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Start coding or <u>generate</u> with AI.

import pandas as pd

df = pd.read\_csv('data.csv')

print(df.to\_string())

p: =::-(	(	,,		
<b>→</b> ▼	Duration	Pulse	Maxpulse	Calories
	60	110	130	409.1
1	60	117	145	479.0
2	60	103	135	340.0
3	45	109	175	282.4
4	45	117	148	406.0
5	60	102	127	300.0
6	60	110	136	374.0
7	45	104	134	253.3
8	30	109	133	195.1
9	60	98	124	269.0
10	60	103	147	329.3
11	60	100	120	250.7
12	60	106	128	345.3
13	60	104	132	379.3
14	60	98	123	275.0
15	60	98	120	215.2
16	60	100	120	300.0
17	45	90	112	NaN
18	60	103	123	323.0
19	45	97	125	243.0
20	60	108	131	364.2
21	45	100	119	282.0
22	60	130	101	300.0
23	45	105	132	246.0
24	60	102	126	334.5
25	60	100	120	250.0
26	60	92	118	241.0
27	60	103	132	NaN
28	60	100	132	280.0
29	60	102	129	380.3
30	60	92	115	243.0
31	45	90	112	180.1
32	60	101	124	299.0
33	60	93	113	223.0
34	60	107	136	361.0
35	60	114	140	415.0
36	60	102	127	300.0
37	60	100	120	300.0
38	60	100	120	300.0
39	45	104	129	266.0
40	45	90	112	180.1

41	60	98	126	286.0
42	60	100	122	329.4
43	60	111	138	400.0
44	60	111	131	397.0
45	60	99	119	273.0
46	60	109	153	387.6
47	45	111	136	300.0
48	45	108	129	298.0
49	60	111	139	397.6
50	60	107	136	380.2
51	80	123	146	643.1
52	60	106	130	263.0
53	60	118	151	486.0
54	30	136	175	238.0
55	60	121	146	450.7
56	60	118	121	413 A

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import pandas as pd

print(pd.options.display.max\_rows)

**→** 60

import pandas as pd

df = pd.read\_csv('data.csv')

print(df.head(20))

$\rightarrow$		Duration	Pulse	Maxpulse	Calories
	0	60	110	130	409.1
	1	60	117	145	479.0
	2	60	103	135	340.0
	3	45	109	175	282.4
	4	45	117	148	406.0
	5	60	102	127	300.0
	6	60	110	136	374.0
	7	45	104	134	253.3
	8	30	109	133	195.1
	9	60	98	124	269.0
	10	60	103	147	329.3
	11	60	100	120	250.7
	12	60	106	128	345.3
	13	60	104	132	379.3
	14	60	98	123	275.0
	15	60	98	120	215.2
	16	60	100	120	300.0
	17	45	90	112	NaN
	18	60	103	123	323.0
	19	45	97	125	243.0

```
import pandas as pd
```

```
df = pd.read_csv('data.csv')
```

print(df.head())

<b>→</b>		Duration	Pulse	Maxpulse	Calories
	0	60	110	130	409.1
	1	60	117	145	479.0
	2	60	103	135	340.0
	3	45	109	175	282.4
	4	45	117	148	406.0

print(df.tail())

$\overline{\Rightarrow}$		Duration	Pulse	Maxpulse	Calories
	164	60	105	140	290.8
	165	60	110	145	300.0
	166	60	115	145	310.2
	167	75	120	150	320.4
	168	75	125	150	330.4

print(df.info())

<<class 'pandas.core.frame.DataFrame'>
 RangeIndex: 169 entries, 0 to 168
 Data columns (total 4 columns):

#	Column	Non-Null Count	Dtype
0	Duration	169 non-null	int64
1	Pulse	169 non-null	int64
2	Maxpulse	169 non-null	int64
3	Calories	164 non-null	float64
	63 . 6	4/4)	

dtypes: float64(1), int64(3)

memory usage: 5.4 KB

None

import pandas as pd

```
df = pd.read_csv('dirtydata.csv')
```

new\_df = df.dropna()

print(new\_df.to\_string())

	Duration	Date	Pulse	Maxpulse	Calories
0	60	'2020/12/01'	110	130	409.1
1	60	'2020/12/02'	117	145	479.0
2	60	'2020/12/03'	103	135	340.0
3	45	'2020/12/04'	109	175	282.4
4	45	'2020/12/05'	117	148	406.0
	1 2 3	0 60 1 60 2 60 3 45	0 60 '2020/12/01' 1 60 '2020/12/02' 2 60 '2020/12/03' 3 45 '2020/12/04'	0 60 '2020/12/01' 110 1 60 '2020/12/02' 117 2 60 '2020/12/03' 103 3 45 '2020/12/04' 109	0       60       '2020/12/01'       110       130         1       60       '2020/12/02'       117       145         2       60       '2020/12/03'       103       135         3       45       '2020/12/04'       109       175

o PIVI				Data Scie	nce.ipynb - Cois
5	60	'2020/12/06'	102	127	300.0
6	60	'2020/12/07'	110	136	374.0
7	450	'2020/12/08'	104	134	253.3
8	30	'2020/12/09'	109	133	195.1
9	60	'2020/12/10'	98	124	269.0
10	60	'2020/12/11'	103	147	329.3
11	60	'2020/12/12'	100	120	250.7
12	60	'2020/12/12'	100	120	250.7
13	60	'2020/12/13'	106	128	345.3
14	60	'2020/12/14'	104	132	379.3
15	60	'2020/12/15'	98	123	275.0
16	60	'2020/12/16'	98	120	215.2
17	60	'2020/12/17'	100	120	300.0
19	60	'2020/12/19'	103	123	323.0
20	45	'2020/12/20'	97	125	243.0
21	60	'2020/12/21'	108	131	364.2
23	60	'2020/12/23'	130	101	300.0
24	45	'2020/12/24'	105	132	246.0
25	60	'2020/12/25'	102	126	334.5
26	60	20201226	100	120	250.0
27	60	'2020/12/27'	92	118	241.0
29	60	'2020/12/29'	100	132	280.0
30	60	'2020/12/30'	102	129	380.3
31	60	'2020/12/31'	92	115	243.0

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```
import pandas as pd
```

```
df = pd.read_csv('/dirtydata.csv')
new_df = df.dropna()
```

new\_df.fillna(130, inplace = True)
print(df)

$\overline{}$		Dunation	Data	Dulco	Maynulco	Calonios
$\rightarrow$		Duration	Date	Pulse	Maxpulse	Calories
	0	60	'2020/12/01'	110	130	409.1
	1	60	'2020/12/02'	117	145	479.0
	2	60	'2020/12/03'	103	135	340.0
	3	45	'2020/12/04'	109	175	282.4
	4	45	'2020/12/05'	117	148	406.0
	5	60	'2020/12/06'	102	127	300.0
	6	60	'2020/12/07'	110	136	374.0
	7	450	'2020/12/08'	104	134	253.3
	8	30	'2020/12/09'	109	133	195.1
	9	60	'2020/12/10'	98	124	269.0
	10	60	'2020/12/11'	103	147	329.3
	11	60	'2020/12/12'	100	120	250.7
	12	60	'2020/12/12'	100	120	250.7
	13	60	'2020/12/13'	106	128	345.3
	14	60	'2020/12/14'	104	132	379.3
	15	60	'2020/12/15'	98	123	275.0
	16	60	'2020/12/16'	98	120	215.2
	17	60	'2020/12/17'	100	120	300.0

```
18
          45
               '2020/12/18'
                                 90
                                           112
                                                      NaN
19
          60
               '2020/12/19'
                                103
                                           123
                                                    323.0
20
          45
               '2020/12/20'
                                 97
                                           125
                                                    243.0
21
          60
               '2020/12/21'
                                108
                                           131
                                                    364.2
22
          45
                         NaN
                                100
                                           119
                                                    282.0
23
          60
               '2020/12/23'
                                                    300.0
                                130
                                           101
24
          45
               '2020/12/24'
                                105
                                           132
                                                    246.0
25
               '2020/12/25'
          60
                                102
                                           126
                                                    334.5
26
          60
                   20201226
                                100
                                           120
                                                    250.0
27
                                                    241.0
          60
               '2020/12/27'
                                 92
                                           118
28
          60
              '2020/12/28'
                                103
                                           132
                                                      NaN
29
               '2020/12/29'
                                100
                                           132
                                                    280.0
          60
30
          60
              '2020/12/30'
                                102
                                           129
                                                    380.3
31
          60
              '2020/12/31'
                                 92
                                           115
                                                    243.0
```

<ipython-input-2-01a4964b0107>:6: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: <a href="https://pandas.pydata.org/pandas-docs/stable/user\_new\_df.fillna(130, inplace = True">https://pandas.pydata.org/pandas-docs/stable/user\_new\_df.fillna(130, inplace = True)</a>

