Project Task: Week 1

Data Exploration:

A)To import data set into working enviorment ¶

In [1]:
```
import numpy as np
import pandas as pd
from pandas_profiling import ProfileReport
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
input_path = "..\\data\\input\\"
intermediate_path = "..\\data\\intermediate\\"
output_path = "..\\data\\output\\"
```

In [3]:
```
df = pd.read_csv(input_path + "health care diabetes.csv")
```

In [4]:
```
df
```

Out[4]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

768 rows × 9 columns

In [5]:
```
df.to_csv(intermediate_path + "Premodel_Processed_Data.csv", index = False)
```

In [6]:
```
df = pd.read_csv(intermediate_path + "Premodel_Processed_Data.csv")
```

1. Perform descriptive analysis. Understand the variables and their corresponding values. On the columns below, a value of zero does not make sense and thus indicates missing value:

- Glucose
- BloodPressure
- SkinThickness
- Insulin
- BMI

A)To convert zeros into null values

In [7]:
```
df["Glucose"]=df["Glucose"].replace(0,np.nan)
df["BloodPressure"]=df["BloodPressure"].replace(0,np.nan)
df["SkinThickness"]=df["SkinThickness"].replace(0,np.nan)
df["Insulin"]=df["Insulin"].replace(0,np.nan)
df["BMI"]=df["BMI"].replace(0,np.nan)
```

In [8]:
```
df.head()
```

Out[8]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148.0	72.0	35.0	NaN	33.6	0.627	50	1
1	1	85.0	66.0	29.0	NaN	26.6	0.351	31	0
2	8	183.0	64.0	NaN	NaN	23.3	0.672	32	1
3	1	89.0	66.0	23.0	94.0	28.1	0.167	21	0
4	0	137.0	40.0	35.0	168.0	43.1	2.288	33	1

2. Visually explore these variables using histograms. Treat the missing values accordingly.

A)For exploring variables all together we Generate the pandas profiling report

In [9]:
```
pfr = ProfileReport(df)
```

In [10]:
```
pfr.to_file(output_path + "EDA_of_Diabetics_Prediction.html")
```

B)Use KNN- Imputer or Decision Tree Imputer for imputing missing data points

In [11]:
```
from sklearn.impute import KNNImputer
imputer = KNNImputer(n_neighbors=5)
df1 = pd.DataFrame(imputer.fit_transform(df),columns = df.columns)
```

In [12]:
```
df1.head()
```

Out[12]:

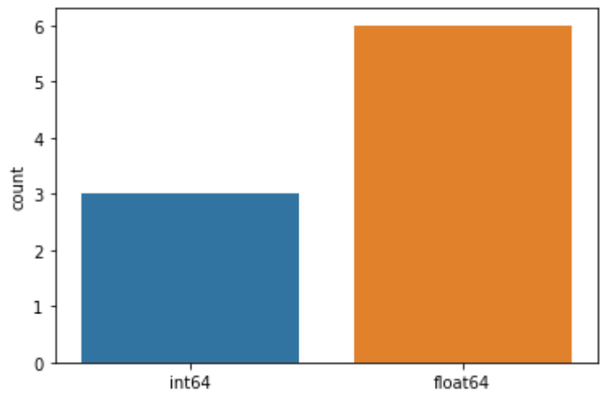
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6.0	148.0	72.0	35.0	169.0	33.6	0.627	50.0	1.0
1	1.0	85.0	66.0	29.0	58.6	26.6	0.351	31.0	0.0
2	8.0	183.0	64.0	25.8	164.6	23.3	0.672	32.0	1.0
3	1.0	89.0	66.0	23.0	94.0	28.1	0.167	21.0	0.0
4	0.0	137.0	40.0	35.0	168.0	43.1	2.288	33.0	1.0

3. There are integer and float data type variables in this dataset. Create a count (frequency) plot describing the data types and the count of variables.

In [13]:
```
import seaborn as sns
```

In [14]:
```
sns.countplot(df.dtypes.map(str))
df.dtypes
```

Out[14]:
```
Pregnancies                 int64
Glucose                   float64
BloodPressure             float64
SkinThickness             float64
Insulin                   float64
BMI                       float64
DiabetesPedigreeFunction  float64
Age                         int64
Outcome                     int64
dtype: object
```



Project Task: Week 2

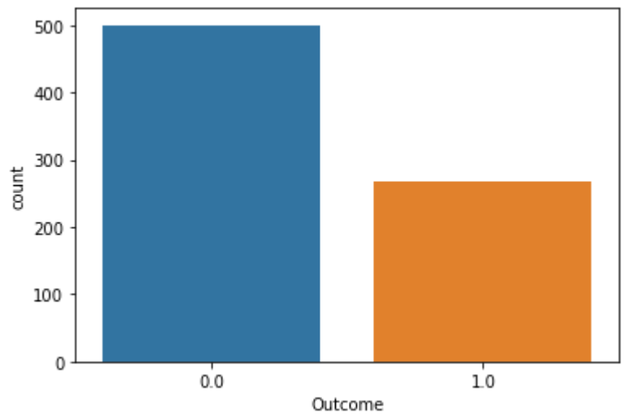
Data Exploration:

1. Check the balance of the data by plotting the count of outcomes by their value. Describe your findings and plan future course of action.

A) To create a plot in notebook with count of different classes of Outcome variable

In [15]:
```
sns.countplot(x="Outcome", data=df1)
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x1c35e4a71f0>

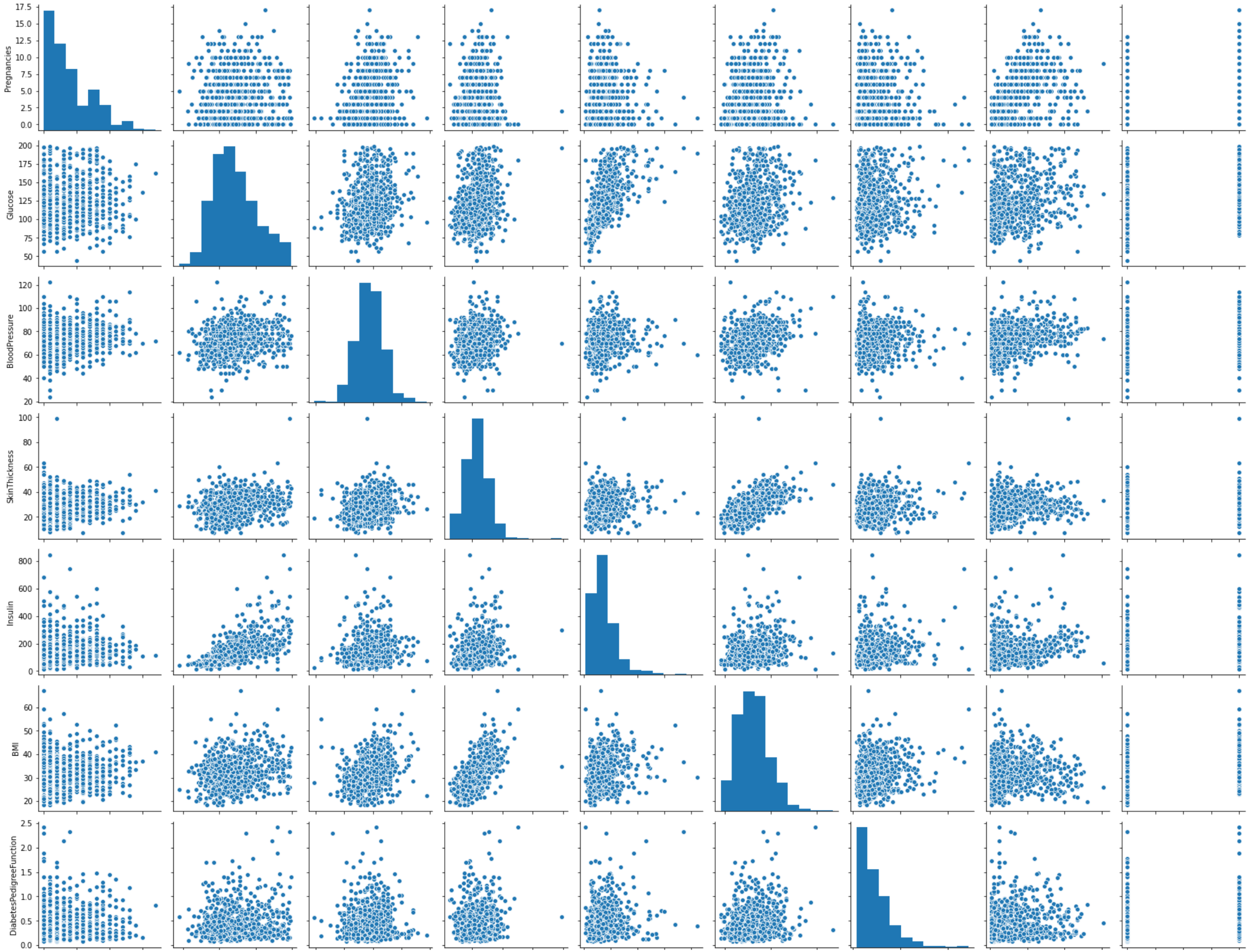


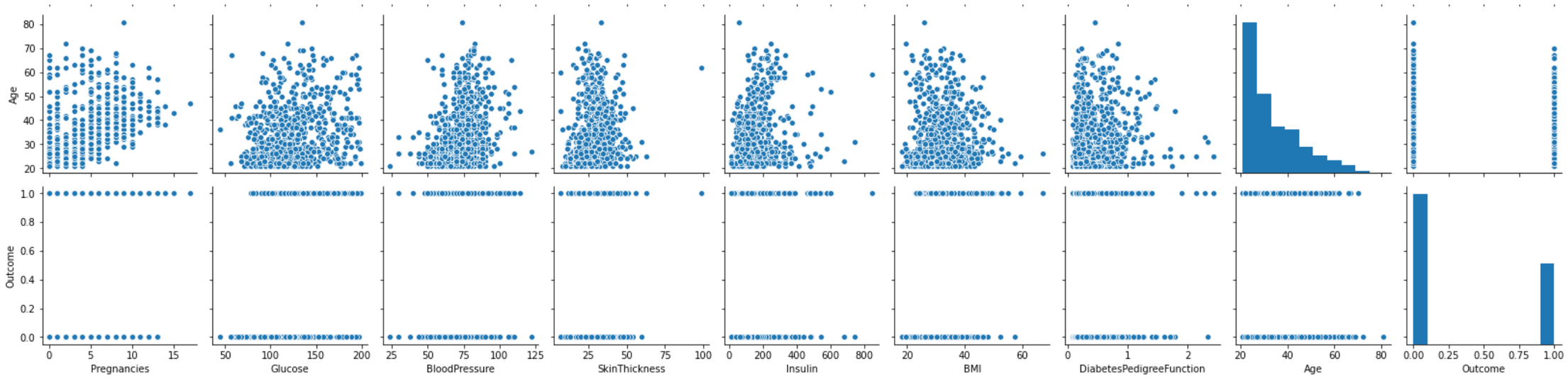
2. Create scatter charts between the pair of variables to understand the relationships. Describe your findings.

A) To Create Scatter plot b/w variables (Independent variable)

In [16]:
```
sns.pairplot(df1)
```

Out[16]: <seaborn.axisgrid.PairGrid at 0x1c35e4dab80>


Pregnancies
Glucose
BloodPressure
SkinThickness
Insulin
BMI
DiabetesPedigreeFunction



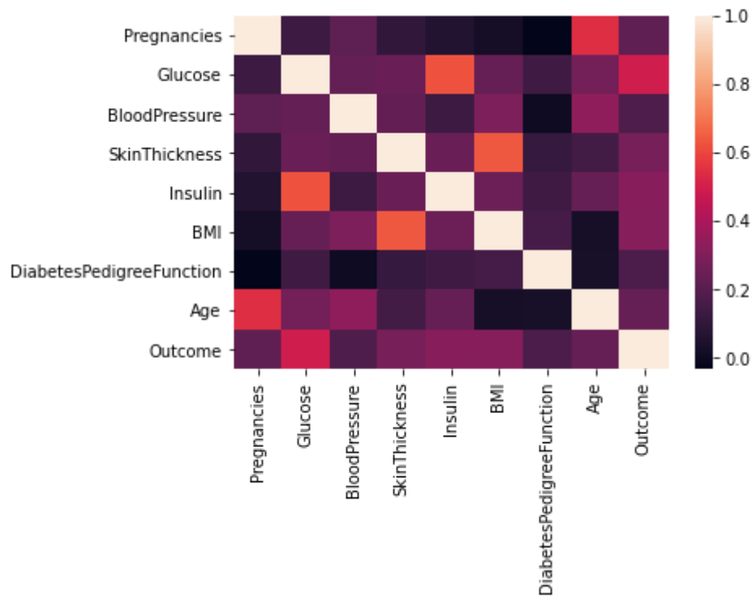
3. Perform correlation analysis. Visually explore it using a heat map.

A)To perform correlation analysis and Visually explore it using a heat map.

In [17]:
```
corr = df1.corr()
print(corr)
sns.heatmap(corr,
        xticklabels=corr.columns,
        yticklabels=corr.columns)
```

```
                           Pregnancies   Glucose  BloodPressure  SkinThickness  \
Pregnancies                   1.000000  0.131230       0.218327       0.102406
Glucose                       0.131230  1.000000       0.233992       0.246807
BloodPressure                 0.218327  0.233992       1.000000       0.230225
SkinThickness                 0.102406  0.246807       0.230225       1.000000
Insulin                       0.061377  0.628432       0.134373       0.245197
BMI                           0.023323  0.238457       0.294618       0.639370
DiabetesPedigreeFunction     -0.033523  0.139226       0.006323       0.113957
Age                           0.544341  0.270115       0.337930       0.149474
Outcome                       0.221898  0.495853       0.176665       0.279530

                            Insulin       BMI  DiabetesPedigreeFunction  \
Pregnancies                0.061377  0.023323                 -0.033523
Glucose                    0.628432  0.238457                  0.139226
BloodPressure              0.134373  0.294618                  0.006323
SkinThickness              0.245197  0.639370                  0.113957
Insulin                    1.000000  0.251185                  0.139713
BMI                        0.251185  1.000000                  0.155259
DiabetesPedigreeFunction   0.139713  0.155259                  1.000000
Age                        0.237708  0.029817                  0.033561
Outcome                    0.320151  0.313882                  0.173844

                                Age   Outcome
Pregnancies                0.544341  0.221898
Glucose                    0.270115  0.495853
BloodPressure              0.337930  0.176665
SkinThickness              0.149474  0.279530
Insulin                    0.237708  0.320151
BMI                        0.029817  0.313882
DiabetesPedigreeFunction   0.033561  0.173844
Age                        1.000000  0.238356
Outcome                    0.238356  1.000000
```

Out[17]: `<matplotlib.axes._subplots.AxesSubplot at 0x1c35c679220>`



B) To come up with conclusion on Co-relation

there is no co-relation between features

Project Task: Week 3

Data Modeling:

1. Devise strategies for model building. It is important to decide the right validation framework. Express your thought process.

A)Dataset Preparation (splitting and normalization)

In [18]:
```
df1.columns
```

Out[18]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

In [19]:
```
#split our X & y

X = df1.drop('Outcome', axis=1)
y = df1.Outcome

print(X.shape)
print(y.shape)
```

```
(768, 8)
(768,)
```

In [20]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X)
X = scaler.transform(X)
```

B)Split our dataset into train and test

In [21]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3 , random_state =21)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(537, 8)
(231, 8)
(537,)
(231,)
```

In [22]:
```
! pip install dabl
```

```
Requirement already satisfied: dabl in c:\users\sanja\anaconda3\lib\site-packages (0.1.9)
Requirement already satisfied: scipy in c:\users\sanja\anaconda3\lib\site-packages (from dabl) (1.5.0)
Requirement already satisfied: scikit-learn in c:\users\sanja\anaconda3\lib\site-packages (from dabl) (0.23.2)
Requirement already satisfied: seaborn in c:\users\sanja\anaconda3\lib\site-packages (from dabl) (0.10.1)
Requirement already satisfied: numpy in c:\users\sanja\anaconda3\lib\site-packages (from dabl) (1.18.5)
Requirement already satisfied: pandas in c:\users\sanja\anaconda3\lib\site-packages (from dabl) (1.0.5)
Requirement already satisfied: matplotlib in c:\users\sanja\anaconda3\lib\site-packages (from dabl) (3.2.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\sanja\anaconda3\lib\site-packages (from scikit-learn->dabl) (2.1.0)
Requirement already satisfied: joblib>=0.11 in c:\users\sanja\anaconda3\lib\site-packages (from scikit-learn->dabl) (0.16.0)
Requirement already satisfied: python-dateutil>=2.6.1 in c:\users\sanja\anaconda3\lib\site-packages (from pandas->dabl) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in c:\users\sanja\anaconda3\lib\site-packages (from pandas->dabl) (2020.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in c:\users\sanja\anaconda3\lib\site-packages (from matplotlib->dabl) (2.4.7)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\sanja\anaconda3\lib\site-packages (from matplotlib->dabl) (1.2.0)
Requirement already satisfied: cycler>=0.10 in c:\users\sanja\anaconda3\lib\site-packages (from matplotlib->dabl) (0.10.0)
Requirement already satisfied: six>=1.5 in c:\users\sanja\anaconda3\lib\site-packages (from python-dateutil>=2.6.1->pandas->dabl) (1.15.0)
```

Baseline Model using DABL SimpleClassifier()

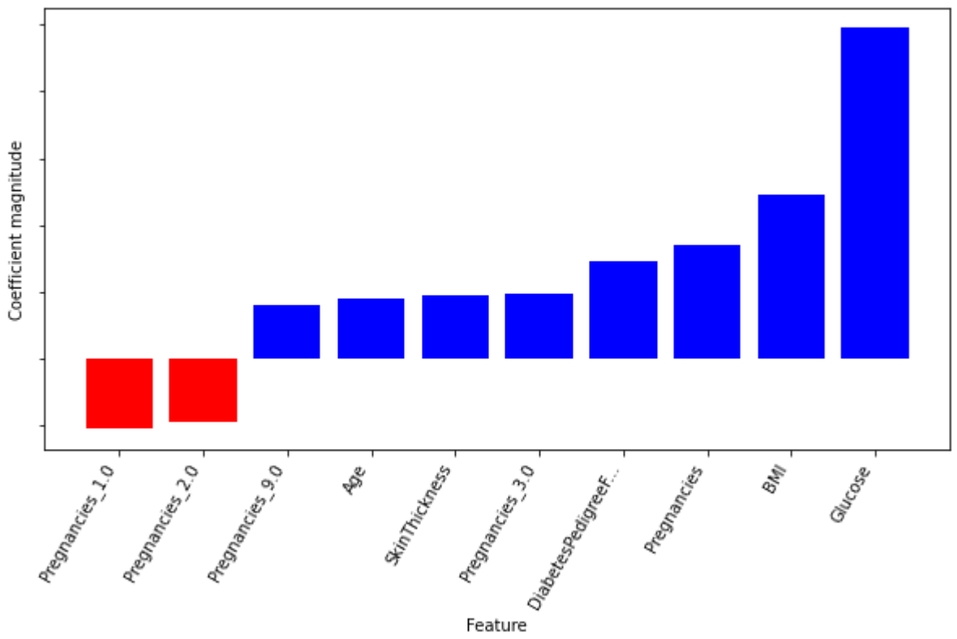
In [23]:
```
import dabl
ec = dabl.SimpleClassifier(random_state=0).fit(df1, target_col='Outcome')
ec
```

