main

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1 Data Preprocessing Project

1.1 Team members

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1.2 Import required modules

[ ]:
```
from scipy.stats import zscore
from sklearn.model_selection import train_test_split
import numpy as np
import pandas as pd
```

1.3 Data Preprocessing

1.3.1 Dataset 1 (London Air)

In this dataset, we use these techniques: dropping fields, removing rows with missing values

Import data

[ ]:
```
laqndata = pd.read_csv('https://raw.githubusercontent.com/dinhphucv/CSC-177/
↪main/Data%20Preprocessing%20Project/data/LaqnData.csv')
```

[ ]:
```
laqndata.iloc[0:5]
```

[ ]:

	Site	Species	ReadingDateTime	Value	Units	Provisional or Ratified
0	HI0	CO	01/01/2022 00:00	NaN	mg m-3	P
1	HI0	CO	01/01/2022 00:15	NaN	mg m-3	P
2	HI0	CO	01/01/2022 00:30	NaN	mg m-3	P
3	HI0	CO	01/01/2022 00:45	NaN	mg m-3	P
4	HI0	CO	01/01/2022 01:00	NaN	mg m-3	P

Remove unnecessary columns This piece of code allows us to remove column 'Provisional or Ratified' which is not necessary.

```
[ ]: laqndata.drop(columns=['Provisional or Ratified'], axis=1, inplace=True)
```

Drop rows with missing values As we can see from the tabular above, some values are NaN. The code below is used to drop all rows with missing values

```
[ ]: print('Number of rows in original data:', laqndata.shape[0])
     laqndata.dropna(inplace=True)
     laqndata
     print('Number of rows after removing NaN:', laqndata.shape[0])
```

```
Number of rows in original data: 175200
Number of rows after removing NaN: 104596
```

```
[ ]: laqndata.iloc[0:5]
```

```
[ ]:       Site Species   ReadingDateTime  Value   Units
     35040  HI0      NO  01/01/2022 00:00    2.4  ug m-3
     35041  HI0      NO  01/01/2022 00:15    2.4  ug m-3
     35042  HI0      NO  01/01/2022 00:30    2.4  ug m-3
     35043  HI0      NO  01/01/2022 00:45    2.4  ug m-3
     35044  HI0      NO  01/01/2022 01:00    1.2  ug m-3
```

1.3.2 Dataset 2 (UNSW-NB15)

In this dataset, we use these techniques to clean the dataset: dropping fields, removing duplicated rows

Import data

```
[ ]: unsw_nb15 = pd.read_csv('https://github.com/dinhphucv/CSC-177/raw/main/
     ↪Data%20Preprocessing%20Project/data/UNSW_NB15.csv')
```

```
[ ]: unsw_nb15.iloc[0:5]
```

```
[ ]:    id       dur proto service state  spkts  dpkts  sbytes  dbytes       rate  \
     0   1  0.121478   tcp       -   FIN      6      4     258     172  74.087490
     1   2  0.649902   tcp       -   FIN     14     38     734   42014  78.473372
     2   3  1.623129   tcp       -   FIN      8     16     364   13186  14.170161
     3   4  1.681642   tcp     ftp   FIN     12     12     628     770  13.677108
     4   5  0.449454   tcp       -   FIN     10      6     534     268  33.373826

        …  ct_dst_sport_ltm  ct_dst_src_ltm  is_ftp_login  ct_ftp_cmd  \
     0  …                 1               1             0           0
     1  …                 1               2             0           0
     2  …                 1               3             0           0
     3  …                 1               3             1           1
```

```
4  …                  1              40             0            0

   ct_flw_http_mthd  ct_src_ltm  ct_srv_dst  is_sm_ips_ports  attack_cat  \
0                 0           1           1                0      Normal
1                 0           1           6                0      Normal
2                 0           2           6                0      Normal
3                 0           2           1                0      Normal
4                 0           2          39                0      Normal

   label
0      0
1      0
2      0
3      0
4      0

[5 rows x 45 columns]
```