```
import pandas as pd

df = pd.read_csv('dirtydata.csv')

x = df["Calories"].mean()

df["Calories"].fillna(x, inplace = True)
print(df)
```

<b>₹</b>		Duration	Date	Pulse	Maxpulse	Calories
	0	60	'2020/12/01'	110	130	409.10
	1	60	'2020/12/02'	117	145	479.00
	2	60	'2020/12/03'	103	135	340.00
	3	45	'2020/12/04'	109	175	282.40
	4	45	'2020/12/05'	117	148	406.00
	5	60	'2020/12/06'	102	127	300.00
	6	60	'2020/12/07'	110	136	374.00
	7	450	'2020/12/08'	104	134	253.30
	8	30	'2020/12/09'	109	133	195.10
	9	60	'2020/12/10'	98	124	269.00
	10	60	'2020/12/11'	103	147	329.30
	11	60	'2020/12/12'	100	120	250.70
	12	60	'2020/12/12'	100	120	250.70
	13	60	'2020/12/13'	106	128	345.30
	14	60	'2020/12/14'	104	132	379.30
	15	60	'2020/12/15'	98	123	275.00
	16	60	'2020/12/16'	98	120	215.20
	17	60	'2020/12/17'	100	120	300.00
	18	45	'2020/12/18'	90	112	304.68
	19	60	'2020/12/19'	103	123	323.00
	20	45	'2020/12/20'	97	125	243.00
	21	60	'2020/12/21'	108	131	364.20

'2020/12/18'

'2020/12/19'

'2020/12/20'

'2020/12/21'

'2020/12/23'

'2020/12/24'

'2020/12/25'

'2020/12/27'

'2020/12/28'

'2020/12/29'

'2020/12/30'

'2020/12/31'

NaN

300.0

323.0

243.0

364.2

282.0

300.0

246.0

334.5

250.0

241.0

300.0

280.0

380.3

243.0

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# Double-click (or enter) to edit

```
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Start coding or <u>generate</u> with AI.

import pandas as pd

df = pd.read_csv('/dirtydata.csv')
```

#df.loc[7, 'Duration'] = 450

df['Duration'][7]=30

print(df)

$\overline{\Rightarrow}$		Duration	Date	Pulse	Maxpulse	Calories
	0	60	'2020/12/01'	110	130	409.1
	1	60	'2020/12/02'	117	145	479.0
	2	60	'2020/12/03'	103	135	340.0
	3	45	'2020/12/04'	109	175	282.4
	4	45	'2020/12/05'	117	148	406.0
	5	60	'2020/12/06'	102	127	300.0
	6	60	'2020/12/07'	110	136	374.0
	7	30	'2020/12/08'	104	134	253.3
	8	30	'2020/12/09'	109	133	195.1
	9	60	'2020/12/10'	98	124	269.0
	10	60	'2020/12/11'	103	147	329.3
	11	60	'2020/12/12'	100	120	250.7
	12	60	'2020/12/12'	100	120	250.7
	13	60	'2020/12/13'	106	128	345.3
	14	60	'2020/12/14'	104	132	379.3
	15	60	'2020/12/15'	98	123	275.0
	16	60	'2020/12/16'	98	120	215.2
	17	60	'2020/12/17'	100	120	300.0
	18	45	'2020/12/18'	90	112	NaN
	19	60	'2020/12/19'	103	123	323.0
	20	45	'2020/12/20'	97	125	243.0
	21	60	'2020/12/21'	108	131	364.2
	22	45	NaN	100	119	282.0
	23	60	'2020/12/23'	130	101	300.0
	24	45	'2020/12/24'	105	132	246.0
	25	60	'2020/12/25'	102	126	334.5

26	60	20201226	100	120	250.0	
27	60	'2020/12/27'	92	118	241.0	
28	60	'2020/12/28'	103	132	NaN	
29	60	'2020/12/29'	100	132	280.0	
30	60	'2020/12/30'	102	129	380.3	
31	60	'2020/12/31'	92	115	243.0	

<ipython-input-5-b717fedb8738>:6: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: <a href="https://pandas.pydata.org/pandas-docs/stable/user\_df">https://pandas.pydata.org/pandas-docs/stable/user\_df</a> df['Duration'][7]=30

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```
import pandas as pd

df = pd.read_csv('dirtydata.csv')

x = df["Calories"].median()

df["Calories"].fillna(x, inplace = True)

print(df.to_string())
```

<b>→</b>		Duration	Date	Pulse	Maxpulse	Calories
Ť	0	60	'2020/12/01'	110	130	409.1
	1	60	'2020/12/02'	117	145	479.0
	2	60	'2020/12/03'	103	135	340.0
	3	45	'2020/12/04'	109	175	282.4
	4	45	'2020/12/05'	117	148	406.0
	5	60	'2020/12/06'	102	127	300.0
	6	60	'2020/12/07'	110	136	374.0
	7	450	'2020/12/08'	104	134	253.3
	8	30	'2020/12/09'	109	133	195.1
	9	60	'2020/12/10'	98	124	269.0
	10	60	'2020/12/11'	103	147	329.3
	11	60	'2020/12/12'	100	120	250.7
	12	60	'2020/12/12'	100	120	250.7
	13	60	'2020/12/13'	106	128	345.3
	14	60	'2020/12/14'	104	132	379.3
	15	60	'2020/12/15'	98	123	275.0
	16	60	'2020/12/16'	98	120	215.2
	17	60	'2020/12/17'	100	120	300.0
	18	45	'2020/12/18'	90	112	291.2
	19	60	'2020/12/19'	103	123	323.0
	20	45	'2020/12/20'	97	125	243.0
	21	60	'2020/12/21'	108	131	364.2
	22	45	NaN	100	119	282.0
	23	60	'2020/12/23'	130	101	300.0
	24	45	'2020/12/24'	105	132	246.0
	25	60	'2020/12/25'	102	126	334.5
	26	60	20201226	100	120	250.0

```
AttributeError
                                            Traceback (most recent call last)
    <ipython-input-16-cb0037b66813> in <cell line: 16>()
         15 #Two lines to make our compiler able to draw:
    ---> 16 plt.savefig(sys.stdout.buffer)
         17 sys.stdout.flush()
         18
    AttributeError: 'OutStream' object has no attribute 'buffer'
from google.colab import drive
drive.mount('/content/drive')
#Three lines to make our compiler able to draw:
import sys
import matplotlib
matplotlib.use('Agg')
import pandas as pd
import matplotlib.pyplot as plt
df = pd.read csv('/dirtydata.csv')
df.plot()
plt.show()
#Two lines to make our compiler able to draw:
plt.savefig(sys.stdout.buffer)
sys.stdout.flush()
          ______
    AttributeError
                                            Traceback (most recent call last)
    <ipython-input-14-584da5154f8d> in <cell line: 16>()
         14
         15 #Two lines to make our compiler able to draw:
    ---> 16 plt.savefig(sys.stdout.buffer)
         17 sys.stdout.flush()
    AttributeError: 'OutStream' object has no attribute 'buffer'
import pandas
mydataset = {
  'cars': ["BMW", "Volvo", "Ford"],
  'passings': [3, 7, 2]
```

```
}
myvar = pandas.DataFrame(mydataset)
print(myvar)
\rightarrow
                passings
          cars
     0
           BMW
                        3
                        7
       Volvo
     1
     2
          Ford
                        2
import pandas
mydataset = {
  'cars': ["BMW", "Volvo", "Ford"],
  'passings': [3, 7, 2],
  'Reating': [2, 3, 1]
}
myvar = pandas.DataFrame(mydataset)
print(myvar)
\rightarrow
          cars
                passings
                           Reating
     0
           BMW
                        3
                                  2
        Volvo
                        7
                                  3
     1
          Ford
                        2
                                  1
#/dirtydata.csv
import pandas as pd
df = pd.read_csv('/dirtydata.csv')
#new_df = df.dropna()
print(df)
→
                                           Maxpulse
          Duration
                             Date
                                    Pulse
                                                       Calories
                60
                     '2020/12/01'
                                      110
                                                 130
                                                          409.1
     1
                     '2020/12/02'
                60
                                      117
                                                 145
                                                          479.0
     2
                60
                     '2020/12/03'
                                      103
                                                 135
                                                          340.0
     3
                                                          282.4
                45
                     '2020/12/04'
                                      109
                                                 175
     4
                45
                     '2020/12/05'
                                                          406.0
                                      117
                                                 148
     5
                                                 127
                                                          300.0
                60
                     '2020/12/06'
                                      102
     6
                60
                    '2020/12/07'
                                      110
                                                 136
                                                          374.0
     7
               450
                     '2020/12/08'
                                      104
                                                 134
                                                          253.3
     8
                30
                     '2020/12/09'
                                      109
                                                 133
                                                          195.1
                     '2020/12/10'
     9
                60
                                       98
                                                 124
                                                          269.0
                                                 147
                                                          329.3
                     '2020/12/11'
                                      103
```

import pandas as pd

df = pd.read\_csv('/dirtydata.csv')

print(new\_df.to\_string())

new\_df = df.dropna()

 $\overline{\Rightarrow}$ Duration Date Pulse Maxpulse Calories '2020/12/01' 409.1 '2020/12/02' 479.0 '2020/12/03' 340.0 '2020/12/04' 282.4 '2020/12/05' 406.0 '2020/12/06' 300.0 '2020/12/07' 374.0 '2020/12/08' 253.3 '2020/12/09' 195.1 '2020/12/10' 269.0 '2020/12/11' 329.3 '2020/12/12' 250.7 '2020/12/12' 250.7 '2020/12/13' 345.3 '2020/12/14' 379.3 '2020/12/15' 275.0 215.2 '2020/12/16' '2020/12/17' 300.0 '2020/12/19' 323.0 '2020/12/20' 243.0 '2020/12/21' 364.2 '2020/12/23' 300.0 '2020/12/24' 246.0

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'2020/12/21'

'2020/12/23'

'2020/12/24'

'2020/12/25'

'2020/12/27'

'2020/12/28'

'2020/12/29'

'2020/12/30'

'2020/12/31'