```
Running DummyClassifier(strategy='prior')
accuracy: 0.651 average_precision: 0.349 roc_auc: 0.500 recall_macro: 0.500 f1_macro: 0.394
=== new best DummyClassifier(strategy='prior') (using recall_macro):
accuracy: 0.651 average_precision: 0.349 roc_auc: 0.500 recall_macro: 0.500 f1_macro: 0.394

Running GaussianNB()
accuracy: 0.659 average_precision: 0.593 roc_auc: 0.775 recall_macro: 0.522 f1_macro: 0.450
=== new best GaussianNB() (using recall_macro):
accuracy: 0.659 average_precision: 0.593 roc_auc: 0.775 recall_macro: 0.522 f1_macro: 0.450

Running MultinomialNB()
accuracy: 0.672 average_precision: 0.534 roc_auc: 0.700 recall_macro: 0.574 f1_macro: 0.564
=== new best MultinomialNB() (using recall_macro):
accuracy: 0.672 average_precision: 0.534 roc_auc: 0.700 recall_macro: 0.574 f1_macro: 0.564

Running DecisionTreeClassifier(class_weight='balanced', max_depth=1)
accuracy: 0.711 average_precision: 0.506 roc_auc: 0.706 recall_macro: 0.706 f1_macro: 0.694
=== new best DecisionTreeClassifier(class_weight='balanced', max_depth=1) (using recall_macro):
accuracy: 0.711 average_precision: 0.506 roc_auc: 0.706 recall_macro: 0.706 f1_macro: 0.694

Running DecisionTreeClassifier(class_weight='balanced', max_depth=5)
accuracy: 0.711 average_precision: 0.616 roc_auc: 0.766 recall_macro: 0.711 f1_macro: 0.697
=== new best DecisionTreeClassifier(class_weight='balanced', max_depth=5) (using recall_macro):
accuracy: 0.711 average_precision: 0.616 roc_auc: 0.766 recall_macro: 0.711 f1_macro: 0.697

Running DecisionTreeClassifier(class_weight='balanced', min_impurity_decrease=0.01)
accuracy: 0.707 average_precision: 0.606 roc_auc: 0.778 recall_macro: 0.724 f1_macro: 0.698
=== new best DecisionTreeClassifier(class_weight='balanced', min_impurity_decrease=0.01) (using recall_macro):
accuracy: 0.707 average_precision: 0.606 roc_auc: 0.778 recall_macro: 0.724 f1_macro: 0.698

Running LogisticRegression(C=0.1, class_weight='balanced', max_iter=1000)
accuracy: 0.751 average_precision: 0.722 roc_auc: 0.835 recall_macro: 0.743 f1_macro: 0.734
=== new best LogisticRegression(C=0.1, class_weight='balanced', max_iter=1000) (using recall_macro):
accuracy: 0.751 average_precision: 0.722 roc_auc: 0.835 recall_macro: 0.743 f1_macro: 0.734

Running LogisticRegression(class_weight='balanced', max_iter=1000)
accuracy: 0.745 average_precision: 0.714 roc_auc: 0.828 recall_macro: 0.732 f1_macro: 0.726

Best model:
LogisticRegression(C=0.1, class_weight='balanced', max_iter=1000)
Best Scores:
accuracy: 0.751 average_precision: 0.722 roc_auc: 0.835 recall_macro: 0.743 f1_macro: 0.734
```

Out[23]:
```
SimpleClassifier(random_state=0)
```

Feature Importance using DABL on Best Model: Logistic Regression

In [24]:
```
dabl.explain(ec)
```



2. Apply an appropriate classification algorithm to build a model. Compare various models with the results from KNN algorithm.

A)To Create a base classifier model for the prediction

In [25]:
```
from sklearn.svm import SVC
svc_model = SVC()
svc_model.fit(X_train,y_train)
svm_pred = svc_model.predict(X_test)
#R2 score
print("R2 Value : {}". format(svc_model.score(X_test,y_test)))
```

```
R2 Value : 0.7229437229437229
```

In [26]:
```
from sklearn.linear_model import LogisticRegression
logReg = LogisticRegression()
logReg.fit(X_train,y_train)
y_test_log_pred = logReg.predict(X_test)
#R2 score
print("R2 Value : {}". format(logReg.score(X_test,y_test)))
```

```
R2 Value : 0.7445887445887446
```

In [27]:
```
from sklearn.naive_bayes import BernoulliNB
nb_clf = BernoulliNB()
nb_clf.fit(X_train,y_train)
nb_pred=nb_clf.predict(X_test)
#R2 score
print("R2 Value : {}". format(nb_clf.score(X_test,y_test)))
```

```
R2 Value : 0.7142857142857143
```

In [28]:
```
from sklearn.tree import DecisionTreeClassifier
decision_tree = DecisionTreeClassifier(criterion='entropy')
decision_tree.fit(X_train,y_train)
ds_predicted = decision_tree.predict(X_test)
#R2 score
print("R2 Value : {}". format(decision_tree.score(X_test,y_test)))
```

```
R2 Value : 0.6666666666666666
```

In [29]:
```
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators=100,random_state= 21)
classifier.fit(X_train,y_train)
y_pred_redom_forest= classifier.predict(X_test)
#R2 score
print("R2 Value : {}". format(classifier.score(X_test,y_test)))
```

```
R2 Value : 0.7402597402597403
```

In [30]:
```
from xgboost import XGBClassifier
xgboost = XGBClassifier()
xgboost.fit(X_train,y_train)
xgb_pred = xgboost.predict(X_test)
#R2 score
print("R2 Value : {}". format(xgboost.score(X_test,y_test)))
```

```
[10:35:47] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starting in XGBoost 1.3.0, the default evaluation metric used with the objec
tive 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
R2 Value : 0.7229437229437229
```

B)To Create KNN classifier models for the prediction

In [31]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train,y_train)
y_test_knn_pred = knn.predict(X_test)
#R2 score
print("R2 Value : {}". format(knn.score(X_test,y_test)))
```

```
R2 Value : 0.683982683982684
```

C)To compare various models with the results from KNN algorithm

In [32]:
```
from sklearn import metrics
from sklearn.metrics import accuracy_score
print('Accuracy Score for test data in logistic model is')
print(metrics.accuracy_score(y_test,y_test_log_pred)*100)
print('Accuracy Score for test data in rendom forest model is')
print(metrics.accuracy_score(y_pred_redom_forest,y_test)*100)
print('Accuracy Score for test data in support vector machine model is:')
print(metrics.accuracy_score(y_test,svm_pred)*100)
print('Accuracy Score for test data in xgboast model is')
print(metrics.accuracy_score(xgb_pred ,y_test)*100)
print('Accuracy Score for test data in Naive Bayes model is')
print(metrics.accuracy_score(nb_pred,y_test)*100)
print('Accuracy Score for test data in KNN model is:')
print(metrics.accuracy_score(y_test,y_test_knn_pred)*100)
print('Accuracy Score for test data in Decision Tree model is')
print(metrics.accuracy_score(ds_predicted,y_test)*100)
```

```
Accuracy Score for test data in logistic model is
74.45887445887446
Accuracy Score for test data in rendom forest model is
74.02597402597402
Accuracy Score for test data in support vector machine model is:
72.2943722943723
Accuracy Score for test data in xgboast model is
72.2943722943723
Accuracy Score for test data in Naive Bayes model is
71.42857142857143
Accuracy Score for test data in KNN model is:
68.3982683982684
Accuracy Score for test data in Decision Tree model is
66.66666666666666
```

D)conclusion

From all of the above algorithams the logistic model clssifier has the highest accuracy of 74.45887445887446%

and rendom forest clssifier has the second highest accuracy of 74.02597402597402

Project Task: Week 4

Data Modeling:

1.Create a classification report by analysing sensitivity, specificity, AUC(ROC curve) etc. Please try to be as descriptive as possible to explain what values of these parameter you settled for? any why?

In [33]:
```
from sklearn.metrics import classification_report,confusion_matrix
```

A)Creating a classification report and analysing sensitivity, specificity score of each of the classifiers

In [34]:
```
print("classification report  and confusion matrix of support vector machine model is")
print(classification_report(y_test , svm_pred))
cm1 = confusion_matrix(y_test ,svm_pred)
print('Confusion Matrix : \n', cm1)
sensitivity1 = cm1[0,0]/(cm1[0,0]+cm1[0,1])
specificity1 = cm1[1,1]/(cm1[1,0]+cm1[1,1])
```

```
classification report  and confusion matrix of support vector machine model is
              precision    recall  f1-score   support

         0.0       0.72      0.90      0.80       144
         1.0       0.73      0.43      0.54        87

    accuracy                           0.72       231
   macro avg       0.72      0.66      0.67       231
weighted avg       0.72      0.72      0.70       231

Confusion Matrix :
 [[130  14]
 [ 50  37]]
```

In [35]:
```
print("classification report  and confusion matrix  of logistic model is")
print(classification_report(y_test , y_test_log_pred))
cm2 = confusion_matrix(y_test ,  y_test_log_pred)
print('Confusion Matrix : \n', cm2)
sensitivity2 = cm2[0,0]/(cm2[0,0]+cm2[0,1])
specificity2 = cm2[1,1]/(cm2[1,0]+cm2[1,1])
```

```
classification report  and confusion matrix  of logistic model is
              precision    recall  f1-score   support

         0.0       0.74      0.90      0.82       144
         1.0       0.75      0.48      0.59        87

    accuracy                           0.74       231
   macro avg       0.75      0.69      0.70       231
weighted avg       0.75      0.74      0.73       231

Confusion Matrix :
 [[130  14]
 [ 45  42]]
```

In [36]:
```
print("classification report  and confusion matrix of Naive Bayes model is")
print(classification_report(y_test ,nb_pred))
cm3 = confusion_matrix(y_test ,nb_pred)
print('Confusion Matrix : \n', cm3)
sensitivity3 = cm3[0,0]/(cm3[0,0]+cm3[0,1])
specificity3 = cm3[1,1]/(cm3[1,0]+cm3[1,1])
```

```
classification report  and confusion matrix of Naive Bayes model is
              precision    recall  f1-score   support

         0.0       0.73      0.85      0.79       144
         1.0       0.66      0.49      0.57        87

    accuracy                           0.71       231
   macro avg       0.70      0.67      0.68       231
weighted avg       0.71      0.71      0.70       231

Confusion Matrix :
 [[122  22]
 [ 44  43]]
```

In [37]:
```
print("classification report  and confusion matrix of Decision Tree model is")
print(classification_report(y_test ,ds_predicted))
cm4 = confusion_matrix(ds_predicted ,y_test)
print('Confusion Matrix : \n', cm4)
sensitivity4 = cm4[0,0]/(cm4[0,0]+cm4[0,1])
specificity4 = cm4[1,1]/(cm4[1,0]+cm4[1,1])
```

```
classification report  and confusion matrix of Decision Tree model is
              precision    recall  f1-score   support

         0.0       0.73      0.74      0.73       144
         1.0       0.56      0.55      0.55        87

    accuracy                           0.67       231
   macro avg       0.64      0.64      0.64       231
weighted avg       0.67      0.67      0.67       231

Confusion Matrix :
 [[106  39]
 [ 38  48]]
```

In [38]:
```
print("classification report and confusion matrix of rendom forest model is")
print(classification_report(y_test , y_pred_redom_forest))
cm5 = confusion_matrix(y_test ,  y_pred_redom_forest)
print('Confusion Matrix : \n', cm5)
sensitivity5 = cm5[0,0]/(cm5[0,0]+cm5[0,1])
specificity5 = cm5[1,1]/(cm5[1,0]+cm5[1,1])
```

```
classification report and confusion matrix of rendom forest model is
              precision    recall  f1-score   support

         0.0       0.74      0.89      0.81       144
         1.0       0.73      0.49      0.59        87

    accuracy                           0.74       231
   macro avg       0.74      0.69      0.70       231
weighted avg       0.74      0.74      0.73       231

Confusion Matrix :
 [[128  16]
 [ 44  43]]
```

In [39]:
```
print("classification report and confusion matrix of xgboast model is")
print(classification_report(y_test , xgb_pred))
cm6 = confusion_matrix(y_test ,  xgb_pred)
print('Confusion Matrix : \n', cm6)
sensitivity6 = cm6[0,0]/(cm6[0,0]+cm6[0,1])
specificity6 = cm6[1,1]/(cm6[1,0]+cm6[1,1])
```

```
classification report and confusion matrix of xgboast model is
              precision    recall  f1-score   support

         0.0       0.74      0.85      0.79       144
         1.0       0.67      0.52      0.58        87

    accuracy                           0.72       231
   macro avg       0.71      0.68      0.69       231
weighted avg       0.72      0.72      0.71       231

Confusion Matrix :
 [[122  22]
 [ 42  45]]
```

In [40]:
```
print("classification report  and confusion matrix of knn model is")
print(classification_report(y_test , y_test_knn_pred))
cm7 = confusion_matrix(y_test , y_test_knn_pred)
print('Confusion Matrix : \n', cm7)
sensitivity7 = cm7[0,0]/(cm7[0,0]+cm7[0,1])
specificity7 = cm7[1,1]/(cm7[1,0]+cm7[1,1])
```

```
classification report  and confusion matrix of knn model is
              precision    recall  f1-score   support

         0.0       0.71      0.83      0.77       144
         1.0       0.61      0.44      0.51        87

    accuracy                           0.68       231
   macro avg       0.66      0.64      0.64       231
weighted avg       0.67      0.68      0.67       231

Confusion Matrix :
 [[120  24]
 [ 49  38]]
```

In [41]:
```
print('Sensitivity of logistic model:', sensitivity2)
print('Sensitivity of svm model:', sensitivity1)
print('Sensitivity of rendom forest model:', sensitivity5)
print('Sensitivity of Naive Bayes model:', sensitivity3)
print('Sensitivity of xgboast model:', sensitivity6 )
print('Sensitivity of knn model:', sensitivity7 )
print('Sensitivity of Decision Tree model:', sensitivity4)
```

```
Sensitivity of logistic model: 0.9027777777777778
Sensitivity of svm model: 0.9027777777777778
Sensitivity of rendom forest model: 0.8888888888888888
Sensitivity of Naive Bayes model: 0.8472222222222222
Sensitivity of xgboast model: 0.8472222222222222
Sensitivity of knn model: 0.8333333333333334
Sensitivity of Decision Tree model: 0.7310344827586207
```

In [42]:
```
print('Specificity of Decision Tree model:', specificity4)
print('Specificity of xgboast model:', specificity6)
print('Specificity of Naive Bayes model:', specificity3)
print('Specificity of rendom forest model:', specificity5)
print('Specificity of logistic model:', specificity2)
print('Specificity of knn model: ', specificity7)
print('Specificity of svm:', specificity1)
```

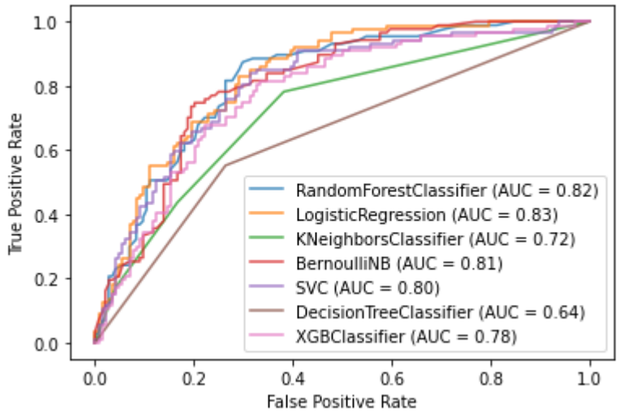
```
Specificity of Decision Tree model: 0.5581395348837209
Specificity of xgboast model: 0.5172413793103449
Specificity of Naive Bayes model: 0.4942528735632184
Specificity of rendom forest model: 0.4942528735632184
Specificity of logistic model: 0.4827586206896552
Specificity of knn model:  0.4367816091954023
Specificity of svm: 0.42528735632183906
```

B)Now lets create ROC cure and check out the area under curve of each classifier

In [43]:
```
from sklearn.metrics import plot_roc_curve
```

In [44]:
```
import matplotlib.pyplot as plt
```

In [46]:
```
ax=plt.gca()
rfc_disp = plot_roc_curve(classifier, X_test, y_test, ax=ax, alpha=0.8)
logReg_disp = plot_roc_curve(logReg , X_test, y_test,ax=ax, alpha=0.8)
knn_disp = plot_roc_curve(knn, X_test, y_test,ax=ax, alpha=0.8)
nb_disp = plot_roc_curve(nb_clf, X_test, y_test,ax=ax, alpha=0.8)
svm_disp = plot_roc_curve(svc_model, X_test, y_test,ax=ax, alpha=0.8)
dis_tree_disp = plot_roc_curve(decision_tree, X_test, y_test,ax=ax, alpha=0.8)
xgb_disp = plot_roc_curve(xgboost, X_test, y_test,ax=ax, alpha=0.8)
plt.show()
```



C)To explain what values of all the above parameter are salected ? and why ?

1.Accuracy - (True possitive + True negative)/Total number of predictions

accuracy in this case means -: The patients which are correctly predicted as having diabetis or not having diabetis with respect to total no. of predictions.

accuracy should be high to say that model is a good fit. From the above accuracy comperison we found that

logistic model classifier has the highest accuracy that is 74.45887445887446%

rendom forest model is at second possition with accuracy of 74.02597402597402%

2.From classificasion report

A)precision-:TruePositives /actual results

actual results=(TruePositives + FalsePositives)

Precision quantifies the number of positive class predictions that actually belong to the positive class.

Higher precision means that an algorithm returns more relevant results than irrelevant ones

so, our model should have high precison

logistic regression model classifier is most precised from all the above classifier with precision of - 75%

rendom forest classifier is second most precised from all the above classifier with precision of - 74%

B)recall-:TruePositives / predicted results

predicted results=(TruePositives +False Negative)

Recall quantifies the number of positive class predictions made out of all positive examples in the dataset.

high recall means that an algorithm returns most of the relevant results (whether or not irrelevant ones are also returned)

so, our model should have high recall.

logistic regression model classifier has the highest recall value from all the above classifier with recall of - 89%

rendom forest classifier has the second highest recall value from all the above classifier with recall of - 89%

C)F1-score-: (2 *Precision* Recall) / (Precision + Recall)

F-Measure provides a single score that balances both the concerns of precision and recall in one number.

hance a best fit model should have high f1-scre

logistic regression classifier has the best f1-score of -82%

rendom forest classifier has the second best f1-score of -81%

3. From analysis of sensitivity, specificity, AUC(ROC curve)

A)Sensitivity(True Positive rate) -:TruePositives /(TruePositives +FalseNegative)

measures the proportion of positives that are correctly identified. high Sensitivity means that an algorithm returns most of the relevant results (whether or not irrelevant ones are also returned)

In our business case sensitivity signifies that how many womens are having diabeties from all those womens are correctly classified as having or not having diabeties

so, our model should have high Sensitivity.

Sensitivity of logistic model: 0.9027777777777778

Sensitivity of rendom forest model: 0.8888888888888888

B)Specificity(True Negative rate)-:(True Negative)/(TrueNegative+FalsePositives)

measures the proportion of negatives that are correctly identified

In our business case Specificity signifies that how many womens are not having diabeties from all those womens that are correctly classified as having or not having diabeties.

so, our model should have high Specificity.

