# ▼ Importing Libraries and Data

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df=pd.read_csv('/content/diabetes.csv')
df
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome	
0	6	148	72	35	0	33.6	0.627	50	1	ıl.
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

## EDL (Exploratory Data Analysis)

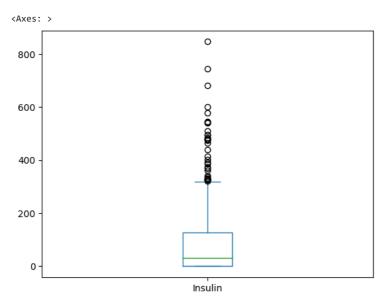
df.describe()

```
df.info()
    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 768 entries, 0 to 767
   Data columns (total 9 columns):
                            Non-Null Count Dtype
    # Column
       -----
                             -----
    0 Pregnancies
                            768 non-null
                                         int64
                            768 non-null
       Glucose
                                         int64
       BloodPressure
                            768 non-null
                                          int64
                            768 non-null
       SkinThickness
                                         int64
       Insulin
                             768 non-null
                                          int64
                             768 non-null
                                          float64
       DiabetesPedigreeFunction 768 non-null
                                          float64
                             768 non-null
                                          int64
       Age
    8 Outcome
                             768 non-null
                                          int64
   dtypes: float64(2), int64(7)
   memory usage: 54.1 KB
df.size
    6912
df.shape
    (768, 9)
df.columns
```

Pregn	ancie	es .	Glucose	Blo	odPre	ssure	Skin	Thick	ness	Ι	nsuli	.n		BMI
t 768.0	00000	0 768	3.000000	)	768.0	00000	7	768.00	0000	768.	00000	00	768.000	000
3.8	84505	2 120	).894531		69.1	05469		20.53	6458	79.	79947	9	31.992	578
3.5	36957	'8 31	.972618	3	19.3	55807		15.95	2218	115.	24400	2	7.884	160
0.0	00000	00 0	0.000000	)	0.0	00000		0.00	0000	0.	00000	0	0.000	000
he Nulll	Value	es												
^ -	00000		, ,,,,,,,		70.0	^^^^		~~ ~~		^^			00 000	^^^
.sum()														
encies se Pressure nickness in cesPedig me	5	unctio	0 0 0 0 0 0 0											
L)		.,												
i lasonii Lasonii	768. 3. 3. 0. ne Nulll  .sum() ncies e ressure ickness n esPedig e int64 df.desc ) col].ur	768.00000 3.84505 3.36957 0.000000 ne NullI Value .sum() ncies e ressure ickness n esPedigreeFu e int64 df.described ) col].unique	768.000000 768 3.845052 120 3.369578 31 0.0000000 0 ne NullI Values .sum() ncies e ressure ickness n esPedigreeFunctio e int64  df.describe(): ) col].unique())	768.000000 768.000000 3.845052 120.894531 3.369578 31.972618 0.000000 0.0000000 ne NullI Values .sum() ncies 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	768.000000 768.000000  3.845052 120.894531  3.369578 31.972618  0.000000 0.0000000  ne NullI Values  .sum()  ncies 0 e 0 ressure 0 ickness 0 n 0 esPedigreeFunction 0 e 0 int64  df.describe(): ) col].unique())	768.000000 768.000000 768.0  3.845052 120.894531 69.1  3.369578 31.972618 19.3  0.000000 0.000000 0.0  ne NullI Values  .sum()  ncies 0 e 0 ressure 0 ickness 0 n 0 esPedigreeFunction 0 e 0 int64  df.describe(): ) col].unique())	768.000000 768.000000 768.000000  3.845052 120.894531 69.105469  3.369578 31.972618 19.355807  0.000000 0.000000 0.000000  ne NullI Values  .sum()  ncies 0 e 0 ressure 0 ickness 0 n 0 esPedigreeFunction 0 e 0 int64  df.describe(): ) col].unique())	768.000000 768.000000 768.000000 7 3.845052 120.894531 69.105469 3.369578 31.972618 19.355807 0.000000 0.000000 0.000000  ne NullI Values  .sum()  ncies 0 e 0 ressure 0 ickness 0 n 0 esPedigreeFunction 0 e 0 int64  df.describe(): ) col].unique())	768.000000 768.000000 768.000000 768.00  3.845052 120.894531 69.105469 20.53  3.369578 31.972618 19.355807 15.95  0.000000 0.000000 0.000000 0.000000  ne NullI Values  .sum()  ncies 0 e 0 ressure 0 ickness 0 n 0 esPedigreeFunction 0 0 e 0 int64  df.describe(): ) col].unique())	768.000000 768.000000 768.000000 768.000000  3.845052 120.894531 69.105469 20.536458  3.369578 31.972618 19.355807 15.952218  0.000000 0.000000 0.000000 0.000000  ne NullI Values  .sum()  ncies 0 e 0 0 ressure 0 0 ickness 0 n 0 0 esPedigreeFunction 0 0 e 0 0 int64  df.describe(): ) col].unique())	768.000000 768.000000 768.000000 768.000000 768.  3.845052 120.894531 69.105469 20.536458 79.  3.369578 31.972618 19.355807 15.952218 115.  0.000000 0.000000 0.000000 0.000000 0.000000	768.000000 768.000000 768.000000 768.000000 768.000000 3.845052 120.894531 69.105469 20.536458 79.79947 3.369578 31.972618 19.355807 15.952218 115.24400 0.000000 0.000000 0.000000 0.000000 0.000000	768.000000 768.000000 768.000000 768.000000  3.845052 120.894531 69.105469 20.536458 79.799479  3.369578 31.972618 19.355807 15.952218 115.244002  0.000000 0.000000 0.000000 0.000000 0.000000	768.000000 768.000000 768.000000 768.000000 768.000000 768.000000 3.845052 120.894531 69.105469 20.536458 79.799479 31.992 3.369578 31.972618 19.355807 15.952218 115.244002 7.884 0.000000 0.000000 0.000000 0.000000 0.000000

```
df.plot.box()
plt.xticks(rotation=45)
      (array([1, 2, 3, 4, 5, 6, 7, 8, 9]),
  [Text(1, 0, 'Pregnancies'),
  Text(2, 0, 'Glucose'),
         Text(3, 0, 'BloodPressure'),
         Text(4, 0, 'SkinThickness'),
         Text(5, 0, 'Insulin'),
         Text(6, 0, 'BMI'),
         Text(7, 0, 'DiabetesPedigreeFunction'),
         Text(8, 0, 'Age'),
Text(9, 0, 'Outcome')])
                                                       0
        800
                                                       0
                                                      0
        600
                                                      400
        200
```