#### Data Science Class no-17

364.2

282.0

300.0

246.0

334.5

250.0

241.0

280.0

380.3

243.0

9.0

```
import pandas as pd
import numpy as np
bigmart_train=pd.read_csv('/content/Test.csv')
bigmart train.info()
→ <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 5681 entries, 0 to 5680
     Data columns (total 11 columns):
          Column
                                     Non-Null Count Dtype
     _ _ _
      0
          Item Identifier
                                      5681 non-null
                                                      object
      1
          Item_Weight
                                     4705 non-null
                                                      float64
      2
          Item_Fat_Content
                                     5681 non-null
                                                      object
      3
          Item_Visibility
                                     5681 non-null
                                                      float64
      4
          Item_Type
                                     5681 non-null
                                                      object
      5
          Item MRP
                                     5681 non-null
                                                      float64
      6
          Outlet_Identifier
                                     5681 non-null
                                                      object
                                     5681 non-null
                                                      int64
          Outlet_Establishment_Year
          Outlet_Size
                                     4075 non-null
                                                      object
          Outlet_Location_Type
      9
                                     5681 non-null
                                                      object
      10 Outlet_Type
                                      5681 non-null
                                                      object
     dtypes: float64(3), int64(1), object(7)
     memory usage: 488.3+ KB
print(bigmart_train['Item_Identifier'].unique(),bigmart_train['Item_Fat_Content'].unique(),b
     ['FDW58' 'FDW14' 'NCN55' ... 'NCI29' 'FDP28' 'FDF04'] ['Low Fat' 'reg' 'Regular' 'LF' ']
      'Health and Hygiene' 'Breads' 'Hard Drinks' 'Seafood' 'Soft Drinks'
      'Household' 'Frozen Foods' 'Meat' 'Canned' 'Starchy Foods' 'Breakfast'] ['OUT049' 'OUT0
      'OUT013' 'OUT035']
import pandas as pd
import numpy as np
bigmart_train=pd.read_csv('/content/Test.csv')
#bigmart train.info()
print(bigmart_train)
\rightarrow
          Item_Identifier Item_Weight Item_Fat_Content Item_Visibility \
     0
                    FDW58
                                20.750
                                                 Low Fat
                                                                 0.007565
     1
                    FDW14
                                 8.300
                                                                 0.038428
                                                     reg
     2
                    NCN55
                                14.600
                                                 Low Fat
                                                                 0.099575
     3
                    FDQ58
                                 7.315
                                                 Low Fat
                                                                 0.015388
     4
                    FDY38
                                   NaN
                                                 Regular
                                                                 0.118599
                      . . .
                                                     . . .
     . . .
                                    . . .
                                                                       . . .
     5676
                    FDB58
                                10.500
                                                 Regular
                                                                 0.013496
     5677
                    FDD47
                                 7.600
                                                 Regular
                                                                 0.142991
                                                 Low Fat
     5678
                    NC017
                                10.000
                                                                 0.073529
     5679
                    FDJ26
                                15.300
                                                 Regular
                                                                 0.000000
                                                                 0.104720
     5680
                    FDU37
                                 9.500
                                                 Regular
```

https://colab.research.google.com/drive/1oQJE0LIPg9ojVQPopT5OsqDjEKLxscpq#scrollTo=2HSmLpfoRWES&printMode=true

Item\_Type Item\_MRP Outlet\_Identifier \

https://colab.research.google.com/drive/1oQJE0LIPg9ojVQPopT5OsqDjEKLxscpq#scrollTo=2HSmLpfoRWES&printMode=true

print(categorical\_columns)

```
Categorical Columns Based on Data Type:
['Item_Identifier', 'Item_Fat_Content', 'Item_Type', 'Outlet_Identifier', 'Outlet_Size',
```

### One hot Encoding

```
from sklearn.preprocessing import OneHotEncoder
def one hot encode(bigmart train, categorical columns):
   # Initialize the OneHotEncoder
   encoder_bigmart = OneHotEncoder(sparse_output=False, drop='first') # drop='first' to av
   # Fit and transform the categorical columns
   encoded_data_mart = encoder_bigmart.fit_transform(bigmart_train[categorical_columns])
   # Get the new column names
   encoded_columns_new = encoder_bigmart.get_feature_names_out(categorical_columns)
   # Create a DataFrame with the encoded data
   encoded df new data = pd.DataFrame(encoded data mart, columns=encoded columns new)
   # Drop the original categorical columns and concatenate the new one-hot encoded columns
   bigmart_train = bigmart_train.drop(categorical_columns, axis=1)
   bigmart_train = pd.concat([bigmart_train, encoded_df_new_data], axis=1)
   return bigmart_train
   # Identify categorical columns
categorical_columns = bigmart_train.select_dtypes(include=['object', 'category']).columns.tc
# Call the function to encode the DataFrame
bigmart_train_encoded = one_hot_encode(bigmart_train.copy(), categorical_columns)
# Print the encoded DataFrame
#print(bigmart_train_encoded)
print(bigmart_train_encoded.head())
```

```
\rightarrow
        Item_Weight Item_Visibility Item_MRP Outlet_Establishment_Year \
    0
             20.750
                             0.007565 107.8622
                                                                        1999
    1
              8.300
                             0.038428
                                       87.3198
                                                                        2007
    2
             14.600
                             0.099575 241.7538
                                                                        1998
    3
              7.315
                             0.015388 155.0340
                                                                        2007
    4
                NaN
                             0.118599 234.2300
                                                                        1985
```

Item\_Identifier\_DRA24 Item\_Identifier\_DRA59 Item\_Identifier\_DRB01 \

```
# Identify categorical columns
categorical_columns = bigmart_train.select_dtypes(include=['object', 'category']).columns.tc
# Call the function to encode the DataFrame
bigmart_train_encoded = one_hot_encode(bigmart_train.copy(), categorical_columns)
# Print the encoded DataFrame
```

```
#print(bigmart_train_encoded)
print(bigmart_train_encoded.head())
import pandas as pd
from sklearn.preprocessing import LabelEncoder
# Assuming your dataset is already loaded as 'df'
# Identify categorical columns (non-numerical columns)
categorical columns = bigmart_train.select_dtypes(include=['object', 'category']).columns.tc
# Initialize LabelEncoder
label encoders = {}
# Apply label encoding to each categorical column
for col in categorical_columns:
    label_encoders[col] = LabelEncoder()
    bigmart_train[col] = label_encoders[col].fit_transform(bigmart_train[col])
#print("Dataset after Label Encoding:")
#print(bigmart_train.head())
bigmart_train.info()
```

### **Data Info Finding**

```
import pandas as pd
import numpy as np
bigmart_train=pd.read_csv('/content/customer.csv')
bigmart_train.info()
<<class 'pandas.core.frame.DataFrame'>
    RangeIndex: 50 entries, 0 to 49
    Data columns (total 5 columns):
         Column
                 Non-Null Count Dtype
         ----
                   -----
                                   ----
                   50 non-null
                                   int64
         age
                  50 non-null
         gender
                                   object
                  50 non-null
     2
         review
                                   object
         education 50 non-null
                                   object
         purchased 50 non-null
                                   object
    dtypes: int64(1), object(4)
    memory usage: 2.1+ KB
print(bigmart_train['age'].unique(),bigmart_train['gender'].unique(),bigmart_train['rev
    [30 68 70 72 16 31 18 60 65 74 98 51 57 15 75 59 22 19 97 32 96 53 69 48
     83 73 92 89 86 34 94 45 76 39 23 27 77 61 64 38 25] ['Female' 'Male'] ['Average' 'Poor'
```

#### One Hot Encoding

```
from sklearn.preprocessing import OneHotEncoder
def one hot encode(bigmart train, categorical columns):
   # Initialize the OneHotEncoder
   encoder bigmart = OneHotEncoder(sparse output=False, drop='first') # drop='first'
   # Fit and transform the categorical columns
   encoded_data_mart = encoder_bigmart.fit_transform(bigmart_train[categorical_columns
   # Get the new column names
   encoded_columns_new = encoder_bigmart.get_feature_names_out(categorical_columns)
   # Create a DataFrame with the encoded data
   encoded df new data = pd.DataFrame(encoded_data_mart, columns=encoded_columns_new)
   # Drop the original categorical columns and concatenate the new one-hot encoded columns
   bigmart train = bigmart train.drop(categorical columns, axis=1)
   bigmart_train = pd.concat([bigmart_train, encoded_df_new_data], axis=1)
   return bigmart train
# Identify categorical columns
categorical_columns = bigmart_train.select_dtypes(include=['object', 'category']).column
# Call the function to encode the DataFrame
bigmart_train_encoded = one_hot_encode(bigmart_train.copy(), categorical_columns)
# Print the encoded DataFrame
#print(bigmart train encoded)
print(bigmart train encoded.head())
print(bigmart_train_encoded.head())
             gender_Male review_Good review_Poor education_School education_UG \
        age
         30
                     0.0
                                  0.0
                                               0.0
                                                                  1.0
                                                                                0.0
                     0.0
                                               1.0
     1
         68
                                  0.0
                                                                  0.0
                                                                                1.0
     2
         70
                     0.0
                                  1.0
                                               0.0
                                                                  0.0
                                                                                0.0
     3
         72
                     0.0
                                  1.0
                                               0.0
                                                                  0.0
                                                                                0.0
         16
                     0.0
                                  0.0
                                               0.0
                                                                  0.0
                                                                                1.0
        purchased_Yes
     0
                  0.0
                  0.0
     1
     2
                  0.0
     3
                  0.0
     4
                  0.0
```

```
from sklearn.preprocessing import OneHotEncoder
def one_hot_encode(bigmart_train, categorical_columns):
    # Initialize the OneHotEncoder
    encoder_bigmart = OneHotEncoder(sparse_output=False, drop='first') # drop='first' to av
    # Fit and transform the categorical columns
    encoded data mart = encoder bigmart.fit transform(bigmart train[categorical columns])
    # Get the new column names
    encoded_columns_new = encoder_bigmart.get_feature_names_out(categorical_columns)
    # Create a DataFrame with the encoded data
    encoded_df_new_data = pd.DataFrame(encoded_data_mart, columns=encoded_columns_new)
    # Drop the original categorical columns and concatenate the new one-hot encoded columns
    bigmart_train = bigmart_train.drop(categorical_columns, axis=1)
    bigmart_train = pd.concat([bigmart_train, encoded_df_new_data], axis=1)
    return bigmart train
 # Identify categorical columns
categorical_columns = bigmart_train.select_dtypes(include=['object', 'category']).columns.tc
# Call the function to encode the DataFrame
bigmart_train_encoded = one_hot_encode(bigmart_train.copy(), categorical_columns)
# Print the encoded DataFrame
#print(bigmart train encoded)
print(bigmart train encoded.head())
print(bigmart_train_encoded.head())
Start coding or generate with AI.
Class no 18
Start coding or generate with AI.
import pandas
filename = '/content/pima-indians-diabetes.data.csv'
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
data = pandas.read_csv(filename, names=names)
print(data.shape)
→ (768, 9)
```

```
# Load CSV using Pandas
import pandas
filename = 'pima-indians-diabetes.data.csv'
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
data = pandas.read_csv(filename, names=names)
print(data.shape)
```

```
→ (768, 9)
```

