Correlation and more data analisys

In [ ]:
```
# Load libraries
import pandas as pd
from sklearn.tree import DecisionTreeClassifier # Import Decision Tree Classifier
from sklearn.model_selection import train_test_split # Import train_test_split function
from sklearn import metrics #Import scikit-learn metrics module for accuracy calculation
import seaborn as sns
```

In [2]:
```
# Load dataset
pima = pd.read_csv("../diabetes.csv")
```

In [18]:
```
#split dataset in features and target variable
feature_cols = ['Pregnancies', 'Insulin', 'BMI', 'Age','Glucose','BloodPressure','DiabetesPedigreeFunction','SkinThickness']
X = pima[feature_cols] # Features (independent variables)
y = pima.Outcome
```

In [19]:
```
X.describe()
```

Out[19]:

	Pregnancies	Insulin	BMI	Age	Glucose	BloodPressure	DiabetesPe
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	79.799479	31.992578	33.240885	120.894531	69.105469	
std	3.369578	115.244002	7.884160	11.760232	31.972618	19.355807	
min	0.000000	0.000000	0.000000	21.000000	0.000000	0.000000	
25%	1.000000	0.000000	27.300000	24.000000	99.000000	62.000000	
50%	3.000000	30.500000	32.000000	29.000000	117.000000	72.000000	
75%	6.000000	127.250000	36.600000	41.000000	140.250000	80.000000	
max	17.000000	846.000000	67.100000	81.000000	199.000000	122.000000	

In [20]:
```
y.describe()
```

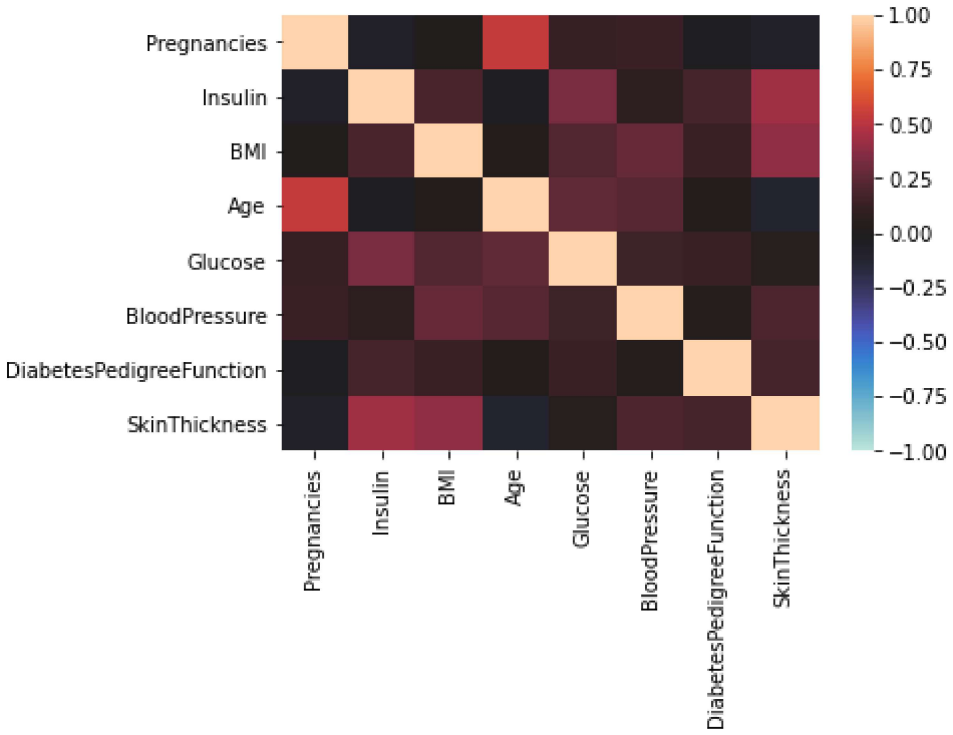
Out[20]:
```
count    768.000000
mean       0.348958
std        0.476951
min        0.000000
25%        0.000000
50%        0.000000
75%        1.000000
max        1.000000
Name: Outcome, dtype: float64
```

In [15]:
```
corr = X.corr()
X.corr()
```

Out[15]:

	Pregnancies	Insulin	BMI	Age	Glucose	BloodPressure
Pregnancies	1.000000	-0.073535	0.017683	0.544341	0.129459	0.141282
Insulin	-0.073535	1.000000	0.197859	-0.042163	0.331357	0.088933
BMI	0.017683	0.197859	1.000000	0.036242	0.221071	0.281805
Age	0.544341	-0.042163	0.036242	1.000000	0.263514	0.239528
Glucose	0.129459	0.331357	0.221071	0.263514	1.000000	0.152590
BloodPressure	0.141282	0.088933	0.281805	0.239528	0.152590	1.000000
DiabetesPedigreeFunction	-0.033523	0.185071	0.140647	0.033561	0.137337	0.041265
SkinThickness	-0.081672	0.436783	0.392573	-0.113970	0.057328	0.207371

In [16]:
```
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
)
```



We can see, that taking all the independent variables, we don't have some big correlations, being the biggest one the Age/Pregnancies one.

First Iteration

In [21]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, rand
om_state=1)
```

In [22]:
```
# import the class
from sklearn.linear_model import LogisticRegression

# instantiate the model (using the default parameters)
logreg = LogisticRegression()

# fit the model with data
logreg.fit(X_train,y_train)

# Predict labels
y_pred=logreg.predict(X_test)
```

```
C:\Users\rober\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:
762: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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

In [23]:
```
# import the metrics class
from sklearn import metrics
cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
cnf_matrix
```

Out[23]:
```
array([[109,  14],
       [ 29,  40]], dtype=int64)
```

In [26]:
```
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Precision:",metrics.precision_score(y_test, y_pred))
print("Recall:",metrics.recall_score(y_test, y_pred))

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

```
Accuracy: 0.7760416666666666
Precision: 0.7407407407407407
Recall: 0.5797101449275363
              precision    recall  f1-score   support

           0       0.79      0.89      0.84       123
           1       0.74      0.58      0.65        69

    accuracy                           0.78       192
   macro avg       0.77      0.73      0.74       192
weighted avg       0.77      0.78      0.77       192
```

Second iteration

Removing the two biggest correlation values, Age/Pregnancies and skinTickness/Insulin.

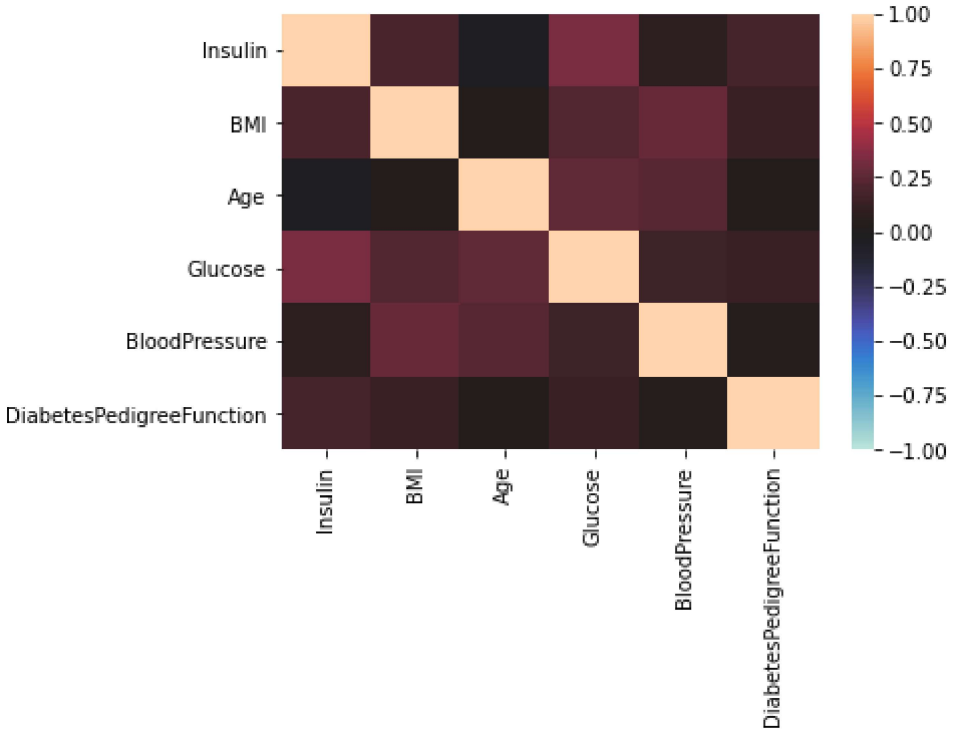
In [32]:
```
feature_cols = ['Insulin', 'BMI', 'Age','Glucose','BloodPressure','DiabetesPed
igreeFunction']
X = pima[feature_cols] # Features (independent variables)
```

In [33]:
```
corr = X.corr()
X.corr()
```

Out[33]:

	Insulin	BMI	Age	Glucose	BloodPressure	DiabetesPedi
Insulin	1.000000	0.197859	-0.042163	0.331357	0.088933	
BMI	0.197859	1.000000	0.036242	0.221071	0.281805	
Age	-0.042163	0.036242	1.000000	0.263514	0.239528	
Glucose	0.331357	0.221071	0.263514	1.000000	0.152590	
BloodPressure	0.088933	0.281805	0.239528	0.152590	1.000000	
DiabetesPedigreeFunction	0.185071	0.140647	0.033561	0.137337	0.041265	

In [34]:
```
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
)
```



In [35]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, rand
om_state=1)

# instantiate the model (using the default parameters)
logreg = LogisticRegression()

# fit the model with data
logreg.fit(X_train,y_train)

# Predict labels
y_pred=logreg.predict(X_test)

cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
cnf_matrix
```

