Assignment: Riju Sathyan

Real-world scenario The project uses the following data sets to demonstrate the various learnings throughout the course.

Source Description	Source/File Name	Source Link
Premier League Standings 22 Seasons	EPL_standings_2000-2022.csv	https://www.kaggle.com/datasets/quadeer15sh/premier-league-standings-11-seasons-20102021
Champion League History - UK Teams	Wiki page table	https://en.wikipedia.org/wiki/English_football_clubs_in_internatio
Diabetes Data	diabetes.csv	https://www.kaggle.com/code/mathchi/diagnostic-a-patient-has-diabetes/data

Importing Data: Web Scraping & Analysing Data

In [1]:

```
#import required modules
import requests
import pandas as pd
import numpy as np
import re
import matplotlib.pyplot as plt
import seaborn as sns

# This Wiki sourced dataset is being used to validate the information in the other d
url = 'https://en.wikipedia.org/wiki/English_football_clubs_in_international_competi
page = requests.get(url)
df_wiki = pd.read_html(url)
df_wiki[3] #Check the correct table from Wiki Page is being picked up
```

Out[1]:

	Season	Club	Progress	Score	Opponents	Venue(s)
0	1955–56	None entered	None entered	None entered	None entered	None entered
1	1956–57	Manchester United	Semi-finals	3–5	Real Madrid	1–3 at Santiago Bernabéu2–2 at Old Trafford
2	1957–58	Manchester United	Semi-finals	2–5	Milan	2–1 at Old Trafford0–4 at San Siro
3	1958–59	Manchester United	First round	NaN	Young Boys	Walkover – United withdrawn by the Football Le...
4	1958–59	Wolverhampton Wanderers	First round	3–4	Schalke 04	2–2 at Molineux1–2 at Glückauf-Kampfbahn
...	...	...	...	...	...	...
139	2020–21	Chelsea	Winners	1–0	Manchester City	Estádio do Dragão
140	2021–22	Manchester United	Round of 16	1–2	Atlético Madrid	1–1 at Wanda Metropolitano0–1 at Old Trafford
141	2021–22	Chelsea	Quarter-finals	4–5 (a.e.t.)	Real Madrid	1–3 at Stamford Bridge3–2 at Santiago Bernabéu

	Season	Club	Progress	Score	Opponents	Venue(s)
142	2021–22	Manchester City	Semi-finals	5–6 (a.e.t.)	Real Madrid	4–3 at Etihad Stadium1–3 at Santiago Bernabéu
143	2021–22	Liverpool	Final	0–1	Real Madrid	Stade de France

144 rows × 6 columns

In [2]:
```
# Only Season & Club columns required
df_wiki[3][['Season','Club']].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144 entries, 0 to 143
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Season  144 non-null    object
 1   Club    144 non-null    object
dtypes: object(2)
memory usage: 2.4+ KB
```

In [3]:
```
df_wiki[3][['Season','Club']].describe()
```

Out[3]:

	Season	Club
count	144	144
unique	67	19
top	2005–06	Manchester United
freq	5	31

In [4]:
```
#Create new dataframe to check for referential integrity of Season column
df_SeasonsCL = pd.DataFrame(df_wiki[3]['Season'],  columns=['Season'])
df_SeasonsCL['Season'] = df_SeasonsCL['Season'].str.replace('–','-')

#Use Regex to check for inconsistent text formats
df_SeasonsCL['DQ_Season'] = df_SeasonsCL['Season'].str.contains(r'\d\d\d\d\-\d\d$',

#review exceptions
print(df_SeasonsCL.loc[df_SeasonsCL['DQ_Season'] == False])
```

```
        Season  DQ_Season
42  1990-91[a]      False
53   1999-2000      False
54   1999-2000      False
55   1999-2000      False
```

In [5]:
```
#Update incorrectly formatted values
df_SeasonsCL.loc[42,['Season']] = '1990-91'
df_SeasonsCL.loc[53,['Season']] = '1999-00'
df_SeasonsCL.loc[54,['Season']] = '1999-00'
df_SeasonsCL.loc[55,['Season']] = '1999-00'
```

In [6]:
```
#Create a dataframe with CL season unique values, sort columns and then create a PL
# ie this seasons CL entrants qualified from last seasons Premier League final stand
```

```
df_seasons =  pd.DataFrame(df_SeasonsCL['Season'].unique(), columns=['CL Season'])
df_seasons.rename({'CL Season': 'Season CL'}, axis=1, inplace=True)
df_seasons.sort_values(by=['Season CL'])
df_seasons['Season PL']= df_seasons.shift(1) #shift rows, so create one season quali

#Create a CL Season to Premier League (PL) qualification mapping dictionary
sm_d={}

# Iterate over column names & create dictionary, where key = CL season and item = PL
for i,j in df_seasons.iterrows():
   sm_d[df_seasons['Season CL'][i]] = df_seasons['Season PL'][i]
```

In [7]:

```
# Create new data frame with Season & Club
zipped = list(zip(df_SeasonsCL['Season'], df_wiki[3]['Club']))
df_English_teams_qualified =  pd.DataFrame(zipped, columns=['Season','Club'])
df_English_teams_qualified.rename({'Season': 'Season CL'}, axis=1, inplace=True)

#create an empty list
df_English_teams_qualified['Season PLq'] = ''

# Iterate over Champions League Season and add appropriate Premier League Qualificat
for i,j in  df_English_teams_qualified.iterrows():
    df_English_teams_qualified['Season PLq'][i] = sm_d[df_English_teams_qualified['S

df_English_teams_qualified.drop('Season CL', axis=1, inplace=True)
df_English_teams_qualified.tail(99)
```

Out[7]:

	Club	Season PLq
45	Manchester United	1992-93
46	Manchester United	1993-94
47	Blackburn Rovers	1994-95
48	Manchester United	1995-96
49	Newcastle United	1996-97
...	...	...
139	Chelsea	2019-20
140	Manchester United	2020-21
141	Chelsea	2020-21
142	Manchester City	2020-21
143	Liverpool	2020-21

99 rows × 2 columns

Importing Data: Import CSV & Analysing Data

In [8]:

```
#Import League data from csv
df_EPLs = pd.read_csv("datasets/EPL_standings_2000-2022.csv")
df_EPLs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 440 entries, 0 to 439
Data columns (total 12 columns):
 #   Column                          Non-Null Count  Dtype
```

```
---  ------                       --------------  -----
 0   Season                       440 non-null    object
 1   Pos                          440 non-null    int64
 2   Team                         440 non-null    object
 3   Pld                          440 non-null    int64
 4   W                            440 non-null    int64
 5   D                            440 non-null    int64
 6   L                            440 non-null    int64
 7   GF                           440 non-null    int64
 8   GA                           440 non-null    int64
 9   GD                           440 non-null    int64
 10  Pts                          440 non-null    int64
 11  Qualification or relegation  440 non-null    object
dtypes: int64(9), object(3)
memory usage: 41.4+ KB
```

In [9]:

```
#remove records where Season is 2021-22
df_EPLs = df_EPLs[~df_EPLs['Season'].isin(['2021-22'])]
```

In [10]:

```
df_EPLs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 420 entries, 0 to 419
Data columns (total 12 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Season                       420 non-null    object
 1   Pos                          420 non-null    int64
 2   Team                         420 non-null    object
 3   Pld                          420 non-null    int64
 4   W                            420 non-null    int64
 5   D                            420 non-null    int64
 6   L                            420 non-null    int64
 7   GF                           420 non-null    int64
 8   GA                           420 non-null    int64
 9   GD                           420 non-null    int64
 10  Pts                          420 non-null    int64
 11  Qualification or relegation  420 non-null    object
dtypes: int64(9), object(3)
memory usage: 42.7+ KB
```

