#MAJOR PROJECT 1 -Choose any dataset of ur choice and apply suitable REGRESSION/CLASSIFIER
#Dataset - '/content/Asia\_cup\_1984\_to\_2018.csv'

#1.Take a dataset and create dataframe
import pandas as pd
df = pd.read\_csv("/content/Asia\_cup\_1984\_to\_2018.csv")
df

	Match id	Team_1	Team_2	Format	Ground	Year	Toss	Selection
0	1	Pakistan	Sri Lanka	ODI	Sharjah	1984	Sri Lanka	Bowling
1	2	India	Sri Lanka	ODI	Sharjah	1984	India	Bowling
2	3	India	Pakistan	ODI	Sharjah	1984	India	Batting
3	4	Sri Lanka	Pakistan	ODI	Colombo(PSS)	1986	Sri Lanka	Bowling
4	5	Bangladesh	Pakistan	ODI	Moratuwa	1986	Pakistan	Bowling
109	110	India	Pakistan	ODI	Dubai(DSC)	2018	Pakistan	Batting
110	111	Afghanistan	Bangladesh	ODI	Abu Dhabi	2018	Bangladesh	Batting
111	112	Afghanistan	India	ODI	Dubai(DSC)	2018	Afghanistan	Batting
112	113	Bangladesh	Pakistan	ODI	Abu Dhabi	2018	Bangladesh	Batting
113	114	Bangladesh	India	ODI	Dubai(DSC)	2018	India	Bowling

114 rows × 28 columns



#To display the information present in the table
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 114 entries, 0 to 113
Data columns (total 28 columns):

#	Column	Non-Null Count	Dtype
0	Match id	114 non-null	int64
1	Team_1	114 non-null	object
2	Team_2	114 non-null	object
3	Format	114 non-null	object
4	Ground	114 non-null	object
5	Year	114 non-null	int64
6	Toss	114 non-null	object
7	Selection	114 non-null	object
8	fi_score	114 non-null	float64
9	fi_wickets	114 non-null	float64
10	fi_4s	114 non-null	float64

11	fi 6c	11/	non null	£100+64
11	fi_6s		non-null	float64
12	fi_extra	114	non-null	float64
13	fi_run_rate	114	non-null	float64
14	fi_avg_str_rate	114	non-null	float64
15	fi_max_score	114	non-null	float64
16	<pre>fi_max_indv_wickets</pre>	114	non-null	float64
17	Player Of The Match	113	non-null	object
18	Result	114	non-null	object
19	si_score	114	non-null	float64
20	si_wickets	114	non-null	float64
21	si_4s	114	non-null	float64
22	si_6s	114	non-null	float64
23	si_extras	114	non-null	float64
24	si_run_rate	114	non-null	float64
25	si_avg_str_rate	114	non-null	float64
26	<pre>si_max_indv_wickets</pre>	114	non-null	float64
27	<pre>si_max_indv_wickets.1</pre>	114	non-null	float64
dtype	es: float64(18), int64(	2), (	object(8)	

memory usage: 25.1+ KB

df.shape #114 rows and 28 columns

(114, 28)

df.size #total no of elements

3192

#To check the number to null values present df.isnull()

	Match id	Team_1	Team_2	Format	Ground	Year	Toss	Selection	fi_score	fi_wicl
0	False	False	False	False	False	False	False	False	False	F
1	False	False	False	False	False	False	False	False	False	F
2	False	False	False	False	False	False	False	False	False	F
3	False	False	False	False	False	False	False	False	False	F
4	False	False	False	False	False	False	False	False	False	F
109	False	False	False	False	False	False	False	False	False	F
110	False	False	False	False	False	False	False	False	False	F
111	False	False	False	False	False	False	False	False	False	F
112	False	False	False	False	False	False	False	False	False	F
113	False	False	False	False	False	False	False	False	False	F