Start coding or generate with AI.

```
# Load CSV using Pandas from URL
import pandas
url = "/content/pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
data = pandas.read_csv(url, names=names)
print (data.to_string())
```

<b>→</b>		preg	plas	pres	skin	test	mass	pedi	age	class
	0	6	148	72	35	0	33.6	0.627	50	1
	1	1	85	66	29	0	26.6	0.351	31	0
	2	8	183	64	0	0	23.3	0.672	32	1
	3	1	89	66	23	94	28.1	0.167	21	0
	4	0	137	40	35	168	43.1	2.288	33	1
	5	5	116	74	0	0	25.6	0.201	30	0
	6	3	78	50	32	88	31.0	0.248	26	1
	7	10	115	0	0	0	35.3	0.134	29	0
	8	2	197	70	45	543	30.5	0.158	53	1
	9	8	125	96	0	0	0.0	0.232	54	1
	10	4	110	92	0	0	37.6	0.191	30	0
	11	10	168	74	0	0	38.0	0.537	34	1
	12	10	139	80	0	0	27.1	1.441	57	0
	13	1	189	60	23	846	30.1	0.398	59	1
	14	5	166	72	19	175	25.8	0.587	51	1
	15	7	100	0	0	0	30.0	0.484	32	1
	16	0	118	84	47	230	45.8	0.551	31	1
	17	7	107	74	0	0	29.6	0.254	31	1
	18	1	103	30	38	83	43.3	0.183	33	0
	19	1	115	70	30	96	34.6	0.529	32	1
	20	3	126	88	41	235	39.3	0.704	27	0
	21	8	99	84	0	0	35.4	0.388	50	0
	22	7	196	90	0	0	39.8	0.451	41	1
	23	9	119	80	35	0	29.0	0.263	29	1
	24	11	143	94	33	146	36.6	0.254	51	1
	25	10	125	70	26	115	31.1	0.205	41	1
	26	7	147	76	0	0	39.4	0.257	43	1
	27	1	97	66	15	140	23.2	0.487	22	0
	28	13	145	82	19	110	22.2	0.245	57	0
	29	5	117	92	0	0	34.1	0.337	38	0
	30	5	109	75	26	0	36.0	0.546	60	0

```
31
         3
             158
                      76
                            36
                                  245
                                        31.6
                                               0.851
                                                        28
                            11
32
         3
              88
                      58
                                   54
                                        24.8
                                              0.267
                                                        22
                                                                 0
33
         6
              92
                      92
                             0
                                               0.188
                                                                 0
                                    0
                                        19.9
                                                        28
34
        10
             122
                      78
                            31
                                    0
                                        27.6
                                               0.512
                                                        45
                                                                 0
35
         4
             103
                      60
                            33
                                  192
                                        24.0
                                               0.966
                                                        33
                                                                 0
36
        11
             138
                      76
                             0
                                    0
                                        33.2
                                               0.420
                                                        35
                                                                 0
         9
                                                                 1
37
             102
                      76
                            37
                                    0
                                        32.9
                                               0.665
                                                        46
38
         2
              90
                                                                 1
                      68
                            42
                                    0
                                        38.2
                                              0.503
                                                        27
39
         4
                      72
                            47
                                        37.1
                                               1.390
                                                                 1
             111
                                  207
                                                        56
40
         3
                            25
                                   70
                                        34.0
                                              0.271
                                                                 0
             180
                      64
                                                        26
         7
                                                                 0
41
             133
                      84
                             0
                                    0
                                        40.2
                                              0.696
                                                        37
42
         7
             106
                      92
                            18
                                        22.7
                                               0.235
                                                                 0
                                    0
                                                        48
43
         9
             171
                    110
                            24
                                  240
                                        45.4
                                              0.721
                                                        54
                                                                 1
44
         7
             159
                             0
                                        27.4
                                              0.294
                                                                 0
                      64
                                    0
                                                        40
45
         0
             180
                      66
                            39
                                    0
                                        42.0
                                              1.893
                                                        25
                                                                 1
46
         1
             146
                                              0.564
                                                                 0
                      56
                             0
                                    0
                                        29.7
                                                        29
47
         2
              71
                     70
                            27
                                    0
                                        28.0
                                              0.586
                                                        22
                                                                 0
48
         7
             103
                      66
                            32
                                    0
                                        39.1
                                               0.344
                                                                 1
                                                        31
         7
49
             105
                      0
                             0
                                    0
                                         0.0
                                              0.305
                                                        24
                                                                 0
50
         1
             103
                      80
                            11
                                   82
                                        19.4
                                              0.491
                                                        22
                                                                 0
51
         1
             101
                      50
                            15
                                   36
                                        24.2
                                              0.526
                                                        26
                                                                 0
         5
52
              88
                      66
                            21
                                   23
                                        24.4
                                               0.342
                                                        30
53
         8
             176
                      90
                            34
                                  300
                                        33.7
                                               0.467
                                                        58
                                                                 1
54
         7
             150
                      66
                            42
                                  342
                                               0.718
                                                        42
                                                                 0
                                        34.7
         1
              73
                                                                 0
55
                      50
                            10
                                    0
                                        23.0
                                              0.248
                                                        21
         7
56
             187
                      68
                            39
                                                        41
                                                                 1
                                  304
                                        37.7
                                              0.254
```

```
# Load CSV using Pandas from URL
import pandas
url = "/content/pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
data = pandas.read_csv(url, names=names)
data.info()
```

<<class 'pandas.core.frame.DataFrame'>
 RangeIndex: 768 entries, 0 to 767
 Data columns (total 9 columns):
 # Column Non-Null Count Dtype

```
0
             768 non-null
                              int64
    preg
             768 non-null
                              int64
1
    plas
2
             768 non-null
                              int64
    pres
3
    skin
             768 non-null
                              int64
4
    test
             768 non-null
                              int64
5
    mass
             768 non-null
                              float64
6
            768 non-null
                              float64
    pedi
7
             768 non-null
    age
                              int64
    class
             768 non-null
                              int64
```

dtypes: float64(2), int64(7)
memory usage: 54.1 KB

print(data.head(20))

$\overline{\Rightarrow}$		preg	plas	pres	skin	test	mass	pedi	age	class
_	0	6	148	72	35	0	33.6	0.627	50	1
	1	1	85	66	29	0	26.6	0.351	31	0
	2	8	183	64	0	0	23.3	0.672	32	1
	3	1	89	66	23	94	28.1	0.167	21	0
	4	0	137	40	35	168	43.1	2.288	33	1
	5	5	116	74	0	0	25.6	0.201	30	0
	6	3	78	50	32	88	31.0	0.248	26	1
	7	10	115	0	0	0	35.3	0.134	29	0
	8	2	197	70	45	543	30.5	0.158	53	1
	9	8	125	96	0	0	0.0	0.232	54	1
	10	4	110	92	0	0	37.6	0.191	30	0
	11	10	168	74	0	0	38.0	0.537	34	1
	12	10	139	80	0	0	27.1	1.441	57	0
	13	1	189	60	23	846	30.1	0.398	59	1
	14	5	166	72	19	175	25.8	0.587	51	1
	15	7	100	0	0	0	30.0	0.484	32	1
	16	0	118	84	47	230	45.8	0.551	31	1
	17	7	107	74	0	0	29.6	0.254	31	1
	18	1	103	30	38	83	43.3	0.183	33	0
	19	1	115	70	30	96	34.6	0.529	32	1

print(data.shape)

**→** (768, 9)

Start coding or generate with AI.

Start coding or generate with AI.

