```
# Predict
y_pred = r_model.predict(X_test)
```

[ ]:
```
# Print regression line intercept
print("Regression line intercept:  ", r_model.intercept_)
```

```
Regression line intercept:   150.7216500022098
```

[ ]:
```
# pair coefficients with column names
print("Regression line coefficients:  ")
list(zip(feature_cols, r_model.coef_))
```

```
Regression line coefficients:
```

[ ]:
```
[('bmi', 670.6039310683593),
 ('bp', 312.99842754860697),
 ('s5', 441.0526840947035)]
```

[ ]:
```
comparison_df = pd.DataFrame({"Actual":y_test, "Predicted":y_pred})
comparison_df
```

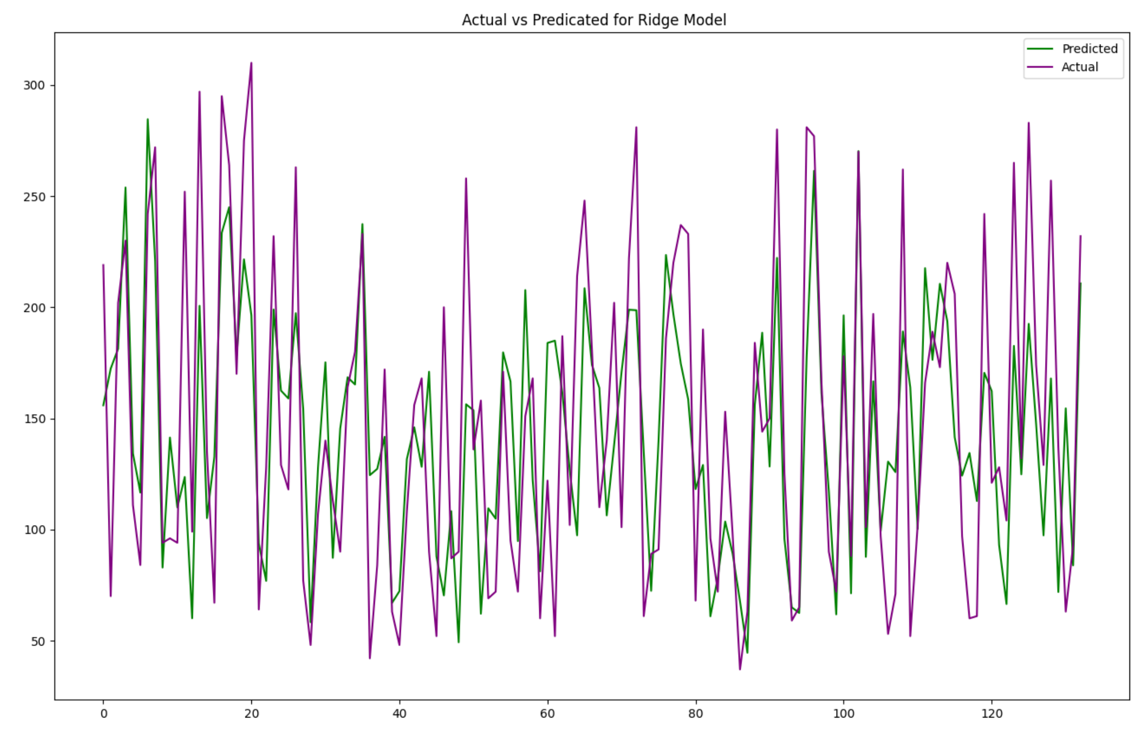
[ ]:

	Actual	Predicted
287	219.0	155.856622

```
211    70.0  172.386360
72    202.0  181.340652
321   230.0  253.909026
73    111.0  134.198505
..      ...         ...
238   257.0  167.947537
26    137.0   71.839637
7      63.0  154.509137
401    93.0   83.824725
108   232.0  210.724370

[133 rows x 2 columns]
```

[ ]:
```python
# Plot Actual vs Predicted for Ridge Model
plt.figure(figsize=(16, 10))
plt.plot(range(len(y_pred)), y_pred, color= "green", label = "Predicted")
plt.plot(range(len(y_test)),y_test, color = "purple", label = "Actual")
plt.legend(loc="upper right")
plt.title(" Actual vs Predicated for Ridge Model")
```

[ ]:
```
Text(0.5, 1.0, ' Actual vs Predicated for Ridge Model')
```



[ ]:
```python
# Load metrics library
```

```
from sklearn.metrics import mean_absolute_error,r2_score,␣
↪mean_absolute_percentage_error
from sklearn.metrics import mean_squared_error, median_absolute_error
```