Check and save 'unsw_nb15' dataset shape

```
[ ]: unsw_nb15_original_shape = unsw_nb15.shape
     print('Number of instances/records:', unsw_nb15_original_shape[0])
     print('Number of features/attributes:', unsw_nb15_original_shape[1])
```

```
Number of instances/records: 175341
Number of features/attributes: 45
```

Remove unnecessary columns The code below allows us to remove multiple categorical ('id' and 'attack_cat') as we are only interested in whether the connect is an attack rather than the attack type. Also, the id shouldn't have any meaning or effect on the output.

```
[ ]: unsw_nb15.drop(columns=['id', 'attack_cat'], axis=1, inplace=True)
```

Check and remove duplicated rows Here, we remove all duplicated rows. We have to do this after removing 'id' columns as the id may prevent us from remove duplicating data.

```
[ ]: print('Duplicated rows in \'unsw_nb15\' dataset:', unsw_nb15.duplicated().sum())
     if unsw_nb15.duplicated().sum() > 0:
       unsw_nb15.drop_duplicates(inplace=True)
```

```
Duplicated rows in 'unsw_nb15' dataset: 74072
```

```
[ ]: print('\'unsw_nb15\' original shape:', unsw_nb15_original_shape)
     print('\'unsw_nb15\' current shape:', unsw_nb15.shape)
```

```
'unsw_nb15' original shape: (175341, 45)
'unsw_nb15' current shape: (101269, 43)
```

1.3.3 Dataset 3 (diabetes)

In this dataset, we use these techniques: shuffling, sorting,saving dataframe

Import data

[ ]:
```
diabetes = pd.read_csv('https://raw.githubusercontent.com/dinhphucv/CSC-177/
↪main/Data%20Preprocessing%20Project/data/diabetes.csv')
```

[ ]:
```
diabetes.iloc[0:5]
```

[ ]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
```

Check and save 'diabetes' dataset shape

[ ]:
```
diabetes_original_shape = diabetes.shape
print('Number or instances/records:', diabetes_original_shape[0])
print('Number or features/attributes:', diabetes_original_shape[1])
```

```
Number or instances/records: 768
Number or features/attributes: 9
```

Check and remove duplicated rows

[ ]:
```
print('Duplicated rows in \'diabetes\' dataset:', diabetes.duplicated().sum())
```

```
Duplicated rows in 'diabetes' dataset: 0
```

Outliers

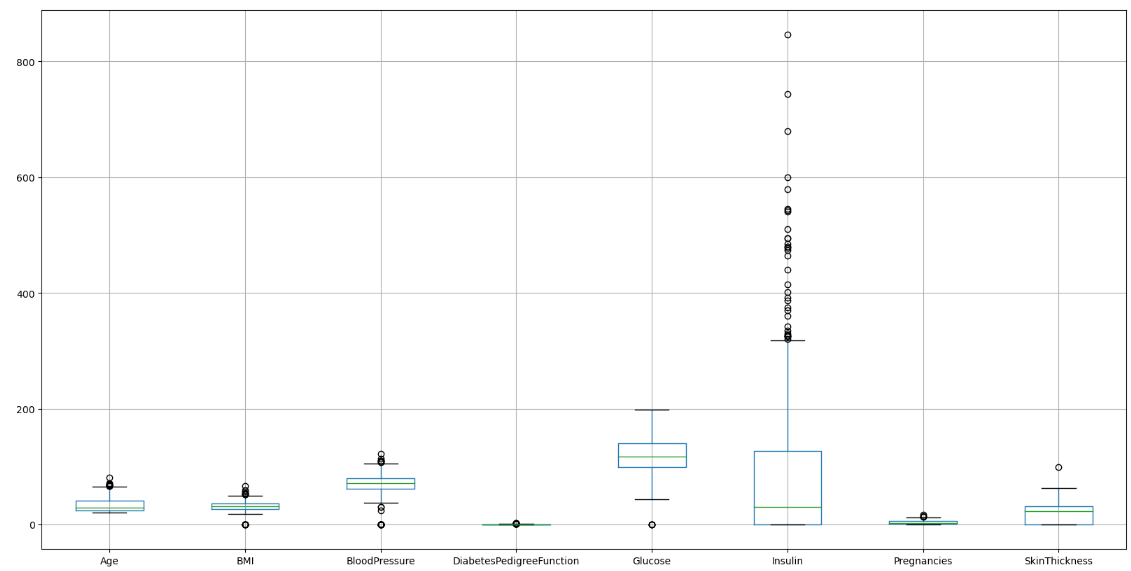
[ ]:
```
diabetes[diabetes.columns.difference(['Outcome'])].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 8 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Age                       768 non-null    int64
 1   BMI                       768 non-null    float64
 2   BloodPressure             768 non-null    int64
 3   DiabetesPedigreeFunction  768 non-null    float64
```