In [11]:

```
df_EPLs.describe()
```

Out[11]:

	Pos	Pld	W	D	L	GF	GA	GD
count	420.000000	420.0	420.000000	420.000000	420.000000	420.000000	420.000000	420.000000
mean	10.500000	38.0	14.245238	9.509524	14.245238	50.735714	50.735714	0.000000
std	5.773158	0.0	5.956834	2.821230	5.509753	15.598457	12.723202	25.647696
min	1.000000	38.0	1.000000	2.000000	0.000000	20.000000	15.000000	-69.000000
25%	5.750000	38.0	10.000000	8.000000	10.000000	40.000000	42.000000	-18.250000
50%	10.500000	38.0	13.000000	9.000000	15.000000	47.000000	51.000000	-6.500000
75%	15.250000	38.0	18.000000	11.000000	18.000000	59.250000	59.000000	16.500000
max	20.000000	38.0	32.000000	17.000000	29.000000	106.000000	89.000000	79.000000

In [12]:
```
#Convert text field to Boolean for Champion League qualification usgin regex
df_EPLs['CLQ_chk'] = df_EPLs['Qualification or relegation'].str.contains(r'(?=.*[Qq]
df_EPLs
```

Out[12]:

	Season	Pos	Team	Pld	W	D	L	GF	GA	GD	Pts	Qualification or relegation	CLQ_chk
0	2000-01	1	Manchester United	38	24	8	6	79	31	48	80	Qualification for the Champions League first g...	True
1	2000-01	2	Arsenal	38	20	10	8	63	38	25	70	Qualification for the Champions League first g...	True
2	2000-01	3	Liverpool	38	20	9	9	71	39	32	69	Qualification for the Champions League third q...	True
3	2000-01	4	Leeds United	38	20	8	10	64	43	21	68	Qualification for the UEFA Cup first round[a]	False
4	2000-01	5	Ipswich Town	38	20	6	12	57	42	15	66	Qualification for the UEFA Cup first round[a]	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...
415	2020-21	16	Brighton & Hove Albion	38	9	14	15	40	46	-6	41	Not Applicable	False
416	2020-21	17	Burnley	38	10	9	19	33	55	-22	39	Not Applicable	False
417	2020-21	18	Fulham	38	5	13	20	27	53	-26	28	Relegation to the EFL Championship	False
418	2020-21	19	West Bromwich Albion	38	5	11	22	35	76	-41	26	Relegation to the EFL Championship	False
419	2020-21	20	Sheffield United	38	7	2	29	20	63	-43	23	Relegation to the EFL Championship	False

420 rows × 13 columns

In [13]:
```
df_EPLs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 420 entries, 0 to 419
Data columns (total 13 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Season                       420 non-null    object
 1   Pos                          420 non-null    int64
 2   Team                         420 non-null    object
 3   Pld                          420 non-null    int64
 4   W                            420 non-null    int64
 5   D                            420 non-null    int64
 6   L                            420 non-null    int64
 7   GF                           420 non-null    int64
 8   GA                           420 non-null    int64
```

```
 9   GD                          420 non-null    int64
 10  Pts                         420 non-null    int64
 11  Qualification or relegation 420 non-null    object
 12  CLQ_chk                     420 non-null    bool
dtypes: bool(1), int64(9), object(3)
memory usage: 43.1+ KB
```

In [14]:

```
# create dataframe of unique team names for both datasets
df_ETQ_Teams_Unique = pd.DataFrame(df_English_teams_qualified['Club'].unique(), colu
df_EPLs_Teams_Unique = pd.DataFrame(df_EPLs['Team'].unique(), columns=['Original_EPL
df_ETQ_Teams_Unique
```

Out[14]:

	Original_ETQ_Name
0	None entered
1	Manchester United
2	Wolverhampton Wanderers
3	Burnley
4	Tottenham Hotspur
5	Ipswich Town
6	Everton
7	Liverpool
8	Manchester City
9	Leeds United
10	Arsenal
11	Derby County
12	Nottingham Forest
13	Aston Villa
14	Banned
15	Blackburn Rovers
16	Newcastle United
17	Chelsea
18	Leicester City

In [15]:

```
# merge the two unique datasets to create new columns to validate is the names are c
df_Team_Names_Map = pd.merge(df_EPLs_Teams_Unique, df_ETQ_Teams_Unique, left_on=['Or
df_Team_Names_Map['Match_chk'] = np.where((df_Team_Names_Map['Original_EPLs_Name'] =
df_Team_Names_Map
```

Out[15]:

	Original_EPLs_Name	Original_ETQ_Name	Match_chk
0	NaN	None entered	False
1	Manchester United	Manchester United	True
2	Wolverhampton Wanderers	Wolverhampton Wanderers	True
3	Burnley	Burnley	True

	Original_EPLs_Name	Original_ETQ_Name	Match_chk
4	Tottenham Hotspur	Tottenham Hotspur	True
5	Ipswich Town	Ipswich Town	True
6	Everton	Everton	True
7	Liverpool	Liverpool	True
8	Manchester City	Manchester City	True
9	Leeds United	Leeds United	True
10	Arsenal	Arsenal	True
11	Derby County	Derby County	True
12	NaN	Nottingham Forest	False
13	Aston Villa	Aston Villa	True
14	NaN	Banned	False
15	Blackburn Rovers	Blackburn Rovers	True
16	Newcastle United	Newcastle United	True
17	Chelsea	Chelsea	True
18	Leicester City	Leicester City	True

In [16]:

```
# merge the full datasets
df_final_table = pd.merge(df_EPLs, df_English_teams_qualified, left_on=['Season','Te
df_final_table.head()
```

Out[16]:

	Season	Pos	Team	Pld	W	D	L	GF	GA	GD	Pts	Qualification or relegation	CLQ_chk	Club
0	2000-01	1	Manchester United	38	24	8	6	79	31	48	80	Qualification for the Champions League first g...	True	Manchester United
1	2000-01	2	Arsenal	38	20	10	8	63	38	25	70	Qualification for the Champions League first g...	True	Arsenal
2	2000-01	3	Liverpool	38	20	9	9	71	39	32	69	Qualification for the Champions League third q...	True	Liverpool
3	2000-01	4	Leeds United	38	20	8	10	64	43	21	68	Qualification for the UEFA Cup first round[a]	False	NaN
4	2000-01	5	Ipswich Town	38	20	6	12	57	42	15	66	Qualification for the UEFA Cup first round[a]	False	NaN

In [17]:

```
# Validate the Champions League qualification is the same from both underlying data
print("Unmatched Team Names: ", df_final_table.loc[(df_final_table['Club'].isna()) &
```

```
Unmatched Team Names:  0
```

In [18]:

```
#drop duplicated columns and tidy up column names
df_final_table.drop(['Club','Season PLq', 'Qualification or relegation'], axis=1, in
df_final_table.rename({'CLQ_chk': 'CL Qualified'}, axis=1, inplace=True)
df_final_table.head()
```

Out[18]:

	Season	Pos	Team	Pld	W	D	L	GF	GA	GD	Pts	CL Qualified
0	2000-01	1	Manchester United	38	24	8	6	79	31	48	80	True
1	2000-01	2	Arsenal	38	20	10	8	63	38	25	70	True
2	2000-01	3	Liverpool	38	20	9	9	71	39	32	69	True
3	2000-01	4	Leeds United	38	20	8	10	64	43	21	68	False
4	2000-01	5	Ipswich Town	38	20	6	12	57	42	15	66	False