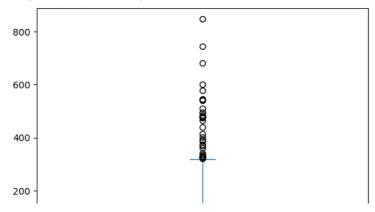
df['Insulin'].plot(kind='box')



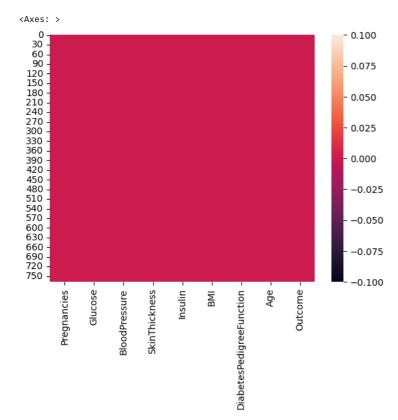
```
a=df['Insulin'].describe()
b=df['Insulin'].plot(kind='box')
print(a)
print(b)
```

count 768.000000
mean 79.799479
std 115.244002
min 0.000000
25% 0.000000
50% 30.500000
75% 127.250000
max 846.000000
Name: Insulin, dtype: float

Name: Insulin, dtype: float64 Axes(0.125,0.11;0.775x0.77)

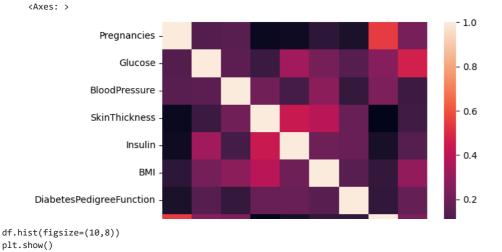


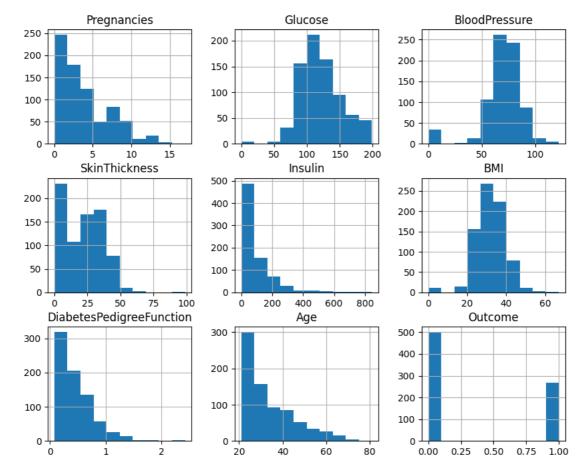
sns.heatmap(df.isnull())



