```
# MAJOR PROJECT 1 - Choose any dataset 0f your choice and apply suitable REGRESSOR/CLAS
#Dataset -'/content/TikTok_songs_2020.csv'
```

```
#1.Take a dataset and create dataframe
import pandas as pd
df = pd.read_csv("/content/TikTok_songs_2020.csv")
df
```

	track_name	artist_name	artist_pop	album	track_pop	danceability	energy
0	Say So	Doja Cat	88	Hot Pink	80	0.787	0.673
1	Blinding Lights	The Weeknd	93	After Hours	90	0.514	0.730
2	Supalonely (feat. Gus Dapperton)	BENEE	67	Hey u x	63	0.862	0.631
3	Savage	Megan Thee Stallion	82	Suga	70	0.843	0.741
4	Moral of the Story	Ashe	68	Moral of the Story	76	0.572	0.406
...	...	...	...	...	...	...	...
287	Buttons	The Pussycat Dolls	68	PCD	65	0.570	0.821
288	Get Busy	Sean Paul	79	Dutty Rock	74	0.735	0.824
289	ROCKSTAR (feat. Roddy Ricch)	DaBaby	82	BLAME IT ON BABY	80	0.746	0.690
290	Who Says	Selena Gomez & The Scene	67	When The Sun Goes Down	76	0.682	0.927
291	Crystal Dolphin	Engelwood	50	Crust FM	60	0.558	0.776

292 rows × 18 columns

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 292 entries, 0 to 291
Data columns (total 18 columns):
```

```
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   track_name        292 non-null    object 
 1   artist_name       292 non-null    object 
 2   artist_pop        292 non-null    int64  
 3   album             292 non-null    object 
 4   track_pop         292 non-null    int64  
 5   danceability      292 non-null    float64
 6   energy            292 non-null    float64
 7   loudness          292 non-null    float64
 8   mode              292 non-null    int64  
 9   key               292 non-null    int64  
 10  speechiness       292 non-null    float64
 11  acousticness      292 non-null    float64
 12  instrumentalness  292 non-null    float64
 13  liveness          292 non-null    float64
 14  valence           292 non-null    float64
 15  tempo             292 non-null    float64
 16  time_signature    292 non-null    int64  
 17  duration_ms       292 non-null    int64  
dtypes: float64(9), int64(6), object(3)
memory usage: 41.2+ KB
```

```
df.shape
```

```
(292, 18)
```

```
df.size
```

```
5256
```

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

track_name	artist_name	artist_pop	album	track_pop	danceability	energy

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

	track_name	artist_name	artist_pop	album	track_pop	danceability	energy
0	Say So	Doja Cat	88	Hot Pink	80	0.787	0.673
1	Blinding Lights	The Weeknd	93	After Hours	90	0.514	0.730
2	Supalonely (feat. Gus Dapperton)	BENEE	67	Hey u x	63	0.862	0.631
3	Savage	Megan Thee Stallion	82	Suga	70	0.843	0.741
4	Moral of the Story	Ashe	68	Moral of the Story	76	0.572	0.406

```
#To display last 5 row indexes
df.tail
```

```
<bound method NDFrame.tail of                              track_name
artist_name  artist_pop  \
0                                 Say So                    Doja Cat          88
1                        Blinding Lights                 The Weeknd          93
2     Supalonely (feat. Gus Dapperton)                      BENEE          67
3                                 Savage         Megan Thee Stallion          82
4                     Moral of the Story                       Ashe          68
..                                   ...                         ...         ...
287                              Buttons          The Pussycat Dolls          68
288                             Get Busy                  Sean Paul          79
289         ROCKSTAR (feat. Roddy Ricch)                     DaBaby          82
290                            Who Says  Selena Gomez & The Scene          67
291                      Crystal Dolphin                  Engelwood          50

                     album  track_pop  danceability  energy  loudness  mode  \
0                 Hot Pink         80         0.787   0.673    -4.583     0
1              After Hours         90         0.514   0.730    -5.934     1
2                  Hey u x         63         0.862   0.631    -4.746     1
3                     Suga         70         0.843   0.741    -5.609     1
4       Moral of the Story         76         0.572   0.406    -8.624     1
..                     ...        ...           ...     ...       ...   ...
287                    PCD         65         0.570   0.821    -4.380     1
288             Dutty Rock         74         0.735   0.824    -4.143     0
289         BLAME IT ON BABY         80         0.746   0.690    -7.956     1
290  When The Sun Goes Down         76         0.682   0.927    -2.915     1
291                Crust FM         60         0.558   0.776    -6.868     1

     key  speechiness  acousticness  instrumentalness  liveness  valence  \
0     11       0.1590       0.26400          0.000003    0.0904    0.779
```