114 rows × 28 columns

# To display 1st 5 rows indexes
df.head()

	Match id	Team_1	Team_2	Format	Ground	Year	Toss	Selection	fi_scc
0	1	Pakistan	Sri Lanka	ODI	Sharjah	1984	Sri Lanka	Bowling	18
1	2	India	Sri Lanka	ODI	Sharjah	1984	India	Bowling	9.
2	3	India	Pakistan	ODI	Sharjah	1984	India	Batting	18
3	4	Sri Lanka	Pakistan	ODI	Colombo(PSS)	1986	Sri Lanka	Bowling	110
4	5	Bangladesh	Pakistan	ODI	Moratuwa	1986	Pakistan	Bowling	9,

5 rows × 28 columns

#To display last 5 row indexes
df.tail()

	Match id	Team_1	Team_2	Format	Ground	Year	Toss	Selection	f
109	110	India	Pakistan	ODI	Dubai(DSC)	2018	Pakistan	Batting	
110	111	Afghanistan	Bangladesh	ODI	Abu Dhabi	2018	Bangladesh	Batting	
111	112	Afghanistan	India	ODI	Dubai(DSC)	2018	Afghanistan	Batting	
112	113	Bangladesh	Pakistan	ODI	Abu Dhabi	2018	Bangladesh	Batting	
113	114	Bangladesh	India	ODI	Dubai(DSC)	2018	India	Bowling	

5 rows × 28 columns

#2.preprocessing - Filtering of Data(to remove Format columns)
df\_numeric = df\_numeric.drop(['Match id'],axis =1)#axis = 1 -column,axis = 0 -row
df\_numeric

	Year	fi_score	fi_wickets	fi_4s	fi_6s	fi_extra	fi_run_rate	fi_avg_str_rat
0	1984	187.0	9.0	9.0	3.0	21.0	4.06	52.04
1	1984	97.0	0.0	9.0	0.0	14.0	4.47	60.48
2	1984	188.0	4.0	13.0	3.0	17.0	4.08	60.2
3	1986	116.0	10.0	10.0	0.0	14.0	3.42	37.8
4	1986	94.0	10.0	0.0	0.0	9.0	2.64	24.6
109	2018	238.0	1.0	24.0	6.0	1.0	6.02	91.3
110	2018	246.0	7.0	20.0	3.0	8.0	4.92	76.19
111	2018	252.0	8.0	17.0	11.0	7.0	5.04	54.19
112	2018	239.0	10.0	17.0	1.0	9.0	4.89	73.23
113	2018	222.0	10.0	17.0	4.0	7.0	4.57	49.98

114 rows × 19 columns

#We want to consider only the numeric data
#so we will create a new dataframe with only numeric data
df\_numeric = df.select\_dtypes(include = ['float64','int64'])
df\_numeric

	Match id	Year	fi_score	fi_wickets	fi_4s	fi_6s	fi_extra	fi_run_rate	fi_avg_
0	1	1984	187.0	9.0	9.0	3.0	21.0	4.06	
1	2	1984	97.0	0.0	9.0	0.0	14.0	4.47	
2	3	1984	188.0	4.0	13.0	3.0	17.0	4.08	
3	4	1986	116.0	10.0	10.0	0.0	14.0	3.42	
4	5	1986	94.0	10.0	0.0	0.0	9.0	2.64	
								•••	
109	110	2018	238.0	1.0	24.0	6.0	1.0	6.02	
110	111	2018	246.0	7.0	20.0	3.0	8.0	4.92	
111	112	2018	252.0	8.0	17.0	11.0	7.0	5.04	
112	113	2018	239.0	10.0	17.0	1.0	9.0	4.89	
113	114	2018	222.0	10.0	17.0	4.0	7.0	4.57	

114 rows × 20 columns

#To display the table information which contains only numeric data
df numeric.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 114 entries, 0 to 113
Data columns (total 20 columns):