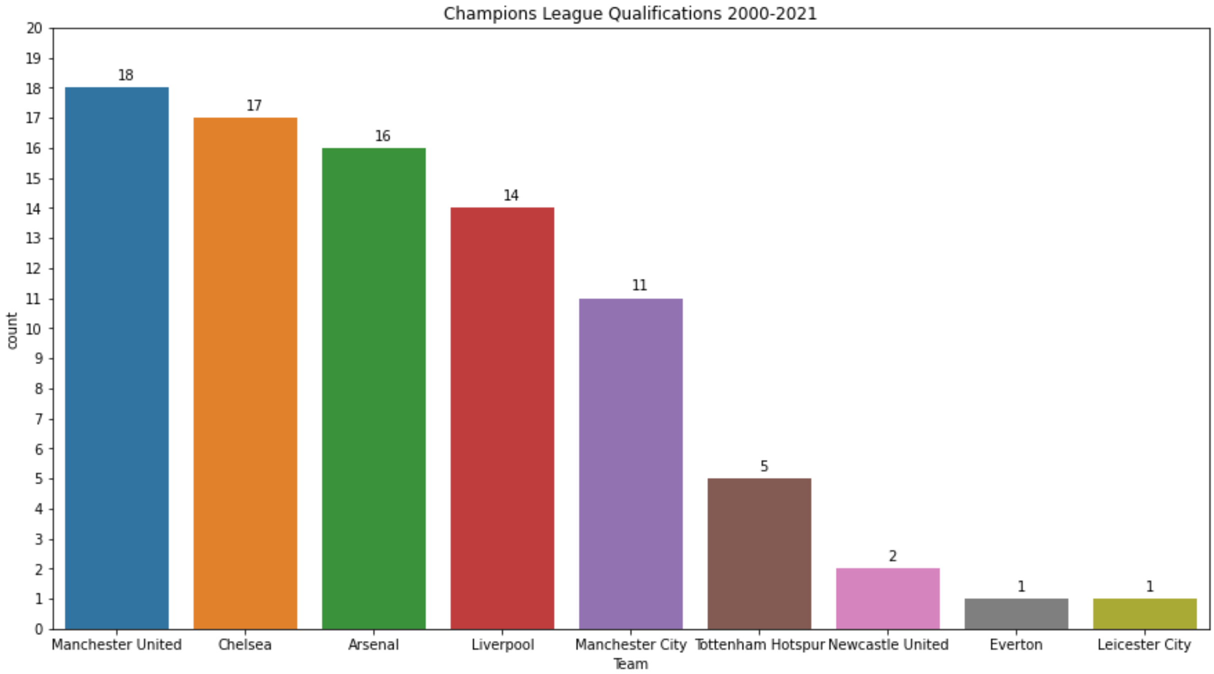
In [19]:

```
df_final_table.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 420 entries, 0 to 419
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   Season        420 non-null    object
 1   Pos           420 non-null    int64 
 2   Team          420 non-null    object
 3   Pld           420 non-null    int64 
 4   W             420 non-null    int64 
 5   D             420 non-null    int64 
 6   L             420 non-null    int64 
 7   GF            420 non-null    int64 
 8   GA            420 non-null    int64 
 9   GD            420 non-null    int64 
 10  Pts           420 non-null    int64 
 11  CL Qualified  420 non-null    bool  
dtypes: bool(1), int64(9), object(2)
memory usage: 39.8+ KB
```

In [20]:

```
# create a countplot to visualise some results
plt.figure(figsize=(15,8))

ax = sns.countplot(x=df_final_table[df_final_table['CL Qualified'] == True]['Team'],
                   order=df_final_table[df_final_table['CL Qualified'] == True]['Tea
ax.set(title='Champions League Qualifications 2000-2021')
ax.set_yticks(range(21))

for p in ax.patches:
    height = p.get_height()
    ax.text(x = p.get_x()+(p.get_width()/2),  y = height+0.25, s = '{:.0f}'.format(h

#save chart as png file
plt.savefig('plots/PL2000-21 most qualifications countplot.png')
plt.show()
```



In [21]:

```
#define two functions
def get_teams():
    '''This function accesses the df_final_table and returns stats all the Team name
that played in the Premier League between 2000-2021.
'''

    df_teams_unique = df_final_table['Team'].unique()
    df_teams_unique = np.sort(df_teams_unique)
    return df_teams_unique

def get_history(my_team):
    '''This function accesses the df_final_table and returns stats on Champions Leag
Pass in the team name as the parameter.  The returned results will be in the form of

(i) Team name (use get_teams(), for a full list)
(ii) Seasons where team qualified
(iii) Seasons where team did not qualify
(iv) To seasons in Premier League over the period of the dataset
(v) Lowest points to achieve qualification
(vi) Highest points when team did not qualify
'''

    df_qualified = df_final_table[(df_final_table['CL Qualified'] == True) & (df_fin
    qualified = df_qualified.shape[0]
    qualified_min_points = df_qualified['Pts'].min()

    df_dnq = df_final_table[(df_final_table['CL Qualified'] == False) & (df_final_ta
    dnq = df_dnq.shape[0]
    dnq_max_points = df_dnq['Pts'].max()

    total_seasons = qualified + dnq
    return (my_team, qualified, dnq, total_seasons, qualified_min_points, dnq_max_po
```

In [22]:

```
#check get_history
print(get_history.__doc__)
```

```
This function accesses the df_final_table and returns stats on Champions League qual
ification between 2000-2021..
```

```
Pass in the team name as the parameter.  The returned results will be in the form of
a tuple, and contain:

(i) Team name (use get_teams(), for a full list)
(ii) Seasons where team qualified
(iii) Seasons where team did not qualify
(iv) To seasons in Premier League over the period of the dataset
(v) Lowest points to achieve qualification
(vi) Highest points when team did not qualify
```

In [23]:

```
#call the first function, and return results as a variable
all_teams = get_teams()
```

In [24]:

```
#iterate through the first 10 elements and call get_history function.
for x in all_teams[0:9]:
    print(get_history(x))
```

```
('Arsenal', 16, 5, 21, 67, 75)
('Aston Villa', 0, 18, 18, nan, 64)
('Birmingham City', 0, 7, 7, nan, 50)
('Blackburn Rovers', 0, 11, 11, nan, 63)
('Blackpool', 0, 1, 1, nan, 39)
('Bolton Wanderers', 0, 11, 11, nan, 58)
('Bournemouth', 0, 5, 5, nan, 46)
('Bradford City', 0, 1, 1, nan, 26)
('Brighton & Hove Albion', 0, 4, 4, nan, 41)
```

In [ ]:

Machine Learning

In [25]:

```
# Import necessary modules
from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn import svm
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.model_selection import GridSearchCV

#from sklearn.preprocessing import StandardScaler
#from sklearn.metrics import f1_score
#from sklearn.preprocessing import MinMaxScaler
#from sklearn.metrics import classification_report
#from sklearn.metrics import roc_auc_score
```

In [26]:

```
# Load dataset
df = pd.read_csv("datasets/diabetes.csv")
df
```

Out[26]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	A
0	6	148	72	35	0	33.6	0.627	

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

768 rows × 9 columns

In [27]:

```
# Print DataFrame information
df.info()
```

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

In [28]:

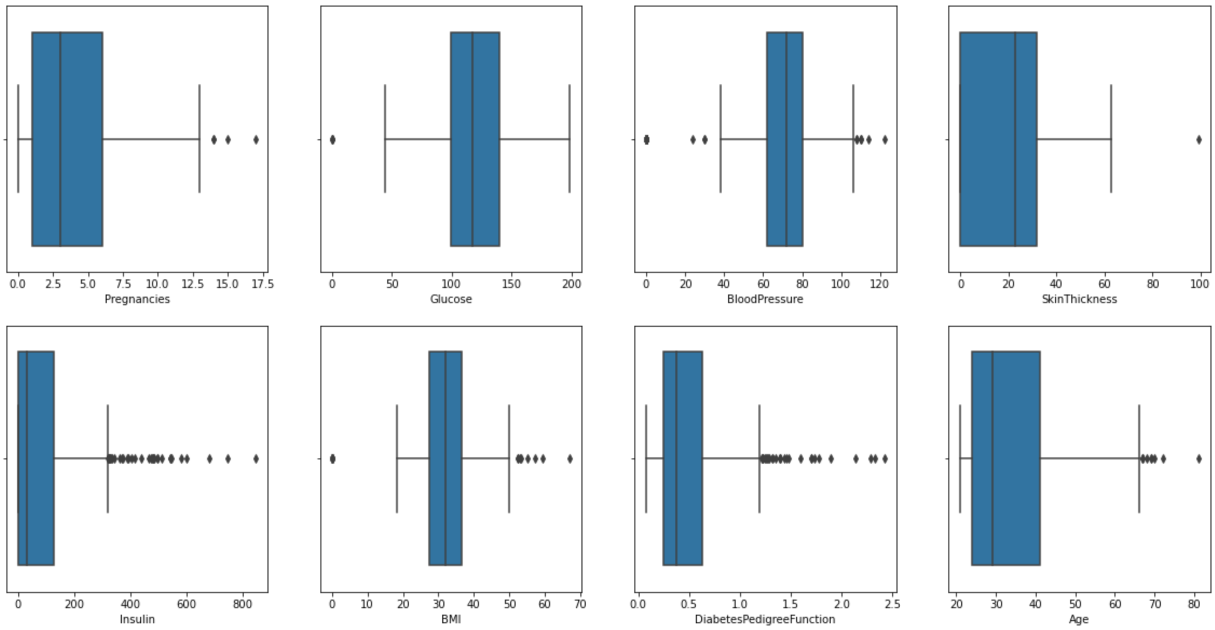
```
# Print summary statistics
df.describe()
```

Out[28]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedi
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

In [29]:

```
#Univariate analysis
columns = df.columns
counter = 1

f = plt.figure(figsize=(20,10))

for col in df.columns[0:-1]:
    f.add_subplot(2,4,counter)
    sns.boxplot(x=df[col])
    counter = counter + 1
```



In [30]:

```
# Replace zero values as numpy NaN and show sum of NaNs by column
col_dq = ["Glucose","BloodPressure","SkinThickness","Insulin","BMI"]  # Zero preganc
df[col_dq] = df[col_dq].replace(['0',0], np.nan)
df.isnull().sum()
```

Out[30]:

```
Pregnancies                   0
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
Age                           0
Outcome                       0
dtype: int64
```

In [31]:

```
df.describe()
```

Out[31]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedig
count	768.000000	763.000000	733.000000	541.000000	394.000000	757.000000	
mean	3.845052	121.686763	72.405184	29.153420	155.548223	32.457464	
std	3.369578	30.535641	12.382158	10.476982	118.775855	6.924988	
min	0.000000	44.000000	24.000000	7.000000	14.000000	18.200000	

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedi
25%	1.000000	99.000000	64.000000	22.000000	76.250000	27.500000	
50%	3.000000	117.000000	72.000000	29.000000	125.000000	32.300000	
75%	6.000000	141.000000	80.000000	36.000000	190.000000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

In [32]:

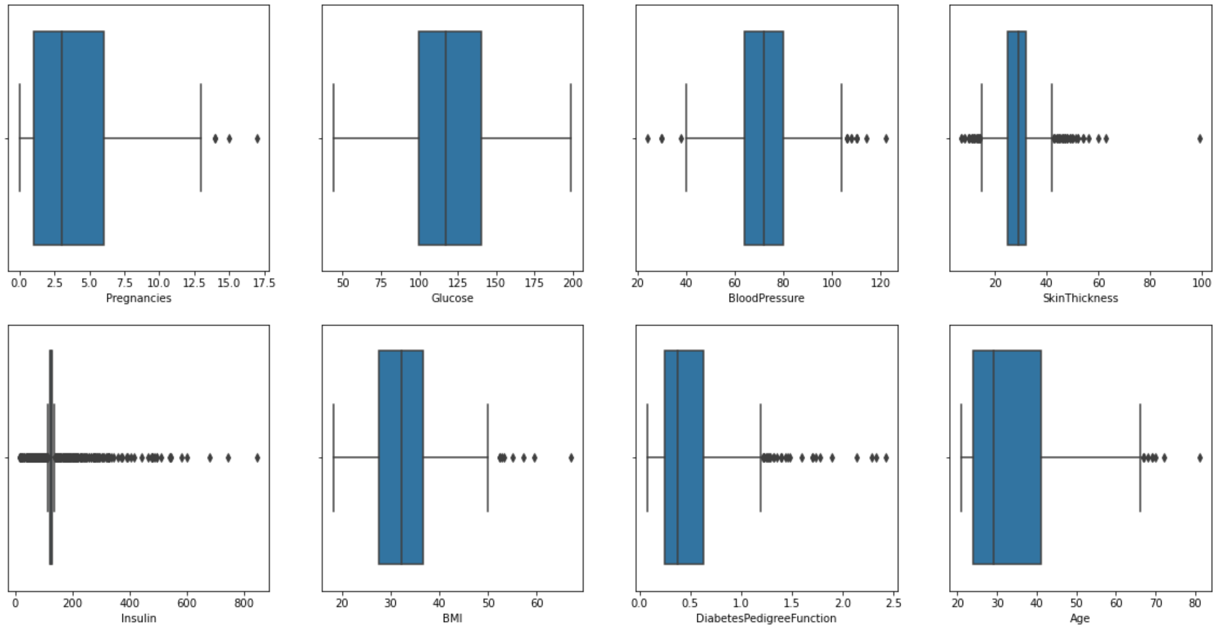
```
# fill NaN values with column median
df[col_dq] = df[col_dq].fillna(df[col_dq].median())
df.describe()
```

Out[32]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedi
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	121.656250	72.386719	29.108073	140.671875	32.455208	
std	3.369578	30.438286	12.096642	8.791221	86.383060	6.875177	
min	0.000000	44.000000	24.000000	7.000000	14.000000	18.200000	
25%	1.000000	99.750000	64.000000	25.000000	121.500000	27.500000	
50%	3.000000	117.000000	72.000000	29.000000	125.000000	32.300000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

In [33]:

```
#Univariate analysis - recheck
counter = 1

f = plt.figure(figsize=(20,10))

for col in df.columns[0:8]:
    f.add_subplot(2,4,counter)
    sns.boxplot(x=df[col])
    counter = counter + 1
```



In [34]:

```
#Confirm shape of dataframe
print("DF Shape (before outliers removed): ", df.shape)
```

```
DF Shape (before outliers removed):  (768, 9)
```