Specificity of Decision Tree model: 0.5116279069767442

Specificity of logistic model: 0.4827586206896552

C)AUC(ROC curve)-:Plot of a classifier with x-axis as false positive rate and y-axis as true positive rate

A receiver operating characteristic curve, or ROC curve, is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied.

with change of the throushold values the curve should note move away from the y-axis as much as possible as it increases the false positive rate. which means that it will increase the probablity of classifyig a persion to have dibeties which actually does not have diabeties.

logistic regression model (auc)-83%

rendom forest classifier (auc)-82%

D)Conclusion

From all above analysis we found that

rendom forest classifier and logistic regression classifier are the best fitting models.

one should go with the rendom forest model if higher specificity required

whereas, one should chose logistic regression model if need higher sensitivity

validating framework= Running Grid Search on both the algoritham to find best one directly

In [47]:
```
from sklearn.model_selection import GridSearchCV
logReg_params = {'C': [0.1, 0.01],
                     'tol': [0.001, 0.01],
                     'max_iter': [1000, 2000]}
classifier1 = RandomForestClassifier()
classifier_params = {'n_estimators': [25,50,100],
                      'max_depth': [25,30],
                      'min_samples_leaf': [2,4],
                      'min_samples_split': [4,6,3]}
grid = zip([logReg,classifier1],[logReg_params,classifier_params])

best_clf = None
# perform grid search and select the model with best cv set scores
for model_pipeline, param in grid:
    temp = GridSearchCV(model_pipeline,param_grid=param, cv=10, n_jobs=-1)
    temp.fit(X_train,y_train)
    if best_clf is None:
        best_clf = temp
    else:
        if temp.best_score_ > best_clf.best_score_:
            best_clf = temp
print ("Best CV Score",best_clf.best_score_)
print ("Model Parameters",best_clf.best_params_)
print("Best Estimator",best_clf.best_estimator_)
```

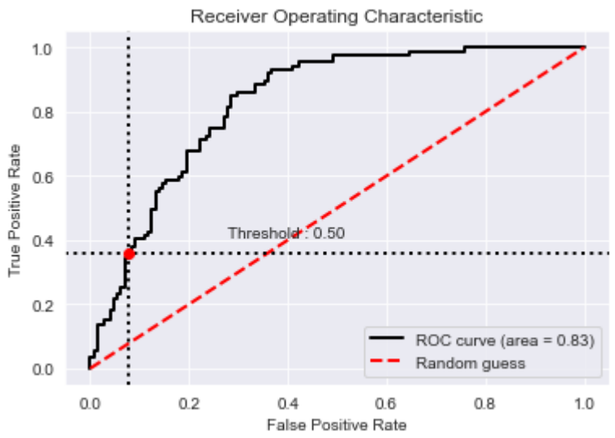
```
Best CV Score 0.7914395527603075
Model Parameters {'C': 0.01, 'max_iter': 1000, 'tol': 0.001}
Best Estimator LogisticRegression(C=0.01, max_iter=1000, tol=0.001)
```

In [48]:
```
predictions = best_clf.predict(X_test)
probs = best_clf.predict_proba(X_test)[:, 1]
print("Classification Report")
print (classification_report(y_test,predictions))
cm = confusion_matrix(y_test,predictions)
print('Confusion Matrix : \n', cm)
sensitivity = cm[0,0]/(cm[0,0]+cm[0,1])
specificity = cm[1,1]/(cm7[1,0]+cm[1,1])
print(sensitivity)
print(specificity)
```

```
Classification Report
              precision    recall  f1-score   support

         0.0       0.70      0.92      0.80       144
         1.0       0.73      0.34      0.47        87

    accuracy                           0.71       231
   macro avg       0.72      0.63      0.63       231
weighted avg       0.71      0.71      0.67       231

Confusion Matrix :
 [[133  11]
 [ 57  30]]
0.9236111111111112
0.379746835443038
```

In [49]:
```
! pip install plot_metric
from plot_metric.functions import BinaryClassification
# Visualisation with plot_metric
bc = BinaryClassification(y_test,probs, labels=["Class 1", "Class 2"])

# Figures
plt.figure()
bc.plot_roc_curve()
plt.show()
```

```
Requirement already satisfied: plot_metric in c:\users\sanja\anaconda3\lib\site-packages (0.0.6)
Requirement already satisfied: scikit-learn>=0.21.2 in c:\users\sanja\anaconda3\lib\site-packages (from plot_metric) (0.23.2)
Requirement already satisfied: numpy>=1.15.4 in c:\users\sanja\anaconda3\lib\site-packages (from plot_metric) (1.18.5)
Requirement already satisfied: matplotlib>=3.0.2 in c:\users\sanja\anaconda3\lib\site-packages (from plot_metric) (3.2.2)
Requirement already satisfied: pandas>=0.23.4 in c:\users\sanja\anaconda3\lib\site-packages (from plot_metric) (1.0.5)
Requirement already satisfied: colorlover>=0.3.0 in c:\users\sanja\anaconda3\lib\site-packages (from plot_metric) (0.3.0)
Requirement already satisfied: seaborn>=0.9.0 in c:\users\sanja\anaconda3\lib\site-packages (from plot_metric) (0.10.1)
Requirement already satisfied: scipy>=1.1.0 in c:\users\sanja\anaconda3\lib\site-packages (from plot_metric) (1.5.0)
Requirement already satisfied: joblib>=0.11 in c:\users\sanja\anaconda3\lib\site-packages (from scikit-learn>=0.21.2->plot_metric) (0.16.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\sanja\anaconda3\lib\site-packages (from scikit-learn>=0.21.2->plot_metric) (2.1.0)
Requirement already satisfied: cycler>=0.10 in c:\users\sanja\anaconda3\lib\site-packages (from matplotlib>=3.0.2->plot_metric) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\sanja\anaconda3\lib\site-packages (from matplotlib>=3.0.2->plot_metric) (1.2.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in c:\users\sanja\anaconda3\lib\site-packages (from matplotlib>=3.0.2->plot_metric) (2.4.7)
Requirement already satisfied: python-dateutil>=2.1 in c:\users\sanja\anaconda3\lib\site-packages (from matplotlib>=3.0.2->plot_metric) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in c:\users\sanja\anaconda3\lib\site-packages (from pandas>=0.23.4->plot_metric) (2020.1)
Requirement already satisfied: six in c:\users\sanja\anaconda3\lib\site-packages (from cycler>=0.10->matplotlib>=3.0.2->plot_metric) (1.15.0)
```



In [50]:
```
! pip install pycaret
```

```
Requirement already satisfied: pycaret in c:\users\sanja\anaconda3\lib\site-packages (2.2.3)
Requirement already satisfied: pyod in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (0.8.7)
Requirement already satisfied: umap-learn in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (0.5.1)
Requirement already satisfied: plotly>=4.4.1 in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (4.14.3)
Requirement already satisfied: matplotlib in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (3.2.2)
Requirement already satisfied: joblib in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (0.16.0)
Requirement already satisfied: imbalanced-learn>=0.7.0 in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (0.8.0)
Requirement already satisfied: scikit-plot in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (0.3.7)
Requirement already satisfied: wordcloud in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (1.8.1)
Requirement already satisfied: textblob in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (0.15.3)
Requirement already satisfied: seaborn in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (0.10.1)
Requirement already satisfied: xgboost>=1.1.0 in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (1.3.3)
Requirement already satisfied: lightgbm>=2.3.1 in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (3.1.1)
Requirement already satisfied: cufflinks>=0.17.0 in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (0.17.3)
Requirement already satisfied: ipywidgets in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (7.5.1)
Requirement already satisfied: kmodes>=0.10.1 in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (0.11.0)
Requirement already satisfied: catboost>=0.23.2 in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (0.24.4)
Requirement already satisfied: nltk in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (3.5)
Requirement already satisfied: IPython in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (7.16.1)
Requirement already satisfied: spacy in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (3.0.3)
Requirement already satisfied: pandas-profiling>=2.8.0 in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (2.10.0)
Requirement already satisfied: mlflow in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (1.13.1)
Requirement already satisfied: numpy>=1.17 in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (1.18.5)
Requirement already satisfied: scikit-learn==0.23.2 in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (0.23.2)
Requirement already satisfied: gensim in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (3.8.3)
Requirement already satisfied: pyLDAvis in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (3.2.1)
Requirement already satisfied: pandas in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (1.0.5)
Requirement already satisfied: yellowbrick>=1.0.1 in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (1.3.post1)
Requirement already satisfied: mlxtend in c:\users\sanja\anaconda3\lib\site-packages (from pycaret) (0.18.0)
Requirement already satisfied: six in c:\users\sanja\anaconda3\lib\site-packages (from pyod->pycaret) (1.15.0)
Requirement already satisfied: statsmodels in c:\users\sanja\anaconda3\lib\site-packages (from pyod->pycaret) (0.11.1)
Requirement already satisfied: scipy>=0.19.1 in c:\users\sanja\anaconda3\lib\site-packages (from pyod->pycaret) (1.5.0)
Requirement already satisfied: numba>=0.35 in c:\users\sanja\anaconda3\lib\site-packages (from pyod->pycaret) (0.50.1)
Requirement already satisfied: pynndescent>=0.5 in c:\users\sanja\anaconda3\lib\site-packages (from umap-learn->pycaret) (0.5.2)
Requirement already satisfied: retrying>=1.3.3 in c:\users\sanja\anaconda3\lib\site-packages (from plotly>=4.4.1->pycaret) (1.3.3)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in c:\users\sanja\anaconda3\lib\site-packages (from matplotlib->pycaret) (2.4.7)
Requirement already satisfied: python-dateutil>=2.1 in c:\users\sanja\anaconda3\lib\site-packages (from matplotlib->pycaret) (2.8.1)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\sanja\anaconda3\lib\site-packages (from matplotlib->pycaret) (1.2.0)
Requirement already satisfied: cycler>=0.10 in c:\users\sanja\anaconda3\lib\site-packages (from matplotlib->pycaret) (0.10.0)
Requirement already satisfied: pillow in c:\users\sanja\anaconda3\lib\site-packages (from wordcloud->pycaret) (7.2.0)
Requirement already satisfied: wheel in c:\users\sanja\anaconda3\lib\site-packages (from lightgbm>=2.3.1->pycaret) (0.34.2)
Requirement already satisfied: setuptools>=34.4.1 in c:\users\sanja\anaconda3\lib\site-packages (from cufflinks>=0.17.0->pycaret) (49.2.0.post20200714)
Requirement already satisfied: colorlover>=0.2.1 in c:\users\sanja\anaconda3\lib\site-packages (from cufflinks>=0.17.0->pycaret) (0.3.0)
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Requirement already satisfied: widgetsnbextension~=3.5.0 in c:\users\sanja\anaconda3\lib\site-packages (from ipywidgets->pycaret) (3.5.1)
Requirement already satisfied: ipykernel>=4.5.1 in c:\users\sanja\anaconda3\lib\site-packages (from ipywidgets->pycaret) (5.3.2)
Requirement already satisfied: graphviz in c:\users\sanja\anaconda3\lib\site-packages (from catboost>=0.23.2->pycaret) (0.16)
Requirement already satisfied: regex in c:\users\sanja\anaconda3\lib\site-packages (from nltk->pycaret) (2020.6.8)
Requirement already satisfied: tqdm in c:\users\sanja\anaconda3\lib\site-packages (from nltk->pycaret) (4.56.0)
Requirement already satisfied: click in c:\users\sanja\anaconda3\lib\site-packages (from nltk->pycaret) (7.1.2)
Requirement already satisfied: pygments in c:\users\sanja\anaconda3\lib\site-packages (from IPython->pycaret) (2.6.1)
Requirement already satisfied: jedi>=0.10 in c:\users\sanja\anaconda3\lib\site-packages (from IPython->pycaret) (0.17.1)
Requirement already satisfied: prompt-toolkit!=3.0.0,!=3.0.1,<3.1.0,>=2.0.0 in c:\users\sanja\anaconda3\lib\site-packages (from IPython->pycaret) (3.0.5)
Requirement already satisfied: pickleshare in c:\users\sanja\anaconda3\lib\site-packages (from IPython->pycaret) (0.7.5)
Requirement already satisfied: backcall in c:\users\sanja\anaconda3\lib\site-packages (from IPython->pycaret) (0.2.0)
Requirement already satisfied: colorama; sys_platform == "win32" in c:\users\sanja\anaconda3\lib\site-packages (from IPython->pycaret) (0.4.3)
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Requirement already satisfied: jinja2 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (2.11.2)
Requirement already satisfied: thinc<8.1.0,>=8.0.0 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (8.0.1)
Requirement already satisfied: preshed<3.1.0,>=3.0.2 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (3.0.5)
```

```
Requirement already satisfied: spacy-legacy<3.1.0,>=3.0.0 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (3.0.1)
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (1.0.5)
Requirement already satisfied: srsly<3.0.0,>=2.4.0 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (2.4.0)
Requirement already satisfied: wasabi<1.1.0,>=0.8.1 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (0.8.2)
Requirement already satisfied: packaging>=20.0 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (20.4)
Requirement already satisfied: cymem<2.1.0,>=2.0.2 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (2.0.5)
Requirement already satisfied: typer<0.4.0,>=0.3.0 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (0.3.2)
Requirement already satisfied: requests<3.0.0,>=2.13.0 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (2.24.0)
Requirement already satisfied: blis<0.8.0,>=0.4.0 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (0.7.4)
Requirement already satisfied: pydantic<1.8.0,>=1.7.1 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (1.7.3)
Requirement already satisfied: pathy in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (0.4.0)
Requirement already satisfied: catalogue<2.1.0,>=2.0.1 in c:\users\sanja\anaconda3\lib\site-packages (from spacy->pycaret) (2.0.1)
Requirement already satisfied: htmlmin>=0.1.12 in c:\users\sanja\anaconda3\lib\site-packages (from pandas-profiling>=2.8.0->pycaret) (0.1.12)
Requirement already satisfied: phik>=0.10.0 in c:\users\sanja\anaconda3\lib\site-packages (from pandas-profiling>=2.8.0->pycaret) (0.11.0)
Requirement already satisfied: missingno>=0.4.2 in c:\users\sanja\anaconda3\lib\site-packages (from pandas-profiling>=2.8.0->pycaret) (0.4.2)
Requirement already satisfied: tangled-up-in-unicode>=0.0.6 in c:\users\sanja\anaconda3\lib\site-packages (from pandas-profiling>=2.8.0->pycaret) (0.0.6)
Requirement already satisfied: confuse>=1.0.0 in c:\users\sanja\anaconda3\lib\site-packages (from pandas-profiling>=2.8.0->pycaret) (1.4.0)
Requirement already satisfied: visions[type_image_path]==0.6.0 in c:\users\sanja\anaconda3\lib\site-packages (from pandas-profiling>=2.8.0->pycaret) (0.6.0)
Requirement already satisfied: attrs>=19.3.0 in c:\users\sanja\anaconda3\lib\site-packages (from pandas-profiling>=2.8.0->pycaret) (19.3.0)
Requirement already satisfied: databricks-cli>=0.8.7 in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (0.14.1)
Requirement already satisfied: sqlparse>=0.3.1 in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (0.4.1)
Requirement already satisfied: gitpython>=2.1.0 in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (3.1.13)
Requirement already satisfied: querystring-parser in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (1.2.4)
Requirement already satisfied: docker>=4.0.0 in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (4.4.3)
Requirement already satisfied: sqlalchemy in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (1.3.18)
Requirement already satisfied: protobuf>=3.6.0 in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (3.15.0)
Requirement already satisfied: cloudpickle in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (1.5.0)
Requirement already satisfied: prometheus-flask-exporter in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (0.18.1)
Requirement already satisfied: entrypoints in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (0.3)
Requirement already satisfied: azure-storage-blob>=12.0.0 in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (12.7.1)
Requirement already satisfied: waitress; platform_system == "Windows" in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (1.4.4)
Requirement already satisfied: alembic<=1.4.1 in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (1.4.1)
Requirement already satisfied: Flask in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (1.1.2)
Requirement already satisfied: pyyaml in c:\users\sanja\anaconda3\lib\site-packages (from mlflow->pycaret) (5.3.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\sanja\anaconda3\lib\site-packages (from scikit-learn==0.23.2->pycaret) (2.1.0)
Requirement already satisfied: smart-open>=1.8.1 in c:\users\sanja\anaconda3\lib\site-packages (from gensim->pycaret) (4.2.0)
Requirement already satisfied: Cython==0.29.14 in c:\users\sanja\anaconda3\lib\site-packages (from gensim->pycaret) (0.29.14)
Requirement already satisfied: funcy in c:\users\sanja\anaconda3\lib\site-packages (from pyLDAvis->pycaret) (1.15)
Requirement already satisfied: future in c:\users\sanja\anaconda3\lib\site-packages (from pyLDAvis->pycaret) (0.18.2)
Requirement already satisfied: numexpr in c:\users\sanja\anaconda3\lib\site-packages (from pyLDAvis->pycaret) (2.7.1)
Requirement already satisfied: pytz>=2017.2 in c:\users\sanja\anaconda3\lib\site-packages (from pandas->pycaret) (2020.1)
Requirement already satisfied: patsy>=0.5 in c:\users\sanja\anaconda3\lib\site-packages (from statsmodels->pyod->pycaret) (0.5.1)
Requirement already satisfied: llvmlite<0.34,>=0.33.0.dev0 in c:\users\sanja\anaconda3\lib\site-packages (from numba>=0.35->pyod->pycaret) (0.33.0+1.g022ab0f)
Requirement already satisfied: ipython-genutils in c:\users\sanja\anaconda3\lib\site-packages (from nbformat>=4.2.0->ipywidgets->pycaret) (0.2.0)
Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in c:\users\sanja\anaconda3\lib\site-packages (from nbformat>=4.2.0->ipywidgets->pycaret) (3.2.0)
Requirement already satisfied: jupyter-core in c:\users\sanja\anaconda3\lib\site-packages (from nbformat>=4.2.0->ipywidgets->pycaret) (4.6.3)
Requirement already satisfied: notebook>=4.4.1 in c:\users\sanja\anaconda3\lib\site-packages (from widgetsnbextension~=3.5.0->ipywidgets->pycaret) (6.0.3)
Requirement already satisfied: tornado>=4.2 in c:\users\sanja\anaconda3\lib\site-packages (from ipykernel>=4.5.1->ipywidgets->pycaret) (6.0.4)
Requirement already satisfied: jupyter-client in c:\users\sanja\anaconda3\lib\site-packages (from ipykernel>=4.5.1->ipywidgets->pycaret) (6.1.6)
Requirement already satisfied: parso<0.8.0,>=0.7.0 in c:\users\sanja\anaconda3\lib\site-packages (from jedi>=0.10->IPython->pycaret) (0.7.0)
Requirement already satisfied: wcwidth in c:\users\sanja\anaconda3\lib\site-packages (from prompt-toolkit!=3.0.0,!=3.0.1,<3.1.0,>=2.0.0->IPython->pycaret) (0.2.5)
Requirement already satisfied: MarkupSafe>=0.23 in c:\users\sanja\anaconda3\lib\site-packages (from jinja2->spacy->pycaret) (1.1.1)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\sanja\anaconda3\lib\site-packages (from requests<3.0.0,>=2.13.0->spacy->pycaret) (2020.6.20)
Requirement already satisfied: chardet<4,>=3.0.2 in c:\users\sanja\anaconda3\lib\site-packages (from requests<3.0.0,>=2.13.0->spacy->pycaret) (3.0.4)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in c:\users\sanja\anaconda3\lib\site-packages (from requests<3.0.0,>=2.13.0->spacy->pycaret) (1.25.9)
Requirement already satisfied: idna<3,>=2.5 in c:\users\sanja\anaconda3\lib\site-packages (from requests<3.0.0,>=2.13.0->spacy->pycaret) (2.10)
Requirement already satisfied: networkx>=2.4 in c:\users\sanja\anaconda3\lib\site-packages (from visions[type_image_path]==0.6.0->pandas-profiling>=2.8.0->pycaret) (2.4)
Requirement already satisfied: imagehash; extra == "type_image_path" in c:\users\sanja\anaconda3\lib\site-packages (from visions[type_image_path]==0.6.0->pandas-profiling>=2.8.0-
>pycaret) (4.2.0)
Requirement already satisfied: tabulate>=0.7.7 in c:\users\sanja\anaconda3\lib\site-packages (from databricks-cli>=0.8.7->mlflow->pycaret) (0.8.8)
```

```
Requirement already satisfied: gitdb<5,>=4.0.1 in c:\users\sanja\anaconda3\lib\site-packages (from gitpython>=2.1.0->mlflow->pycaret) (4.0.5)
Requirement already satisfied: websocket-client>=0.32.0 in c:\users\sanja\anaconda3\lib\site-packages (from docker>=4.0.0->mlflow->pycaret) (0.57.0)
```

