Data Preprocessing Project

Team members

Phuc Dinh\ Brian Shao\ Steven Ho\ Alex Souv\ Navteg Khalsa\ Moshley Marcelo

Import required modules

In [317…

```
from scipy.stats import zscore
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
import numpy as np
import pandas as pd
```

Data Preprocessing

Dataset 1 (London Air)

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

Import data

In [270…

```
laqndata = pd.read_csv('https://raw.githubusercontent.com/dinhphucv/CSC-177/main/Data%20
```

In [271…

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

Out[271]:

	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.

In [272…

```
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

In [273…

```
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
```

In [274…
```
laqndata.iloc[0:5]
```

Out[274]:

	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

Dataset 2 (UNSW-NB15)

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

Import data

In [275…
```
unsw_nb15 = pd.read_csv('https://github.com/dinhphucv/CSC-177/raw/main/Data%20Preprocess
```

In [276…
```
unsw_nb15.iloc[0:5]
```

Out[276]:

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

5 rows × 45 columns

Check and save 'unsw_nb15' dataset shape

In [277…
```
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.

In [278...
```
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.

In [279...
```
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
```

In [280...
```
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)
```

Dataset 3 (diabetes)

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

Import data

In [281...
```
diabetes = pd.read_csv('https://raw.githubusercontent.com/dinhphucv/CSC-177/main/Data%20
```

In [282...
```
diabetes.iloc[0:5]
```

Out[282]:

	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

Check and save 'diabetes' dataset shape

In [283...
```
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

In [284...
```
print('Duplicated rows in \'diabetes\' dataset:', diabetes.duplicated().sum())
```

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

Outliers

In [285...
```
diabetes[diabetes.columns.difference(['Outcome'])].info()
```

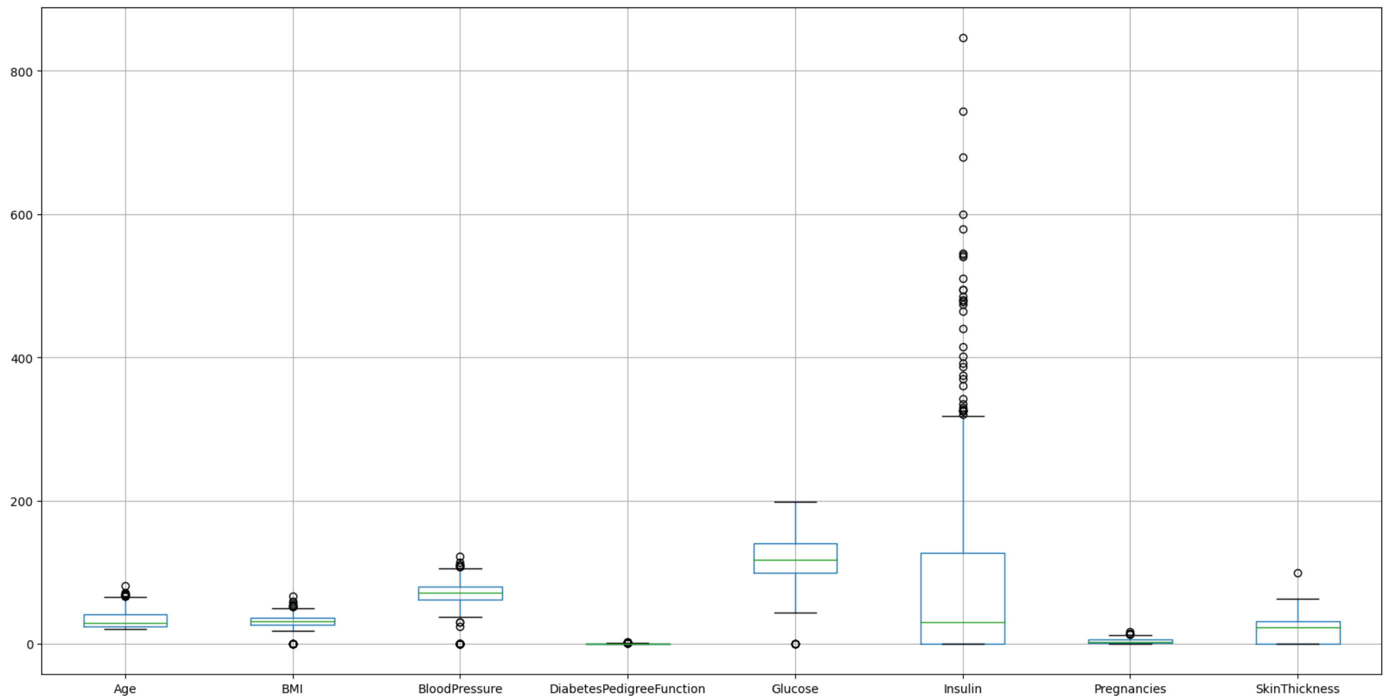
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 8 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Age                       768 non-null    int64  
 1   BMI                   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