In [35]:

```
outlier_column_name = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', '
outlier_column_upper_limit = []
outlier_column_lower_limit = []

#Calculate upper and lower limits for outliers
for c in outlier_column_name:
    upper_limit = df[c].quantile(0.995)
    outlier_column_upper_limit.append(upper_limit)
    lower_limit = df[c].quantile(0.005)
    outlier_column_lower_limit.append(lower_limit)
    print(c, "upper limit: ",upper_limit)
    print(c, "lower limit: ", lower_limit)
    print(" # upper outliers:" , df[df[c] > upper_limit].shape[0] )
    print(" # lower outliers:" , df[df[c] < lower_limit].shape[0] )
    print("")

#Remove outliers
for x in range(len(outlier_column_name)):
    df = df.loc[(df[outlier_column_name[x]] <= outlier_column_upper_limit[x]) &
                (df[outlier_column_name[x]] >= outlier_column_lower_limit[x]) ]
```

```
Pregnancies upper limit:  13.164999999999964
Pregnancies lower limit:  0.0
 # upper outliers: 4
 # lower outliers: 0

Glucose upper limit:  197.0
Glucose lower limit:  60.34
 # upper outliers: 2
 # lower outliers: 4

BloodPressure upper limit:  110.0
BloodPressure lower limit:  39.67
 # upper outliers: 2
 # lower outliers: 4

SkinThickness upper limit:  54.32999999999993
```

```
SkinThickness lower limit:  9.67
 # upper outliers: 4
 # lower outliers: 4

Insulin upper limit:  582.4649999999992
Insulin lower limit:  18.0
 # upper outliers: 4
 # lower outliers: 3

BMI upper limit:  53.496999999999936
BMI lower limit:  18.9845
 # upper outliers: 4
 # lower outliers: 4

DiabetesPedigreeFunction upper limit:  1.9332599999999991
DiabetesPedigreeFunction lower limit:  0.087505
 # upper outliers: 4
 # lower outliers: 4
```

In [36]:

```
#Confirm shape of dataframe
print("DF Shape (after outliers removed): ", df.shape)
```

```
DF Shape (after outliers removed):  (726, 9)
```

In [37]:

```
df.describe()
```

Out[37]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedig
count	726.000000	726.000000	726.000000	726.000000	726.000000	726.000000	
mean	3.851240	121.763085	72.549587	28.960055	137.747934	32.371350	
std	3.265691	29.510518	11.412136	8.065751	75.030466	6.386259	
min	0.000000	61.000000	44.000000	10.000000	18.000000	19.100000	
25%	1.000000	100.000000	64.000000	25.000000	125.000000	27.600000	
50%	3.000000	117.000000	72.000000	29.000000	125.000000	32.300000	
75%	6.000000	140.000000	80.000000	32.000000	125.750000	36.375000	
max	13.000000	197.000000	110.000000	54.000000	579.000000	52.900000	

In [38]:

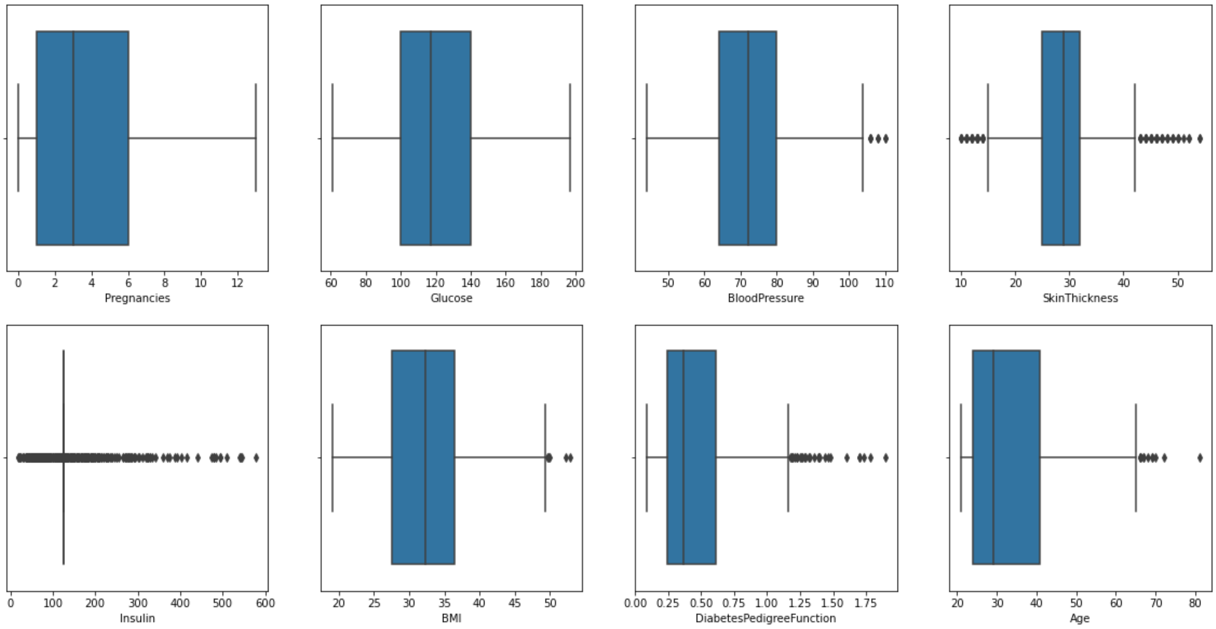
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 726 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               726 non-null    int64
 1   Glucose                   726 non-null    float64
 2   BloodPressure             726 non-null    float64
 3   SkinThickness             726 non-null    float64
 4   Insulin                   726 non-null    float64
 5   BMI                       726 non-null    float64
 6   DiabetesPedigreeFunction  726 non-null    float64
 7   Age                       726 non-null    int64
 8   Outcome                   726 non-null    int64
```

```
dtypes: float64(6), int64(3)
memory usage: 56.7 KB
```

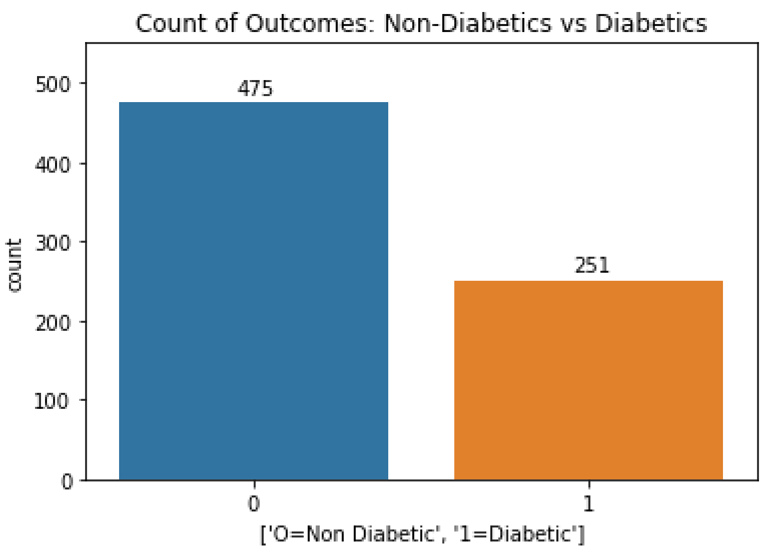
In [39]:

```
#Univariate analysis - recheck again!
f = plt.figure(figsize=(20,10))
counter =1