In [51]:
```
from pycaret import classification
classification_setup = classification.setup(data= df1, target='Outcome')
```

	Description	Value
0	session_id	8408
1	Target	Outcome
2	Target Type	Binary
3	Label Encoded	0.0: 0, 1.0: 1
4	Original Data	(768, 9)
5	Missing Values	False
6	Numeric Features	8
7	Categorical Features	0
8	Ordinal Features	False
9	High Cardinality Features	False
10	High Cardinality Method	None
11	Transformed Train Set	(537, 8)
12	Transformed Test Set	(231, 8)
13	Shuffle Train-Test	True
14	Stratify Train-Test	False
15	Fold Generator	StratifiedKFold
16	Fold Number	10
17	CPU Jobs	-1
18	Use GPU	False
19	Log Experiment	False
20	Experiment Name	clf-default-name
21	USI	3a45
22	Imputation Type	simple
23	Iterative Imputation Iteration	None
24	Numeric Imputer	mean
25	Iterative Imputation Numeric Model	None
26	Categorical Imputer	constant
27	Iterative Imputation Categorical Model	None
28	Unknown Categoricals Handling	least_frequent
29	Normalize	False
30	Normalize Method	None
31	Transformation	False
32	Transformation Method	None
33	PCA	False
34	PCA Method	None
35	PCA Components	None
36	Ignore Low Variance	False
37	Combine Rare Levels	False

	Description	Value
38	Rare Level Threshold	None
39	Numeric Binning	False
40	Remove Outliers	False
41	Outliers Threshold	None
42	Remove Multicollinearity	False
43	Multicollinearity Threshold	None
44	Clustering	False
45	Clustering Iteration	None
46	Polynomial Features	False
47	Polynomial Degree	None
48	Trignometry Features	False
49	Polynomial Threshold	None
50	Group Features	False
51	Feature Selection	False
52	Features Selection Threshold	None
53	Feature Interaction	False
54	Feature Ratio	False
55	Interaction Threshold	None
56	Fix Imbalance	False
57	Fix Imbalance Method	SMOTE