```
 4   Glucose                   768 non-null    int64
 5   Insulin                   768 non-null    int64
 6   Pregnancies               768 non-null    int64
 7   SkinThickness             768 non-null    int64
dtypes: float64(2), int64(6)
memory usage: 48.1 KB
```

[ ]:
```
diabetes_2 = diabetes[diabetes.columns.difference(['Outcome'])].copy()
diabetes_2.boxplot(figsize=(20,10))
```

[ ]:
```
<Axes: >
```



The boxplots suggest that there're some abnormally high values in all columns. The code below shows the results of standardizing the columns of the data. We also discarding the outliner with Z score > 3 or Z <=-3

[ ]:
```
Z = (diabetes_2-diabetes_2.mean())/diabetes_2.std()
Z
```

[ ]:

	Age	BMI	BloodPressure	DiabetesPedigreeFunction	Glucose	\
0	1.425067	0.203880	0.149543	0.468187	0.847771	
1	-0.190548	-0.683976	-0.160441	-0.364823	-1.122665	
2	-0.105515	-1.102537	-0.263769	0.604004	1.942458	
3	-1.040871	-0.493721	-0.160441	-0.920163	-0.997558	
4	-0.020483	1.408828	-1.503707	5.481337	0.503727	
..	…	…	…	…	…	
763	2.530487	0.115094	0.356200	-0.908090	-0.622237	
764	-0.530677	0.609757	0.046215	-0.398023	0.034575	
765	-0.275580	-0.734711	0.149543	-0.684747	0.003299	

```
766  1.169970 -0.240048      -0.470426                 -0.370859  0.159683
767 -0.870806 -0.201997       0.046215                 -0.473476 -0.872451

      Insulin  Pregnancies  SkinThickness
0   -0.692439     0.639530       0.906679
1   -0.692439    -0.844335       0.530556
2   -0.692439     1.233077      -1.287373
3    0.123221    -0.844335       0.154433
4    0.765337    -1.141108       0.906679
..        …           …             …
763  0.869464     1.826623       1.721613
764 -0.692439    -0.547562       0.405181
765  0.279412     0.342757       0.154433
766 -0.692439    -0.844335      -1.287373
767 -0.692439    -0.844335       0.655930

[768 rows x 8 columns]
```

[ ]:
```
Z2 = Z.loc[((Z > -3).sum(axis=1)==8) & ((Z <= 3).sum(axis=1)==8),:]
Z2
```

[ ]:
```
          Age       BMI  BloodPressure  DiabetesPedigreeFunction   Glucose  \
0    1.425067  0.203880       0.149543                  0.468187  0.847771
1   -0.190548 -0.683976      -0.160441                 -0.364823 -1.122665
2   -0.105515 -1.102537      -0.263769                  0.604004  1.942458
3   -1.040871 -0.493721      -0.160441                 -0.920163 -0.997558
5   -0.275580 -0.810813       0.252871                 -0.817546 -0.153085
..        …         …            …                         …         …
763  2.530487  0.115094       0.356200                 -0.908090 -0.622237
764 -0.530677  0.609757       0.046215                 -0.398023  0.034575
765 -0.275580 -0.734711       0.149543                 -0.684747  0.003299
766  1.169970 -0.240048      -0.470426                 -0.370859  0.159683
767 -0.870806 -0.201997       0.046215                 -0.473476 -0.872451