```
1      1       0.0598       0.00146          0.000095    0.0897    0.334
2      7       0.0515       0.29100          0.000209    0.1230    0.841
3     11       0.3340       0.02520          0.000000    0.0960    0.680
4     10       0.0427       0.58700          0.000004    0.1020    0.265
..   ...          ...           ...               ...       ...      ...
287    2       0.2670       0.17800          0.000000    0.2890    0.408
288   10       0.0360       0.61500          0.000000    0.1580    0.726
289   11       0.1640       0.24700          0.000000    0.1010    0.497
290    4       0.0479       0.08430          0.000000    0.1490    0.744
291    9       0.1790       0.33000          0.000445    0.4100    0.247

       tempo  time_signature  duration_ms
0    110.962               4       237893
1    171.005               4       200040
2    128.978               4       223488
3    168.983               4       155497
4    119.812               4       201084
..       ...             ...          ...
287  210.857               4       225560
288  100.202               4       211666
289   89.977               4       181733
290  101.019               4       195613
291  128.064               4       114660

[292 rows x 18 columns]>
```

```
#We want to consider only the numeric data
#So we will create a new dataframe with only numeruic data
df_numeric = df.select_dtypes(include = ['float64','int64'])
df_numeric
```

	artist_pop	track_pop	danceability	energy	loudness	mode	key	speechine
0	88	80	0.787	0.673	-4.583	0	11	0.15
1	93	90	0.514	0.730	-5.934	1	1	0.05
2	67	63	0.862	0.631	-4.746	1	7	0.05
3	82	70	0.843	0.741	-5.609	1	11	0.33
4	68	76	0.572	0.406	-8.624	1	10	0.04
...	...	...	...	...	...	...	...	
287	68	65	0.570	0.821	-4.380	1	2	0.26
288	79	74	0.735	0.824	-4.143	0	10	0.03
289	82	80	0.746	0.690	-7.956	1	11	0.16
290	67	76	0.682	0.927	-2.915	1	4	0.04
291	50	60	0.558	0.776	-6.868	1	9	0.17

292 rows × 15 columns

```
#Now we have to drop or remove the artist_pop and Symbling column
```

```
df_numeric = df_numeric.drop(['artist_pop'],axis = 1)#axis = 1 - column,axis = 0 - rows
df_numeric
```

	track_pop	danceability	energy	loudness	mode	key	speechiness	acoustic
0	80	0.787	0.673	-4.583	0	11	0.1590	0.2
1	90	0.514	0.730	-5.934	1	1	0.0598	0.0
2	63	0.862	0.631	-4.746	1	7	0.0515	0.2
3	70	0.843	0.741	-5.609	1	11	0.3340	0.0
4	76	0.572	0.406	-8.624	1	10	0.0427	0.5
...	...	...	...	...	...	...	...	
287	65	0.570	0.821	-4.380	1	2	0.2670	0.1
288	74	0.735	0.824	-4.143	0	10	0.0360	0.6
289	80	0.746	0.690	-7.956	1	11	0.1640	0.2
290	76	0.682	0.927	-2.915	1	4	0.0479	0.0
291	60	0.558	0.776	-6.868	1	9	0.1790	0.3

292 rows × 14 columns

```
df_numeric.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 292 entries, 0 to 291
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   track_pop         292 non-null    int64  
 1   danceability      292 non-null    float64
 2   energy            292 non-null    float64
 3   loudness          292 non-null    float64
 4   mode              292 non-null    int64  
 5   key               292 non-null    int64  
 6   speechiness       292 non-null    float64
 7   acousticness      292 non-null    float64
 8   instrumentalness  292 non-null    float64
 9   liveness          292 non-null    float64
 10  valence           292 non-null    float64
 11  tempo             292 non-null    float64
 12  time_signature    292 non-null    int64  
 13  duration_ms       292 non-null    int64  
dtypes: float64(9), int64(5)
memory usage: 32.1 KB
```