In [52]:
```
classification.compare_models()
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
ridge	Ridge Classifier	0.7541	0.0000	0.5085	0.6918	0.5825	0.4148	0.4268	0.0310
lr	Logistic Regression	0.7505	0.8121	0.5029	0.6813	0.5754	0.4054	0.4165	0.2760
lda	Linear Discriminant Analysis	0.7504	0.8113	0.5085	0.6813	0.5789	0.4077	0.4184	0.0110
ada	Ada Boost Classifier	0.7448	0.7931	0.5792	0.6416	0.6067	0.4193	0.4219	0.0300
gbc	Gradient Boosting Classifier	0.7430	0.8072	0.5848	0.6441	0.6072	0.4179	0.4236	0.0390
rf	Random Forest Classifier	0.7429	0.8148	0.5456	0.6517	0.5882	0.4045	0.4119	0.0770
et	Extra Trees Classifier	0.7411	0.8159	0.4971	0.6660	0.5627	0.3856	0.3979	0.0730
nb	Naive Bayes	0.7374	0.7965	0.5851	0.6259	0.6019	0.4070	0.4096	0.0070
catboost	CatBoost Classifier	0.7299	0.8211	0.5187	0.6301	0.5638	0.3719	0.3791	1.7310
lightgbm	Light Gradient Boosting Machine	0.7282	0.7889	0.5518	0.6121	0.5753	0.3777	0.3821	0.1510
qda	Quadratic Discriminant Analysis	0.7262	0.7738	0.5032	0.6169	0.5528	0.3595	0.3637	0.0320
xgboost	Extreme Gradient Boosting	0.7115	0.7812	0.5468	0.5804	0.5603	0.3468	0.3488	0.2220
knn	K Neighbors Classifier	0.7041	0.7396	0.5146	0.5809	0.5382	0.3236	0.3299	0.0120
dt	Decision Tree Classifier	0.6686	0.6329	0.5234	0.5232	0.5182	0.2667	0.2700	0.0070
svm	SVM - Linear Kernel	0.6236	0.0000	0.3985	0.4798	0.3217	0.1373	0.1834	0.0180

Out[52]:
```
RidgeClassifier(alpha=1.0, class_weight=None, copy_X=True, fit_intercept=True,
                max_iter=None, normalize=False, random_state=8408,
                solver='auto', tol=0.001)
```

Best Model: AdaBoost Classifier

In [53]:
```
classification_cat = classification.create_model('ada')
```

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	0.7778	0.8256	0.6667	0.6667	0.6667	0.5000	0.5000
1	0.8148	0.8480	0.6667	0.7500	0.7059	0.5714	0.5735
2	0.7222	0.7515	0.5556	0.5882	0.5714	0.3662	0.3665
3	0.6296	0.7037	0.5000	0.4500	0.4737	0.1892	0.1898
4	0.7222	0.7820	0.4737	0.6429	0.5455	0.3520	0.3605
5	0.8333	0.8767	0.6842	0.8125	0.7429	0.6209	0.6259
6	0.7593	0.8406	0.5789	0.6875	0.6286	0.4524	0.4561
7	0.6981	0.7508	0.5000	0.5625	0.5294	0.3083	0.3095