# print (data.head())

<b>₹</b>		preg	plas	pres	skin	test	mass	pedi	age	class
	0	6	148	72	35	0	33.6	0.627	50	1
	1	1	85	66	29	0	26.6	0.351	31	0
	2	8	183	64	0	0	23.3	0.672	32	1
	3	1	89	66	23	94	28.1	0.167	21	0
	4	a	137	40	35	168	43.1	2.288	33	1

# print(data.head(999))

$\overline{2}$		preg	plas	pres	skin	test	mass	pedi	age	class
	0	6	148	72	35	0	33.6	0.627	50	1
	1	1	85	66	29	0	26.6	0.351	31	0
	2	8	183	64	0	0	23.3	0.672	32	1
	3	1	89	66	23	94	28.1	0.167	21	0
	4	0	137	40	35	168	43.1	2.288	33	1
	763	10	101	76	48	180	32.9	0.171	63	0
	764	2	122	70	27	0	36.8	0.340	27	0
	765	5	121	72	23	112	26.2	0.245	30	0

766 1 126 60 0 0 30.1 0.349 47 767 1 93 70 31 0 30.4 0.315 23

[768 rows x 9 columns]

#### data.describe()



```
plas
                                                 skin
                                                             test
             preg
                                     pres
                                                                         mass
                                                                                      pedi
count 768.000000 768.000000
                               768.000000 768.000000 768.000000 768.000000 768.000000
mean
         3.845052 120.894531
                                69.105469
                                            20.536458
                                                         79.799479
                                                                     31.992578
                                                                                  0.471876
 std
         3.369578
                    31.972618
                                19.355807
                                            15.952218
                                                       115.244002
                                                                      7.884160
                                                                                  0.331329
min
         0.000000
                     0.000000
                                 0.000000
                                             0.000000
                                                          0.000000
                                                                      0.000000
                                                                                  0.078000
25%
         1.000000
                    99.000000
                                62.000000
                                             0.000000
                                                         0.000000
                                                                     27.300000
                                                                                  0.243750
50%
         3.000000
                   117.000000
                                72.000000
                                            23.000000
                                                         30.500000
                                                                     32.000000
                                                                                  0.372500
75%
         6.000000
                   140.250000
                                80.000000
                                            32.000000
                                                       127.250000
                                                                     36.600000
                                                                                  0.626250
                               122.000000
                                            99.000000 846.000000
                                                                     67.100000
                                                                                  2.420000
max
        17.000000
                   199.000000
```

```
# synthetic classification dataset
from numpy import where
from sklearn.datasets import make_classification
from matplotlib import pyplot
# define dataset
X, y = make_classification(n_samples=1000, n_features=2, n_informative=2, n_redundant=0, n_c
# create scatter plot for samples from each class
for class_value in range(2):
    # get row indexes for samples with this class
    row_ix = where(y == class_value)
    # create scatter of these samples
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1])
# show the plot
pyplot.show()
```



```
import numpy as np
np.random.seed(10)
# generating 10 random values for each of the two variables
X = np.random.randn(10)
Y = np.random.randn(10)
# computing the correlation matrix
C = np.corrcoef(X,Y)
print(C)
```

```
(1. 0.37258014)
[0.37258014]
```

```
# Exploring Iris Dataset
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm
from scipy import stats
from pandas import read_csv
```

```
# define the location of the dataset
path = r"https://raw.githubusercontent.com/jbrownlee/Datasets/master/iris.csv"
```

# load the dataset and use df as a data frame
iris\_df = read\_csv(path, header=None)
# show the first few rows of the data
iris\_df.head()

<b>→</b>		0	1	2	3	4
	0	5.1	3.5	1.4	0.2	Iris-setosa
	1	4.9	3.0	1.4	0.2	Iris-setosa
	2	4.7	3.2	1.3	0.2	Iris-setosa
	3	4.6	3.1	1.5	0.2	Iris-setosa
	4	5.0	3.6	1.4	0.2	Iris-setosa

### print(iris\_df.head(20))

$\rightarrow \overline{}$		0	1	2	3	4
	0	5.1	3.5	1.4	0.2	Iris-setosa
	1	4.9	3.0	1.4	0.2	Iris-setosa
	2	4.7	3.2	1.3	0.2	Iris-setosa
	3	4.6	3.1	1.5	0.2	Iris-setosa
	4	5.0	3.6	1.4	0.2	Iris-setosa
	5	5.4	3.9	1.7	0.4	Iris-setosa
	6	4.6	3.4	1.4	0.3	Iris-setosa
	7	5.0	3.4	1.5	0.2	Iris-setosa
	8	4.4	2.9	1.4	0.2	Iris-setosa
	9	4.9	3.1	1.5	0.1	Iris-setosa
	10	5.4	3.7	1.5	0.2	Iris-setosa
	11	4.8	3.4	1.6	0.2	Iris-setosa
	12	4.8	3.0	1.4	0.1	Iris-setosa
	13	4.3	3.0	1.1	0.1	Iris-setosa
	14	5.8	4.0	1.2	0.2	Iris-setosa
	15	5.7	4.4	1.5	0.4	Iris-setosa
	16	5.4	3.9	1.3	0.4	Iris-setosa
	17	5.1	3.5	1.4	0.3	Iris-setosa
	18	5.7	3.8	1.7	0.3	Iris-setosa
	19	5.1	3.8	1.5	0.3	Iris-setosa

# print(iris\_df.to\_string())

$\rightarrow$		0	1	2	3	4
	0	5.1	3.5	1.4	0.2	Iris-setosa
	1	4.9	3.0	1.4	0.2	Iris-setosa
	2	4.7	3.2	1.3	0.2	Iris-setosa
	3	4.6	3.1	1.5	0.2	Iris-setosa
	4	5.0	3.6	1.4	0.2	Iris-setosa
	5	5.4	3.9	1.7	0.4	Iris-setosa
	6	4.6	3.4	1.4	0.3	Iris-setosa
	7	5.0	3.4	1.5	0.2	Iris-setosa
	8	4.4	2.9	1.4	0.2	Iris-setosa

```
9
     4.9
           3.1
                1.5
                      0.1
                                Iris-setosa
10
     5.4
           3.7
                1.5
                      0.2
                                Iris-setosa
11
     4.8
           3.4
                1.6
                      0.2
                                Iris-setosa
12
     4.8
           3.0
                1.4
                      0.1
                                Iris-setosa
13
     4.3
           3.0
                1.1
                      0.1
                                Iris-setosa
14
     5.8
           4.0
                1.2
                      0.2
                                Iris-setosa
15
     5.7
           4.4
                1.5
                      0.4
                                Iris-setosa
16
     5.4
           3.9
                1.3
                      0.4
                                Iris-setosa
17
     5.1
           3.5
                      0.3
                                Iris-setosa
                1.4
18
     5.7
           3.8
                1.7
                      0.3
                                Iris-setosa
19
     5.1
           3.8
                1.5
                      0.3
                                Iris-setosa
20
     5.4
           3.4
                1.7
                      0.2
                                Iris-setosa
21
     5.1
           3.7
                1.5
                      0.4
                                Iris-setosa
22
                      0.2
     4.6
           3.6
                1.0
                                Iris-setosa
23
     5.1
           3.3
                1.7
                      0.5
                                Iris-setosa
24
     4.8
           3.4
                1.9
                      0.2
                                Iris-setosa
25
     5.0
           3.0
                1.6
                      0.2
                                Iris-setosa
26
           3.4
                      0.4
                                Iris-setosa
     5.0
                1.6
27
     5.2
           3.5
                1.5
                      0.2
                                Iris-setosa
28
     5.2
           3.4
                1.4
                      0.2
                                Iris-setosa
29
     4.7
           3.2
                1.6
                      0.2
                                Iris-setosa
30
     4.8
           3.1
                1.6
                      0.2
                                Iris-setosa
31
     5.4
           3.4
                1.5
                      0.4
                                Iris-setosa
32
     5.2
           4.1
                1.5
                      0.1
                                Iris-setosa
33
     5.5
           4.2
                1.4
                      0.2
                                Iris-setosa
34
                                Iris-setosa
     4.9
           3.1
                1.5
                      0.1
35
           3.2
                      0.2
     5.0
                1.2
                                Iris-setosa
     5.5
           3.5
                1.3
36
                      0.2
                                Iris-setosa
37
     4.9
           3.1
                1.5
                      0.1
                                Iris-setosa
38
     4.4
           3.0
                1.3
                      0.2
                                Iris-setosa
39
     5.1
           3.4
                1.5
                      0.2
                                Iris-setosa
40
     5.0
           3.5
                1.3
                      0.3
                                Iris-setosa
41
     4.5
           2.3
                1.3
                      0.3
                                Iris-setosa
42
     4.4
           3.2
                      0.2
                                Iris-setosa
                1.3
43
     5.0
           3.5
                1.6
                      0.6
                                Iris-setosa
44
     5.1
           3.8
                1.9
                      0.4
                                Iris-setosa
45
     4.8
           3.0
                1.4
                      0.3
                                Iris-setosa
46
     5.1
           3.8
                1.6
                      0.2
                                Iris-setosa
47
     4.6
           3.2
                      0.2
                                Iris-setosa
                1.4
48
     5.3
           3.7
                1.5
                      0.2
                                Iris-setosa
49
     5.0
           3.3
                1.4
                      0.2
                                Iris-setosa
     7.0
                      1.4
50
           3.2
                4.7
                           Iris-versicolor
           3.2
51
     6.4
                4.5
                      1.5
                            Iris-versicolor
52
     6.9
           3.1
                4.9
                      1.5
                            Iris-versicolor
53
     5.5
           2.3
                4.0
                      1.3
                            Iris-versicolor
54
     6.5
           2.8
                4.6
                      1.5
                           Iris-versicolor
55
     5.7
           2.8
                4.5
                      1.3
                            Iris-versicolor
56
           3.3
                4.7
                      1.6
                           Iris-versicolor
```

# show the names of the columns or features
iris\_df.columns

→ Index([0, 1, 2, 3, 4], dtype='int64')

