```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt



import seaborn as sns

df=pd.read_csv('https://raw.githubusercontent.com/YBI-Foundation/Dataset/main/MPG.csv')

df
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year
0	18.0	8	307.0	130.0	3504	12.0	70
1	15.0	8	350.0	165.0	3693	11.5	70
2	18.0	8	318.0	150.0	3436	11.0	70
3	16.0	8	304.0	150.0	3433	12.0	70
4	17.0	8	302.0	140.0	3449	10.5	70
...	...	...	...	...	...	...	...
393	27.0	4	140.0	86.0	2790	15.6	82

```
df.head()
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year	or
0	18.0	8	307.0	130.0	3504	12.0	70	
1	15.0	8	350.0	165.0	3693	11.5	70	

```
df.nunique()
```

```
mpg             129
cylinders         5
displacement     82
horsepower       93
weight          351
acceleration     95
model_year       13
origin            3
name            305
dtype: int64
```

```
#data Preprocessing
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64
 2   displacement  398 non-null    float64
 3   horsepower    392 non-null    float64
 4   weight        398 non-null    int64
 5   acceleration  398 non-null    float64
 6   model_year    398 non-null    int64
 7   origin        398 non-null    object
 8   name          398 non-null    object
dtypes: float64(4), int64(3), object(2)
memory usage: 28.1+ KB
```

```
df.describe()  #summary statistics
```

	mpg	cylinders	displacement	horsepower	weight	acceleration
count	398.000000	398.000000	398.000000	392.000000	398.000000	398.000000
mean	23.514573	5.454774	193.425879	104.469388	2970.424623	15.568090
std	7.815984	1.701004	104.269838	38.491160	846.841774	2.757689
min	9.000000	3.000000	68.000000	46.000000	1613.000000	8.000000
25%	17.500000	4.000000	104.250000	75.000000	2223.750000	13.825000
50%	23.000000	4.000000	148.500000	93.500000	2803.500000	15.500000
75%	29.000000	8.000000	262.000000	126.000000	3608.000000	17.175000
max	46.600000	8.000000	455.000000	230.000000	5140.000000	24.800000

```
df.corr()
```