```
#divide the data into i/p and o/p
#output - track_name
#input - All the columns expect the track_name column
```

```
x = df_numeric.iloc[:,0:13].values
x
```

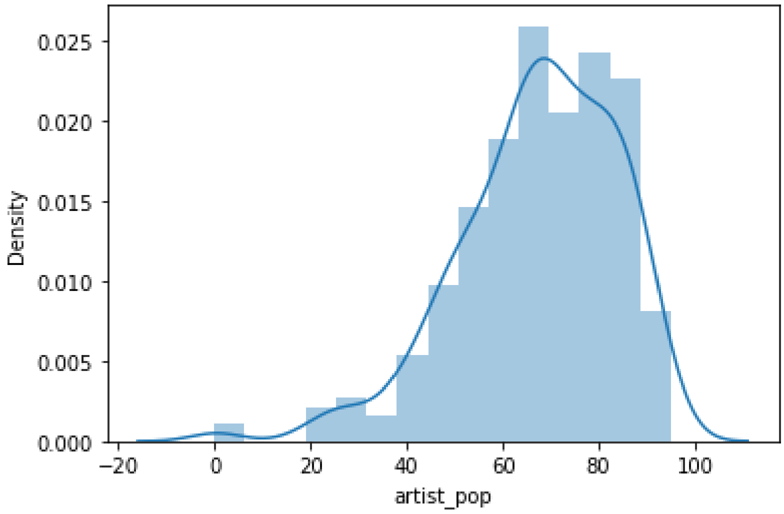
```
array([[ 80.   ,   0.787,   0.673, ...,   0.779, 110.962,   4.   ],
       [ 90.   ,   0.514,   0.73 , ...,   0.334, 171.005,   4.   ],
       [ 63.   ,   0.862,   0.631, ...,   0.841, 128.978,   4.   ],
       ...,
       [ 80.   ,   0.746,   0.69 , ...,   0.497,  89.977,   4.   ],
       [ 76.   ,   0.682,   0.927, ...,   0.744, 101.019,   4.   ],
       [ 60.   ,   0.558,   0.776, ...,   0.247, 128.064,   4.   ]])
```

```
y = df_numeric.iloc[:,13].values
y
```

```
array([237893, 200040, 223488, 155497, 201084, 182200, 161733, 186653,
       170746, 193829, 180147, 210463, 228482, 221820, 223270, 193208,
       216320, 208026, 224661, 158571, 164113, 160000, 188293, 151018,
       164318, 154455, 128926, 106016, 218707, 177856, 179867, 157606,
       154424, 165726, 194253, 170947, 187571, 182693, 173333, 129241,
       239560, 147692, 197217, 147800, 218107, 141673, 176547, 210000,
       222961, 171375, 144013, 141224, 284480, 116630, 386907, 196520,
       154550, 140533, 136839, 134240, 159382, 390639, 242133, 196893,
       205733, 198040, 203093, 162547, 284733, 145920, 163173, 214558,
       133995, 165853, 220779, 163636, 177493, 140527, 195493, 215307,
       237800, 179125, 183290, 194000, 190920, 160097, 215320, 219813,
       205733, 221075, 251013, 110063, 153800,  80842, 232907, 192080,
       238507, 137744, 206221, 263173, 221253, 156443, 216267, 303373,
       224955, 281313, 319467, 159955, 178000, 184060, 205200, 147697,
       157712, 233228, 223258, 177479,  52867, 351467, 154787, 112493,
       116757, 149145, 144935, 229671, 179871, 168387, 137595, 208867,
       242327, 265263, 202667, 177866, 163173, 235988, 235320, 196653,
       230657, 160627,  61466, 100000, 258453, 143613, 180231, 115227,
       281080, 177323, 311867, 167916, 229670, 215200, 166857, 196800,
       195631, 171980, 208729, 248133, 115352, 163902, 200947, 247059,
       176840, 154424, 176960, 260640, 148040, 261880, 272507,  83940,
       200774, 164640, 174000, 278719, 165733, 142044, 232187, 266840,
       210285, 346436, 146523, 197213, 195213, 383547, 219427, 155867,
       204533, 154456, 117363, 215627, 148640, 132303, 174933, 229147,
       216013, 232368, 197933, 144000, 220487,  37632, 160907, 165391,
       279240, 229640, 242001, 180139, 220587, 118075, 177773, 249280,
       230895, 107404, 195429, 181852, 186467, 139413, 237493, 200307,
       115200, 215387, 227267, 157507, 209848, 165938,  68586, 158436,
       209709, 176787, 135016, 180672, 235767, 228173, 253107, 154567,
        60000, 118776, 151579, 166627, 248056, 234093, 153294, 214227,
       205333, 234945, 129371, 207747, 176640, 179133, 163019, 205296,
       276333, 109595, 210329, 235988,  77049, 187709, 223080, 164880,
       467587, 195429, 192177, 209274, 175467, 201990, 250337, 202907,
       223747, 191340, 110253, 337640, 215507, 173938, 188735, 292799,
       163574, 139741, 169020, 320680, 211150, 180161, 158707, 151520,
       246765, 177280, 244760, 279307, 204760, 205347, 206227, 225560,
       211666, 181733, 195613, 114660])
```