8	0.6981	0.7476	0.4444	0.5714	0.5000	0.2886	0.2933
9	0.7925	0.8048	0.7222	0.6842	0.7027	0.5435	0.5439
Mean	0.7448	0.7931	0.5792	0.6416	0.6067	0.4193	0.4219
SD	0.0591	0.0521	0.0944	0.0981	0.0904	0.1329	0.1329

Data Reporting:

2. Create a dashboard in tableau by choosing appropriate chart types and metrics useful for the business. The dashboard must entail the following:

a. Pie chart to describe the diabetic or non-diabetic population

b. Scatter charts between relevant variables to analyze the relationships

c. Histogram or frequency charts to analyze the distribution of the data

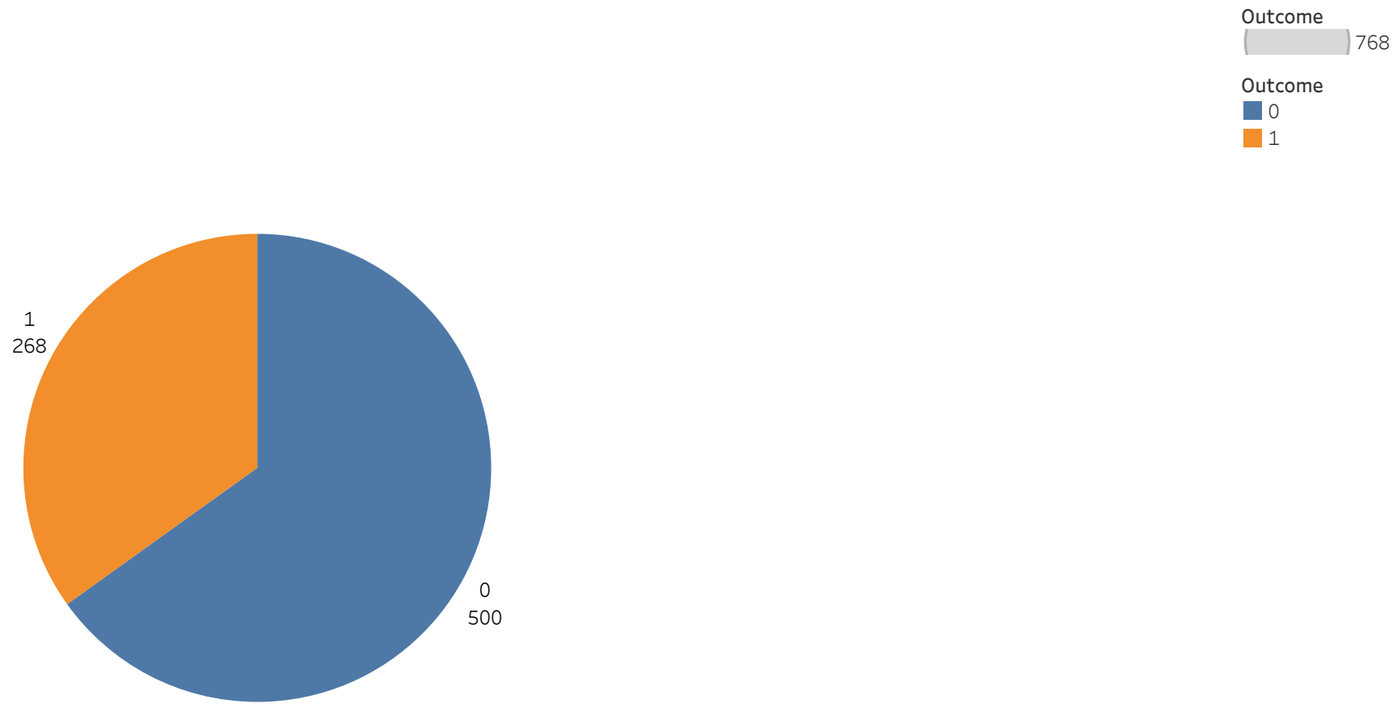
d. Heatmap of correlation analysis among the relevant variables

e. Create bins of these age values: 20-25, 25-30, 30-35, etc. Analyze different variables for these age brackets using a bubble chart.

To craete tableau deshboard lets convert the dataframe data to a csv file and work on tableau software.

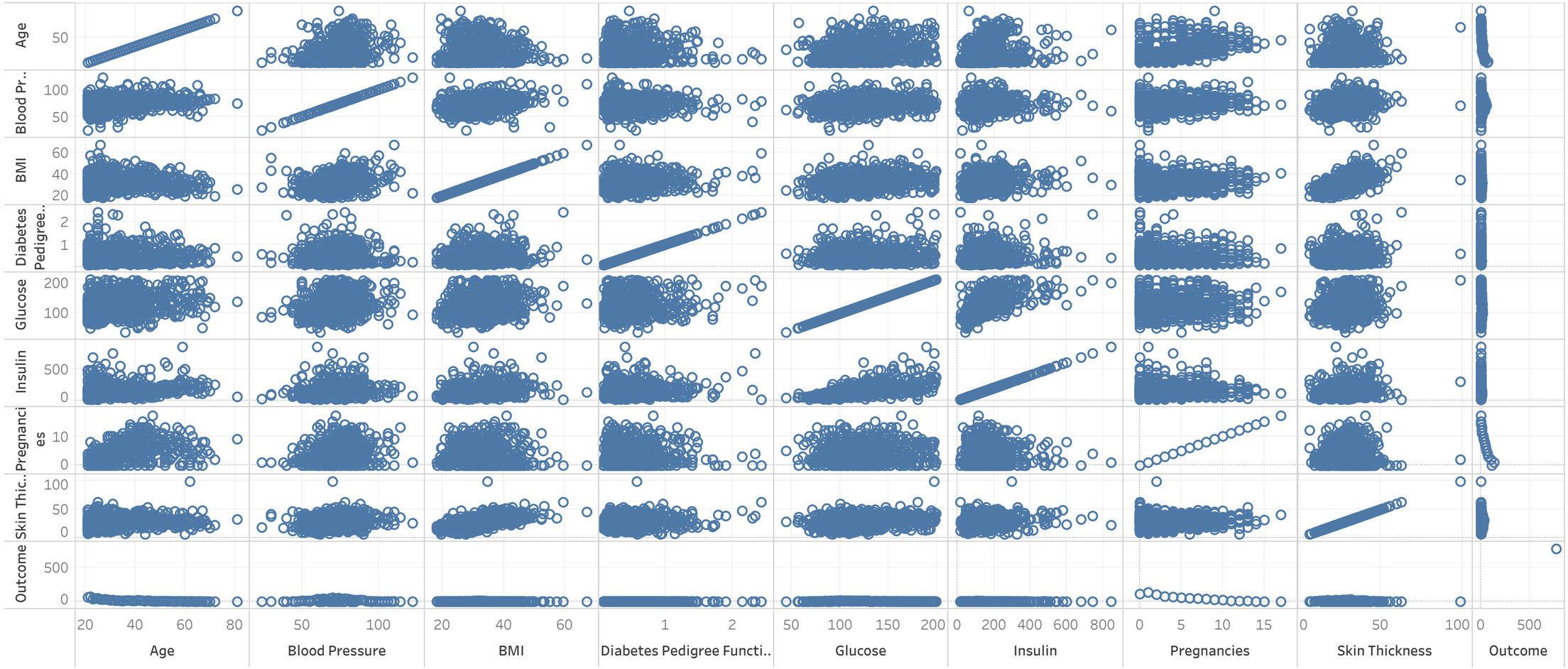
In [54]:
```
df1.to_excel(output_path + "Tableau_healthcare_diabeties.xlsx", index = False)
```

pie chart

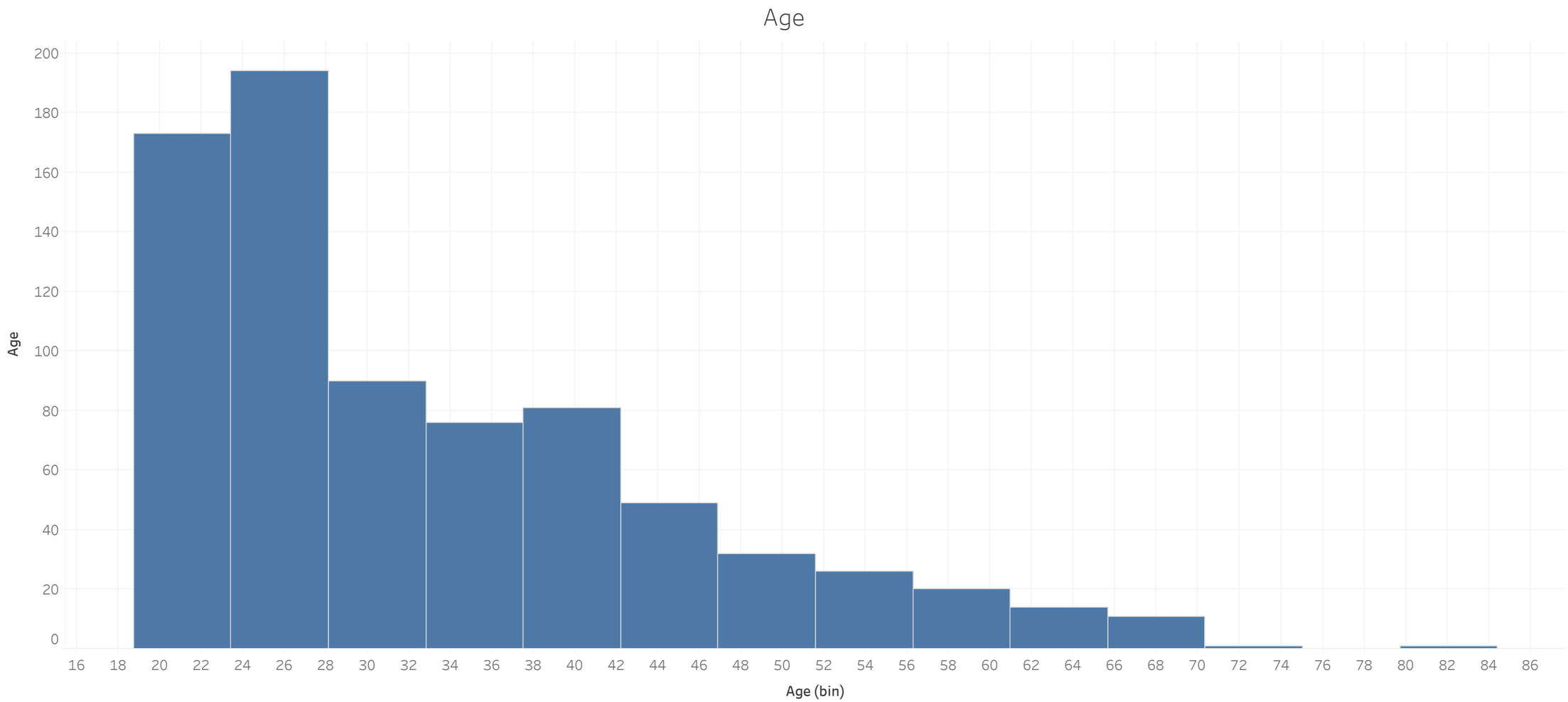


Outcome (copy) and count of Outcome. Color shows details about Outcome (copy). Size shows count of Outcome. The marks are labeled by Outcome (copy) and count of Outcome.

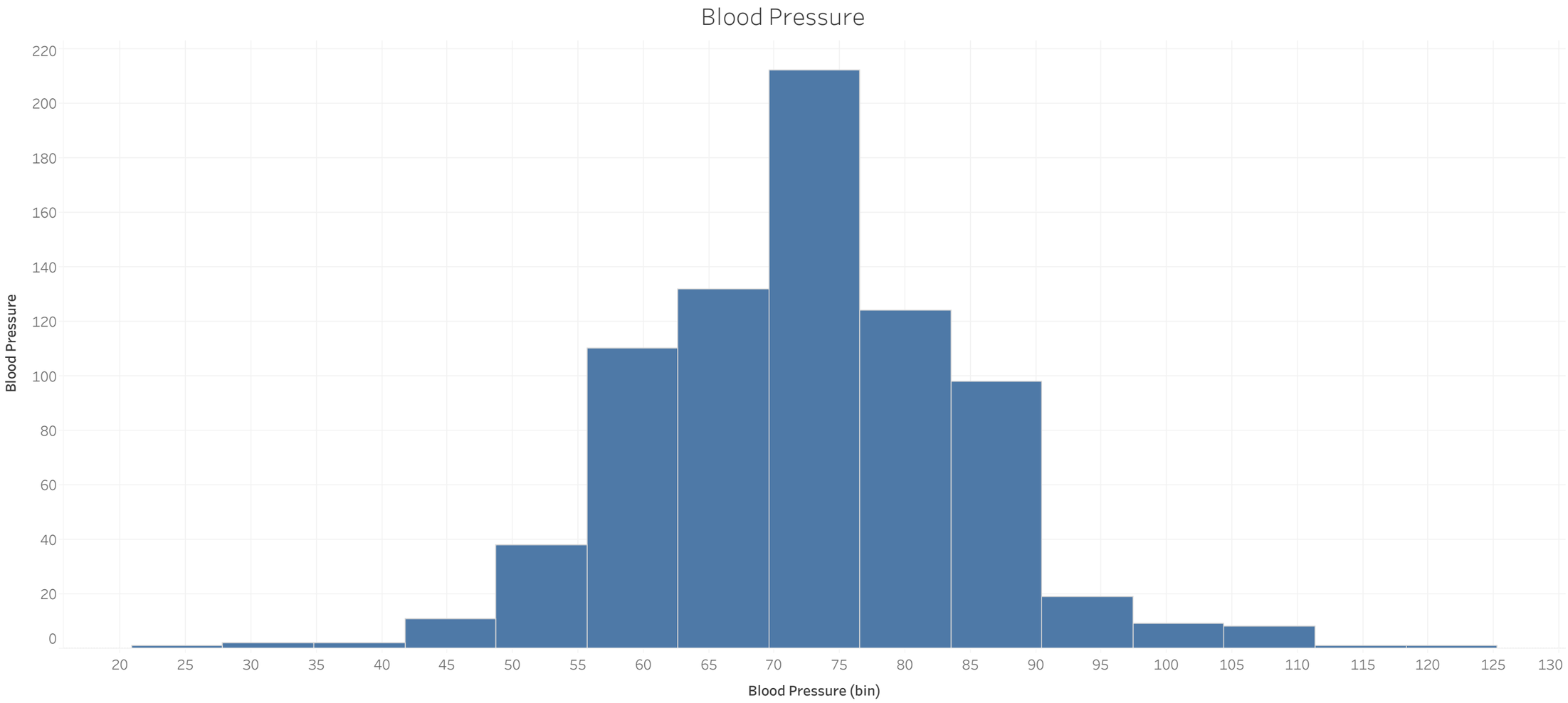
scatter plots



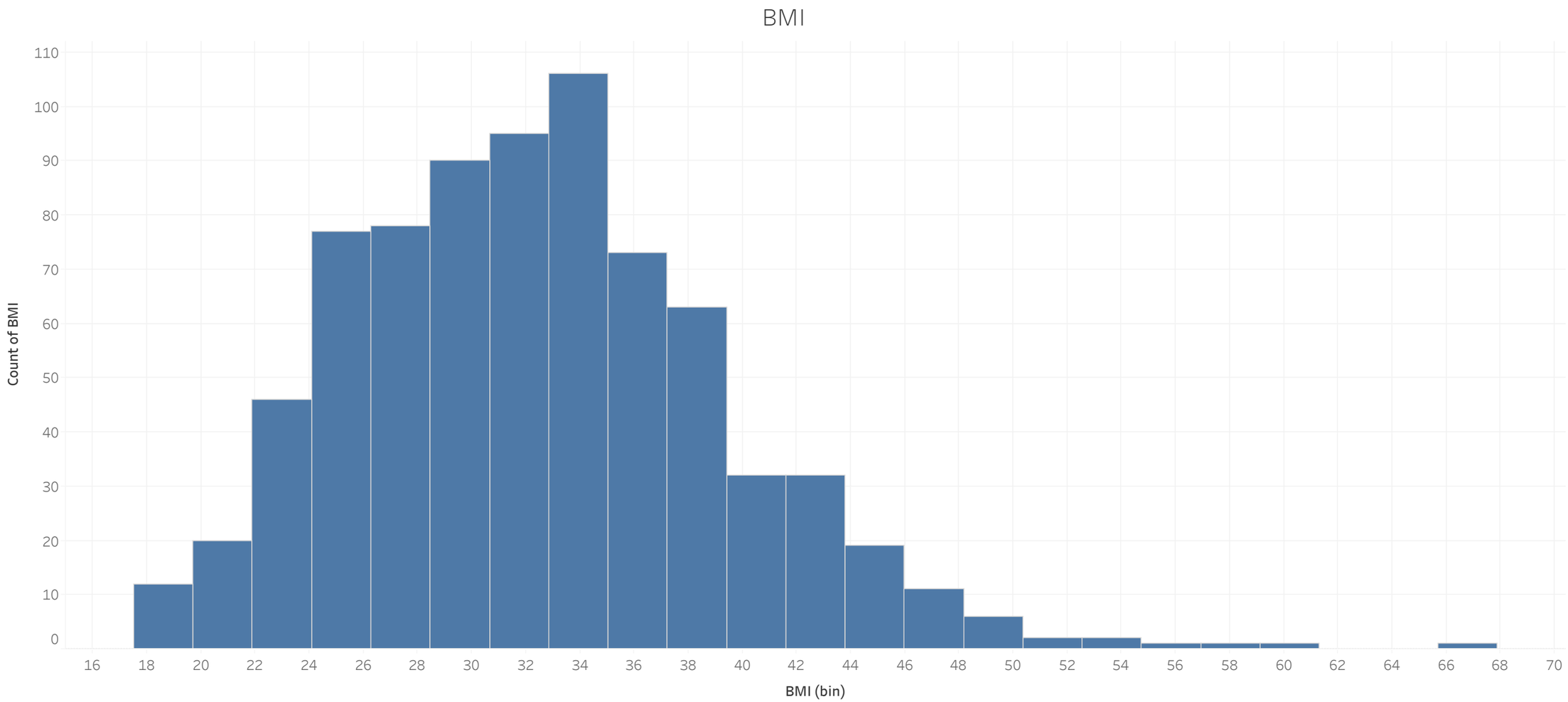
Age, Blood Pressure, BMI, Diabetes Pedigree Function, Glucose, Insulin, Pregnancies, Skin Thickness and count of Outcome vs. Age, Blood Pressure, BMI, Diabetes Pedigree Function, Glucose, Insulin, Pregnancies, Skin Thickness and count of Outcome.



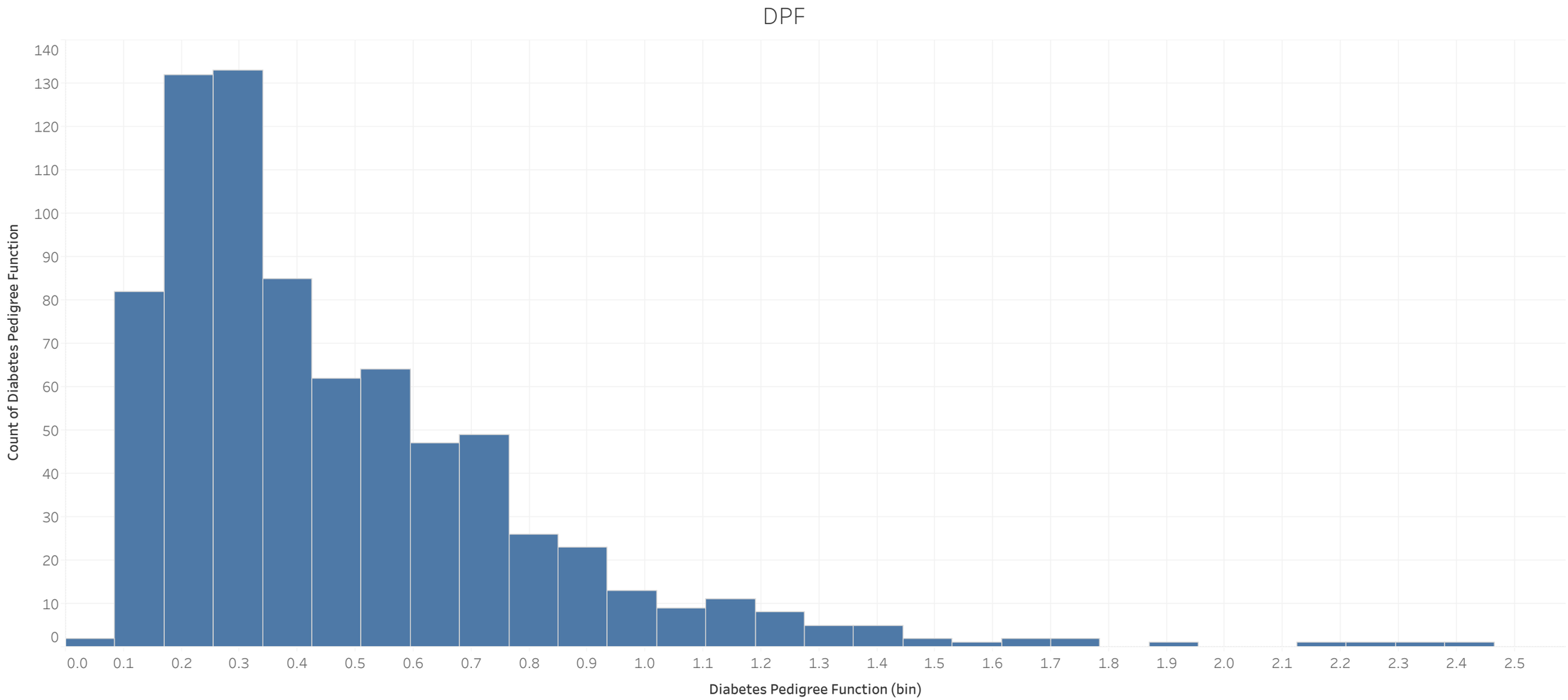
The trend of count of Age for Age (bin).



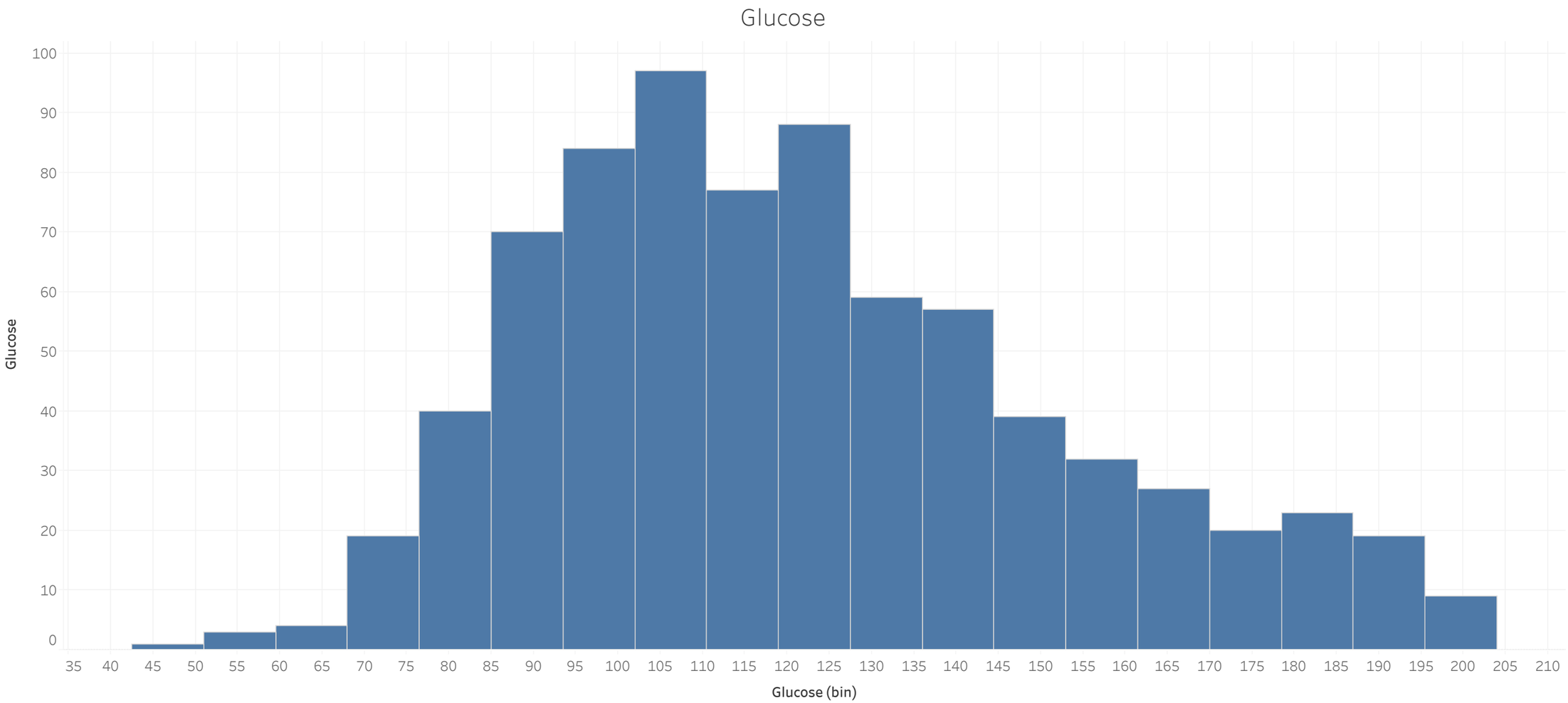
The trend of count of Blood Pressure for Blood Pressure (bin).



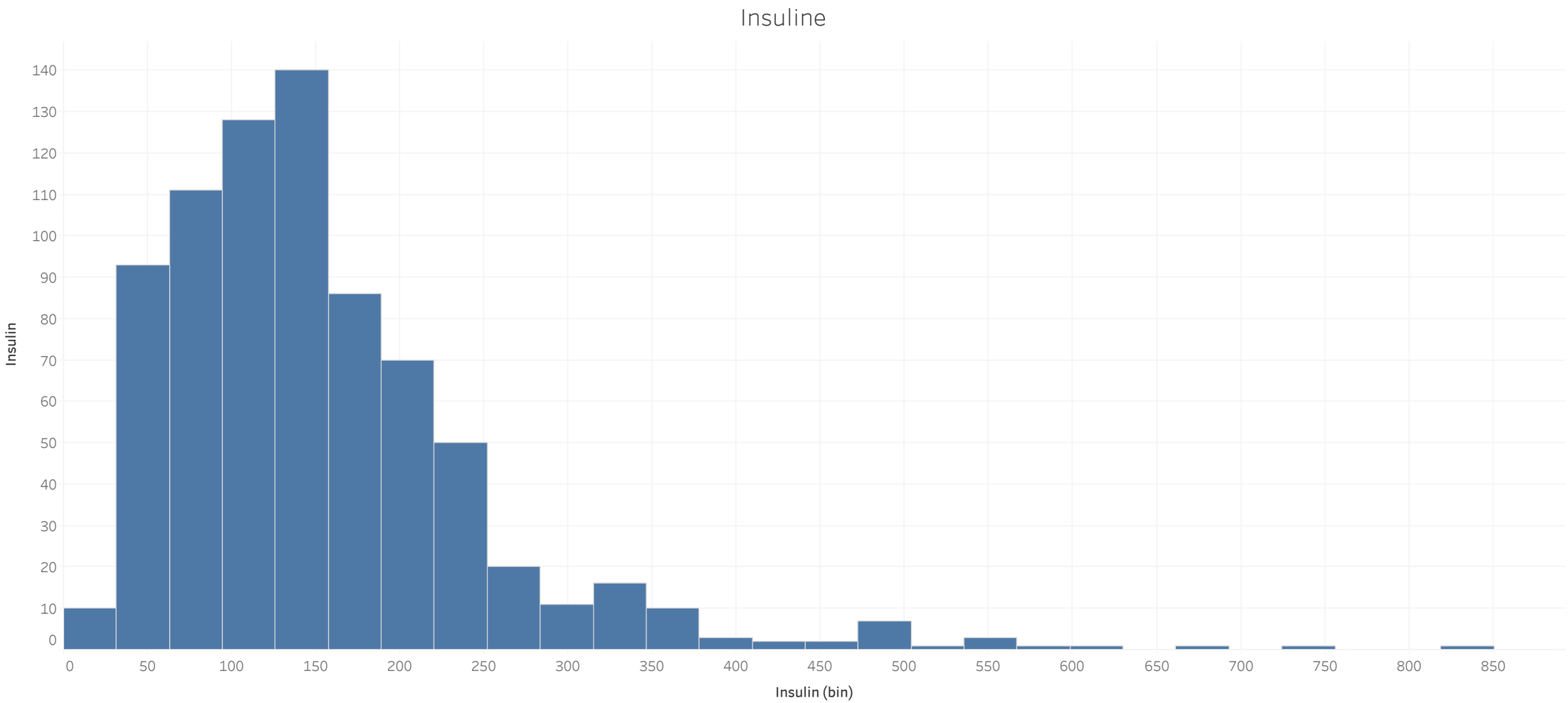
The trend of count of BMI for BMI (bin).



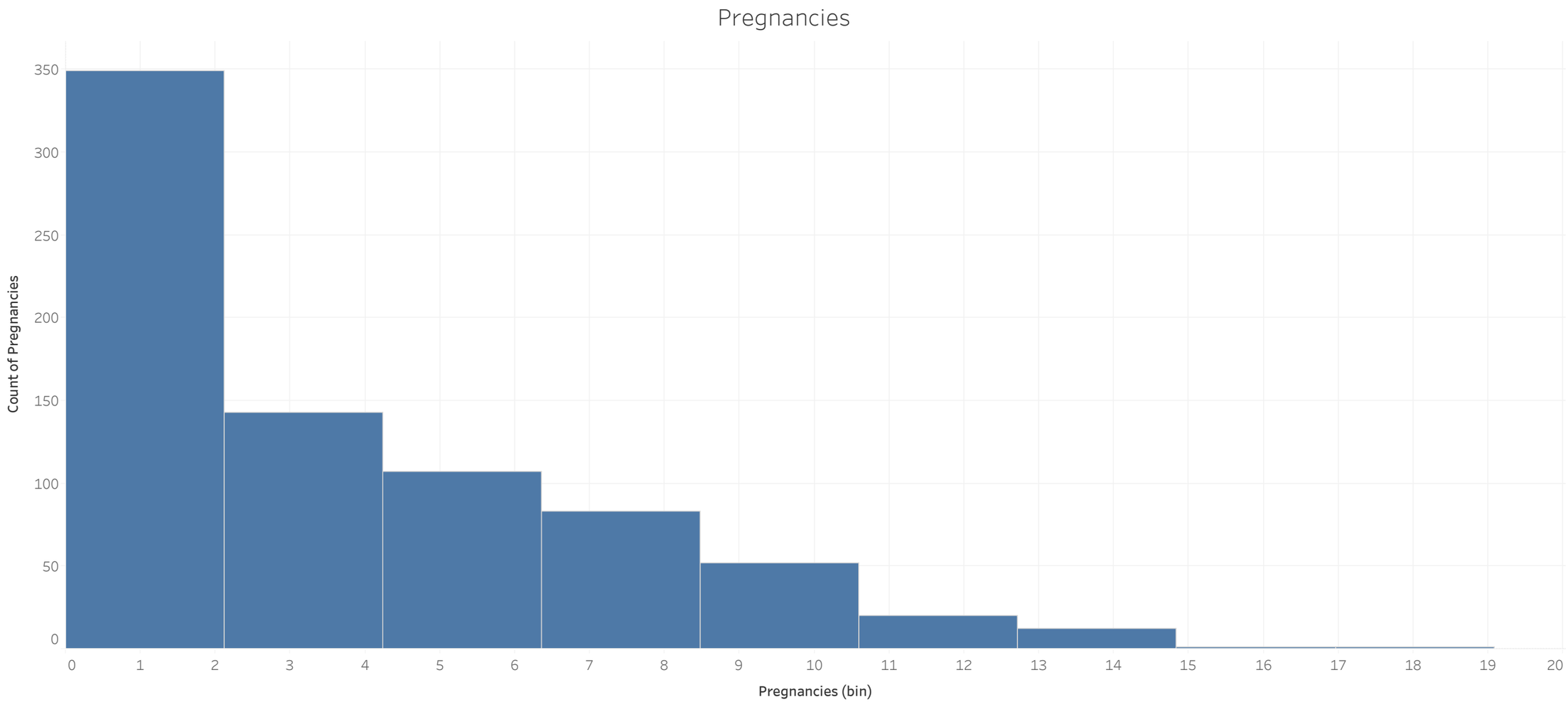
The trend of count of Diabetes Pedigree Function for Diabetes Pedigree Function (bin).



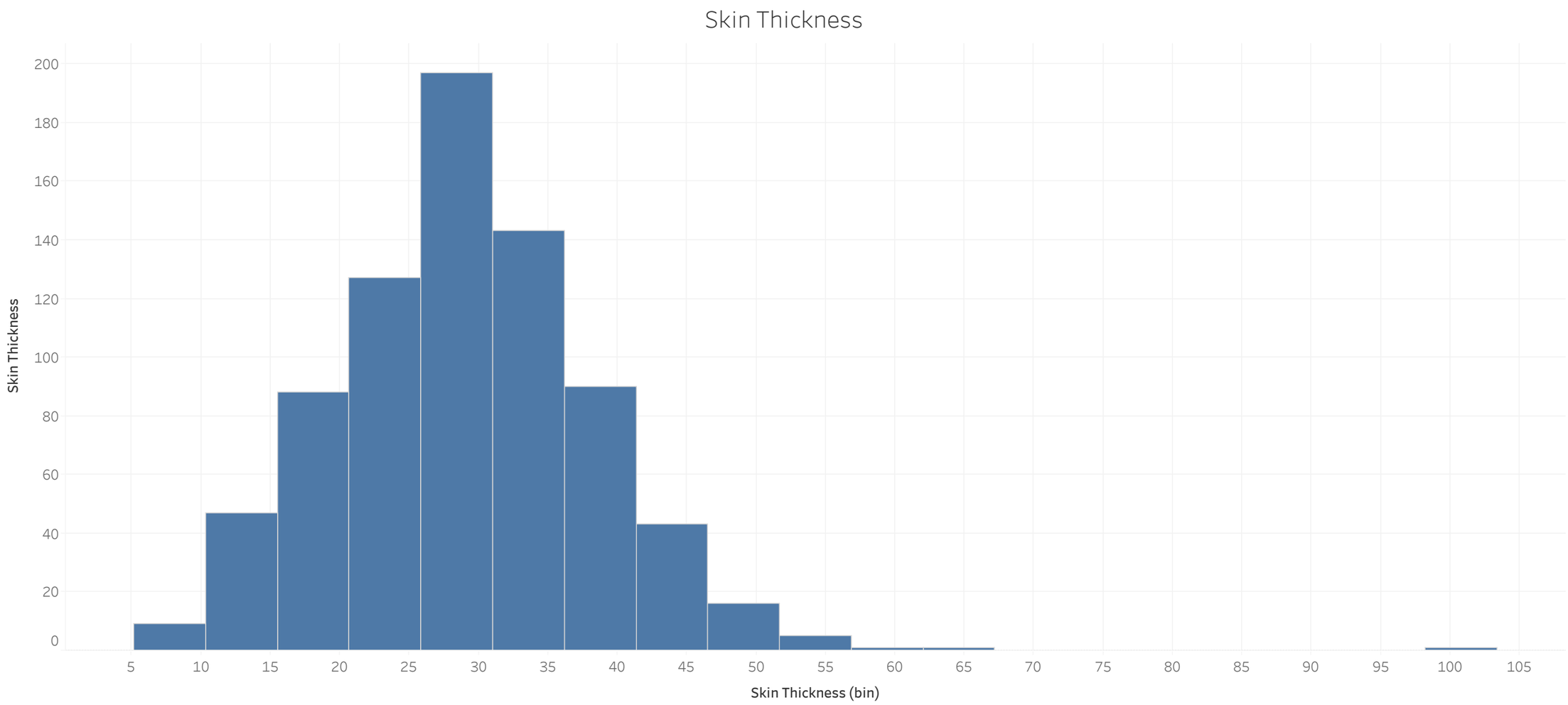
The trend of count of Glucose for Glucose (bin).