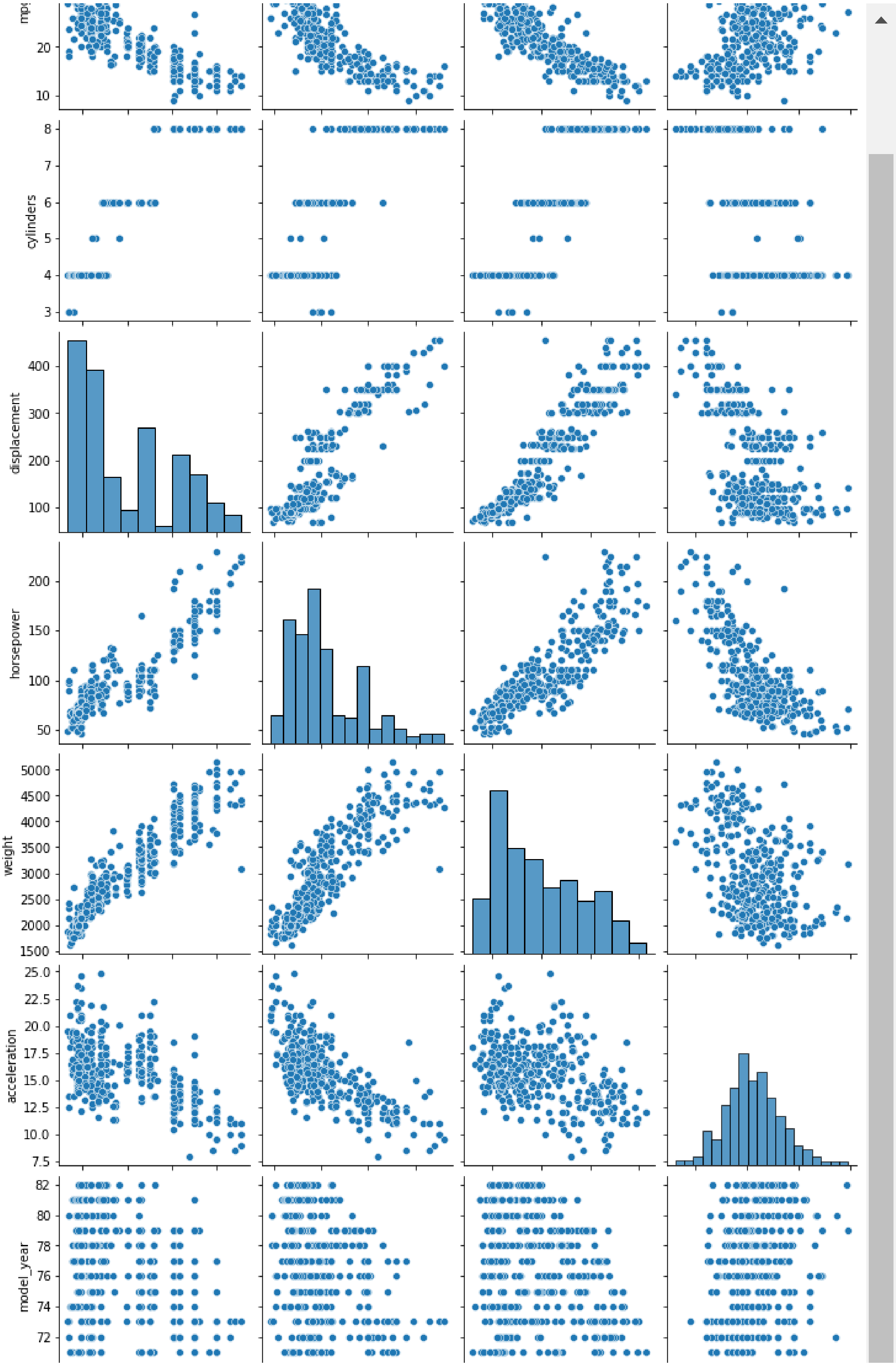
	mpg	cylinders	displacement	horsepower	weight	acceleratio
mpg	1.000000	-0.775396	-0.804203	-0.778427	-0.831741	0.42028
cylinders	-0.775396	1.000000	0.950721	0.842983	0.896017	-0.50541
displacement	-0.804203	0.950721	1.000000	0.897257	0.932824	-0.54368
horsepower	-0.778427	0.842983	0.897257	1.000000	0.864538	-0.68919
weight	-0.831741	0.896017	0.932824	0.864538	1.000000	-0.41745
acceleration	0.420289	-0.505419	-0.543684	-0.689196	-0.417457	1.00000
model_year	0.579267	-0.348746	-0.370164	-0.416361	-0.306564	0.28813

```
df=df.dropna() #get remove missing value
```

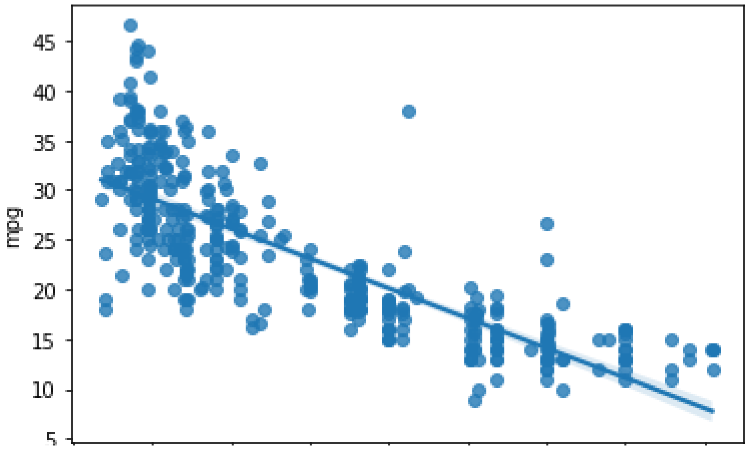
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64
 2   displacement  398 non-null    float64
 3   horsepower    392 non-null    float64
 4   weight        398 non-null    int64
 5   acceleration  398 non-null    float64
 6   model_year    398 non-null    int64
 7   origin        398 non-null    object
 8   name          398 non-null    object
dtypes: float64(4), int64(3), object(2)
memory usage: 28.1+ KB
```