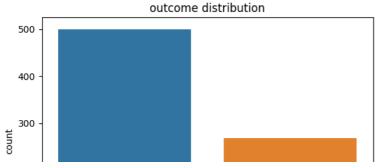
## Correlation Matrix

df.corr()
sns.heatmap(df.corr())





Text(0.5, 1.0, 'outcome distribution')



median=df['BloodPressure'].median()
print('median:',median)
mean=df['BloodPressure'].mean()
print('mean:',mean)

median: 72.0 mean: 69.10546875

sns.distplot(df['BloodPressure'],bins=20)
plt.show(median)

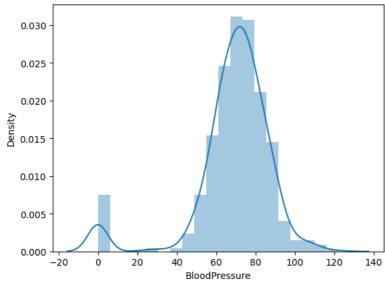
<ipython-input-19-2148420b5fe4>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

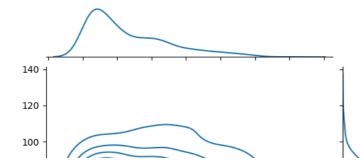
For a guide to updating your code to use the new functions, please see <a href="https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751">https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751</a>





sns.jointplot(data=df,x='Age',y='BloodPressure',kind='kde')