Out[35]:
```
array([[109,  14],
       [ 28,  41]], dtype=int64)
```

In [36]:
```
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Precision:",metrics.precision_score(y_test, y_pred))
print("Recall:",metrics.recall_score(y_test, y_pred))

# Classification report
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.78125
Precision: 0.7454545454545455
Recall: 0.5942028985507246
              precision    recall  f1-score   support

           0       0.80      0.89      0.84       123
           1       0.75      0.59      0.66        69

    accuracy                           0.78       192
   macro avg       0.77      0.74      0.75       192
weighted avg       0.78      0.78      0.77       192
```

Here we can see that we are getting slightly higher values in almost every metric. Lets remove the next 2 highest correlation values.

Third Iteration

Now, we have Insulin/Glucose and BMI/BloodPressure as the highest values, but let's remark that these values are already acceptable for a real analysis, here we will remove them just with the purpose of checking the behaviour of the regression model.

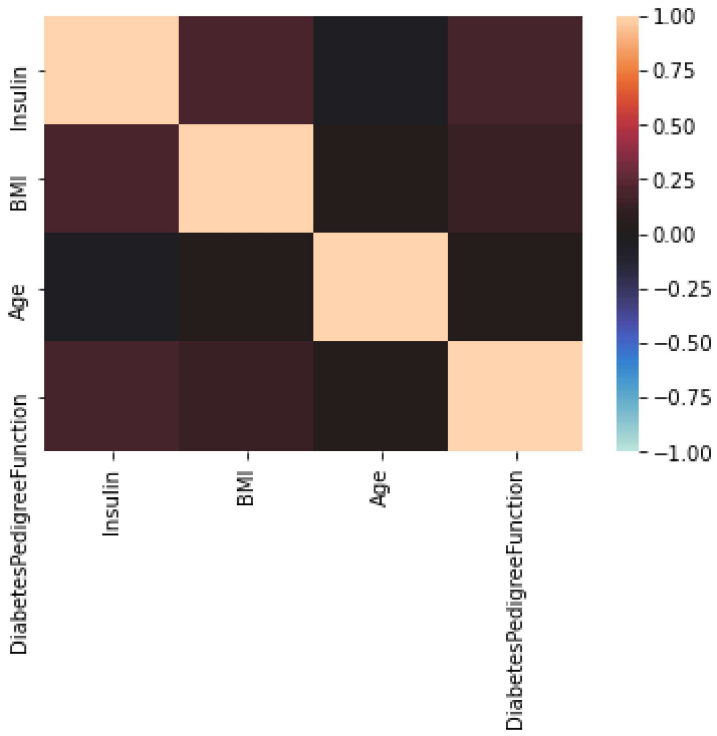
In [37]:
```
feature_cols = ['Insulin', 'BMI', 'Age','DiabetesPedigreeFunction']
X = pima[feature_cols] # Features (independent variables)
```

In [38]:
```
corr = X.corr()
X.corr()
```

Out[38]:

	Insulin	BMI	Age	DiabetesPedigreeFunction
Insulin	1.000000	0.197859	-0.042163	0.185071
BMI	0.197859	1.000000	0.036242	0.140647
Age	-0.042163	0.036242	1.000000	0.033561
DiabetesPedigreeFunction	0.185071	0.140647	0.033561	1.000000

In [39]:
```
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
)
```



In [40]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, rand
om_state=1)