```
#data visualization
sns.pairplot(df,x_vars=['displacement','horsepower','weight','acceleration'])
```




```
sns.regplot(x='displacement',y='mpg',data=df);
```




```
df.columns
```

```
Index(['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration', 'model_year', 'origin', 'name'],
      dtype='object')
```

```
y=df['mpg']
```

```
y.shape
```

```
(392,)
```

```
X=df[['displacement','horsepower','weight','acceleration']]
```

```
X.shape
```

```
(392, 4)
```

```
#sacling data
from sklearn.preprocessing import StandardScaler
```

```
ss=StandardScaler()
```

```
X=ss.fit_transform(X)
```

```
X
```

```
array([[ 1.07728956,  0.66413273,  0.62054034, -1.285258  ],
       [ 1.48873169,  1.57459447,  0.84333403, -1.46672362],
       [ 1.1825422 ,  1.18439658,  0.54038176, -1.64818924],
       ...,
       [-0.56847897, -0.53247413, -0.80463202, -1.4304305 ],
       [-0.7120053 , -0.66254009, -0.41562716,  1.11008813],
       [-0.72157372, -0.58450051, -0.30364091,  1.40043312]])
```

```
pd.DataFrame(X).describe()
```

	0	1	2	3
count	3.920000e+02	3.920000e+02	3.920000e+02	3.920000e+02
mean	-2.537653e-16	-4.392745e-16	5.607759e-17	6.117555e-16
std	1.001278e+00	1.001278e+00	1.001278e+00	1.001278e+00
min	-1.209563e+00	-1.520975e+00	-1.608575e+00	-2.736983e+00
25%	-8.555316e-01	-7.665929e-01	-8.868535e-01	-6.410551e-01
50%	-4.153842e-01	-2.853488e-01	-2.052109e-01	-1.499869e-02
75%	7.782764e-01	5.600800e-01	7.510927e-01	5.384714e-01
max	2.493416e+00	3.265452e+00	2.549061e+00	3.360262e+00

```
#TRAIN TEST SPLIT DATA
```

```
from sklearn.model_selection import train_test_split
```

```
X_train,X_test,y_train,y_test=train_test_split(X,y,train_size=0.7,random_state=2529)
```

```
X_train.shape,X_test.shape,y_train.shape,y_test.shape
```

```
((274, 4), (118, 4), (274,), (118,))
```

```
#linear Regression Model
from sklearn.linear_model import LinearRegression
```

```
lr=LinearRegression()
```

```
lr.fit(X_train,y_train)
```

```
LinearRegression()
```

```
lr.intercept_
```

```
23.485738559737584
```

```
lr.coef_
```

```
array([-1.05767743, -1.68734727, -4.10787617, -0.11495177])
```

```
#predict Test data
```

```
y_pred=lr.predict(X_test)
```

```
y_pred
```

```
array([18.51865637, 15.09305675, 14.30128789, 23.6753321 , 29.7546115 ,
       23.68796629, 26.61066644, 24.56692437, 15.06260986, 11.94312046,
       24.08050053, 27.96518468, 31.66130278, 31.01309132, 18.32428976,
       19.32795009, 28.08847536, 32.1506879 , 31.15859692, 27.15792144,
       18.82433097, 22.54580176, 26.15598115, 32.36393869, 20.74377679,
        8.78027518, 22.19699435, 18.20614294, 25.00052718, 15.26421552,
       23.13441082, 17.10542257,  9.87180062, 30.00790415, 20.41204655,
       29.11860245, 24.4305187 , 21.72601835, 10.51174626, 13.12426391,
       21.41938406, 19.96113872,  6.19146626, 17.79025345, 22.5493033 ,
       29.34765021, 13.4861847 , 25.88852083, 29.40406946, 22.41841964,
       22.07684766, 16.46575802, 24.06290693, 30.12890046, 10.11318121,
        9.85011438, 28.07543852, 23.41426617, 20.08501128, 30.68234133,
       20.92026393, 26.78370281, 22.9078744 , 14.15936872, 24.6439883 ,
       26.95515832, 15.25709393, 24.11272087, 30.80980589, 14.9770217 ,
       27.67836372, 24.2372919 , 10.92177228, 30.22858779, 30.88687365,
       27.33992044, 31.18447082, 10.8873597 , 27.63510608, 16.49231363,
       25.63229888, 29.49776285, 14.90393439, 32.78670687, 30.37325244,
       30.9262743 , 14.71702373, 27.09633246, 26.69933806, 29.06424799,
       32.45810182, 29.44846898, 31.61239999, 31.57891837, 21.46542321,
       31.76739191, 26.28605476, 28.96419915, 31.09628395, 24.80549594,
       18.76490961, 23.28043777, 23.04466919, 22.14143162, 15.95854367,
       28.62870918, 25.58809869, 11.4040908 , 25.73334842, 30.83500051,
       21.94176255, 15.34532941, 30.37399213, 28.7620624 , 29.3639931 ,
       29.10476703, 20.44662365, 28.11466839])
```

```
#Model Accuracy
from sklearn.metrics import mean_absolute_error,mean_absolute_percentage_error,r2_score
```

```
mean_absolute_error(y_test,y_pred)
```

```
3.3286968643244106
```

```
mean_absolute_percentage_error(y_test,y_pred)
```

```
0.14713035779536746
```

```
r2_score(y_test,y_pred)
```

```
0.7031250746717692
```

```
#Polynomial Regression
from sklearn .preprocessing import PolynomialFeatures
```

```
poly=PolynomialFeatures(degree=2,interaction_only=True,include_bias=False)
```

```
X_train2=poly.fit_transform(X_train)
```

```
X_test2=poly.fit_transform(X_test)
```

```
lr.fit(X_train2,y_train)
```

```
LinearRegression()
```

```
lr.intercept_
```

```
21.27336450063766
```

```
lr.coef_
```

```
array([-2.76070596, -5.00559628, -1.36884133, -0.81225214,  1.24596571,
       -0.12475017, -0.90542822,  1.35064048, -0.17337823,  1.41680398])
```

```
y_pred_poly=lr.predict(X_test2)
```

```
#Model accuracy
from sklearn.metrics import mean_absolute_error,mean_absolute_percentage_error,r2_score
```

```
mean_absolute_error(y_test,y_pred_poly)
```

```
2.7887147720295977
```

```
mean_absolute_percentage_error(y_test,y_pred_poly)
```

```
0.1207401834293869
```

```
r2_score(y_test,y_pred_poly)
```

```
0.7461731314563803
```

```
#Hand written digit prediction-classification model
import pandas as pd
```

```
import numpy as np
```

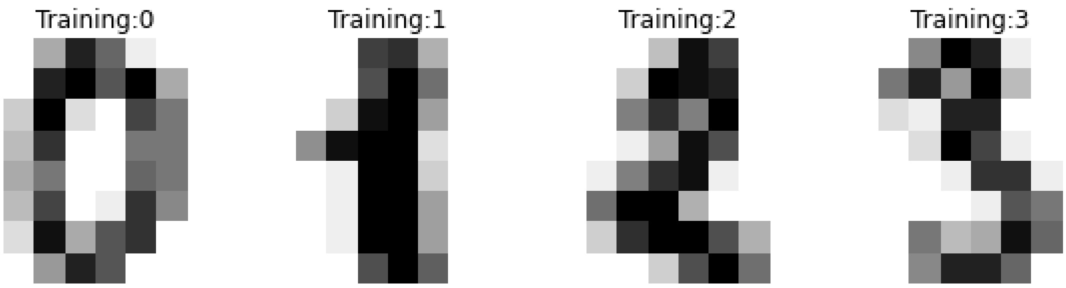
```
import matplotlib.pyplot as plt
```

```
#import data
from sklearn.datasets import load_digits
```

```
df=load_digits()
```

```
_, axes=plt.subplots(nrows=1,ncols=4,figsize=(10,3))
for ax,image,label in zip(axes,df.images,df.target):
  ax.set_axis_off()
  ax.imshow(image,cmap=plt.cm.gray_r,interpolation="nearest")
```

```
    ax.set_title("Training:%i" % label)
```




```
#data processing
#Flatten image
df.images.shape
```

```
(1797, 8, 8)
```

```
df.images[0]
```

```
array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
       [ 0.,  0., 13., 15., 10., 15.,  5.,  0.],
       [ 0.,  3., 15.,  2.,  0., 11.,  8.,  0.],
       [ 0.,  4., 12.,  0.,  0.,  8.,  8.,  0.],
       [ 0.,  5.,  8.,  0.,  0.,  9.,  8.,  0.],
       [ 0.,  4., 11.,  0.,  1., 12.,  7.,  0.],
       [ 0.,  2., 14.,  5., 10., 12.,  0.,  0.],
       [ 0.,  0.,  6., 13., 10.,  0.,  0.,  0.]])
```

```
df.images[0].shape
```

```
(8, 8)
```

```
len(df.images)
```

```
1797
```

```
n_samples=len(df.images)
data=df.images.reshape((n_samples,-1))
```

```
data[0]
```

```
array([ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.,  0.,  0., 13., 15., 10.,
       15.,  5.,  0.,  0.,  3., 15.,  2.,  0., 11.,  8.,  0.,  0.,  4.,
       12.,  0.,  0.,  8.,  8.,  0.,  0.,  5.,  8.,  0.,  0.,  9.,  8.,
        0.,  0.,  4., 11.,  0.,  1., 12.,  7.,  0.,  0.,  2., 14.,  5.,
       10., 12.,  0.,  0.,  0.,  0.,  6., 13., 10.,  0.,  0.,  0.])
```

```
data[0].shape
```

```
(64,)
```

```
data.shape
```

```
(1797, 64)
```

```
#Scaling data
data.min()
```

```
0.0
```

```
data.max()
```

```
16.0
```

```
data=data/16
```

```
data.min()
```

```
0.0
```

```
data.max()
```

```
1.0
```

```
#Train test split data
from sklearn .model_selection import train_test_split
```

```
X_train,X_test,y_train,y_test=train_test_split(data,df.target,test_size=0.7,random_state=2
```

```
X_train.shape,X_test.shape,y_train.shape,y_test.shape
```

```
((539, 64), (1258, 64), (539,), (1258,))
```

```
#Random forest model
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
rf=RandomForestClassifier()
```

```
rf.fit(X_train,y_train)
```

```
RandomForestClassifier()
```

```
#predict test data
y_pred=rf.predict(X_test)
```

```
y_pred
```

```
array([1, 9, 4, ..., 0, 0, 7])
```

```
#Model Accuracy
from sklearn.metrics import confusion_matrix,classification_report
```

```
confusion_matrix(y_test,y_pred)
```

```
array([[119,   0,   0,   0,   1,   0,   0,   0,   0,   0],
       [  0, 130,   1,   1,   0,   2,   0,   0,   0,   0],
       [  0,   0, 118,   0,   0,   0,   0,   1,   1,   0],
       [  0,   0,   1, 111,   0,   1,   0,   1,   9,   2],
       [  0,   3,   0,   0, 115,   0,   0,   2,   2,   0],
       [  0,   0,   0,   0,   2, 117,   0,   0,   0,   2],
       [  1,   0,   0,   0,   2,   0, 126,   0,   0,   0],
       [  0,   0,   0,   0,   1,   0,   0, 130,   0,   0],
       [  0,   5,   2,   1,   0,   2,   0,   1, 112,   1],
       [  0,   0,   0,   5,   0,   5,   0,   5,   3, 114]])
```

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       120
           1       0.94      0.97      0.96       134
           2       0.97      0.98      0.98       120
           3       0.94      0.89      0.91       125
           4       0.95      0.94      0.95       122
           5       0.92      0.97      0.94       121
           6       1.00      0.98      0.99       129
           7       0.93      0.99      0.96       131
           8       0.88      0.90      0.89       124
           9       0.96      0.86      0.91       132

    accuracy                           0.95      1258
   macro avg       0.95      0.95      0.95      1258
weighted avg       0.95      0.95      0.95      1258
```

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