#	Column	Non-Null Count	Dtype
0	Match id	114 non-null	int64
1	Year	114 non-null	int64
2	fi_score	114 non-null	float64
3	fi_wickets	114 non-null	float64
4	fi_4s	114 non-null	float64
5	fi_6s	114 non-null	float64
6	fi_extra	114 non-null	float64
7	fi_run_rate	114 non-null	float64
8	fi_avg_str_rate	114 non-null	float64
9	fi_max_score	114 non-null	float64
10	<pre>fi_max_indv_wickets</pre>	114 non-null	float64
11	si_score	114 non-null	float64
12	si_wickets	114 non-null	float64
13	si_4s	114 non-null	float64
14	si_6s	114 non-null	float64
15	si_extras	114 non-null	float64
16	si_run_rate	114 non-null	float64
17	si_avg_str_rate	114 non-null	float64
18	si_max_indv_wickets	114 non-null	float64
19	<pre>si_max_indv_wickets.1</pre>	114 non-null	float64
		- •	

dtypes: float64(18), int64(2)

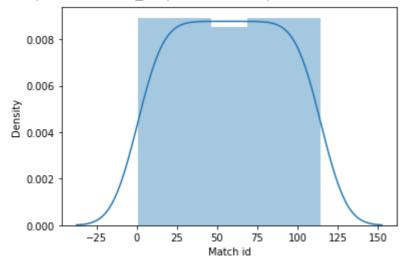
memory usage: 17.9 KB

## **#VISUALIZATION**

import seaborn as sns
sns.distplot(df['Match id'])# # distribution plot

/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: warnings.warn(msg, FutureWarning)