```
#3.VISUALIZATION
import seaborn as sns
sns.distplot(df['artist_pop']) #distribution plot
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWar
  warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7faf9f5c5a10>
```




```
#5.TRAIN and TEST VARIABLES
#sklearn.model_selection - 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 spliting /data allocation happens to the xtrain,x_test,ytrain,ytest vari
#By default the training variables get 75% and testing variables get 25%
```

```
print(x.shape) # 266 rows and 64 columns
print(x_train.shape) # 266 rows and 64 columns (75%)
print(x_test.shape) #266 rows and 32 columns (25%)
```

```
(292, 13)
(219, 13)
(73, 13)
```

```
print(y.shape) #266 rows and 64 columns
print(y_train.shape) #266 rows and 32 colomns (75%)
print(y_test.shape) #266 rows and 32 columns (25%)
```

```
(292,)
(219,)
(73,)
```

```
#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)
```

```
#7.RUN a CLASSIFIER/REGRESSOR/CLUSTERER
from sklearn.linear_model import LinearRegression
model = LinearRegression()
```

```
#8.MODEL FITTING
model.fit(x_train,y_train)
LinearRegression()
```

```
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([204420.76687172, 216621.10522868, 208073.36797116, 246354.63809667,
       220146.06293435, 221457.776425  , 202256.96397327, 180060.96331067,
       222773.44765844, 203117.43492293, 205305.97415318, 214444.17428759,
       165198.66443648, 190373.63953747, 211258.7871104 , 184373.3828675 ,
       211299.93010078, 215797.39363239, 224538.70327434, 220099.80843492,
       187545.67710525, 181169.92456849, 202798.5106638 , 214565.92476261,
       214321.50733066, 198679.51941993, 241930.55317749, 228819.43613548,
       187715.79352519, 254831.15407891, 304728.76458028, 237635.67552424,
       223054.16452454, 218854.79674282, 138766.96731257, 199836.03011388,
       222507.34597188, 186447.29361802, 256415.93793059, 215079.95861074,
       248529.3187128 , 206731.81982134, 243189.24434733, 176504.7022658 ,
       210605.28735211, 203868.54740158, 219477.61410327, 179044.4868585 ,
       225459.81743229, 203068.40545753, 207234.80714253, 242456.44731681,
       240337.10435598, 226810.86969058, 228362.27868767, 194909.00790559,
       208440.3316457 , 208717.5513641 , 223399.11637441, 242725.35693852,
       167886.82690319, 218129.9774878 , 169912.06323051, 229476.85836141,
       236688.03628033, 189692.67646151, 213919.36892938, 208164.26354881,
       233804.34862707, 222909.42740046, 215731.32444599, 211330.09283443,
       179548.42355043])
```

```
print(x_train[10]) #these are scaled/normalised values
```

```
[0.83333333 0.25062035 0.43451708 0.81342339 0.         0.
 0.00760586 0.09266437 0.         0.07275181 0.09708006 0.04088615
 0.5       ]
```

```
#INDIVIDUAL PREDICTION
model.predict([x_train[10]])
```

```
array([252781.42545176])
```