<seaborn.axisgrid.JointGrid at 0x7e0ec4c1c2b0>



pd.plotting.scatter\_matrix(df,figsize=(20,18))

```
<Axes: xlabel='Insulin', ylabel='DiabetesPedigreeFunction'>,
<Axes: xlabel='BMI', ylabel='DiabetesPedigreeFunction'>,
          <Axes: xlabel='DiabetesPedigreeFunction',</pre>
ylabel='DiabetesPedigreeFunction'>,
          <Axes: xlabel='Age', ylabel='DiabetesPedigreeFunction'>,
          <Axes: xlabel='Outcome', ylabel='DiabetesPedigreeFunction'>],
         [<Axes: xlabel='Pregnancies', ylabel='Age'>,
          <Axes: xlabel='Glucose', ylabel='Age'>,
          <Axes: xlabel='BloodPressure', ylabel='Age'>,
<Axes: xlabel='SkinThickness', ylabel='Age'>,
          <Axes: xlabel='Insulin', ylabel='Age'>,
          <Axes: xlabel='BMI', ylabel='Age'>,
<Axes: xlabel='DiabetesPedigreeFunction', ylabel='Age'>,
          <Axes: xlabel='Age', ylabel='Age'>,
<Axes: xlabel='Outcome', ylabel='Age'>],
         [<Axes: xlabel='Pregnancies', ylabel='Outcome'>,
          <Axes: xlabel='Glucose', ylabel='Outcome'>,
          <Axes: xlabel='BloodPressure', ylabel='Outcome'>,
<Axes: xlabel='SkinThickness', ylabel='Outcome'>,
          <Axes: xlabel='Insulin', ylabel='Outcome'>,
          <Axes: xlabel='BMI', ylabel='Outcome'>,
          <Axes: xlabel='DiabetesPedigreeFunction', ylabel='Outcome'>,
          <Axes: xlabel='Age', ylabel='Outcome'>,
<Axes: xlabel='Outcome', ylabel='Outcome'>]], dtype=object)
```

```
pd.plotting.parallel_coordinates(df,'Outcome',color='br')
plt.xticks(rotation=45)
```

```
(array([0, 1, 2, 3, 4, 5, 6, 7]),
[Text(0, 0, 'Pregnancies'),
  Text(1, 0, 'Glucose'),
       Text(2, 0, 'BloodPressure'),
       Text(3, 0, 'SkinThickness'),
       Text(4, 0, 'Insulin'),
       Text(5, 0, 'BMI'),
       Text(6, 0, 'DiabetesPedigreeFunction'),
       Text(7, 0, 'Age')])
                                                                                1
       800
                                                                                0
       600
       400
Training the model with the help of train test split.
importing new libraries.
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
                          %0-
                                                                       0)
Train-test-split
                                                               13
x=df.drop('Outcome',axis=1)
y=df['Outcome']
x\_test, x\_train, y\_test, y\_train=train\_test\_split(x, y, test\_size=0.25)
x_{test,x_{train,y_{test,y_{train}}}
                                                                                BMI \
            Pregnancies Glucose BloodPressure SkinThickness Insulin
      626
                      0
                              125
                                                68
                                                                 0
                                                                           0
                                                                              24.7
      361
                                                70
                                                                 0
                                                                           0 29.8
                      5
                              158
      231
                                                80
                      6
                              134
                                                                37
                                                                         370 46.2
      379
                      a
                               93
                                               100
                                                                39
                                                                          72 43.4
      210
                      2
                              81
                                                60
                                                                22
                                                                           0 27.7
      25
                     10
                              125
                                                70
                                                                26
                                                                         115 31.1
      667
                      10
                              111
                                                70
                                                                27
                                                                           0
                                                                              27.5
      333
                     12
                              106
                                                80
                                                                 0
                                                                           0 23.6
      278
                                                                 0
                                                                           0 24.9
                              114
                              113
                                                76
                                                                           0 33.3
      124
            {\tt DiabetesPedigreeFunction}
      626
                                 0.206
                                          21
      361
                                 0.207
                                         63
      231
                                 0.238
                                         46
      379
                                 1.021
                                         35
      210
                                 0.290
                                         25
      25
                                 0.205
                                         41
      667
                                 0.141
                                         40
                                 0.137
                                         44
      333
                                         57
      278
                                 0.744
      124
                                 0.278
                                         23
      [576 rows x 8 columns],
            {\tt Pregnancies} \quad {\tt Glucose} \quad {\tt BloodPressure} \quad {\tt SkinThickness}
                                                                    Insulin
                                                                               BMI
      364
                      4
                              147
                                                74
                                                                25
                                                                         293 34.9
      459
                      9
                                                74
                                                                33
                                                                          60 25.9
      336
                      0
                              117
                                                 0
                                                                 0
                                                                           0
                                                                              33.8
      635
                     13
                              104
                                                72
                                                                           0 31.2
      401
                              137
                                                61
                                                                0
                                                                          0 24.2
                      6
      258
                              193
                                                50
                                                                         375 25.9
                      1
                                                                16
      718
                              108
                                                60
                                                                         178 35.5
                      1
                                                                46
      269
                      2
                              146
                                                0
                                                                 0
                                                                           0
                                                                              27.5
      692
                      2
                              121
                                                70
                                                                32
                                                                          95 39.1
      521
                              124
                                                80
                                                                         130 33.2
            {\tt DiabetesPedigreeFunction}
                                        Age
      364
                                 0.385
                                         30
      459
                                 0.460
                                          81
      336
                                 0.932
                                         44
      635
                                 0.465
```

```
11/27/23, 7:52 AM
```

```
401
                          0.151
                                   55
258
                          0.655
                                   24
718
                          0.415
                                   24
269
                          0.240
                                   28
692
                          0.886
                                   23
521
                          0.305
                                   26
[192 rows x 8 columns],
626
       0
361
       0
231
       1
379
       0
```

#### Training The Model

#### Making prediction

prediction=model.predict(x\_test)

```
prediction
    array([0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0,
           0,\ 0,\ 1,\ 1,\ 0,\ 0,\ 0,\ 0,\ 0,\ 1,\ 0,\ 1,\ 0,\ 0,\ 0,\ 1,\ 1,\ 0,\ 1,\ 0,
           1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
           0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 1,\ 0,\ 1,\ 0,\ 1,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 1,
           0,\ 0,\ 1,\ 1,\ 0,\ 1,\ 0,\ 0,\ 0,\ 1,\ 1,\ 1,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,
           1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0,
           0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1,
           0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0,
           0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1,
           1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0,
           0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
           0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0,
           1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0,
                                                                  0, 0,
              0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1,
              0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
           1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1,
              0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
           0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1,
           0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1,
           0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0,
              0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1,
           0,\ 0,\ 1,\ 0,\ 1,\ 0,\ 1,\ 1,\ 0,\ 0,\ 0,\ 0,\ 1,\ 0,\ 0,\ 1,\ 1,\ 0,\ 0,\ 0,\ 0,
           0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
           0,
             1, 0, 0, 1,
                          0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0,
           0, 0, 0, 0])
```

After training the model, predictions are made using the test data, which comprises 25% of the total dataset.

```
accuracy=accuracy_score(prediction,y_test)
percentage=f'{accuracy:.0%}'
print('accuracy of train-test-model is', accuracy)
print('percentage of train-test-model is', percentage)

accuracy of train-test-model is 0.758680555555556
percentage of train-test-model is 76%
```

### Hence Our Train Test Model is Correct upto 76%