      Insulin  Pregnancies  SkinThickness
0   -0.692439     0.639530       0.906679
1   -0.692439    -0.844335       0.530556
2   -0.692439     1.233077      -1.287373
3    0.123221    -0.844335       0.154433
5   -0.692439     0.342757      -1.287373
..        …           …             …
763  0.869464     1.826623       1.721613
764 -0.692439    -0.547562       0.405181
765  0.279412     0.342757       0.154433
766 -0.692439    -0.844335      -1.287373
767 -0.692439    -0.844335       0.655930
```

```
[688 rows x 8 columns]
```

Shuffling dataframe Here, we are shuffling dataframe

```
[ ]: # np.random.seed(38)
temp_df = diabetes
temp_df = temp_df.reindex(np.random.permutation(temp_df.index))
temp_df.reset_index(inplace=True, drop=True)
temp_df
```

```
[ ]:      Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              3      116             74             15      105  26.3
1              5      115             76              0        0  31.2
2              7      168             88             42      321  38.2
3              6      190             92              0        0  35.5
4              8       91             82              0        0  35.6
..           …        …            …            …        …    …
763            8      194             80              0        0  26.1
764            6       80             66             30        0  26.2
765            4       95             60             32        0  35.4
766            6      108             44             20      130  24.0
767            1       89             66             23       94  28.1

     DiabetesPedigreeFunction  Age  Outcome
0                       0.107   24        0
1                       0.343   44        1
2                       0.787   40        1
3                       0.278   66        1
4                       0.587   68        0
..                         …    …       …
763                     0.551   67        0
764                     0.313   41        0
765                     0.284   28        0
766                     0.813   35        0
767                     0.167   21        0

[768 rows x 9 columns]
```

Sorting dataframe The below code allows us to sort the data by 'Age' in ascending.

```
[ ]: temp_df = diabetes.sort_values(by='Age', ascending=True)
temp_df
```

```
[ ]:      Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
255            1      113             64             35        0  33.6
60             2       84              0              0        0   0.0
102            0      125             96              0        0  22.5
```

```
182            1       0            74            20       23  27.7
623            0      94            70            27      115  43.5
..           ...     ...           ...           ...      ...   ...
123            5     132            80             0        0  26.8
684            5     136            82             0        0   0.0
666            4     145            82            18        0  32.5
453            2     119             0             0        0  19.6
459            9     134            74            33       60  25.9

     DiabetesPedigreeFunction  Age  Outcome
255                     0.543   21        1
60                      0.304   21        0
102                     0.262   21        0
182                     0.299   21        0
623                     0.347   21        0
..                        ...  ...      ...
123                     0.186   69        0
684                     0.640   69        0
666                     0.235   70        1
453                     0.832   72        0
459                     0.460   81        0

[768 rows x 9 columns]
```

Saving dataframe for later use After doing some data preprocessing, we can export the dataframe as csv for later use. We can continue the work instead of redone it.

[ ]:
```
temp_df.to_csv('data/diabetes-age-sorted.csv', index=False)
```

1.3.4 Dataset 4 (Mobile Phone Price)

In this dataset, we use these techniques: removing duplicated rows, concatenating, calculated fields

Import data

[ ]:
```
mobile_phone_price = pd.read_csv('https://raw.githubusercontent.com/dinhphucv/
  ↪CSC-177/main/Data%20Preprocessing%20Project/data/Mobile_Phone_Price.csv')
mobile_phone_price
```

[ ]:
```
       Brand              Model Storage    RAM  Screen Size (inches)  \
0      Apple       iPhone 13 Pro   128 GB   6 GB                   6.1
1    Samsung   Galaxy S21 Ultra   256 GB  12 GB                   6.8
2    OnePlus              9 Pro   128 GB   8 GB                   6.7
3     Xiaomi   Redmi Note 10 Pro   128 GB   6 GB                  6.67
4     Google            Pixel 6   128 GB   8 GB                   6.4
..       ...                ...      ...    ...                   ...
402  Samsung   Galaxy Note20 5G      128      8                   6.7
403   Xiaomi       Mi 10 Lite 5G      128      6                  6.57
```