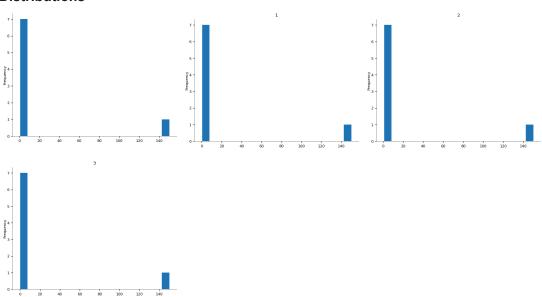
# show the number of rows and columns
iris\_df.shape

# get various summary stats of the data
iris\_df.describe()

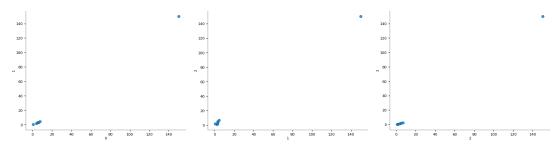


	0	1	2	3
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

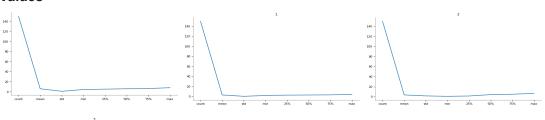
#### **Distributions**



# 2-d distributions



# **Values**





iris\_df.info()

<<class 'pandas.core.frame.DataFrame'> RangeIndex: 150 entries, 0 to 149 Data columns (total 5 columns):

Data	COTUIIII	(COCAL ) COLUMNI	٥).
#	Column	Non-Null Count	Dtype
0	0	150 non-null	float64
1	1	150 non-null	float64
2	2	150 non-null	float64
3	3	150 non-null	float64
4	4	150 non-null	object

dtypes: float64(4), object(1)

memory usage: 6.0+ KB

Start coding or generate with AI.

# Identify rows that contain missing values iris\_df.isnull()

_		_
•	•	
	→	$\overline{}$

<b>Y</b>		0	1	2	3	4
	0	False	False	False	False	False
	1	False	False	False	False	False
	2	False	False	False	False	False
	3	False	False	False	False	False
	4	False	False	False	False	False
	145	False	False	False	False	False
	146	False	False	False	False	False
	147	False	False	False	False	False
	148	False	False	False	False	False
	149	False	False	False	False	False

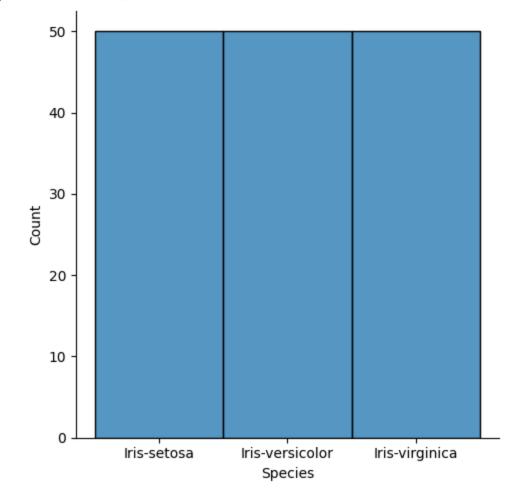
150 rows × 5 columns

iris\_df = read\_csv(path, names=names, header=None)
# Show the first few rows of the data again
iris\_df.head()

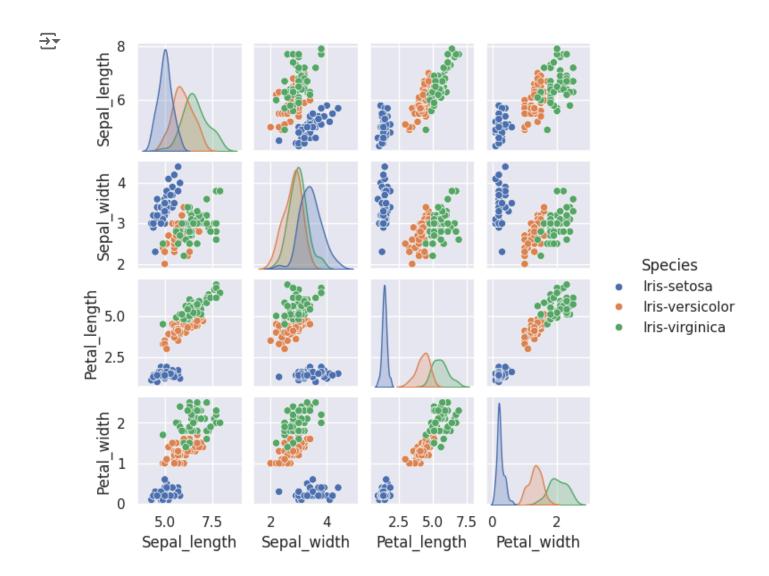
<b>→</b>		Sepal_length	Sepal_width	Petal_length	Petal_width	Species
	0	5.1	3.5	1.4	0.2	Iris-setosa
	1	4.9	3.0	1.4	0.2	Iris-setosa
	2	4.7	3.2	1.3	0.2	Iris-setosa
	3	4.6	3.1	1.5	0.2	Iris-setosa
	4	5.0	3.6	1.4	0.2	Iris-setosa

#Species Distribution
sns.displot(iris\_df['Species'])

→ <seaborn.axisgrid.FacetGrid at 0x7f3e30076530>

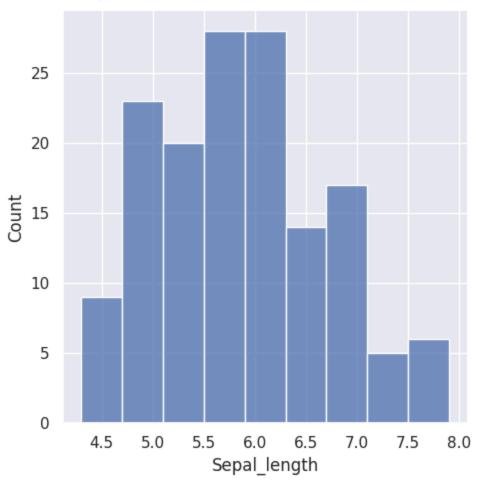


%matplotlib inline
import seaborn as sns; sns.set()
sns.pairplot(iris\_df, hue='Species', height=1.5);



# histogram and Sepal\_length Distribution
sns.displot(iris\_df['Sepal\_length'])

<seaborn.axisgrid.FacetGrid at 0x7f3e2f0c5d20>



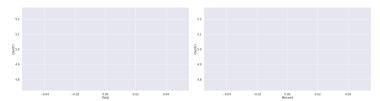
#### # Missing Data

# If more than 15% of the data is missing then we might want to delete the feature (variable total = iris\_df.isnull().sum().sort\_values(ascending=False) percent = (iris\_df.isnull().sum()/iris\_df.isnull().count()).sort\_values(ascending=False) missing\_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent']) missing\_data.head(20)



	Total	Percent
Sepal_length	0	0.0
Sepal_width	0	0.0
Petal_length	0	0.0
Petal_width	0	0.0
Species	0	0.0

#### Time series



```
# Dealing with Missing Data
# First, ensure 'missing_data' exists:
missing_data = iris_df.isnull().sum(axis=1) # Example to calculate missing data row-wise if
# Drop rows with missing data count greater than 1
iris_df = iris_df.drop(missing_data[missing_data > 1].index)
# Check if there's any missing data left
missing_data_check = iris_df.isnull().sum().max() # This will give the maximum number of mi
print(missing_data_check) # Will return 0 if no missing data exists
```

**→** 0

# We can extract the feature matrix and target array from the iris data\_frame
# This would be useful later on when we use Scikit-Learn to perform classification
X\_iris = iris\_df.drop('Species', axis=1)
X\_iris.shape

**→** (150, 4)

# We can extract the feature matrix and target array from the iris data\_frame
# This would be useful later on when we use Scikit-Learn to perform classification
y\_iris = iris\_df['Species']
y\_iris.shape

```
\rightarrow
       File "<ipython-input-56-e68ab886a21c>", line 3
         y_iris = iris_df['Species']
     SyntaxError: unterminated string literal (detected at line 3)
from sklearn.model_selection import train_test_split
# Assuming 'target' is the name of your target variable column
X = iris_df.drop(columns=['Species'])
y = iris_df['Species']
print(f"x data head", X.head())
print(f"y data head",y.head())
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Display the sizes of the splits
print(f"Training set size: {len(X_train)}")
print(f"Test set size: {len(X_test)}")
→ x data head
                    Sepal_length Sepal_width Petal_length Petal_width
                 5.1
     0
                              3.5
                                             1.4
                                                          0.2
     1
                 4.9
                              3.0
                                             1.4
                                                          0.2
     2
                 4.7
                              3.2
                                                          0.2
                                             1.3
     3
                                                          0.2
                 4.6
                              3.1
                                             1.5
     4
                 5.0
                              3.6
                                             1.4
                                                          0.2
     y data head 0 Iris-setosa
          Iris-setosa
     1
     2
          Iris-setosa
     3
          Iris-setosa
          Iris-setosa
     Name: Species, dtype: object
     Training set size: 120
     Test set size: 30
# Check the first few rows of training and testing sets
print("Training data (features):")
print(X_train.head())
print("\nTraining data (target):")
print(y_train.head())
print("\nTesting data (features):")
print(X_test.head())
print("\nTesting data (target):")
print(y_test.head())
→▼ Training data (features):
         Sepal_length Sepal_width Petal_length Petal_width
```

```
# Save the testing features and target to CSV files
X_test.to_csv('X_test.csv', index=False)
y_test.to_csv('y_test.csv', index=False)
import os
os.listdir('/content/')
from google.colab import files
# Download files
files.download('/content/X_train.csv')
files.download('/content/y_train.csv')
files.download('/content/X_test.csv')
files.download('/content/y test.csv')
Class No-20(New Teacher)
import pandas
filename = '/content/Tennis_dataset.csv'
print(filename)
/content/Tennis_dataset.csv
import pandas as pd
df = pd.read_csv('/content/Tennis_dataset.csv')
print(df.to_string())
→
          Outlook Temperature Humidity Windy Play Tennis
     0
            Sunny
                          Hot
                                  High False
     1
            Sunny
                          Hot
                                  High
                                         True
                                                       No
     2
         Overcast
                          Hot
                                  High False
                                                      Yes
     3
             Rain
                         Mild
                                  High
                                        False
                                                      Yes
     4
             Rain
                         Cool
                                Normal False
                                                      Yes
     5
                         Cool
                                Normal
                                        True
             Rain
                                                       No
                                        True
                                Normal
     6
         Overcast
                         Cool
                                                      Yes
     7
            Sunny
                         Mild
                                  High False
                                                       No
     8
                         Cool
                                Normal False
            Sunny
                                                      Yes
     9
                                Normal False
             Rain
                         Mild
                                                      Yes
     10
            Sunny
                         Mild
                                Normal
                                         True
                                                      Yes
                                         True
     11
        0vercast
                         Mild
                                  High
                                                      Yes
     12
         Overcast
                          Hot
                                Normal False
                                                      Yes
     13
             Rain
                         Mild
                                  High
                                         True
                                                       No
Start coding or generate with AI.
import pandas as pd
df = pd.read_csv('/content/Tennis_dataset.csv')
```