<matplotlib.axes.\_subplots.AxesSubplot at 0x7fe1c9426590>



#4.divide the data into i/p and o/p
#output - Smog\_level

```
#input - All the columns except the Smog_level column
x = df_numeric.iloc[:,0:6].values
```

```
array([[1.000e+00, 1.984e+03, 1.870e+02, 9.000e+00, 9.000e+00, 3.000e+00],
       [2.000e+00, 1.984e+03, 9.700e+01, 0.000e+00, 9.000e+00, 0.000e+00],
       [3.000e+00, 1.984e+03, 1.880e+02, 4.000e+00, 1.300e+01, 3.000e+00],
       [4.000e+00, 1.986e+03, 1.160e+02, 1.000e+01, 1.000e+01, 0.000e+00],
       [5.000e+00, 1.986e+03, 9.400e+01, 1.000e+01, 0.000e+00, 0.000e+00],
       [6.000e+00, 1.986e+03, 1.320e+02, 3.000e+00, 0.000e+00, 0.000e+00],
       [7.000e+00, 1.986e+03, 1.950e+02, 5.000e+00, 1.500e+01, 1.000e+00],
       [8.000e+00, 1.988e+03, 1.940e+02, 7.000e+00, 5.000e+00, 0.000e+00],
       [9.000e+00, 1.988e+03, 9.900e+01, 8.000e+00, 5.000e+00, 0.000e+00],
       [1.000e+01, 1.988e+03, 2.540e+02, 1.000e+01, 1.400e+01, 4.000e+00],
       [1.100e+01, 1.988e+03, 1.110e+02, 6.000e+00, 0.000e+00, 0.000e+00],
       [1.200e+01, 1.988e+03, 1.430e+02, 6.000e+00, 8.000e+00, 0.000e+00],
       [1.300e+01, 1.988e+03, 1.180e+02, 8.000e+00, 0.000e+00, 0.000e+00],
       [1.400e+01, 1.988e+03, 1.800e+02, 4.000e+00, 1.000e+01, 3.000e+00],
       [1.500e+01, 1.990e+03, 1.710e+02, 1.000e+00, 1.200e+01, 3.000e+00],
       [1.600e+01, 1.990e+03, 1.780e+02, 1.000e+01, 9.000e+00, 0.000e+00],
       [1.700e+01, 1.990e+03, 1.780e+02, 9.000e+00, 0.000e+00, 0.000e+00],
       [1.800e+01, 1.991e+03, 2.050e+02, 3.000e+00, 7.000e+00, 1.000e+00],
       [1.900e+01, 1.995e+03, 1.630e+02, 1.000e+01, 1.200e+01, 1.000e+00],
       [2.000e+01, 1.995e+03, 1.260e+02, 1.000e+01, 8.000e+00, 0.000e+00],
       [2.100e+01, 1.995e+03, 1.690e+02, 1.000e+01, 1.100e+01, 2.000e+00],
       [2.200e+01, 1.995e+03, 1.510e+02, 8.000e+00, 7.000e+00, 0.000e+00],
       [2.300e+01, 1.995e+03, 2.060e+02, 2.000e+00, 2.400e+01, 1.000e+00],
       [2.400e+01, 1.995e+03, 1.780e+02, 9.000e+00, 5.000e+00, 3.000e+00],
       [2.500e+01, 1.995e+03, 2.330e+02, 2.000e+00, 1.500e+01, 2.000e+00],
       [2.600e+01, 1.997e+03, 2.390e+02, 1.000e+01, 9.000e+00, 1.000e+00],
       [2.700e+01, 1.997e+03, 2.100e+02, 1.000e+01, 1.500e+01, 1.000e+00],
       [2.800e+01, 1.997e+03, 2.310e+02, 4.000e+00, 2.300e+01, 0.000e+00],
       [2.900e+01, 1.997e+03, 0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00],
       [3.000e+01, 1.997e+03, 2.960e+02, 4.000e+00, 3.100e+01, 4.000e+00],
       [3.100e+01, 1.997e+03, 1.300e+02, 8.000e+00, 1.000e+01, 0.000e+00],
       [3.200e+01, 1.997e+03, 2.400e+02, 2.000e+00, 1.900e+01, 6.000e+00],
       [3.300e+01, 2.000e+03, 1.750e+02, 6.000e+00, 8.000e+00, 1.000e+00],
       [3.400e+01, 2.000e+03, 2.490e+02, 6.000e+00, 1.700e+01, 4.000e+00],
       [3.500e+01, 2.000e+03, 2.050e+02, 1.000e+01, 1.800e+01, 2.000e+00],
       [3.600e+01, 2.000e+03, 8.700e+01, 1.000e+01, 7.000e+00, 0.000e+00],
       [3.700e+01, 2.000e+03, 2.510e+02, 1.000e+01, 1.900e+01, 4.000e+00],
       [3.800e+01, 2.000e+03, 1.930e+02, 3.000e+00, 1.400e+01, 3.000e+00],
       [3.900e+01, 2.000e+03, 2.770e+02, 4.000e+00, 1.600e+01, 6.000e+00],
       [4.000e+01, 2.004e+03, 2.210e+02, 9.000e+00, 1.500e+01, 0.000e+00],
       [4.100e+01, 2.004e+03, 2.600e+02, 6.000e+00, 1.700e+01, 1.000e+00],
       [4.200e+01, 2.004e+03, 1.810e+02, 1.000e+01, 1.300e+01, 1.000e+00],
       [4.300e+01, 2.004e+03, 2.390e+02, 1.000e+01, 2.000e+01, 1.000e+00],
       [4.400e+01, 2.004e+03, 1.650e+02, 1.000e+01, 1.700e+01, 1.000e+00],
       [4.500e+01, 2.004e+03, 2.820e+02, 4.000e+00, 1.900e+01, 3.000e+00],
       [4.600e+01, 2.004e+03, 1.770e+02, 1.000e+01, 9.000e+00, 2.000e+00],
       [4.700e+01, 2.004e+03, 1.230e+02, 3.000e+00, 1.000e+01, 0.000e+00],