for col in df.columns[0:8]:
    f.add_subplot(2,4,counter)
    sns.boxplot(x=df[col])
    counter = counter + 1
```



In [40]:

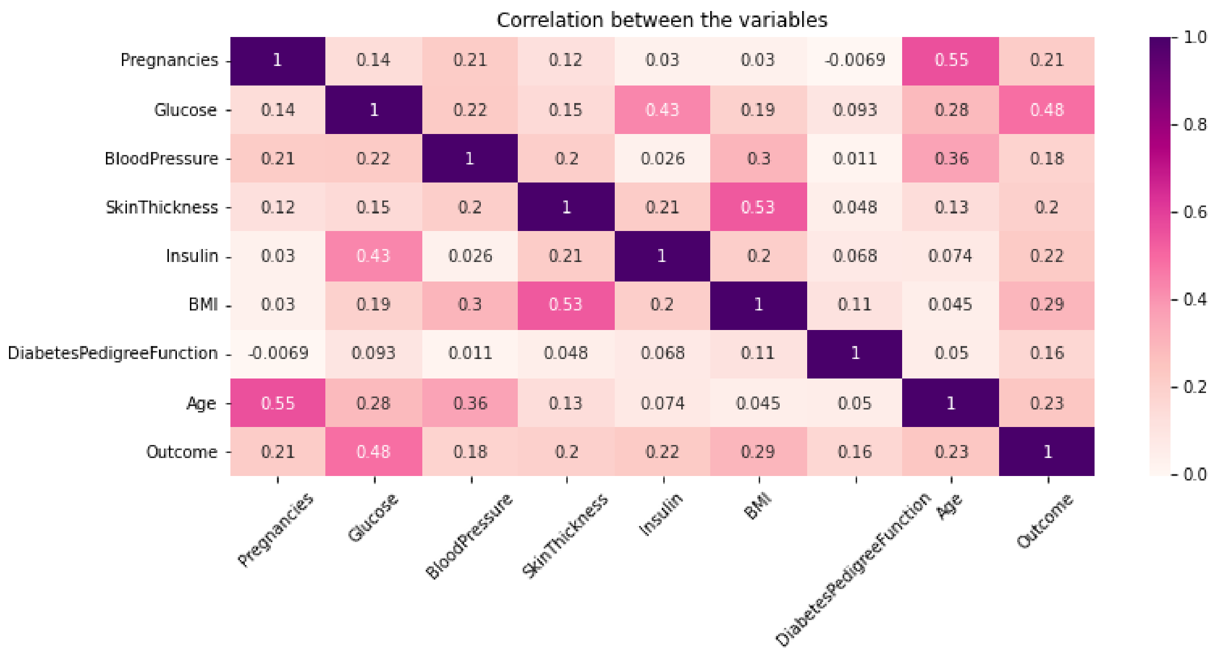
```
#create countplot of outcomes and save plot as png file
ax = sns.countplot(x='Outcome', data=df)
for p in ax.patches:
   ax.annotate('{:.0f}'.format(p.get_height()), (p.get_x()+0.35, p.get_height()+10))
ax.set(ylim=(0, 550), xlabel=['0=Non Diabetic','1=Diabetic'])
ax.set(title='Count of Outcomes: Non-Diabetics vs Diabetics')
plt.savefig('plots/Diabetes outcome countplot.png')
plt.show()
```



In [41]:

```
#create correlation matrix and the heatmap and save plot as png file
plt.subplots(figsize=(12,5))
```

```
table_correlation=df.corr()
sns.heatmap(table_correlation,annot=True,cmap='RdPu')
plt.title('Correlation between the variables')
plt.xticks(rotation=45)
plt.savefig('plots/diabetes correlation matrix heatmap.png')
```



In [42]:

```
df[df['Outcome'] == 0].describe() # Non-diabetic stats
```

Out[42]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedig
count	475.000000	475.000000	475.000000	475.000000	475.000000	475.000000	
mean	3.353684	111.387368	71.073684	27.806316	125.741053	31.012211	
std	3.037939	24.045523	11.258791	8.353753	64.582416	6.184380	
min	0.000000	61.000000	44.000000	10.000000	18.000000	19.100000	
25%	1.000000	94.000000	64.000000	23.000000	95.000000	26.000000	
50%	2.000000	108.000000	72.000000	29.000000	125.000000	30.800000	
75%	5.000000	125.000000	78.000000	31.000000	125.000000	35.300000	
max	13.000000	194.000000	110.000000	54.000000	545.000000	47.900000	

In [43]:

```
df[df['Outcome'] == 1].describe() # Diabetic stats
```

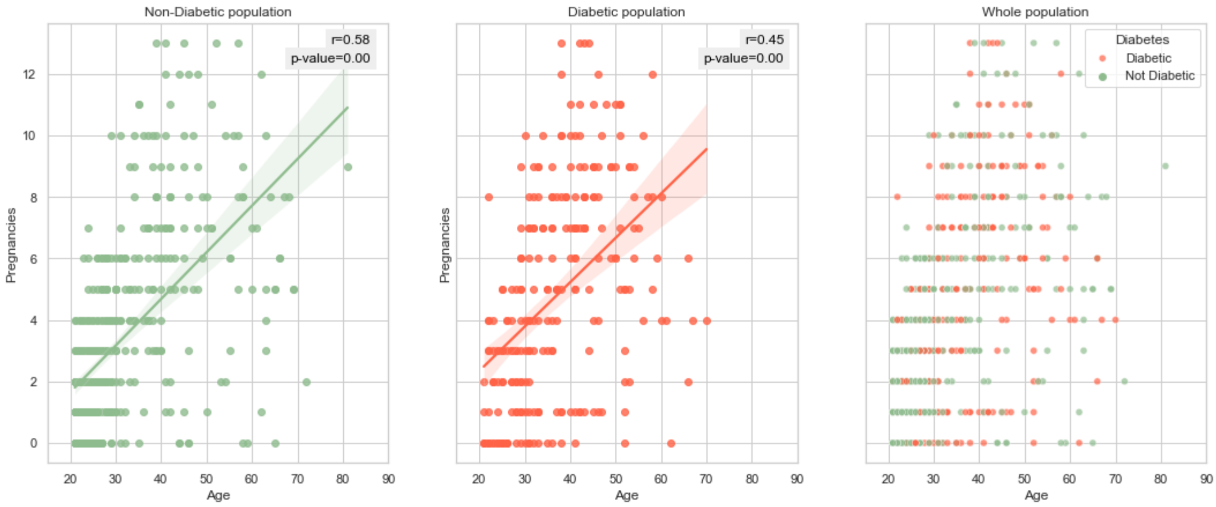
Out[43]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedig
count	251.000000	251.000000	251.000000	251.000000	251.000000	251.000000	
mean	4.792829	141.398406	75.342629	31.143426	160.470120	34.943426	
std	3.474033	28.942160	11.197238	7.002524	87.323961	5.967176	
min	0.000000	78.000000	48.000000	12.000000	29.000000	22.900000	
25%	2.000000	118.500000	68.000000	29.000000	125.000000	30.850000	
50%	4.000000	139.000000	74.000000	29.000000	125.000000	34.100000	

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedig
75%	7.500000	165.500000	82.000000	35.000000	165.000000	38.200000	
max	13.000000	197.000000	110.000000	51.000000	579.000000	52.900000	

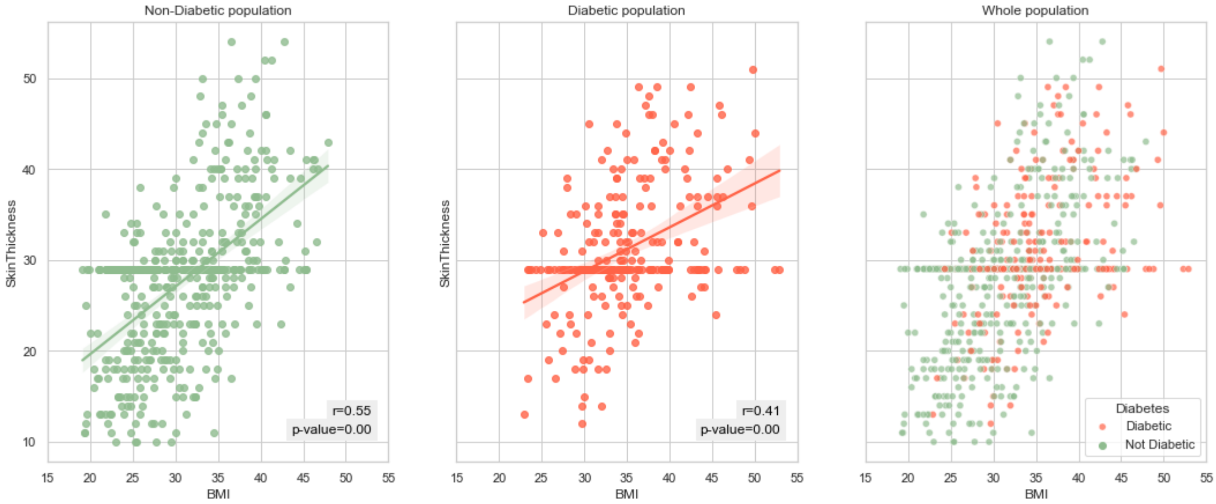
In [44]:

```
#Create subplots on Age vs Pregnancies and save plots as png
d0_ap_stats = stats.pearsonr(df[df['Outcome'] == 0]['Age'],
                             df[df['Outcome'] == 0]['Pregnancies'])

d1_ap_stats = stats.pearsonr(df[df['Outcome'] == 1]['Age'],
                             df[df['Outcome'] == 1]['Pregnancies'])
sns.set()
sns.set_style("whitegrid")
fig, ax = plt.subplots(1,3, figsize=(18, 7),sharey=True)

sns.regplot(x='Age',
            y='Pregnancies',
            data=df[df['Outcome'] == 0],
            ax=ax[0],
            color='darkseagreen'
            );
plt.text(-94, 13, "r={:0.2f}".format(d0_ap_stats[0]), horizontalalignment='right', s
plt.text(-94, 12.4, "p-value={:0.2f}".format(d0_ap_stats[1]), horizontalalignment='r

sns.regplot(x='Age',
            y='Pregnancies',
            data=df[df['Outcome'] == 1],
            ax=ax[1],
            color='tomato'
            );

plt.text(-3, 13, "r={:0.2f}".format(d1_ap_stats[0]), horizontalalignment='right', si
plt.text(-3, 12.4, "p-value={:0.2f}".format(d1_ap_stats[1]), horizontalalignment='ri

sns.scatterplot(x='Age',
                y='Pregnancies',
                data=df,
                hue='Outcome',
                ax=ax[2],
                palette=['darkseagreen','tomato'],
                alpha=0.7)
plt.legend(title='Diabetes', loc='upper right', labels=['Diabetic', 'Not Diabetic'])
ax[0].set(xlim=(15, 90))
ax[0].set_title("Non-Diabetic population")
ax[1].set(xlim=(15, 90))
ax[1].set_title("Diabetic population")
ax[2].set(xlim=(15, 90))
ax[2].set_ylabel("Skin Thickness")
ax[2].set_title("Whole population")
plt.savefig('plots/Age-Pregnancies regplot + scatterplot.png')
plt.show()
```



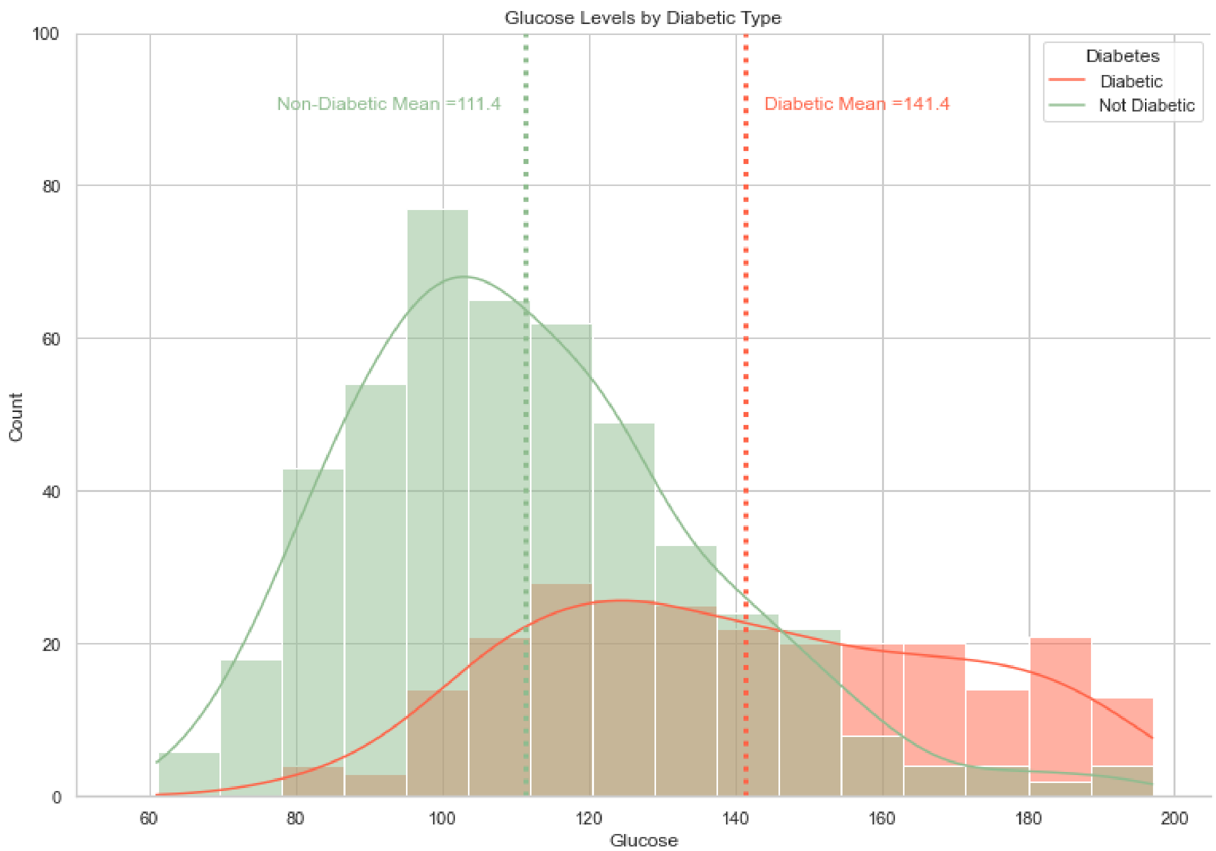
In [45]:

```
#Create subplots on BMI vs SkinThickness and save plots as png
d0_ap_stats = stats.pearsonr(df[df['Outcome'] == 0]['BMI'],
                             df[df['Outcome'] == 0]['SkinThickness'])

d1_ap_stats = stats.pearsonr(df[df['Outcome'] == 1]['BMI'],
                             df[df['Outcome'] == 1]['SkinThickness'])
sns.set()
sns.set_style("whitegrid")
fig, ax = plt.subplots(1,3, figsize=(18, 7),sharey=True)

sns.regplot(x='BMI',
            y='SkinThickness',
            data=df[df['Outcome'] == 0],
            ax=ax[0],
            color='darkseagreen'
            );
plt.text(-43, 13, "r={:0.2f}".format(d0_ap_stats[0]), horizontalalignment='right', s
plt.text(-43, 11, "p-value={:0.2f}".format(d0_ap_stats[1]), horizontalalignment='rig

sns.regplot(x='BMI',
            y='SkinThickness',
            data=df[df['Outcome'] == 1],
            ax=ax[1],
            color='tomato'
            );

plt.text(5, 13, "r={:0.2f}".format(d1_ap_stats[0]), horizontalalignment='right', siz
plt.text(5, 11, "p-value={:0.2f}".format(d1_ap_stats[1]), horizontalalignment='right

sns.scatterplot(x='BMI',
                y='SkinThickness',
                data=df,
                hue='Outcome',
                ax=ax[2],
                palette=['darkseagreen','tomato'],
                alpha=0.7)
plt.legend(title='Diabetes', loc='lower right', labels=['Diabetic', 'Not Diabetic'])
ax[0].set(xlim=(15, 55))
ax[0].set_title("Non-Diabetic population")
ax[1].set(xlim=(15, 55))
ax[1].set_title("Diabetic population")
ax[2].set(xlim=(15, 55))
ax[2].set_ylabel("Skin Thickness")
ax[2].set_title("Whole population")
plt.savefig('plots/BMI-SkinThickness regplot + scatterplot.png')
plt.show()
```



In [46]:

```
#Create distribution plot on Glucose vs Outcome and save plots as png
ax = sns.displot(x=df['Glucose'],hue=df['Outcome'], kde=True, palette=['darkseagreen
plt.legend(title='Diabetes', loc='upper right', labels=['Diabetic', 'Not Diabetic'])
plt.axvline(x=df['Glucose'][df['Outcome'] == 0].mean(),
            color='darkseagreen', linewidth=3, linestyle = 'dotted')
plt.axvline(x=df['Glucose'][df['Outcome'] == 1].mean(),
            color='tomato', linewidth=3, linestyle = 'dotted')
plt.text(108, 90, "Non-Diabetic Mean ={:0.1f}".format(df['Glucose'][df['Outcome'] ==
         fontsize=10,color='darkseagreen', horizontalalignment='right', size=12)
plt.text(144, 90, "Diabetic Mean ={:0.1f}".format(df['Glucose'][df['Outcome'] == 1].
         fontsize=10,color='tomato', horizontalalignment='left', size=12)
ax.set(title='Glucose Levels by Diabetic Type')
ax.set(xlim=(50, 205))
ax.set(ylim=(0, 100))
ax.fig.set_figwidth(12)
ax.fig.set_figheight(8)
plt.savefig('plots/Glucose-Outcome displot.png')
```



In [47]:

```
# create two separate dataframes to have two samples where Ouctome is 0 and 1
glucose0 = df['Glucose'][df['Outcome'] == 0]
glucose1 = df['Glucose'][df['Outcome'] == 1]

print('Non diabetic: mean=%.3f stdv=%.3f' % (np.mean(glucose0), np.std(glucose0)))
print('Diabetic: mean=%.3f stdv=%.3f' % (np.mean(glucose1), np.std(glucose1)))
```

```
Non diabetic: mean=111.387 stdv=24.020
Diabetic: mean=141.398 stdv=28.884
```

In [48]:

```
# Calculate the T-test for the means of two independent samples
stat, p = stats.ttest_ind(glucose0, glucose1)
print("Calculated value=%.4f " % (stat))
print("p-value : %.4f\n"% (p))
print("Test the null hypothesis (H0): both data sets have the same mean.")

#run the test on hypothesis at 99% confidence level
alpha = 0.01
if p > alpha:
        print('Result: Same distributions (fail to reject H0)')
else:
        print('Result: Different distributions (reject H0)')
```

```
Calculated value=-14.8826
p-value : 0.0000

Test the null hypothesis (H0): both data sets have the same mean.
Result: Different distributions (reject H0)
```

In [49]:

```
#Create the machine learning dataframes.
X = df.drop(['Outcome'], axis=1)
y = df['Outcome']

# Split into training and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.4, random_st

# Create dictionary to store results
model_results = {}
```

In [50]:

```
##########################################################
### MODEL FIT & PREDICTIONS USING DEFAULT PARAMETERS  ####
##########################################################

models =[('RDF', RandomForestClassifier(n_estimators=100, random_state = 999), True)
         ('DTC', DecisionTreeClassifier(random_state = 999), True),
         ('SVM' , svm.SVC(kernel='linear'), False),
         ('KNN' , KNeighborsClassifier(), False)]

for name, model, fi_flag in models:
    clf = model
    clf.fit(X_train, y_train)
    y_pred=clf.predict(X_test)

    model_accuracy = metrics.accuracy_score(y_test, y_pred)
    model_results[name] = {"pre hypertuning/default accuracy score": model_accuracy}

    if fi_flag == True :
        feature_imp = pd.Series(clf.feature_importances_,index=X.columns,name=name).
        print("Feature Importance: ",name)
        print(feature_imp)
        print('')
```

```
Feature Importance:  RDF
Glucose                     0.303646
BMI                         0.138453
Age                         0.124576
DiabetesPedigreeFunction    0.110892
BloodPressure               0.090488
Insulin                     0.084993
Pregnancies                 0.081874
SkinThickness               0.065078
Name: RDF, dtype: float64

Feature Importance:  DTC
Glucose                     0.371929
BMI                         0.130469
Age                         0.105302
Pregnancies                 0.100608
BloodPressure               0.089122
Insulin                     0.074707
SkinThickness               0.066267
DiabetesPedigreeFunction    0.061594
Name: DTC, dtype: float64
```

In [51]:

```
##############################
### HYPERPARAMETER TUNING ####
##############################

params_RDF = {'criterion':['gini','entropy'],
              'n_estimators':list(range(10,100,10)),
              'min_samples_leaf':[1,2,3],
              'min_samples_split':[3,4,5,6,7],
              'random_state':[999],
              'n_jobs':[-1]}

params_DTC = {'max_features': ['auto', 'sqrt', 'log2'],
             'min_samples_split': list(range(2,15)),
             'min_samples_leaf':list(range(1,11)),
             'random_state':[999]}

params_SVM = {'C': [6,7,8,9,10,11,12],
              'kernel': ['linear','rbf']}

params_KNN = {'n_neighbors':list(range(1,30)),
              'leaf_size': list(range(1,30)),
              'p': [1,2]}

models_ht =[('RDF', RandomForestClassifier(), params_RDF),
            ('DTC', DecisionTreeClassifier(random_state = 999), params_DTC),
            ('SVM', svm.SVC(), params_SVM),
            ('KNN', KNeighborsClassifier(), params_KNN)
           ]

for name, model, params in models_ht:
    grid = GridSearchCV(model, param_grid=params, n_jobs=-1)
    grid.fit(X_train,y_train)
    #model_results[name].update({"hyper tuning best parameters": grid.best_params_})
    print(name, "Best Hyper Parameters:\n",grid.best_params_)
    prediction=grid.predict(X_test)
    accuracy_score = metrics.accuracy_score(prediction,y_test)
    print(name, "Accuracy:", accuracy_score)
    model_results[name].update({"post hypertuning accuracy score": accuracy_score})
    print("##")
```

```
RDF Best Hyper Parameters:
 {'criterion': 'gini', 'min_samples_leaf': 2, 'min_samples_split': 3, 'n_estimator
s': 90, 'n_jobs': -1, 'random_state': 999}
RDF Accuracy: 0.7353951890034365
##
DTC Best Hyper Parameters:
 {'max_features': 'log2', 'min_samples_leaf': 1, 'min_samples_split': 7, 'random_sta
te': 999}
DTC Accuracy: 0.6529209621993127
##
SVM Best Hyper Parameters:
 {'C': 9, 'kernel': 'linear'}
SVM Accuracy: 0.7250859106529209
##
KNN Best Hyper Parameters:
 {'leaf_size': 1, 'n_neighbors': 8, 'p': 2}
KNN Accuracy: 0.7147766323024055
##
```

In [52]:

```
#add key to dictionary for improvement in accuracy score, for each model, via iterat
for i in model_results:
    accuracy_change = model_results[i]['post hypertuning accuracy score'] - model_re
    model_results[i].update({"improvement in accuracy score": accuracy_change})
```

In [53]:

```
#create dataframe from dicionary and transpose the dataframe
df_model_results = pd.DataFrame(model_results)
df_model_results = df_model_results.T
df_model_results
```

Out[53]:

	pre hypertuning/default accuracy score	post hypertuning accuracy score	improvement in accuracy score
RDF	0.728522	0.735395	0.006873
DTC	0.690722	0.652921	-0.037801
SVM	0.725086	0.725086	0.000000
KNN	0.694158	0.714777	0.020619

In [54]:

```
#Thank you....this concludes the python code.
```

In [ ]: