Data Wrangling II

Perform the following operations using Python on any open source dataset (eg. data.csv)

1. Scan all variables for missing values and inconsistencies. If there are missing values and/or inconsistencies, use any of the suitable techniques to deal with them.
2. Scan all numeric variables for outliers. If there are outliers, use any of the suitable techniques to deal with them.
3. Apply data transformations on at least one of the variables. The purpose of this transformation should be one of the following reasons: to change the scale for better understanding of the variable, to convert a non-linear relation into a linear one, or to decrease the skewness and convert the distribution into a normal distribution. Reason and document your approach properly

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TE B 74

1.Scan all variables for missing values and inconsistencies. If there are missing values and/or inconsistencies, use any of the suitable techniques to deal with them.

In [5]:

```
import pandas as pd
import numpy as np
student = pd.read_csv("/content/StudentsPerformance.csv")
```

In [6]:

```
student.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
 #   Column                       Non-Null Count  Dtype 
---  ------                       --------------  ----- 
 0   gender                       1000 non-null   object
 1   race/ethnicity               1000 non-null   object
 2   parental level of education  1000 non-null   object
 3   lunch                        1000 non-null   object
 4   test_preparation_course      1000 non-null   object
 5   math_score                   991 non-null    float64
 6   reading_score                995 non-null    float64
 7   writing_score                994 non-null    float64
dtypes: float64(3), object(5)
memory usage: 62.6+ KB
```

In [7]:

```
student.isnull().sum()
```

Out[7]:

```
gender                         0
race/ethnicity                 0
parental level of education    0
lunch                          0
test_preparation_course        0
math_score                     9
reading_score                  5
writing_score                  6
dtype: int64
```

In [8]:

```
#filling missing value by mean
student['math_score'].fillna(int(student['math_score'].mean()), inplace=True)
```

In [9]:

```
student.isnull().sum()
```

Out[9]:

```
gender                         0
race/ethnicity                 0
parental level of education    0
lunch                          0
test_preparation_course        0
math_score                     0
reading_score                  5
writing_score                  6
dtype: int64
```

In [10]:

```
# filling a missing value with previous ones
student['reading_score'].fillna(method ='pad',inplace=True)
```

In [11]:

```
student.isnull().sum()
```

Out[11]:

```
gender                         0
race/ethnicity                 0
parental level of education    0
lunch                          0
test_preparation_course        0
math_score                     0
reading_score                  0
writing_score                  6
dtype: int64
```

In [12]:

```
#filling missing value by median
student['writing_score'].fillna(int(student['writing_score'].median()), inplace=True)
```

In [13]:

```
student.isnull().sum()
```

Out[13]:

```
gender                         0
race/ethnicity                 0
parental level of education    0
lunch                          0
test_preparation_course        0
math_score                     0
reading_score                  0
writing_score                  0
dtype: int64
```

2.Scan all numeric variables for outliers. If there are outliers, use any of the suitable techniques to deal with them.

In [14]:

```
from numpy.random import seed
from numpy.random import randn
from numpy import mean
from numpy import std
seed(1)
#univariate dataset- single variable/ attribute
#multivariate detaset-muliple variables/attributes
data=5*randn(10000)+50

print('mean=%.3f stdv=%.3f' %(mean(data), std(data)))
```

```
mean=50.049 stdv=4.994
```

Standard Deviation Method

In [15]:

```
data_mean = mean(data)
data_std = std(data)
cut_off = data_std * 3
lower = data_mean - cut_off
upper = data_mean + cut_off
```

In [16]:

```
outliers=[x for x in data if x<lower or x > upper]
outliers
```

Out[16]:

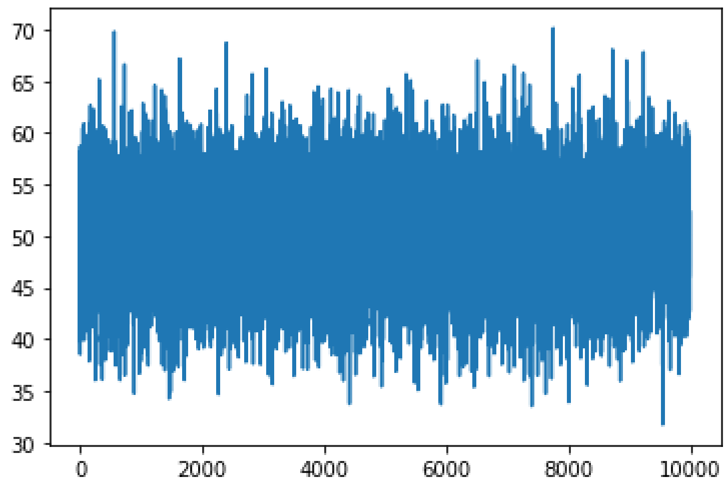
```
[65.15428556186015,
 69.79301352018982,
 66.60539378085183,
 34.73117809786848,
 34.23321274904475,
 34.91984007395351,
 67.1633171589778,
 34.679293219474495,
 68.70124451852294,
 65.67523670043954,
 66.19171598376188,
 33.73482882511691,
 65.66014864070253,
 65.06377284118616,
 34.0469182658796,
 33.6969245211173,
 67.02151137874486,
 65.59239795391275,
 66.49270261640393,
 65.74492012609815,
 33.525707966507426,
 34.72183379792847,
 70.1342452227369,
 33.90433947188079,
 65.55945915508362,
 68.06638503541573,
 66.99057828251213,
 67.80436660352774,
 31.717799503726024]
```

In [17]:

```
import matplotlib.pyplot as plt
plt.plot(data)
```

Out[17]:

```
[<matplotlib.lines.Line2D at 0x7fc37d3a07d0>]
```

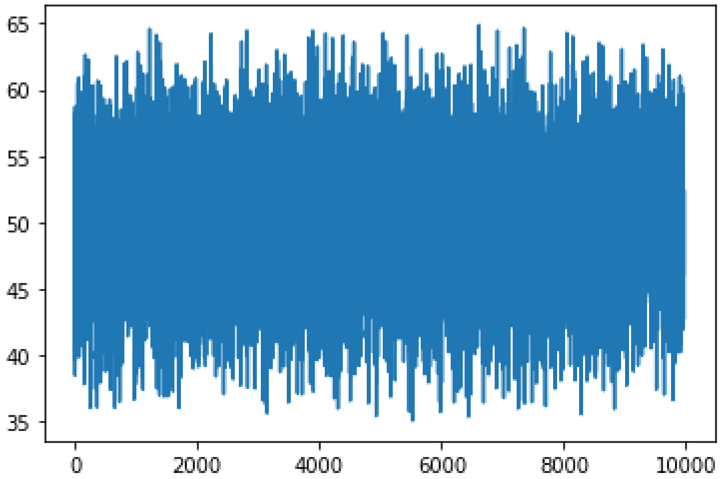


In [18]:

```
outliers_removed=[x for x in data if x>=lower and x<=upper]
plt.plot(outliers_removed)
```

Out[18]:

```
[<matplotlib.lines.Line2D at 0x7fc37d4304d0>]
```



Interquartile Range Method

In [19]:

```
from numpy.lib.function_base import percentile
q25=percentile(data,25)
q75=percentile(data,75)
IQR=q75-q25
cut_off_IQR= IQR * 2
lower=q25-cut_off_IQR
upper= q75 +cut_off_IQR
```

In [20]:

```
outliers_IQR = [x for x in data if x < lower or x > upper]
outliers_IQR
```

Out[20]:

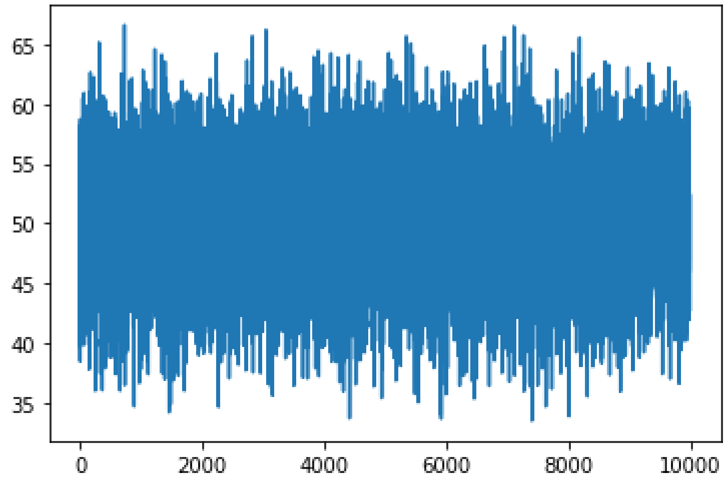
```
[69.79301352018982,
 67.1633171589778,
 68.70124451852294,
 67.02151137874486,
 70.1342452227369,
 68.06638503541573,
 66.99057828251213,
 67.80436660352774,
 31.717799503726024]
```

In [21]:

```
outliers_removed=[x for x in data if x>=lower and x<=upper]
plt.plot(outliers_removed)
```

Out[21]:

```
[<matplotlib.lines.Line2D at 0x7fc37cd8f910>]
```



3.Apply data transformations on at least one of the variables. The purpose of this transformation should be one of the following reasons: to change the scale for better understanding of the variable, to convert a non-linear relation into a linear one, or to decrease the skewness and convert the distribution into a normal distribution.

In [22]:

```
from sklearn.preprocessing import MinMaxScaler
```

In [23]:

```
mms = MinMaxScaler()
```

In [24]:

```
student[['math_score','reading_score','writing_score']] = mms.fit_transform(student[['m
ath_score','reading_score','writing_score']])
```

In [25]:

```
student.head()
```

Out[25]:

	gender	race/ethnicity	parental level of education	lunch	test_preparation_course	math_score	readi
0	female	group B	bachelor's degree	standard	none	0.72	
1	female	group C	some college	standard	completed	0.69	
2	female	group B	master's degree	standard	none	0.90	
3	male	group A	associate's degree	free/reduced	none	0.47	
4	male	group C	some college	standard	none	0.76	