In [305…

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

Out[305]:

```
<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

In [315…

```python
Z = (diabetes_2-diabetes_2.mean())/diabetes_2.std()
Z
```

Out[315]:

	Age	BMI	BloodPressure	DiabetesPedigreeFunction	Glucose	Insulin	Pregnancies	SkinThickn
0	1.425067	0.203880	0.149543	0.468187	0.847771	-0.692439	0.639530	0.906
1	-0.190548	-0.683976	-0.160441	-0.364823	-1.122665	-0.692439	-0.844335	0.530
2	-0.105515	-1.102537	-0.263769	0.604004	1.942458	-0.692439	1.233077	-1.287
3	-1.040871	-0.493721	-0.160441	-0.920163	-0.997558	0.123221	-0.844335	0.154
4	-0.020483	1.408828	-1.503707	5.481337	0.503727	0.765337	-1.141108	0.906
...	...	...	...	...	...	...	...	
763	2.530487	0.115094	0.356200	-0.908090	-0.622237	0.869464	1.826623	1.721
764	-0.530677	0.609757	0.046215	-0.398023	0.034575	-0.692439	-0.547562	0.405

765	-0.275580	-0.734711	0.149543	-0.684747	0.003299	0.279412	0.342757	0.154
766	1.169970	-0.240048	-0.470426	-0.370859	0.159683	-0.692439	-0.844335	-1.287
767	-0.870806	-0.201997	0.046215	-0.473476	-0.872451	-0.692439	-0.844335	0.655

768 rows × 8 columns

In [316...
```
Z2 = Z.loc[((Z > -3).sum(axis=1)==8) & ((Z <= 3).sum(axis=1)==8),:]
Z2
```

Out[316]:

	Age	BMI	BloodPressure	DiabetesPedigreeFunction	Glucose	Insulin	Pregnancies	SkinThickn
0	1.425067	0.203880	0.149543	0.468187	0.847771	-0.692439	0.639530	0.906
1	-0.190548	-0.683976	-0.160441	-0.364823	-1.122665	-0.692439	-0.844335	0.530
2	-0.105515	-1.102537	-0.263769	0.604004	1.942458	-0.692439	1.233077	-1.287
3	-1.040871	-0.493721	-0.160441	-0.920163	-0.997558	0.123221	-0.844335	0.154
5	-0.275580	-0.810813	0.252871	-0.817546	-0.153085	-0.692439	0.342757	-1.287
...	...	...	...	...	...	...	...	
763	2.530487	0.115094	0.356200	-0.908090	-0.622237	0.869464	1.826623	1.721
764	-0.530677	0.609757	0.046215	-0.398023	0.034575	-0.692439	-0.547562	0.405
765	-0.275580	-0.734711	0.149543	-0.684747	0.003299	0.279412	0.342757	0.154
766	1.169970	-0.240048	-0.470426	-0.370859	0.159683	-0.692439	-0.844335	-1.287
767	-0.870806	-0.201997	0.046215	-0.473476	-0.872451	-0.692439	-0.844335	0.655

688 rows × 8 columns

Shuffling dataframe

Here, we are shuffling dataframe

In [ ]:
```
# 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
```

Out[ ]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	9	122	56	0	0	33.3	1.114	33	1
1	0	137	68	14	148	24.8	0.143	21	0
2	1	143	74	22	61	26.2	0.256	21	0
3	2	197	70	99	0	34.7	0.575	62	1
4	6	125	68	30	120	30.0	0.464	32	0
...	...	...	...	...	...	...	...	...	...
763	4	129	86	20	270	35.1	0.231	23	0
764	7	94	64	25	79	33.3	0.738	41	0
765	0	95	80	45	92	36.5	0.330	26	0

766	8	196	76	29	280	37.5	0.605	57	1
767	7	168	88	42	321	38.2	0.787	40	1

768 rows × 9 columns

Sorting dataframe

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

In [ ]:

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

Out[ ]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
255	1	113	64	35	0	33.6	0.543	21	1
60	2	84	0	0	0	0.0	0.304	21	0
102	0	125	96	0	0	22.5	0.262	21	0
182	1	0	74	20	23	27.7	0.299	21	0
623	0	94	70	27	115	43.5	0.347	21	0
...	...	...	...	...	...	...	...	...	...
123	5	132	80	0	0	26.8	0.186	69	0
684	5	136	82	0	0	0.0	0.640	69	0
666	4	145	82	18	0	32.5	0.235	70	1
453	2	119	0	0	0	19.6	0.832	72	0
459	9	134	74	33	60	25.9	0.460	81	0

768 rows × 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.

In [ ]:

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

Dataset 4 (Mobile Phone Price)

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

Import data

In [297…

```
mobile_phone_price = pd.read_csv('https://raw.githubusercontent.com/dinhphucv/CSC-177/ma
mobile_phone_price
```

Out[297]:

	Brand	Model	Storage	RAM	Screen Size (inches)	Camera (MP)	Battery Capacity (mAh)	Price ($)
0	Apple	iPhone 13 Pro	128 GB	6 GB	6.1	12 + 12 + 12	3095	999

1	Samsung	Galaxy S21 Ultra	256 GB	12 GB	6.8	108 + 10 + 10 + 12	5000	1199
2	OnePlus	9 Pro	128 GB	8 GB	6.7	48 + 50 + 8 + 2	4500	899
3	Xiaomi	Redmi Note 10 Pro	128 GB	6 GB	6.67	64 + 8 + 5 + 2	5020	279
4	Google	Pixel 6	128 GB	8 GB	6.4	50 + 12.2	4614	799
...	...	...	...	...	...	...	...	...
402	Samsung	Galaxy Note20 5G	128	8	6.7	12+64+12	4300	1049
403	Xiaomi	Mi 10 Lite 5G	128	6	6.57	48+8+2+2	4160	349
404	Apple	iPhone 12 Pro Max	128	6	6.7	12+12+12	3687	1099
405	Oppo	Reno3	128	8	6.4	48+13+8+2	4025	429
406	Samsung	Galaxy S10 Lite	128	6	6.7	48+12+5	4500	649

407 rows × 8 columns

Concatenating

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

In [298…

```
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 ($)']
```

In [299…

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

Out[299]:

	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 × 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.

In [300…

```
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.

In [301…

```
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.

In [302…

```
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.

In [303…
```
result.insert(len(result.columns),'Price (VND)', (result['Price ($)']*24432.50).round().
result
```

Out[303]:

	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 × 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.

In [304…
```
result['RAM '] = zscore(result['RAM '])
result['Price ($)'] = zscore(result['Price ($)'])
result
```

Out[304]:

	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 × 6 columns

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

In [319…

```
diabetes = pd.read_csv('https://raw.githubusercontent.com/dinhphucv/CSC-177/main/Data%20
diabetes
```

Out[319]:

	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 [320…

```
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=1
```

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

In [323…

```
feature_columns = ['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI', 'Diabe
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: 31.301996307361723
        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: 15.694852459319481
        Testing set std: 16.729051003253563
Insulin
        Training set mean: 81.27256944444444
        Testing set mean: 75.38020833333333
        Training set std: 115.65762221613767
        Testing set std: 114.17978027672036
BMI
        Training set mean: 32.01597222222222
        Testing set mean: 31.922395833333336
        Training set std: 8.12517644550144
        Testing set std: 7.13182297466588
DiabetesPedigreeFunction
        Training set mean: 0.4719513888888889
        Testing set mean: 0.47165104166666666
        Training set std: 0.33581610557459124
        Testing set std: 0.3183402606796537
```

Mean and Std results (incase rerun change the data result):

Glucose\ **Training set mean: 120.52604166666667\ **Testing set mean: 122.0\ **Training set std: 31.301996307361723\ **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: 15.694852459319481\ **Testing set std: 16.729051003253563\ Insulin\ **Training set mean: 81.27256944444444\ **Testing set mean: 75.38020833333333\ **Training set std: 115.65762221613767\ **Testing set std: 114.17978027672036\ BMI\ **Training set mean: 32.01597222222222\ **Testing set mean: 31.922395833333336\ **Training set std: 8.12517644550144\ **Testing set std: 7.13182297466588\ DiabetesPedigreeFunction\ **Training set mean: 0.4719513888888889\ **Testing set mean: 0.47165104166666666\ **Training set std: 0.33581610557459124\ **Testing set std: 0.3183402606796537

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.