# instantiate the model (using the default parameters)
logreg = LogisticRegression()

# fit the model with data
logreg.fit(X_train,y_train)

# Predict labels
y_pred=logreg.predict(X_test)

cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
cnf_matrix
```

Out[40]:
```
array([[105,  18],
       [ 35,  34]], dtype=int64)
```

In [41]:
```
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Precision:",metrics.precision_score(y_test, y_pred))
print("Recall:",metrics.recall_score(y_test, y_pred))

# Classification report
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.7239583333333334
Precision: 0.6538461538461539
Recall: 0.4927536231884058
              precision    recall  f1-score   support

           0       0.75      0.85      0.80       123
           1       0.65      0.49      0.56        69

    accuracy                           0.72       192
   macro avg       0.70      0.67      0.68       192
weighted avg       0.72      0.72      0.71       192
```

As we said in the beggining, as these values were already small enough, now without them, all the metrics are lower than with them.

Fourth Iteration

Now, lets see the behaviour removing the smallest values of correlation, and keeping the highest ones.

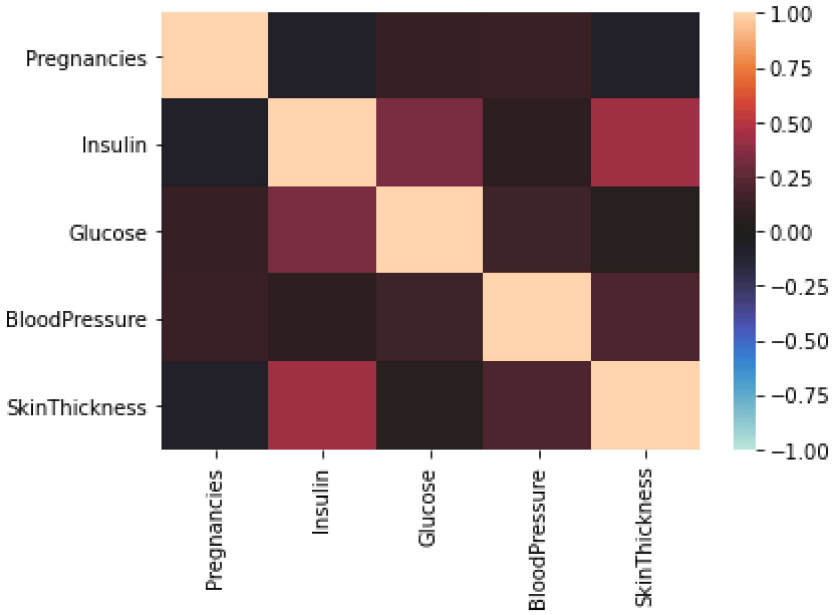
In [42]:
```
feature_cols = ['Pregnancies', 'Insulin','Glucose','BloodPressure','SkinThickn
ess']
X = pima[feature_cols] # Features (independent variables)
```

In [43]:
```
corr = X.corr()
X.corr()
```

Out[43]:

	Pregnancies	Insulin	Glucose	BloodPressure	SkinThickness
Pregnancies	1.000000	-0.073535	0.129459	0.141282	-0.081672
Insulin	-0.073535	1.000000	0.331357	0.088933	0.436783
Glucose	0.129459	0.331357	1.000000	0.152590	0.057328
BloodPressure	0.141282	0.088933	0.152590	1.000000	0.207371
SkinThickness	-0.081672	0.436783	0.057328	0.207371	1.000000

In [44]:
```
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
)
```



In [45]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, rand
om_state=1)

# instantiate the model (using the default parameters)
logreg = LogisticRegression()

# fit the model with data
logreg.fit(X_train,y_train)

# Predict labels
y_pred=logreg.predict(X_test)

cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
cnf_matrix
```

Out[45]:
```
array([[109,  14],
       [ 30,  39]], dtype=int64)
```

In [46]:
```
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Precision:",metrics.precision_score(y_test, y_pred))
print("Recall:",metrics.recall_score(y_test, y_pred))

# Classification report
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.7708333333333334
Precision: 0.7358490566037735
Recall: 0.5652173913043478
              precision    recall  f1-score   support

           0       0.78      0.89      0.83       123
           1       0.74      0.57      0.64        69

    accuracy                           0.77       192
   macro avg       0.76      0.73      0.74       192
weighted avg       0.77      0.77      0.76       192
```

We can see that wee are getting even better metrics than by removing more values that have a little higher correlation, becauset in this case we have a small quantity of total columns, so not all variables are very correlated to each other.