```
404     Apple  iPhone 12 Pro Max      128      6                   6.7
405      Oppo              Reno3      128      8                   6.4
406   Samsung     Galaxy S10 Lite      128      6                   6.7

           Camera (MP)  Battery Capacity (mAh) Price ($)
0         12 + 12 + 12                    3095       999
1    108 + 10 + 10 + 12                   5000      1199
2       48 + 50 + 8 + 2                   4500       899
3        64 + 8 + 5 + 2                   5020       279
4            50 + 12.2                    4614       799
..                  …                      …        …
402           12+64+12                    4300      1049
403           48+8+2+2                    4160       349
404           12+12+12                    3687      1099
405          48+13+8+2                    4025       429
406            48+12+5                    4500       649

[407 rows x 8 columns]
```

Concatenating In this part, we replicate concatenating by creating multiple dataframes and concatenating them into one.

[ ]:
```python
col_brand = mobile_phone_price['Brand']
col_model = mobile_phone_price['Model']
col_storage = mobile_phone_price['Storage ']
col_ram = mobile_phone_price['RAM ']
col_price = mobile_phone_price['Price ($)']
```

[ ]:
```python
result = pd.concat([col_brand, col_model, col_storage, col_ram,␣
  ↪col_price],axis=1)
result
```

[ ]:
```
        Brand              Model Storage   RAM  Price ($)
0       Apple      iPhone 13 Pro   128 GB  6 GB        999
1     Samsung   Galaxy S21 Ultra   256 GB 12 GB       1199
2     OnePlus              9 Pro   128 GB  8 GB        899
3      Xiaomi  Redmi Note 10 Pro   128 GB  6 GB        279
4      Google            Pixel 6   128 GB  8 GB        799
..        …                  …       …     …          …
402   Samsung   Galaxy Note20 5G      128     8       1049
403    Xiaomi       Mi 10 Lite 5G      128     6        349
404     Apple  iPhone 12 Pro Max      128     6       1099
405      Oppo              Reno3      128     8        429
406   Samsung     Galaxy S10 Lite      128     6        649

[407 rows x 5 columns]
```

Removing certain characters in certain columns As we see from the above tabular, the values for Storage, RAM, and Price are not formatted consistently. Some have 'GB', and some do not. The same thing happened with the Price column but with the character '$'. The below code is used to remove that inconsistency.

```
[ ]: result.info()
for column in ['Storage ', 'RAM ']:
  result[column] = result[column].str.replace(r' ?GB', '', regex=True)
result['Price ($)'] = result['Price ($)'].str.replace('[$,]', '', regex=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 407 entries, 0 to 406
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Brand      407 non-null    object
 1   Model      407 non-null    object
 2   Storage    407 non-null    object
 3   RAM        407 non-null    object
 4   Price ($)  407 non-null    object
dtypes: object(5)
memory usage: 16.0+ KB
```

Convert to numeric data type After removing the inconsistent, the dtype of those columns is still an object. The below code is used to convert them back to numeric. If any non-numerics are still left in those columns, errors will occur. If it ran successfully, we converted them to numeric data type.

```
[ ]: for column in ['Storage ', 'RAM ', 'Price ($)']:
  result[column] = pd.to_numeric(result[column])
result.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 407 entries, 0 to 406
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Brand      407 non-null    object
 1   Model      407 non-null    object
 2   Storage    407 non-null    int64
 3   RAM        407 non-null    int64
 4   Price ($)  407 non-null    int64
dtypes: int64(3), object(2)
memory usage: 16.0+ KB
```

Check and remove duplicated rows In this step, we remove duplicated rows. We decided to do this after removing inconsistent and converting as there's a chance the collecter accidentally recollected the data and added inconsistent to it.