The trend of count of Insulin for Insulin (bin).

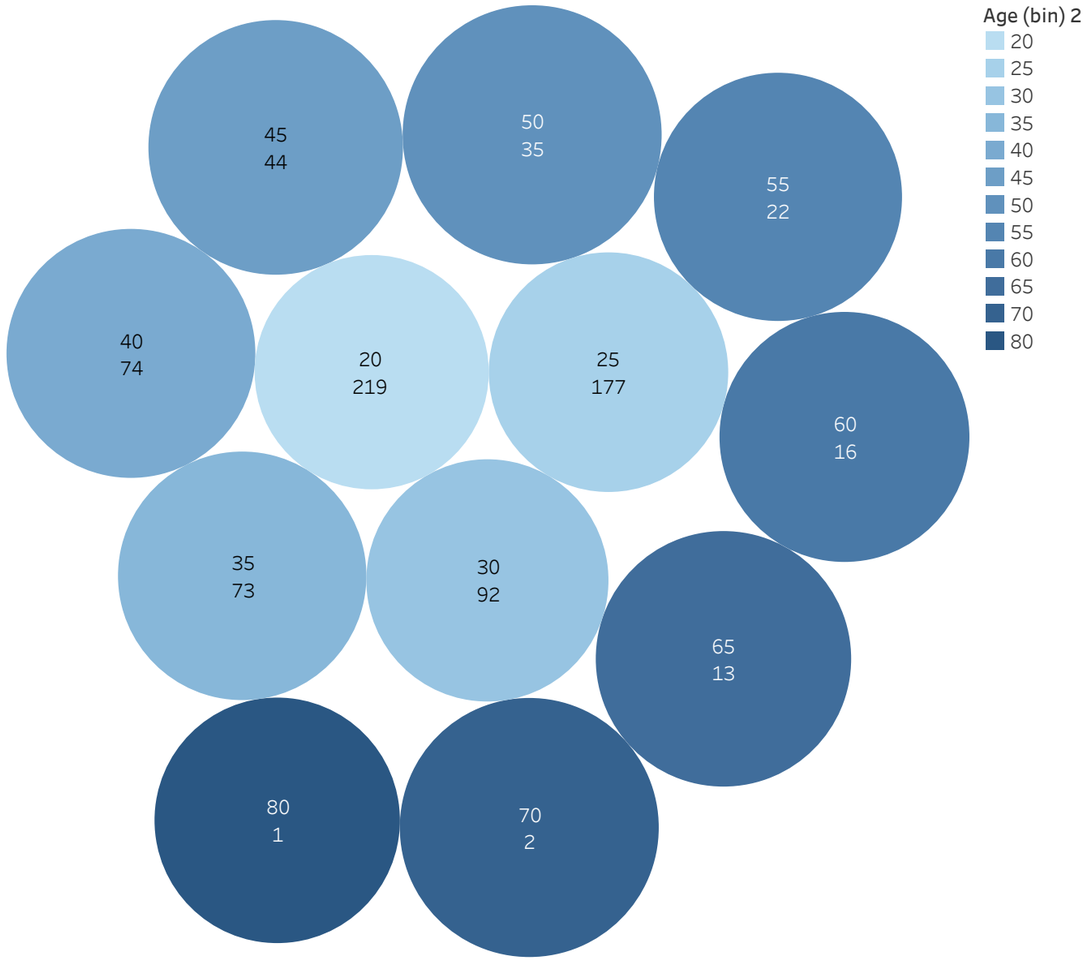


The trend of count of Pregnancies for Pregnancies (bin).



The trend of count of Skin Thickness for Skin Thickness (bin).

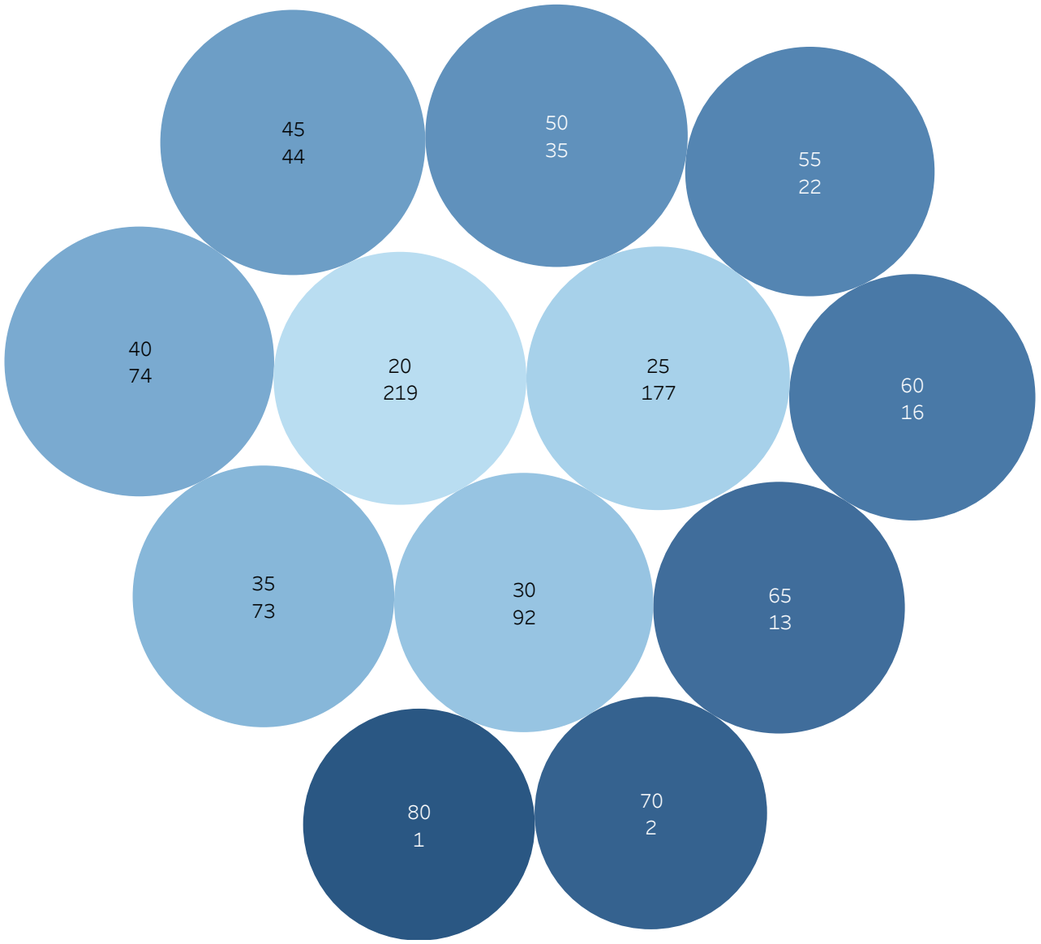
Age vs Blood Pressure



Age (bin) 2
- 20
- 25
- 30
- 35
- 40
- 45
- 50
- 55
- 60
- 65
- 70
- 80

Age (bin) 2 and count of Blood Pressure. Color shows details about Age (bin) 2. Size shows average of Blood Pressure. The marks are labeled by Age (bin) 2 and count of Blood Pressure.

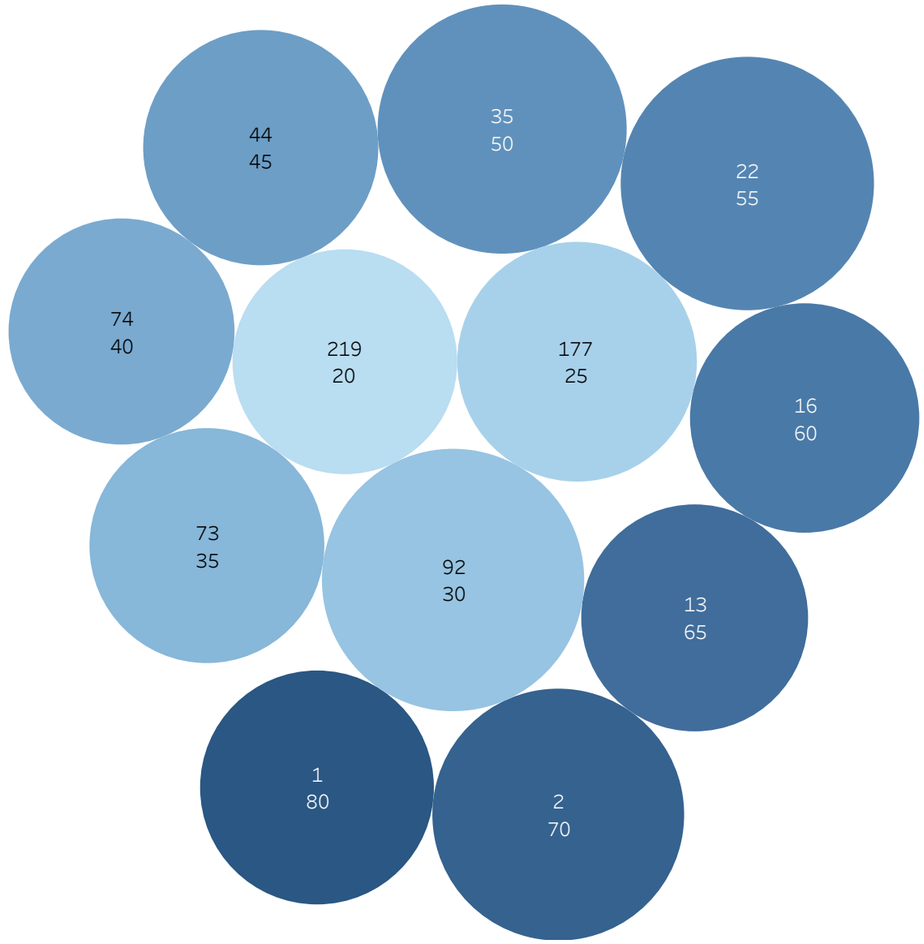
Age vs BMI



Age (bin) 2
- 20
- 25
- 30
- 35
- 40
- 45
- 50
- 55
- 60
- 65
- 70
- 80

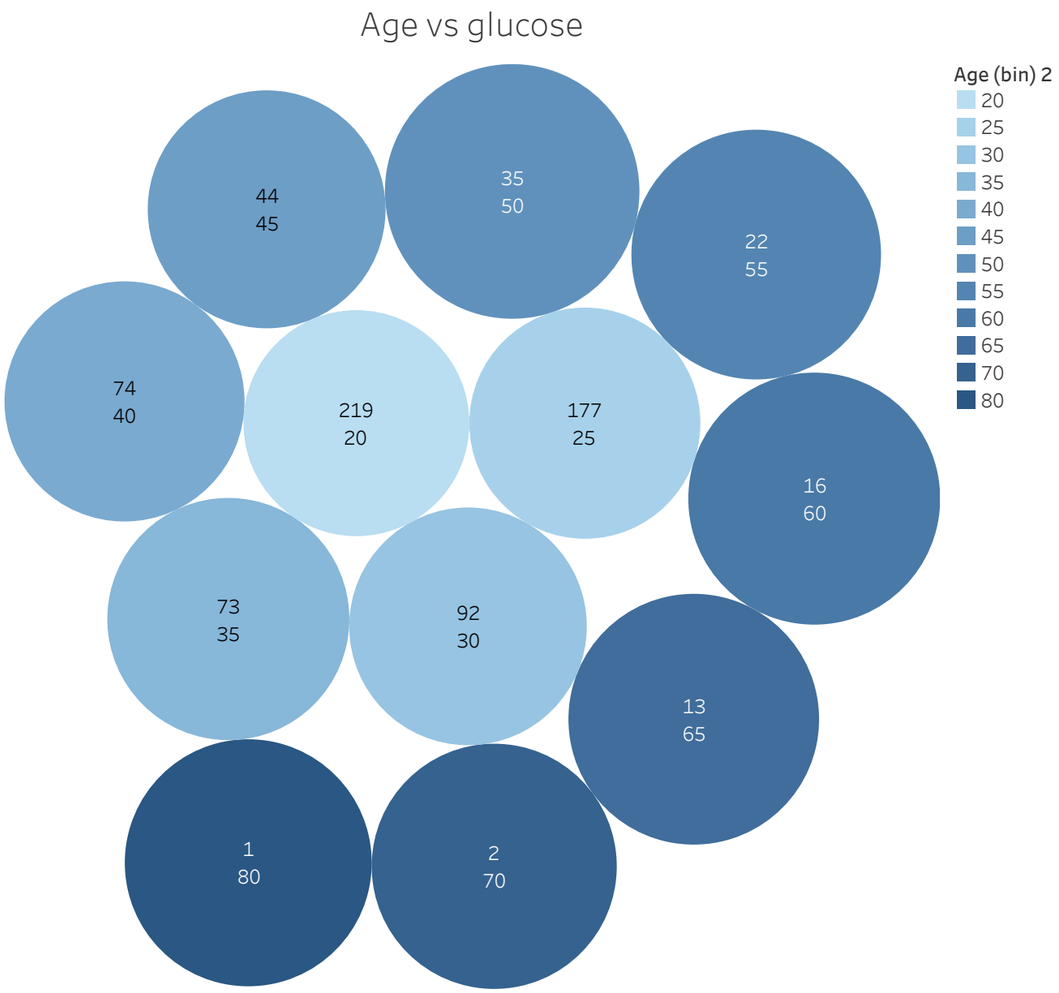
Age (bin) 2 and count of BMI. Color shows details about Age (bin) 2. Size shows average of BMI. The marks are labeled by Age (bin) 2 and count of BMI.

Age vs DBF

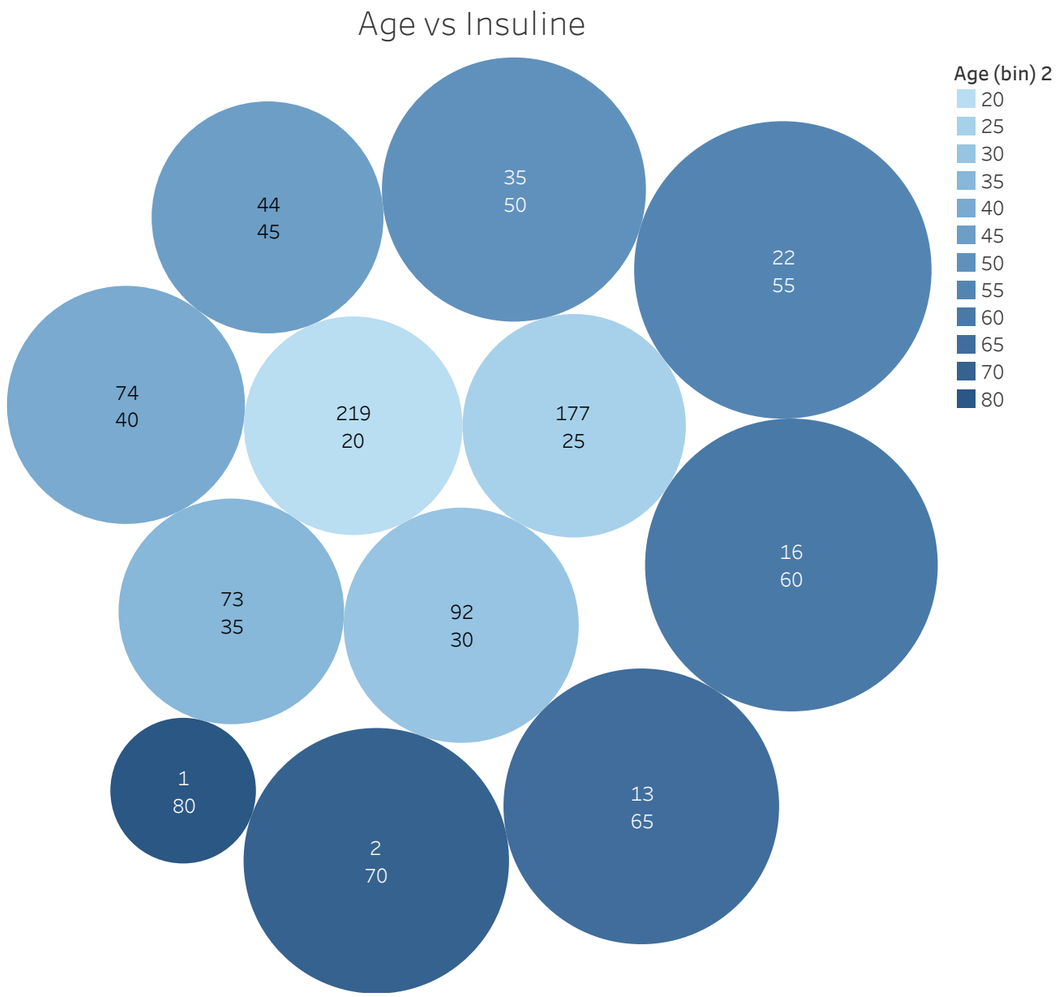


Age (bin) 2
20
25
30
35
40
45
50
55
60
65
70
80

Count of Diabetes Pedigree Function and Age (bin) 2. Color shows details about Age (bin) 2. Size shows average of Diabetes Pedigree Function. The marks are labeled by count of Diabetes Pedigree Function and Age (bin) 2.

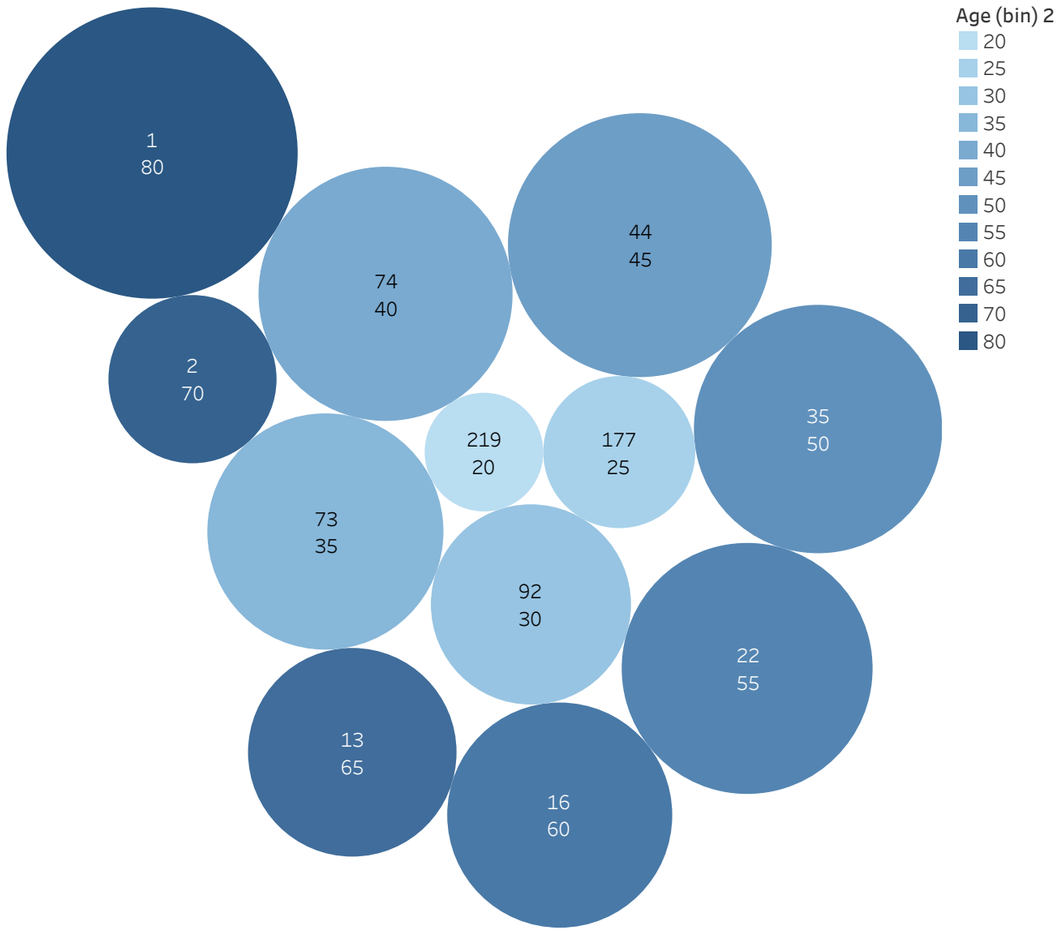


Count of Glucose and Age (bin) 2. Color shows details about Age (bin) 2. Size shows average of Glucose. The marks are labeled by count of Glucose and Age (bin) 2.



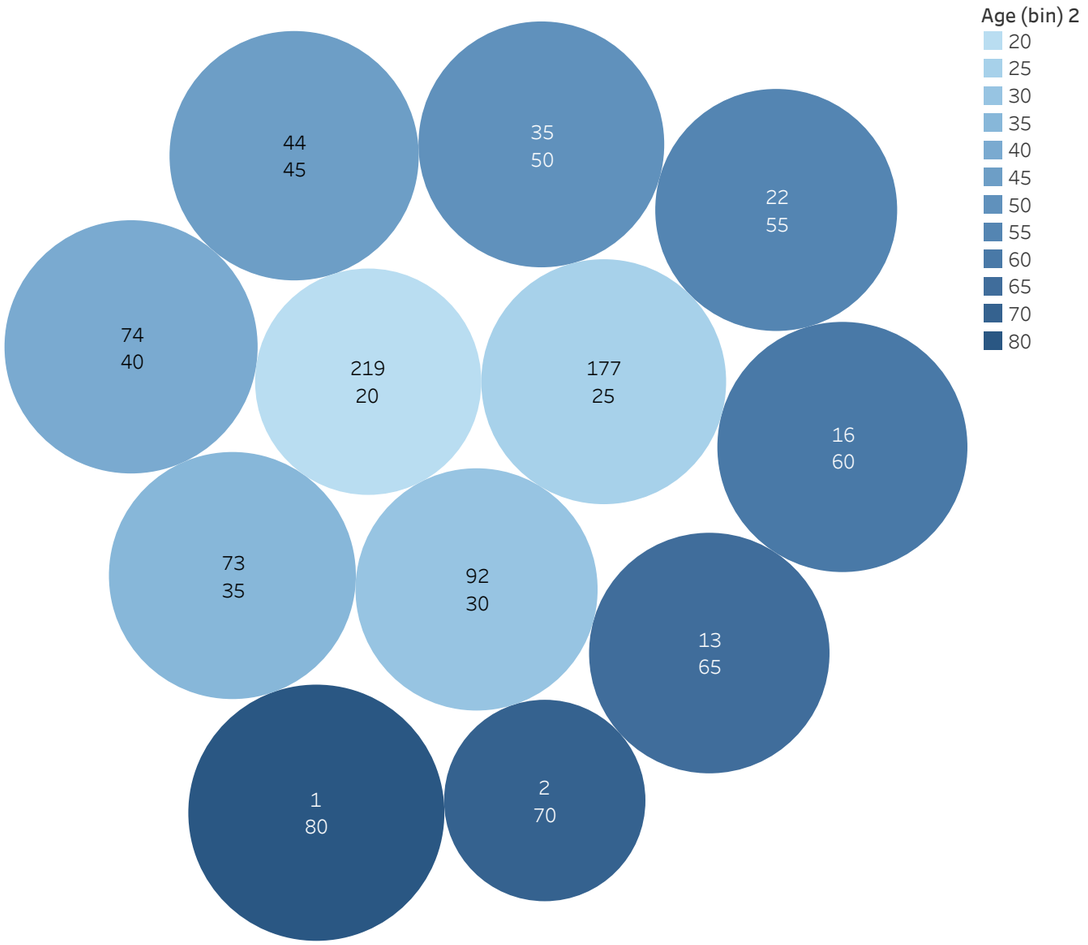
Count of Insulin and Age (bin) 2. Color shows details about Age (bin) 2. Size shows average of Insulin. The marks are labeled by count of Insulin and Age (bin) 2.

Age vs Pregnancies



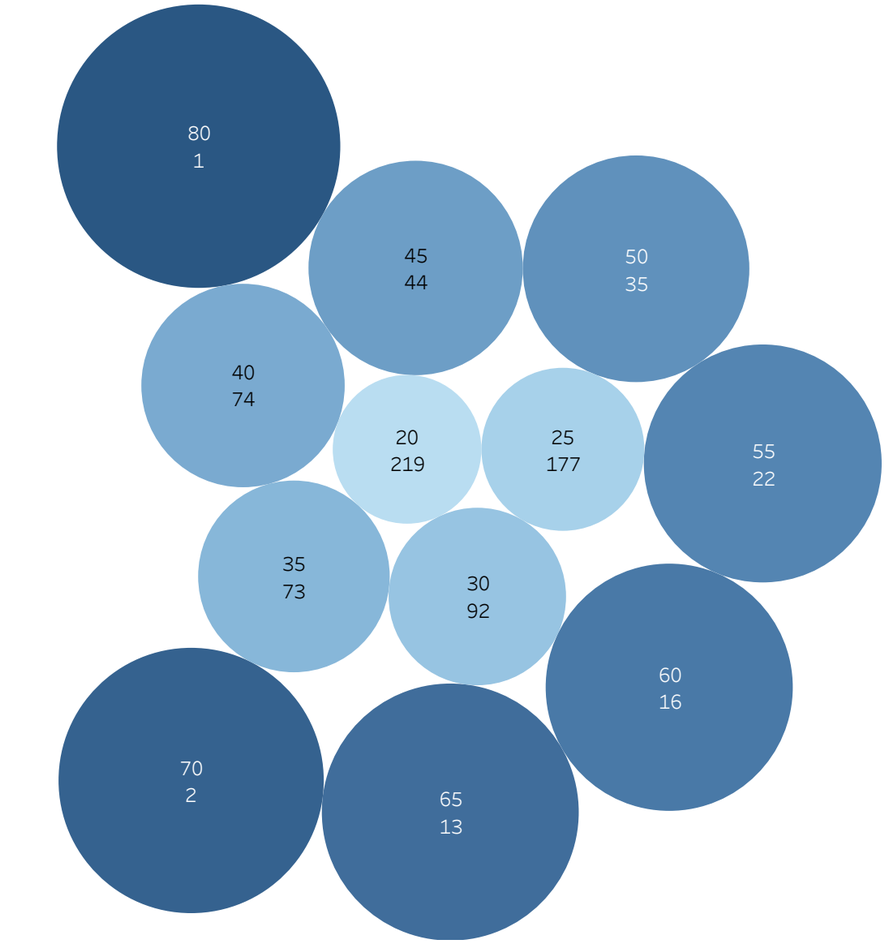
Count of Pregnancies and Age (bin) 2. Color shows details about Age (bin) 2. Size shows average of Pregnancies. The marks are labeled by count of Pregnancies and Age (bin) 2.

Age vs Skin Thickness



Count of Skin Thickness and Age (bin) 2. Color shows details about Age (bin) 2. Size shows average of Skin Thickness. The marks are labeled by count of Skin Thickness and Age (bin) 2.

age vs age

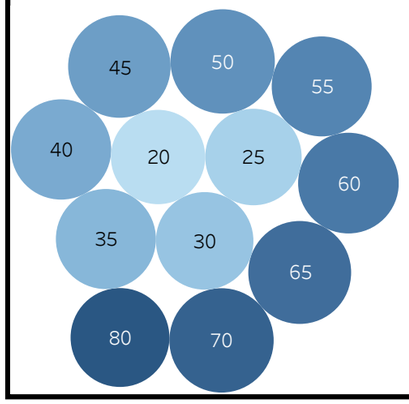


Age (bin) 2
- 20
- 25
- 30
- 35
- 40