df.head()

<b>→</b>		Outlook	Temperature	Humidity	Windy	Play Tennis
	0	Sunny	Hot	High	False	No
	1	Sunny	Hot	High	True	No
	2	Overcast	Hot	High	False	Yes
	3	Rain	Mild	High	False	Yes
	4	Rain	Cool	Normal	False	Yes

df.to\_string()

$\rightarrow$	1	Ou	tlook	Temp	peratu	ıre Hu	ımidit	y Wir	ndy Play	Tenr	nis\n0		Sunny		Н	ot	Н	ig
	h	False	<u> </u>		No\n1		Sunn	У	Hot		High	True	!		No\n2	٥v	erc	as
	t		Hot		High	Fals	ie .	`	Yes\n3		Rain		Mild		High	Fals	e	
	Yes	s∖n4	1	Rain		Coc	ol N	ormal	False		Yes	\n5	1	Rain		Coc	1	N
	orr	nal	True		N	lo∖n6	0ve	rcast	(	Cool	Norm	nal	True		Yes	s\n7		
	Sur	าทy	ı	Mild	H	ligh	False		No\ı	า8	Sun	nny	(	Cool	Norr	nal	Fal	se
	Yes	s\n9	I	Rain		Mi]	.d N	ormal	False		Yes	\n10	S	unny		Mil	.d	Ν
		_																

import pandas as pd
df = pd.read\_csv('/content/Iris.csv')
df.head()

<b>→</b>		Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
	0	1	5.1	3.5	1.4	0.2	Iris-setosa
	1	2	4.9	3.0	1.4	0.2	Iris-setosa
	2	3	4.7	3.2	1.3	0.2	Iris-setosa
	3	4	4.6	3.1	1.5	0.2	Iris-setosa
	4	5	5.0	3.6	1.4	0.2	Iris-setosa

Start coding or generate with AI.

### **Project Python**

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
```

### Load your dataset

# Select features (assuming 'Temperature' is the target and others are features)

```
# Print the actual column names to check for discrepancies
print(data.columns)

# Modify the 'features' list to match the actual column names
features = ['Year', 'Month', 'avg'] # Example: Corrected column names
# If your column names have spaces, try enclosing them in backticks: `Daily Avg`
# Adjust based on the output of data.columns

# Select the desired columns
data = data[features]
```

```
'], dtype='object')
   Index(['
                                                Station :Khulna
                                              Traceback (most recent call last)
    <ipython-input-29-513968a9f5b9> in <cell line: 10>()
          9 # Select the desired columns
     ---> 10 data = data[features]
                                     – 🐧 2 frames 🗕
    /usr/local/lib/python3.10/dist-packages/pandas/core/indexes/base.py in
    _raise_if_missing(self, key, indexer, axis_name)
                    if nmissing:
       6247
                        if nmissing == len(indexer):
        6248
                             raise KeyError(f"None of [{key}] are in the [{axis_name}]")
    -> 6249
       6250
       6251
                        not_found = list(ensure_index(key)[missing_mask.nonzero()
    [0]].unique())
    KeyError: "None of [Index(['Year', 'Month', 'avg'], dtype='object')] are in the
     [columns]"
Start coding or generate with AI.
```

## Temperature Prediction with Python and Machine Learning FOR Dhaka City Corporation.

```
import pandas as pd
weather = pd.read_csv("/content/weather.csv", index_col="DATE")
weather
```



	STATION	NAME	PRCP	TAVG	TMAX	TMIN
DATE						
1990-01-01	BGM00041923	TEJGAON, BG	0.00	63	74.0	53.0
1990-01-03	BGM00041923	TEJGAON, BG	0.00	61	75.0	52.0
1990-01-04	BGM00041923	TEJGAON, BG	NaN	64	NaN	53.0
1990-01-06	BGM00041923	TEJGAON, BG	0.00	63	74.0	53.0
1990-01-07	BGM00041923	TEJGAON, BG	0.00	64	77.0	55.0
2024-10-21	BGM00041923	TEJGAON, BG	0.00	83	NaN	76.0
2024-10-22	BGM00041923	TEJGAON, BG	0.00	86	NaN	77.0
2024-10-23	BGM00041923	TEJGAON, BG	0.10	83	NaN	NaN
2024-10-24	BGM00041923	TEJGAON, BG	0.61	76	82.0	NaN
2024-10-25	BGM00041923	TEJGAON, BG	0.01	83	90.0	72.0

8403 rows × 6 columns

null\_pct = weather.apply(pd.isnull).sum()/weather.shape[0]
null\_pct



	0
STATION	0.000000
NAME	0.000000
PRCP	0.114007
TAVG	0.000000
TMAX	0.124360
TMIN	0.669166

dtype: float64

weather.apply(pd.isnull).sum()

dtype: int64

```
valid_columns = weather.columns[null_pct < .05]</pre>
```

valid\_columns

```
Index(['STATION', 'NAME', 'TAVG'], dtype='object')
```

```
weather = weather[valid_columns].copy()
```

weather.columns = weather.columns.str.lower()

name tavg



		36461011	Traine	Lave			
	DATE						
	1990-01-01	BGM00041923	TEJGAON, BO	63			
	1990-01-03	BGM00041923	TEJGAON, BO	61			
	1990-01-04	BGM00041923	TEJGAON, BO	64			
	1990-01-06	BGM00041923	TEJGAON, BO	63			
	1990-01-07	BGM00041923	TEJGAON, BO	64			
	•••						
	2024-10-21	BGM00041923	TEJGAON, BO	83			
	2024-10-22	BGM00041923	TEJGAON, BO	86			
	2024-10-23	BGM00041923	TEJGAON, BO	83			
	2024-10-24	BGM00041923	TEJGAON, BO	76			
	2024-10-25	BGM00041923	TEJGAON, BO	83			
	8403 rows × 3	3 columns					
<pre>weather['tavg'] = weather['tavg'].fillna(weather['tavg'].mean() # Display the modified dataset print(weather) print(weather.info())</pre>							
<b>→</b>	DATE	station	name	tavg			
		BGM00041923 BGM00041923	TEJGAON, BG TEJGAON, BG	63 61 64			

station

```
\overline{\Rightarrow}
                  BGM00041923 TEJGAON, BG
                                                64
    1990-01-04
    1990-01-06
                  BGM00041923 TEJGAON, BG
                                                63
    1990-01-07
                  BGM00041923 TEJGAON, BG
                                                64
     . . .
                           . . .
                                               . . .
                                TEJGAON, BG
    2024-10-21
                  BGM00041923
                                                83
    2024-10-22
                  BGM00041923
                               TEJGAON, BG
                                                86
                                TEJGAON, BG
                                                83
    2024-10-23
                  BGM00041923
                                TEJGAON, BG
                                                76
    2024-10-24
                  BGM00041923
    2024-10-25
                  BGM00041923
                                TEJGAON, BG
                                                83
    [8403 rows x 3 columns]
```

<class 'pandas.core.frame.DataFrame'>

Data columns (total 3 columns):

station 8403 non-null

Column

name tavg

0

1

Index: 8403 entries, 1990-01-01 to 2024-10-25

8403 non-null

8403 non-null

Non-Null Count Dtype

object

object

int64

```
dtypes: int64(1), object(2)
     memory usage: 262.6+ KB
     None
weather = weather.ffill()
weather.apply(pd.isnull).sum()
\overline{\Rightarrow}
               0
      station
       name
               0
        tavg
               0
     dtype: int64
weather.apply(lambda x: (x == 9999).sum())
\overline{\Rightarrow}
               0
      station 0
       name
               0
       tavg
               0
     dtype: int64
weather.dtypes
\overline{\Rightarrow}
                    0
      station object
       name
               object
                int64
        tavg
     dtype: object
weather.index
→ Index(['1990-01-01', '1990-01-03', '1990-01-04', '1990-01-06', '1990-01-07',
              '1990-01-08', '1990-01-09', '1990-01-10', '1990-01-12', '1990-01-13',
              '2024-10-16', '2024-10-17', '2024-10-18', '2024-10-19', '2024-10-20',
              '2024-10-21', '2024-10-22', '2024-10-23', '2024-10-24', '2024-10-25'],
            dtype='object', name='DATE', length=8403)
```

weather.index = pd.to\_datetime(weather.index)
weather.index.year.value\_counts().sort\_index()



_	-		-	4
•	()	ш	n	

DATE	
1990	257
1991	290
1992	343
1993	321
1994	250
1995	289
1996	284
1997	166
1998	172
1999	132
2000	209
2001	278
2002	225
2003	201
2004	193
2005	230
2006	291
2007	214
2008	170
2009	290
2010	269
2011	99
2012	148
2013	185
2014	318
2015	329
2016	312
2017	296
2018	311