```
[ ]: print('Duplicated rows in \'result\' dataset:', result.duplicated().sum())
if result.duplicated().sum() > 0:
  result.drop_duplicates(inplace=True)
```

```
Duplicated rows in 'result' dataset: 60
```

Calculated Fields After removing all the duplicated, we can add a calculated field into the current dataframe. Here we add a new column 'Price (in VND)' and it will be calculated from 'Price ($)'. In this piece of code, we also use round() to round the output as Vietnamese currency is always integer.

```
[ ]: result.insert(len(result.columns),'Price (VND)', (result['Price ($)']*24432.50).
 ↪round().astype(int))
result
```

```
[ ]:      Brand              Model  Storage  RAM  Price ($)  Price (VND)
0      Apple       iPhone 13 Pro      128    6        999     24408068
1    Samsung    Galaxy S21 Ultra      256   12       1199     29294568
2    OnePlus               9 Pro      128    8        899     21964818
3     Xiaomi   Redmi Note 10 Pro      128    6        279      6816668
4     Google             Pixel 6      128    8        799     19521568
..       …                   …     …    …       …          …
401   Huawei            P30 Lite      128    4        329      8038292
402  Samsung     Galaxy Note20 5G      128    8       1049     25629692
403   Xiaomi       Mi 10 Lite 5G      128    6        349      8526942
404    Apple   iPhone 12 Pro Max      128    6       1099     26851318
405     Oppo              Reno3       128    8        429     10481542

[347 rows x 6 columns]
```

Feature Normalization In this step, I use the zscore function to calculate the zscore of 'RAM' and 'Price ($)'. These new values will help us to easily idicate whether the spec, price is below, near, or above the average. We decided to didn't calculate the zscore for Price in VND as it is just a calculated from other field and also has some rouding.

```
[ ]: result['RAM '] = zscore(result['RAM '])
result['Price ($)'] = zscore(result['Price ($)'])
result
```

```
[ ]:      Brand              Model  Storage       RAM  Price ($)  Price (VND)
0      Apple       iPhone 13 Pro      128  0.045702   1.909644     24408068
1    Samsung    Galaxy S21 Ultra      256  2.485475   2.558537     29294568
2    OnePlus               9 Pro      128  0.858959   1.585197     21964818
3     Xiaomi   Redmi Note 10 Pro      128  0.045702  -0.426371      6816668
4     Google             Pixel 6      128  0.858959   1.260751     19521568
..       …                   …     …       …         …           …
401   Huawei            P30 Lite      128 -0.767556  -0.264148      8038292
402  Samsung     Galaxy Note20 5G      128  0.858959   2.071867     25629692
```

```
403   Xiaomi       Mi 10 Lite 5G        128  0.045702  -0.199259      8526942
404    Apple  iPhone 12 Pro Max        128  0.045702   2.234090     26851318
405     Oppo              Reno3        128  0.858959   0.060298     10481542

[347 rows x 6 columns]
```

1.4 Data split

In this part, we decided to work with our diabetes dataset as the dataset is pretty much clean and we want to predict diabetes based on other attribute. Here we use all of the columns exept the Outcome as x. And the Outcome column for Y. We split the data, 75% for training and 25% for testing

[ ]:
```
diabetes = pd.read_csv('https://raw.githubusercontent.com/dinhphucv/CSC-177/
    ↪main/Data%20Preprocessing%20Project/data/diabetes.csv')
diabetes
```

[ ]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              6      148             72             35        0  33.6
1              1       85             66             29        0  26.6
2              8      183             64              0        0  23.3
3              1       89             66             23       94  28.1
4              0      137             40             35      168  43.1
..           …        …             …             …       …    …
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     DiabetesPedigreeFunction  Age  Outcome
0                       0.627   50        1
1                       0.351   31        0
2                       0.672   32        1
3                       0.167   21        0
4                       2.288   33        1
..                        …   …       …
763                     0.171   63        0
764                     0.340   27        0
765                     0.245   30        0
766                     0.349   47        1
767                     0.315   23        0

[768 rows x 9 columns]
```