- 45
- 50
- 55
- 60
- 65
- 70
- 80

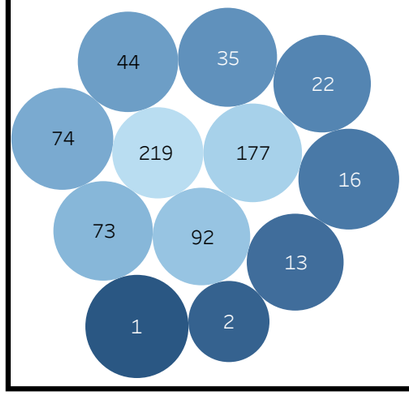
Age (bin) 2 and count of Age. Color shows details about Age (bin) 2. Size shows average of Age. The marks are labeled by Age (bin) 2 and count of Age.

Bubble charts

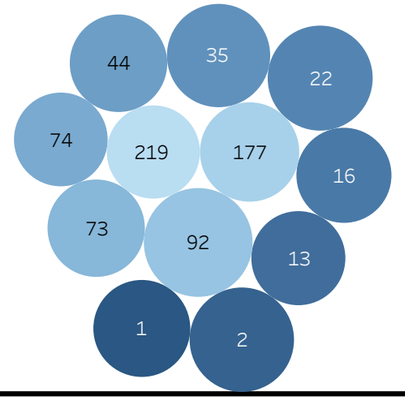
Age vs Blood Pressure



Age vs Skin Thickness

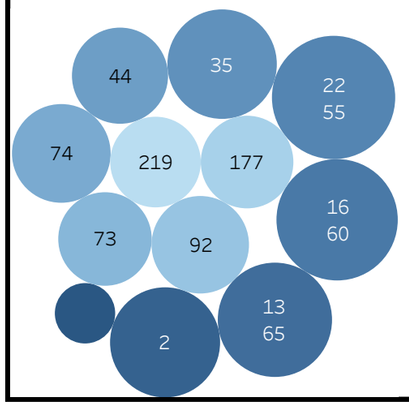


Age vs DBF

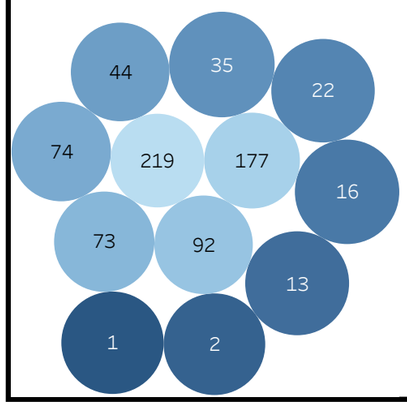


Age (bin) 2
20
25
30
35
40
45
50
55
60
65
70
80

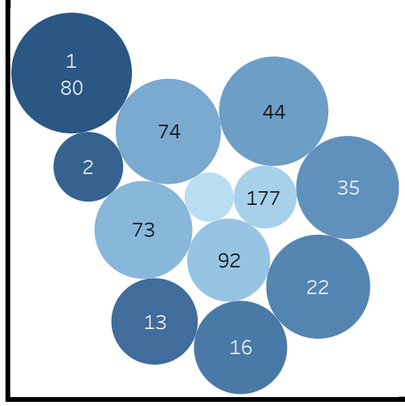
Age vs Insuline



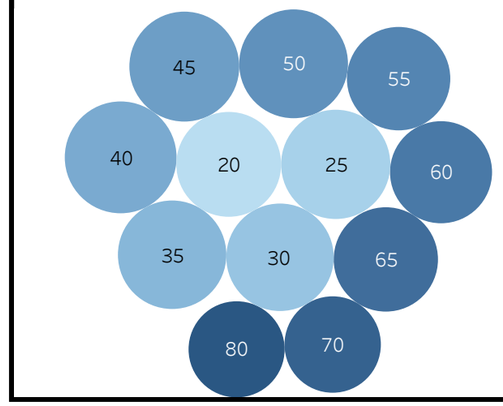
Age vs glucose



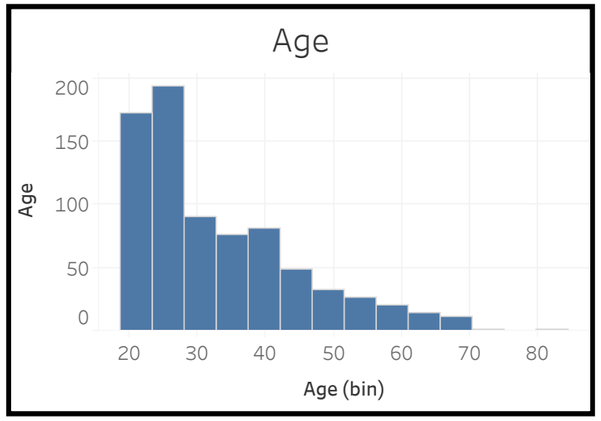
Age vs Pregnancies

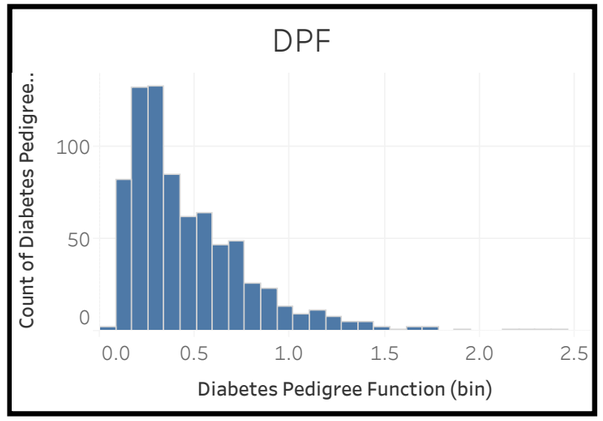


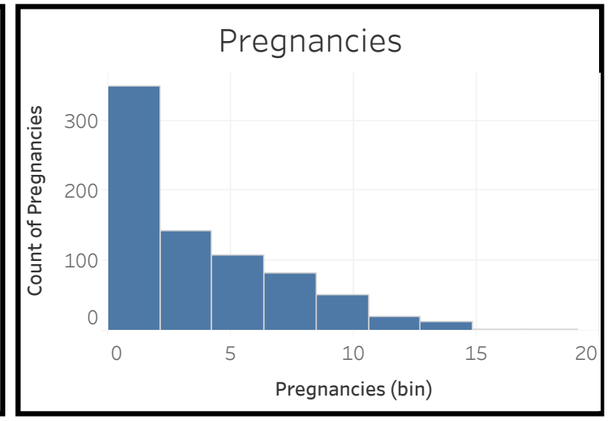
Age vs BMI

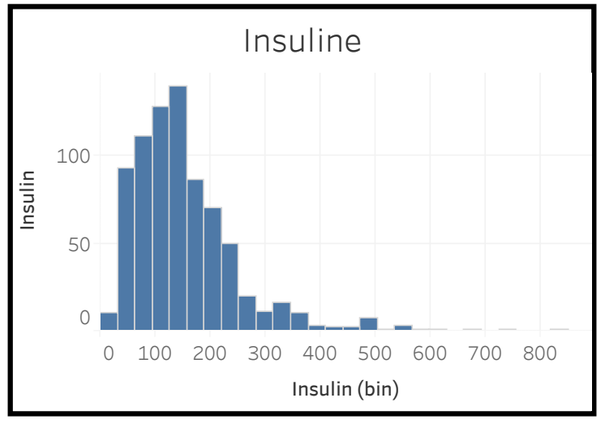


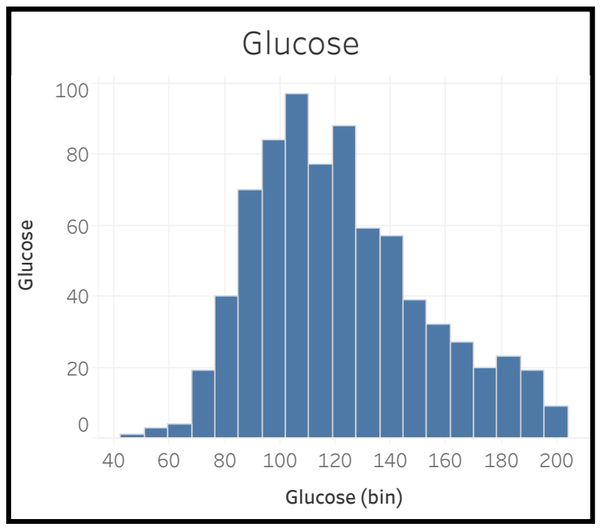
histogram/frequency plots

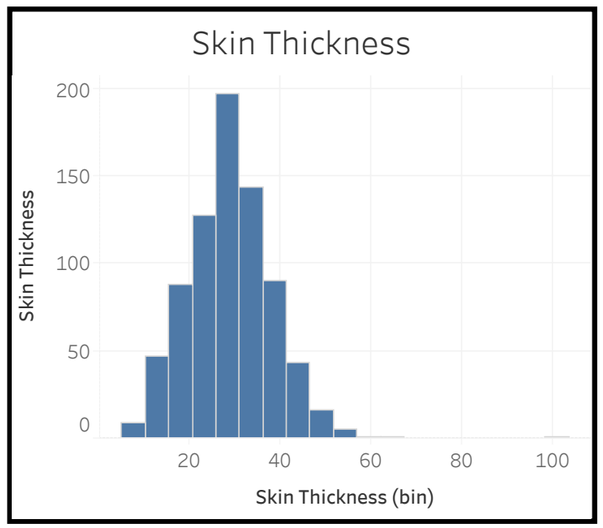


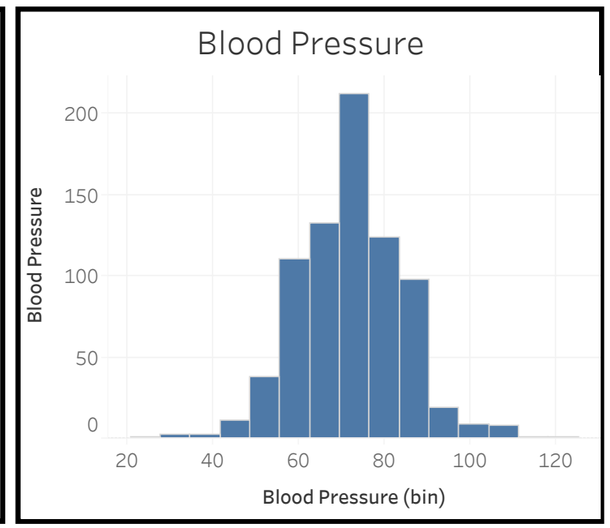


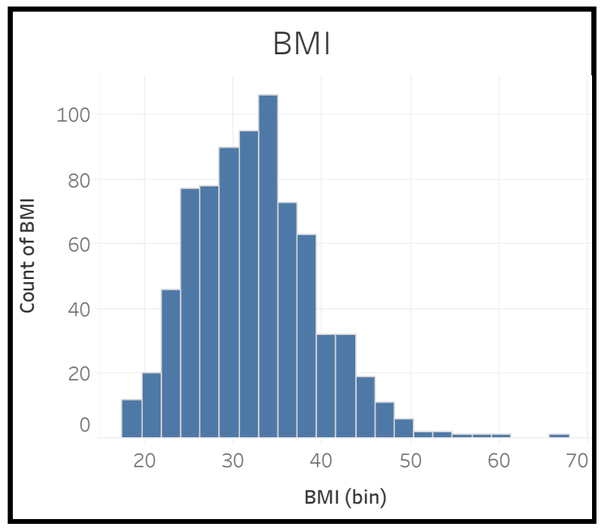






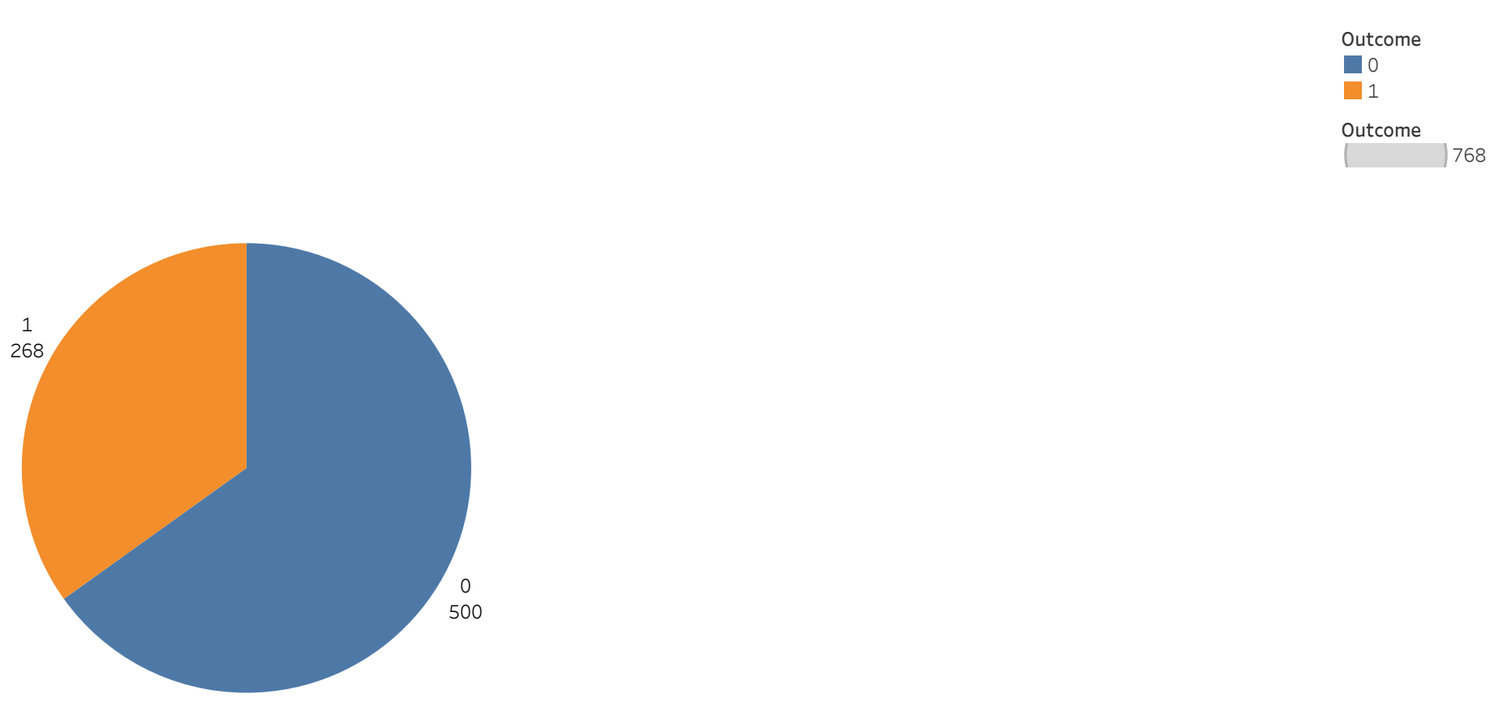






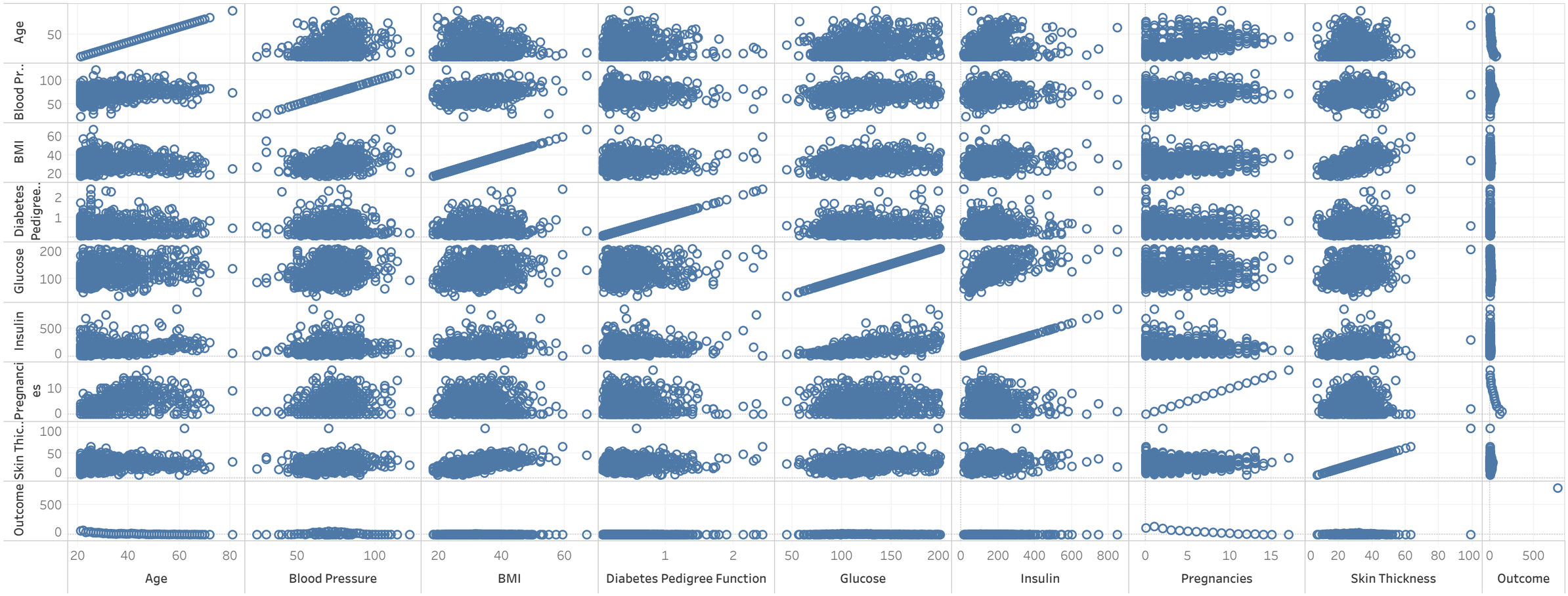
Story-Diabetes and Digestive and Kidney Diseases.

1 2 3 4



Story-Diabetes and Digestive and Kidney Diseases.

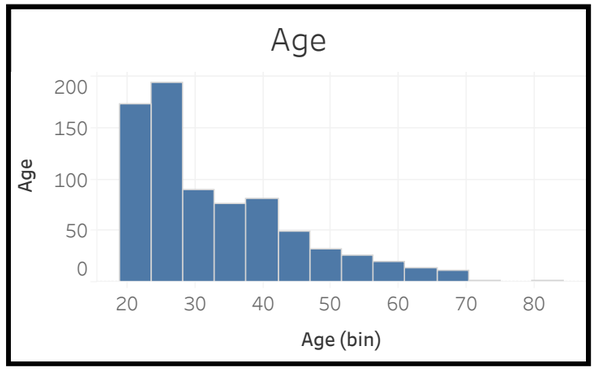
1 2 3 4

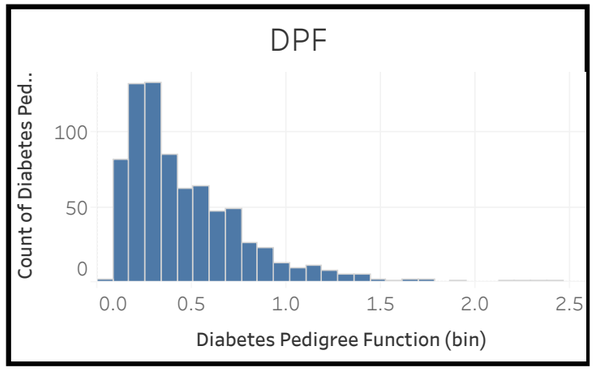


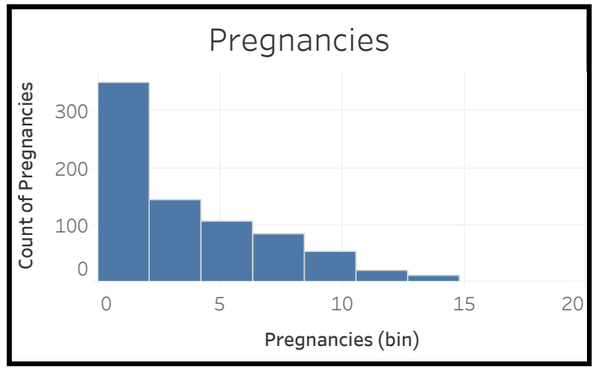
Story-Diabetes and Digestive and Kidney Diseases.

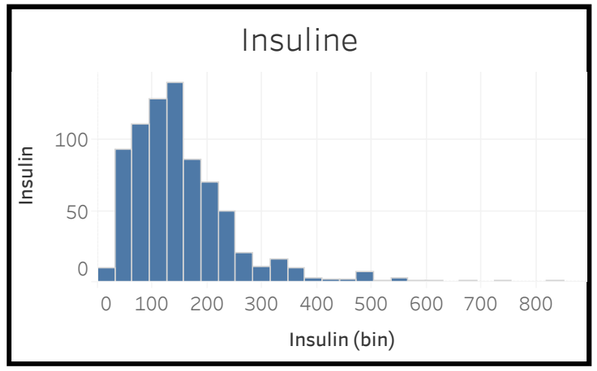
1 2 3 4

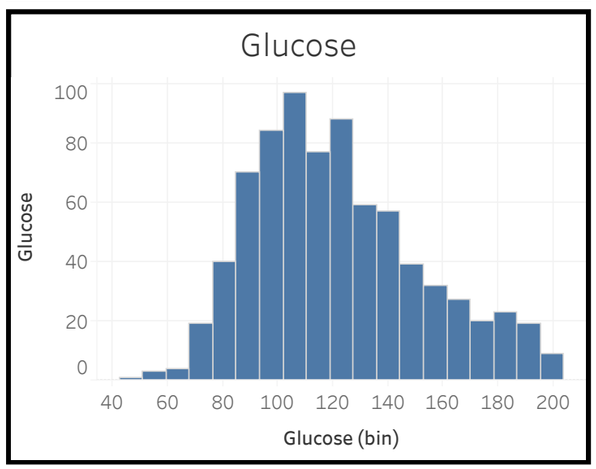
histogram/frequency plots

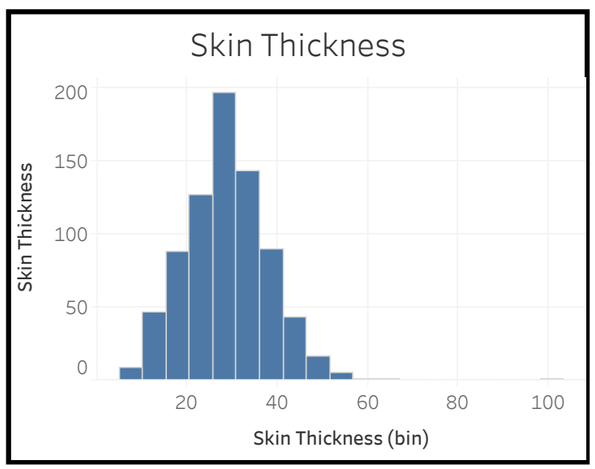


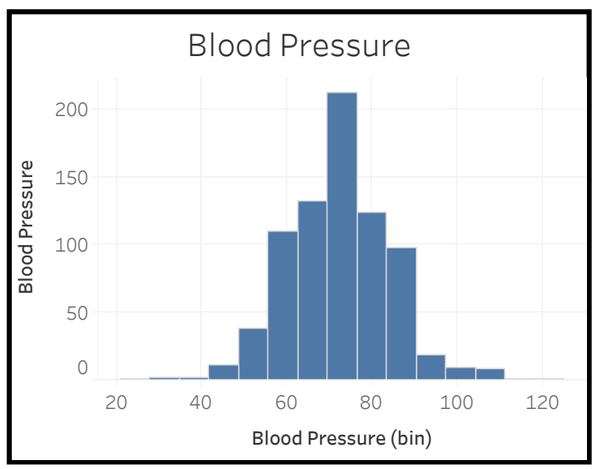


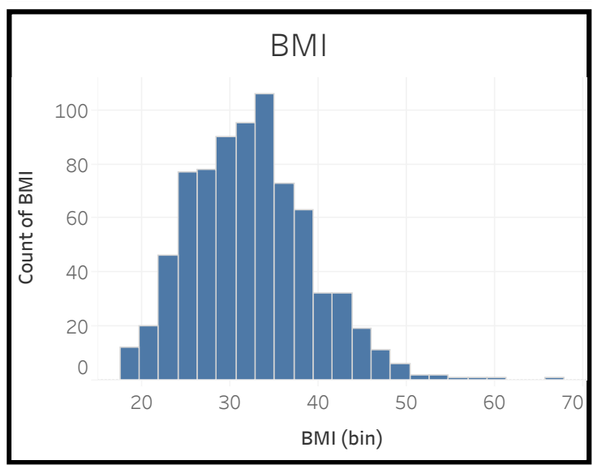










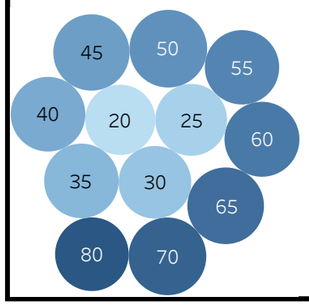


Story-Diabetes and Digestive and Kidney Diseases.

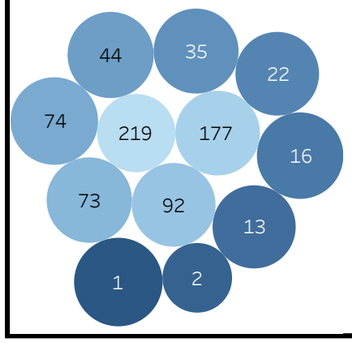
1 2 3 4

Bubble charts

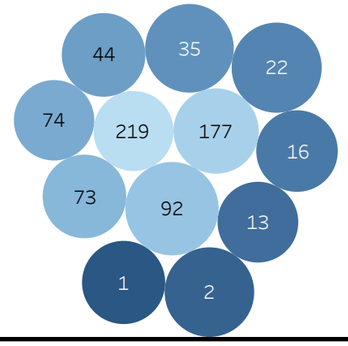
Age vs Blood Pressure



Age vs Skin Thickness

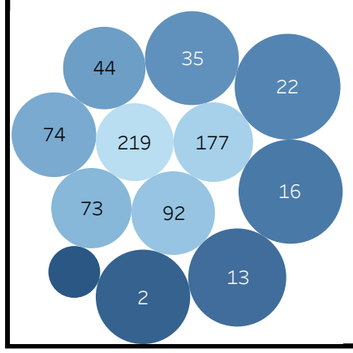


Age vs DBF

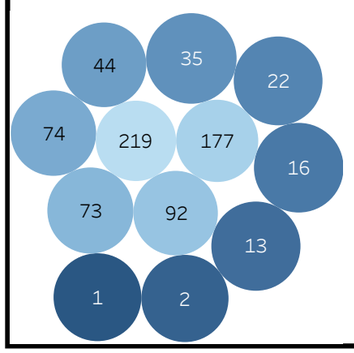


Age (bin) 2
20
25
30
35
40
45
50
55
60
65
70
80

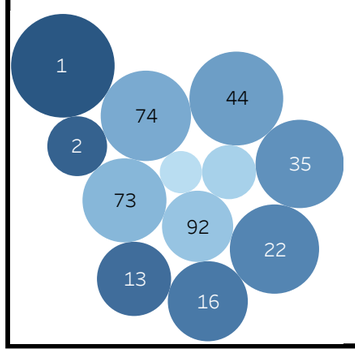
Age vs Insuline



Age vs glucose



Age vs Pregnancies



Age vs BMI