[ ]:
```
#R2 Score
# R Squared measures how much of the dependent variable variation is explained␣
↪by the independent variables in the model.
# The extent model features can be used to explain the target

print("R2 Score:  ", round(r2_score(y_test,y_pred),2))

# Root Mean Squared Error (RMSE)
# How far apart the predicted values are from the actual values in a dataset ,␣
↪on average

print("Root Mean Squared Error:  ", round(np.sqrt(mean_squared_error(y_test,␣
↪y_pred)),2))

# Mean Square Error (MSE)
# Average squared error between actual and predicted values
# Used to determine if the model has become more or less accurate from previous␣
↪run

print("Mean Squared Error: ", round(mean_squared_error(y_test, y_pred),2))

# Mean Absolute Error (MAE)
# Average error between actual and predicted values
# The closer to 0 the more accurate the model is

print("Mean Absolute Error:  ", round(mean_absolute_error(y_test, y_pred),2))

# Mean Absolute Percentage Error (MAPE)
# Calculates the mean percentage deviation between predictions and actual values

print("Mean Absolute Percentage Error:  ",␣
↪round(mean_absolute_percentage_error(y_test, y_pred)*100,2))

# Median Absolute Error (MedAE)
# Median of all absolute percentage errors calculated between the predictions␣
↪and their corresponding actual values.

print("Median Absolute Error:  ", round(median_absolute_error(y_test,y_pred),2))
```

```
R2 Score:   0.48
Root Mean Squared Error:   53.13
Mean Squared Error:  2822.41
Mean Absolute Error:   43.31
```

```
Mean Absolute Percentage Error:   37.78
Median Absolute Error:   35.22
```

Ridge Regression Root Mean Squared Error (RMSE) is high, an indication this model does not predict well for this data.

1.7 RandomForestRegressor () Linear Regression Model

1.7.1 RandomForestRegressor Linear Regression - Hyperparameter Optimization

What are the best parameters for the RandomForestRegressor based on this data?

[ ]:
```
from sklearn.ensemble import RandomForestRegressor
rf_model = RandomForestRegressor(random_state=1)
rf_cv = RepeatedKFold(n_splits=15, n_repeats=5, random_state=1)

# Define hyperparameter search space
rf_space = dict()
rf_space['n_estimators'] = [5, 20, 50, 100]  # number of trees in the random␣
↪forest
rf_space['max_features'] = ['auto', 'sqrt', 'log2'] # number of features in␣
↪consideration at every split
rf_space['max_depth'] = [int(x) for x in np.linspace(10, 120, num = 12)] #␣
↪maximum number of levels allowed in each decision tree
rf_space['min_samples_split'] = [2, 5, 10, 15,20] # minimum sample number to␣
↪split a node
rf_space['min_samples_leaf'] = [1, 2,5,10,15] # minimum sample number that can␣
↪be stored in a leaf node
rf_space['bootstrap'] = [True, False] # method used to sample data points
rf_space['criterion'] = ['squared_error', 'absolute_error', 'friedman_mse',␣
↪'poisson']
rf_space['oob_score'] = [True, False]

# Define hyperparameter search
rf_search = RandomizedSearchCV(rf_model,rf_space, n_iter=250, verbose=2,␣
↪scoring='neg_mean_absolute_error', n_jobs=-1, cv=rf_cv, random_state=42)

# Execute hyperparameter search
rf_result = rf_search.fit(X,y)

# Summarize result. Print optimal parameters for the model with score
print('Best Score: %s'% rf_result.best_score_)
print('Best Hyperparameters: %s'% rf_result.best_params_)
```

```
Fitting 75 folds for each of 250 candidates, totalling 18750 fits
Best Score: -46.346623343026415
Best Hyperparameters: {'oob_score': False, 'n_estimators': 50,
'min_samples_split': 15, 'min_samples_leaf': 15, 'max_features': 'auto',
'max_depth': 10, 'criterion': 'squared_error', 'bootstrap': True}
```

1.7.2 RandomForestRegressor Linear Regression - Define, Fit, Predict, Metrics

[ ]:
```
# Build Model



# Split into Train and Test datasets
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,␣
↪random_state=1)

# Define model using best hyperparameters
rfr_model = RandomForestRegressor(oob_score=False, n_estimators=50,␣
↪min_samples_split=15, min_samples_leaf=15, max_features= 'auto', max_depth=␣
↪10, criterion= 'squared_error', bootstrap= True,random_state=1)

# Fit model
rfr_model.fit(X_train,y_train)

# Predict
rfr_pred = rfr_model.predict(X_test)

# Metrics
#R2 Score
# R Squared measures how much of the dependent variable variation is explained␣
↪by the independent variables in the model.
# The extent model features can be used to explain the target

print("R2 Score:  ", round(r2_score(y_test,rfr_pred),2))

# Root Mean Squared Error (RMSE)
# How far apart the predicted values are from the actual values in a dataset ,␣
↪on average

print("Root Mean Squared Error:  ", round(np.sqrt(mean_squared_error(y_test,␣
↪rfr_pred)),2))

# Mean Square Error (MSE)
# Average squared error between actual and predicted values
# Used to determine if the model has become more or less accurate from previous␣
↪run

print("Mean Squared Error: ", round(mean_squared_error(y_test, rfr_pred),2))

# Mean Absolute Error (MAE)
# Average error between actual and predicted values
# The closer to 0 the more accurate the model is

print("Mean Absolute Error:  ", round(mean_absolute_error(y_test, rfr_pred),2))
```

```
# Mean Absolute Percentage Error (MAPE)
# Calculates the mean percentage deviation between predictions and actual values

print("Mean Absolute Percentage Error:  ",␣
 ↪round(mean_absolute_percentage_error(y_test, rfr_pred)*100,2))

# Median Absolute Error (MedAE)
# Median of all absolute percentage errors calculated between the predictions␣
 ↪and their corresponding actual values.

print("Median Absolute Error:  ",␣
 ↪round(median_absolute_error(y_test,rfr_pred),2))
```

```
R2 Score:   0.25
Root Mean Squared Error:   61.52
Mean Squared Error:  3785.26
Mean Absolute Error:   47.73
Mean Absolute Percentage Error:   38.47
Median Absolute Error:   38.59
```

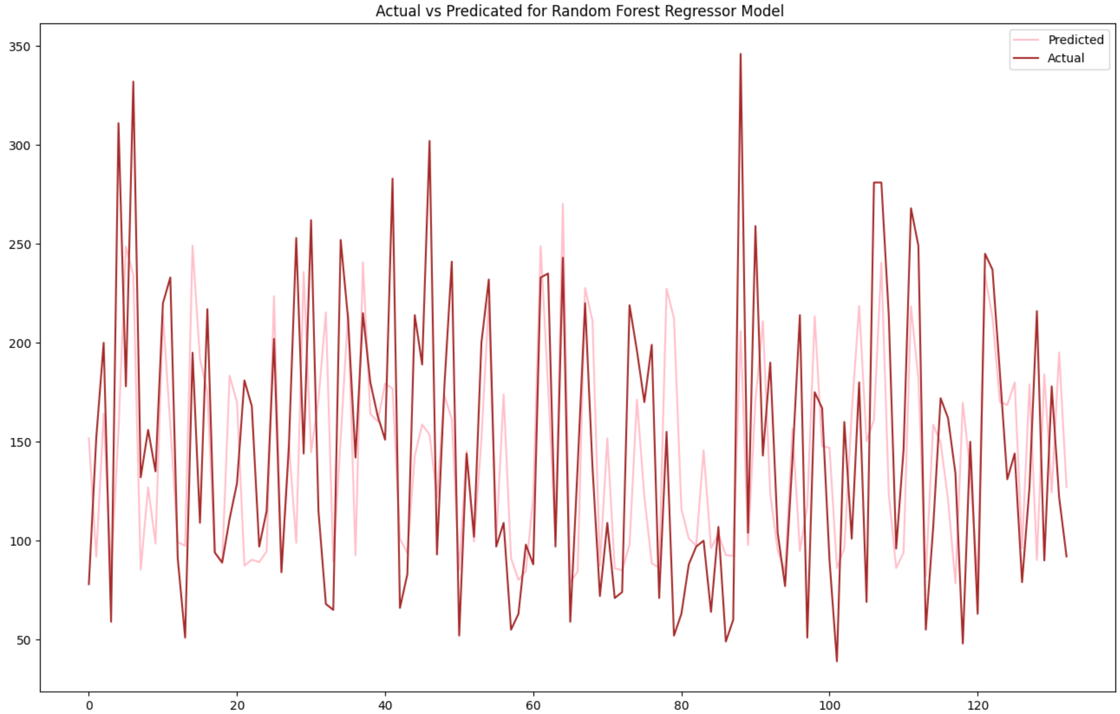
Random Forest Regressor Root Mean Squared Error (RMSE) is high, an indication the model is not predicting well for this data.

[ ]:
```
comparison_df = pd.DataFrame({"Actual":y_test, "Predicted":rfr_pred})
comparison_df
```

[ ]:
```
     Actual   Predicted
246    78.0  151.744689
425   152.0   91.830184
293   200.0  164.207053
31     59.0   84.120702
359   311.0  155.535303
..      …          …
340   216.0   90.257294
39     90.0  184.091787
191   178.0  124.373111
320   122.0  195.112630
98     92.0  127.029903

[133 rows x 2 columns]
```

[ ]:
```
# Plot Actual vs Predicted for Random Forest Regresssor
plt.figure(figsize=(16, 10))
plt.plot(range(len(y_pred)), rfr_pred, color= "pink", label = "Predicted")
plt.plot(range(len(y_test)),y_test, color = "brown", label = "Actual")
plt.legend(loc="upper right")
plt.title(" Actual vs Predicated for Random Forest Regressor Model")
```

```
[ ]: Text(0.5, 1.0, ' Actual vs Predicated for Random Forest Regressor Model')
```



1.8 Conclusion

Ridge Regression had the lowest RMSE score out of the three models that were used. Although none of the models performed particularly well at forecasting values for this data, that would theoretically make the Ridge model the best model. An RMSE that is close to zero is ideal.

OLS 1	OLS 2	OLS 3	Ridge Regression	Random Forest Regressor
53.48	55.17	55.53	53.13	61.52

```
[ ]:
```