[ ]:
```
x = diabetes[diabetes.columns.difference(['Outcome'])]
y = diabetes['Outcome']
```

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25,␣
  ↪random_state=12)
```

[ ]:
```
print(x.columns)
```

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

The below code is used to calculating the mean and std of certain columns in both training and testing set.

[ ]:
```
feature_columns = ['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',␣
  ↪'BMI', 'DiabetesPedigreeFunction']
for column in feature_columns:
  print(column)
  print('\tTraining set mean:', x_train[column].mean())
  print('\tTesting set mean:', x_test[column].mean())
  print('\tTraining set std:', x_train[column].std())
  print('\tTesting set std:', x_test[column].std())
```

```
Glucose
        Training set mean: 120.52604166666667
        Testing set mean: 122.0
        Training set std: 31.30199630736171
        Testing set std: 33.96625982181027
BloodPressure
        Training set mean: 68.94965277777777
        Testing set mean: 69.57291666666667
        Training set std: 19.113006722286883
        Testing set std: 20.110555584040394
SkinThickness
        Training set mean: 20.73263888888889
        Testing set mean: 19.947916666666668
        Training set std: 15.694852459319465
        Testing set std: 16.72905100325358
Insulin
        Training set mean: 81.27256944444444
        Testing set mean: 75.38020833333333
        Training set std: 115.65762221613798
        Testing set std: 114.17978027672025
BMI
        Training set mean: 32.01597222222222
        Testing set mean: 31.922395833333336
        Training set std: 8.125176445501436
        Testing set std: 7.131822974665879
DiabetesPedigreeFunction
        Training set mean: 0.47195138888888889
        Testing set mean: 0.47165104166666666
```

```
Training set std: 0.3358161055745912
Testing set std: 0.3183402606796537
```

1.4.1 Mean and Std results (in case rerun change the data result):

Glucose
********Training set mean: 120.52604166666667
********Testing set mean: 122.0
********Training set std: 31.30199630736171
********Testing set std: 33.96625982181027
BloodPressure
********Training set mean: 68.94965277777777
********Testing set mean: 69.57291666666667
********Training set std: 19.113006722286883
********Testing set std: 20.110555584040394
SkinThickness
********Training set mean: 20.73263888888889
********Testing set mean: 19.947916666666668
********Training set std: 15.694852459319465
********Testing set std: 16.72905100325358
Insulin
********Training set mean: 81.27256944444444
********Testing set mean: 75.38020833333333
********Training set std: 115.65762221613798
********Testing set std: 114.17978027672025
BMI
********Training set mean: 32.01597222222222
********Testing set mean: 31.922395833333336
********Training set std: 8.125176445501436
********Testing set std: 7.131822974665879
DiabetesPedigreeFunction
********Training set mean: 0.4719513888888889
********Testing set mean: 0.47165104166666666
********Training set std: 0.3358161055745912
********Testing set std: 0.3183402606796537

1.5 Developing and documenting human insights with human interpretation on preprocessed data and possible effect on predictions.

We already learned that data quality is essential and poor data quality is an unfolding disaster. Here, we only deal with small datasets and already see why data preprocessing takes so much time. We must eliminate missing data, unnecessary features, duplicate data, outliers, or inconsistencies. After cleaning the data, our dataset is smaller, more manageable for us to read, and easier for the model to process. Data preprocessing ensures that we and the model are working with accurate and reliable information, which can lead to more accurate predictions.

1.6 Compare the two sets: the training data and the test data and analyze it, developing an intuition and meaning of your results.

Splitting data is an essential step in machine learning. The training set will only be used to train, and the test set (unseen data) will be used to test how well a model is generalized. This process will prevent overfitting when the model performs well on the training set but poorly on the test set. In our case, the mean and std of columns from the two datasets are pretty close together.