       [4.800e+01, 2.004e+03, 1.910e+02, 0.000e+00, 1.500e+01, 0.000e+00],
       [4.900e+01, 2.004e+03, 2.410e+02, 8.000e+00, 1.800e+01, 1.000e+00],
       [5.000e+01, 2.004e+03, 2.670e+02, 9.000e+00, 2.000e+01, 3.000e+00],
       [5.100e+01, 2.004e+03, 1.660e+02, 1.000e+01, 1.200e+01, 0.000e+00],
       [5.200e+01, 2.004e+03, 2.280e+02, 9.000e+00, 1.800e+01, 0.000e+00],
       [5.300e+01, 2.008e+03, 3.000e+02, 8.000e+00, 2.200e+01, 1.000e+00],
       [5.400e+01, 2.008e+03, 2.880e+02, 9.000e+00, 3.000e+01, 1.000e+00],
       [5.500e+01, 2.008e+03, 2.260e+02, 7.000e+00, 1.300e+01, 2.000e+00],
```

```
[5.600e+01, 2.008e+03, 1.180e+02, 1.000e+01, 1.700e+01, 0.000e+00],
            [5.700e+01, 2.008e+03, 2.990e+02, 4.000e+00, 3.300e+01, 1.000e+00],
y = df_numeric.iloc[:,6]
У
            21.0
     1
            14.0
     2
            17.0
     3
            14.0
     4
             9.0
            . . .
     109
             1.0
     110
             8.0
     111
             7.0
     112
             9.0
             7.0
     113
     Name: fi_extra, Length: 114, dtype: float64
#5.TRAIN AND TEST VARIABLES
#sklearn.model_seletion - package , train_test_split - library
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,random_state = 0)
#whatever data splitting/data allocation happens to the x_train,x_test,y_train,y_test vari
#By default the training variables get 75% and testing variables get 25%
print(x.shape) #114 rows and 28 columns
print(x_train.shape) #114 rows and columns (75%)
print(y_test.shape) # 114 rows and 28 cos(25%)
     (114, 6)
     (85, 6)
     (29,)
print(y.shape) #114 rows and 28 cos
print(y train.shape) #114 rows and 28 cols (75%)
print(y_test.shape) # 114 rows and 28 cols (25%)
     (114,)
     (85,)
     (29,)
#6.SCALING or NORMALISATION -DONE ONLY FOR INPUTS
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.fit_transform(x_test)
```

```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
#8.MODEL FITTING
model.fit(x_train,y_train)
     LinearRegression()
#9.PREDICT THE OUTPUT
y_pred = model.predict(x_test)# By taking the input testing data, we predict the output
y pred # PREDICTED VALUES
     array([19.20388763, 11.74969049, 7.97064147, 16.22057976, 14.96798661,
            13.86047521, 4.04739576, 11.35167488, 5.95182177, 11.66279533,
            15.61103646, 9.74944617, 13.46438146, 10.69219968, 2.40998563,
             2.08202763, 17.18781815, 12.18514381, 15.81112326, 11.79051201,
            18.31871304, 4.35290049, 17.39604029, 12.82253352, 15.5967685,
            11.23292956, 11.81577119, 4.11380785, 5.55326804])
y_test # ACTUAL VALUES
     33
            17.0
     10
            15.0
     90
            10.0
     7
             7.0
     24
             9.0
     73
            14.0
     113
            7.0
     22
            17.0
     94
            4.0
     2
            17.0
     48
            38.0
     89
            6.0
     51
            32.0
     71
            18.0
     105
            4.0
     93
            14.0
     59
            3.0
            21.0
     66
     16
            20.0
     13
            12.0
            24.0
     68
     106
            7.0
     26
            18.0
     50
            37.0
     82
            11.0
     8
            13.0
     30
            19.0
     102
             4.0
     91
             5.0
     Name: fi_extra, dtype: float64
print(x_train[10]) # these are scaled/normalised values
```

https://colab.research.google.com/drive/1dBBOL\_TAkkbb0stNCtlLuAlgX307yeM6#scrollTo=Lu7MLi1k2avG&printMode=true

0.4

0.97142857 0.36363636]

[0.67857143 0.82352941 1.

8/9

#INDIVIDUAL PREDICTION
model.predict([x\_train[10]])

array([12.96713636])

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