# Importing the required libraries for EDA

- # Project Title Blood Prediction by State
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#

import pandas as pd
import numpy as np
import seaborn as sns

import matplotlib.pyplot as plt

%matplotlib inline
sns.set(color\_codes=True)

Loading the data into the data frame

df= pd.read\_csv("sample\_data/State\_BD.csv")

# Display the top 5 rows
df.head(5)

	date	state	daily	blood_a	blood_b	blood_o	blood_ab	location_centre	location_mobile	type_wl
0	1/1/2006	Johor	87	19	20	45	3	87	0	
1	2/1/2006	Johor	15	4	3	6	2	15	0	
2	3/1/2006	Johor	8	2	2	4	0	8	0	
3	4/1/2006	Johor	33	7	11	12	3	33	0	
4	5/1/2006	Johor	20	3	8	8	1	20	0	



# Display the bottom 5 rows
df.tail(5)

	date	state	daily	blood_a	blood_b	blood_o	blood_ab	location_centre	location_mobile
79997	2/11/2022	W.P. Kuala Lumpur	407	100	125	175	7	87	320
79998	3/11/2022	W.P. Kuala Lumpur	368	98	117	148	5	89	279
79999	4/11/2022	W.P. Kuala Lumpur	242	62	65	106	8	123	119
80000	5/11/2022	W.P. Kuala Lumpur	817	212	243	340	22	140	677
80001	6/11/2022	W.P. Kuala Lumpur	1004	248	255	475	26	140	864



Checking the types of data

df.dtypes

date	object
state	object
daily	int64
blood_a	int64
blood_b	int64
blood_o	int64
blood_ab	int64
location_centre	int64
location_mobile	int64

```
type_wholeblood
                             int64
type_apheresis_platelet
                             int64
type_apheresis_plasma
                             int64
type_other
                             int64
social_civilian
                             int64
social_student
                             int64
social_policearmy
                             int64
{\tt donations\_new}
                             int64
donations_regular
                             int64
{\tt donations\_irregular}
                             int64
dtype: object
```

## Dropping irrelevant columns

df = df.drop(['donations\_regular', 'donations\_new','date','location\_centre', 'location\_mobile','type\_wholeblood', 'type\_apheresis\_platele
df.head(5)

	state	daily	blood_a	blood_b	blood_o	blood_ab	7
0	Johor	87	19	20	45	3	
1	Johor	15	4	3	6	2	
2	Johor	8	2	2	4	0	
3	Johor	33	7	11	12	3	
4	Johor	20	3	8	8	1	

df.shape

(80002, 6)

# Dropping the duplicate rows

```
duplicate_rows_df = df[df.duplicated()]
print("number of duplicates row:", duplicate_rows_df.shape)
```

number of duplicates row: (17332, 6)

# Count the number of rows
df.count

<bound< th=""><th>method Data</th><th>aFrame.c</th><th>ount of</th><th></th><th></th><th>state</th><th>daily</th><th>blood_a</th><th>blood_b</th><th>blood_o</th><th>blood_ab</th></bound<>	method Data	aFrame.c	ount of			state	daily	blood_a	blood_b	blood_o	blood_ab
0		Johor	87	19	20	45		3			
1		Johor	15	4	3	6		2			
2		Johor	8	2	2	4		0			
3		Johor	33	7	11	12		3			
4		Johor	20	3	8	8		1			
79997	W.P. Kuala	Lumpur	407	100	125	175		7			
79998	W.P. Kuala	Lumpur	368	98	117	148		5			
79999	W.P. Kuala	Lumpur	242	62	65	106		8			
80000	W.P. Kuala	Lumpur	817	212	243	340		22			
80001	W.P. Kuala	Lumpur	1004	248	255	475		26			

[80002 rows x 6 columns]>

df = df.drop\_duplicates()
df.head(5)

	state	daily	blood_a	blood_b	blood_o	blood_ab	•
0	Johor	87	19	20	45	3	
1	Johor	15	4	3	6	2	
2	Johor	8	2	2	4	0	
3	Johor	33	7	11	12	3	
4	Johor	20	3	8	8	1	

df.count()

state	62670
daily	62670
blood_a	62670
blood_b	62670
blood_o	62670

```
blood_ab 62670
dtype: int64
```

## Dropping the missing or null values.

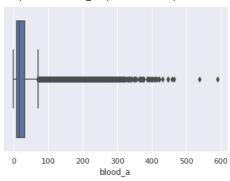
```
print(df.isnull().sum())
     state
     daily
                 0
     blood a
                 0
     blood b
                 0
     blood_o
                 0
     blood_ab
                 0
     dtype: int64
# Dropping the missing values.
df = df.dropna()
df.count()
     state
                 62670
     daily
                 62670
     blood_a
                 62670
                 62670
     blood_b
     blood_o
                 62670
     {\tt blood\_ab}
                 62670
     dtype: int64
 # After dropping the values
print(df.isnull().sum())
     state
                 0
     daily
                 0
     blood_a
                 0
                 0
     blood_b
     blood_o
                 0
     blood_ab
                 0
```

# **Detecting Outliers**

dtype: int64

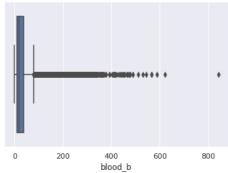
## sns.boxplot(x=df['blood\_a'])

<matplotlib.axes.\_subplots.AxesSubplot at 0x7fb16fccbe80>



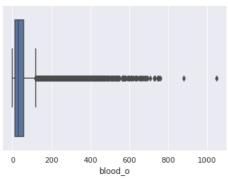
## sns.boxplot(x=df['blood\_b'])

<matplotlib.axes.\_subplots.AxesSubplot at 0x7fb16fbfbe50>



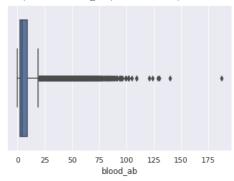
sns.boxplot(x=df['blood\_o'])

<matplotlib.axes.\_subplots.AxesSubplot at 0x7fb16f725fa0>



sns.boxplot(x=df['blood\_ab'])

<matplotlib.axes.\_subplots.AxesSubplot at 0x7fb16f6e4b80>



```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
print(IQR)
                 98.0
     daily
     blood_a
                 25.0
     blood b
                 28.0
     blood_o
                 42.0
     blood_ab
                 7.0
     dtype: float64
df = df[\sim((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).any(axis=1)]
df.shape
```

<ipython-input-19-f4e1682787c4>:1: FutureWarning: Automatic reindexing on DataFrame vs Series comparisons is deprecated and will ra  $df = df[\sim((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).any(axis=1)]$ 

(55544, 6)

# Heat Maps

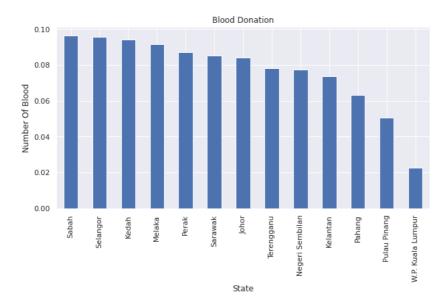
```
plt.figure(figsize=(10,5))
c= df.corr()
sns.heatmap(c,cmap="BrBG",annot=True)
```

₽

```
blood_a blood_b blood_o blood_ab blood_a 1.000000 0.897880 0.905733 0.777772 blood_b 0.897880 1.000000 0.903205 0.785168
```

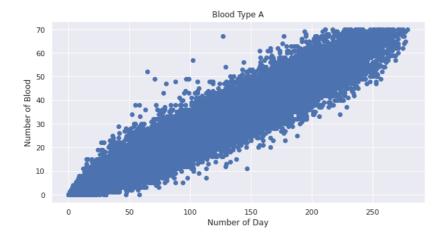
#### Histogram

```
df.state.value_counts(50).nlargest(50).plot(kind='bar', figsize=(10,5))
plt.title("Blood Donation")
plt.ylabel('Number Of Blood')
plt.xlabel('State');
```

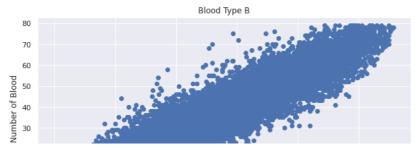


#### Scatterplot

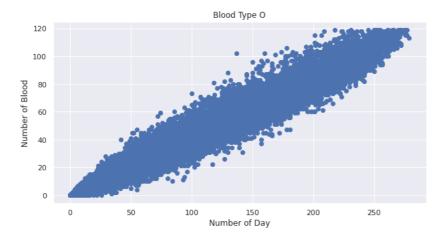
```
fig, ax = plt.subplots(figsize=(10,5))
ax.scatter(df['daily'], df['blood_a'])
ax.set_title('Blood Type A')
ax.set_xlabel('Number of Day')
ax.set_ylabel('Number of Blood')
plt.show()
```



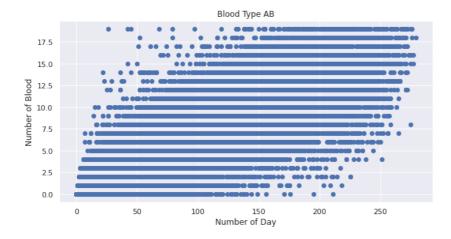
```
fig, ax = plt.subplots(figsize=(10,5))
ax.scatter(df['daily'], df['blood_b'])
ax.set_title('Blood Type B')
ax.set_xlabel('Number of Day')
ax.set_ylabel('Number of Blood')
plt.show()
```



fig, ax = plt.subplots(figsize=(10,5))
ax.scatter(df['daily'], df['blood\_o'])
ax.set\_title('Blood Type 0')
ax.set\_xlabel('Number of Day')
ax.set\_ylabel('Number of Blood')
plt.show()



fig, ax = plt.subplots(figsize=(10,5))
ax.scatter(df['daily'], df['blood\_ab'])
ax.set\_title('Blood Type AB')
ax.set\_xlabel('Number of Day')
ax.set\_ylabel('Number of Blood')
plt.show()



## NN

df.head()

	state	daily	blood_a	blood_b	blood_o	blood_ab	1
0	Johor	87	19	20	45	3	
1	Johor	15	4	3	6	2	
2	Johor	8	2	2	4	0	
3	Johor	33	7	11	12	3	
4	Johor	20	3	8	8	1	

Implementing neural network with Scikit-Learn

```
# drop daily from table
df = df.drop(['daily'], axis=1)
df.head(5)
```

	state	blood_a	blood_b	blood_o	blood_ab	1
0	Johor	19	20	45	3	
1	Johor	4	3	6	2	
2	Johor	2	2	4	0	
3	Johor	7	11	12	3	
4	Johor	3	8	8	1	

```
# Assign data from second four columns to x variables x = df.iloc[:, 1:4]
```

```
# Assign data to y variables
y = df.select_dtypes(include=[object])
```

# y.head(5)

```
state

0 Johor

1 Johor
```

- 2 Johor
- 3 Johor
- 4 Johor

#### y.tail(5)

```
79808 W.P. Kuala Lumpur
79814 W.P. Kuala Lumpur
79876 W.P. Kuala Lumpur
79996 W.P. Kuala Lumpur
79999 W.P. Kuala Lumpur
```

y.state.unique()

```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
```

```
y = y.apply(le.fit_transform)
y.state.unique()
```

```
array([ 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12])
```

## Train, test & split

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.20)
```

# Feature scaling

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(x_train)
```

```
x_{train} = scaler.transform(x_{train})
```

```
x_test = scaler.transform(x_test)
```

#### Training and predicitons

```
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(hidden_layer_sizes=(10, 10, 10), max_iter=1000)
mlp.fit(x_train, y_train.values.ravel())
```

MLPClassifier(hidden\_layer\_sizes=(10, 10, 10), max\_iter=1000)

## Making Predictions

```
predictions = mlp.predict(x_test)
```

# This is formatted as code

## Evaluating the algorithm

from sklearn.metrics import classification\_report, confusion\_matrix
print(confusion\_matrix(y\_test,predictions))
print(classification\_report(y\_test,predictions))

```
[[ 11 191 79
              26 22 42 77
                               0 195 53 161 17
                                                 391
 12 426 69
              35
                  6
                     23
                          73
                               0 117
                                     72 187
                                             13
   1 46 290 10 32 62
                           8
                               0 158
                                     66 144 13
                                                  01
  14 238 103
              49
                  30
                      57
                          81
                               0 192
                                     52 189
                                             13
                                                 25]
 [ 6 115 130
              25
                  33
                      59
                          48
                               0 182
                                     68 182 19
     75 155
              12
                  43
                      80
                          28
                               0 102
                                     64 164
   3
                                                  3]
  24 271 62
              30 18
                     24
                          81
                               0 173
                                     63 163
                                                 41]
   6 159
          20
              25
                       5
                          58
                               1 113
                                                 38]
 「 13 46
          55 26
                  13 23
                                     50 144
                                                 10]
                          45
                               1 622
  16 164 102
                                     87 189
              23
                  26
                     44
                          43
                               0 151
                                                 361
                                             13
 [ 10 182 121
                                     98 247
              27
                  32 60
                         55
                               0 191
                                             12
                                                 13]
   2 150 120
             13
                  30 78
                          33
                               0 103
                                     90 219
                                                  01
                                              0 57]]
   4 94
           1
              19
                   1
                       2
                          22
                               1 26
                                      6
                                          8
             precision
                          recall f1-score
                                            support
          0
                  0.09
                            0.01
                                      0.02
                                                913
          1
                  0.20
                            0.39
                                      0.26
                                               1087
          2
                  0.22
                            0.35
                                      0.27
                                                830
          3
                  0.15
                            0.05
                                      0.07
                                               1043
          4
                  0.11
                            0.04
                                      0.06
                                                867
          5
                            0.11
                                      0.12
                                                750
                  0.14
                                                958
          6
                  0.12
                            0.08
                                      0.10
          7
                  0.33
                            0.00
                                      0.00
                                                561
          8
                  0.27
                            0.59
                                      0.37
                                               1055
          9
                  0.11
                            0.10
                                      0.10
                                                894
          10
                  0.12
                            0.24
                                      0.16
                                               1048
                  0.15
                            0.03
                                      0.05
                                                862
          11
          12
                  0.18
                            0.24
                                      0.20
                                                241
                                      0.18
                                              11109
   accuracy
                  0.17
                            0.17
                                              11109
                                      0.14
   macro avg
weighted avg
                  0.16
                            0.18
                                      0.14
                                              11109
```