```
2019 221
2020 320
2021 25
2022 131
2023 355
2024 279
```

dtype: int64

Start coding or generate with AI.

### Filling with Mean, Median, or Mode

```
weather['tavg'] = weather['tavg'].fillna(weather['tavg'].mean())
# Display the modified dataset
print(weather)
print(weather.info())
```

```
→
                    station
                                   name tavg
    DATE
    1990-01-01
                BGM00041923 TEJGAON, BG
                                           63
    1990-01-03 BGM00041923 TEJGAON, BG
                                           61
                                           64
    1990-01-04
                BGM00041923 TEJGAON, BG
    1990-01-06 BGM00041923 TEJGAON, BG
                                           63
    1990-01-07
                BGM00041923 TEJGAON, BG
                                           64
    2024-10-21 BGM00041923 TEJGAON, BG
                                           83
    2024-10-22 BGM00041923 TEJGAON, BG
                                           86
                                           83
    2024-10-23 BGM00041923 TEJGAON, BG
    2024-10-24 BGM00041923 TEJGAON, BG
                                           76
    2024-10-25 BGM00041923 TEJGAON, BG
                                           83
```

[8403 rows x 3 columns]

<class 'pandas.core.frame.DataFrame'>

DatetimeIndex: 8403 entries, 1990-01-01 to 2024-10-25

Data columns (total 3 columns):

```
# Column Non-Null Count Dtype
--- 0 station 8403 non-null object
1 name 8403 non-null object
2 tavg 8403 non-null int64
```

dtypes: int64(1), object(2)
memory usage: 262.6+ KB

None

weather.index.year.value\_counts().sort\_index()

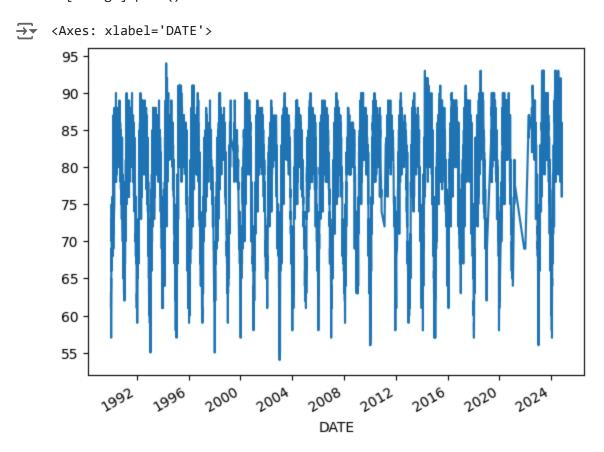


count

DATE	
1990	257
1991	290
1992	343
1993	321
1994	250
1995	289
1996	284
1997	166
1998	172
1999	132
2000	209
2001	278
2002	225
2003	201
2004	193
2005	230
2006	291
2007	214
2008	170
2009	290
2010	269
2011	99
2012	148
2013	185
2014	318
2015	329
2016	312
2017	296
2018	311

dtype: int64

weather["tavg"].plot()



Start coding or generate with AI.

#### **Tomorrow Weather Pattern**

weather["target"] = weather.shift(-1)["tavg"]



	station	name	tavg	target
DATE				
1990-01-01	BGM00041923	TEJGAON, BG	63	61.0
1990-01-03	BGM00041923	TEJGAON, BG	61	64.0
1990-01-04	BGM00041923	TEJGAON, BG	64	63.0
1990-01-06	BGM00041923	TEJGAON, BG	63	64.0
1990-01-07	BGM00041923	TEJGAON, BG	64	65.0
2024-10-21	BGM00041923	TEJGAON, BG	83	86.0
2024-10-22	BGM00041923	TEJGAON, BG	86	83.0
2024-10-23	BGM00041923	TEJGAON, BG	83	76.0
2024-10-24	BGM00041923	TEJGAON, BG	76	83.0
2024-10-25	BGM00041923	TEJGAON, BG	83	NaN

8403 rows × 4 columns

weather = weather.ffill()

name tavg target



station

DATE								
1990-01-01	BGM00041923	TEJGAON, BG	63	61.0				
1990-01-03	BGM00041923	TEJGAON, BG	61	64.0				
1990-01-04	BGM00041923	TEJGAON, BG	64	63.0				
1990-01-06	BGM00041923	TEJGAON, BG	63	64.0				
1990-01-07	BGM00041923	TEJGAON, BG	64	65.0				
2024-10-21	BGM00041923	TEJGAON, BG	83	86.0				
2024-10-22	BGM00041923	TEJGAON, BG	86	83.0				
2024-10-23	BGM00041923	TEJGAON, BG	83	76.0				
2024-10-24	BGM00041923	TEJGAON, BG	76	83.0				
2024-10-25	BGM00041923	TEJGAON, BG	83	83.0				
8403 rows ×	4 columns							
Coom aldoona li		nt Didea						
from sklearn.li	near_model impo	rt klage						
rr = Ridge(alph	a=.1)							
predictors = we	ather.columns[ $\sim$	weather.columns	isin([	"target", "name", "station"])]				
predictors								
		IV						
→ Index(['ta	vg'], dtype='ob	ject")						
<pre>def backtest(weather, model, predictors, start=3650, step=90):     all_predictions = []</pre>								
<pre>for i in range(start, weather.shape[0], step):     train = weather.iloc[:i,:]     test = weather.iloc[i:(i+step),:]</pre>								
model.f	<pre>model.fit(train[predictors], train["target"])</pre>							
<pre>preds = model.predict(test[predictors]) preds = pd.Series(preds, index=test.index) combined = pd.concat([test["target"], preds], axis=1) combined.columns = ["actual", "prediction"]</pre>								

combined["diff"] = (combined["prediction"] - combined["actual"]).abs()

all\_predictions.append(combined)
return pd.concat(all\_predictions)

predictions = backtest(weather, rr, predictors)

from sklearn.metrics import mean\_absolute\_error, mean\_squared\_error
mean\_absolute\_error(predictions["actual"], predictions["prediction"])

2.065274446896808

predictions.sort\_values("diff", ascending=False)

<b>→</b>		actual	prediction	diff
	DATE			
	2014-02-03	79.0	59.625368	19.374632
	2022-01-01	87.0	69.814585	17.185415
	2019-01-13	85.0	69.813581	15.186419
	2014-02-02	58.0	71.610908	13.610908
	2014-12-25	57.0	69.771097	12.771097
	2007-12-26	67.0	67.003209	0.003209
	2015-11-05	79.0	78.997211	0.002789
	2017-07-25	79.0	78.997617	0.002383

4753 rows × 3 columns

2017-04-19

2018-05-18

pd.Series(rr.coef\_, index=predictors)

79.0

79.0

78.997617

78.999381

0.002383

0.000619

**tavg** 0.922487

dtype: float64

```
def pct_diff(old, new):
    return (new - old) / old
def compute_rolling(weather, horizon, col):
    label = f"rolling_{horizon}_{col}"
    weather[label] = weather[col].rolling(horizon).mean()
    weather[f"{label}_pct"] = pct_diff(weather[label], weather[col])
    return weather
rolling_horizons = [3, 14]
for horizon in rolling_horizons:
    for col in ["tavg"]:
        weather = compute_rolling(weather, horizon, col)
def expand_mean(df):
    return df.expanding(1).mean()
for col in ["tavg"]:
    weather[f"month_avg_{col}"] = weather[col].groupby(weather.index.month, group_keys=False
    weather[f"day_avg_{col}"] = weather[col].groupby(weather.index.day_of_year, group_keys=F
```



	station	name	tavg	target	rolling_3_tavg	<pre>rolling_3_tavg_pct</pre>	rolli	
DATE								
1990- 01-01	BGM00041923	TEJGAON, BG	63	61.0	NaN	NaN		
1990- 01-03	BGM00041923	TEJGAON, BG	61	64.0	NaN	NaN		
1990- 01-04	BGM00041923	TEJGAON, BG	64	63.0	62.666667	0.021277		
1990- 01-06	BGM00041923	TEJGAON, BG	63	64.0	62.666667	0.005319		
1990- 01-07	BGM00041923	TEJGAON, BG	64	65.0	63.666667	0.005236		
2024- 10-21	BGM00041923	TEJGAON, BG	83	86.0	83.000000	0.000000		
2024- 10-22	BGM00041923	TEJGAON, BG	86	83.0	84.000000	0.023810		
2024- 10-23	BGM00041923	TEJGAON, BG	83	76.0	84.000000	-0.011905		
2024- 10-24	BGM00041923	TEJGAON, BG	76	83.0	81.666667	-0.069388		
2024- 10-25	BGM00041923	TEJGAON, BG	83	83.0	80.666667	0.028926		
8403 rows × 10 columns								
<b>←</b>								

```
1.9673166596363283
```

predictors.sort\_values("diff", ascending=False)

weather.loc["1990-03-07": "1990-03-17"]

<b>→</b>		station	name	tavg	target	rolling_3_tavg	rolling_3_tavg_pct	rollin
	DATE							
	1990- 03-07	BGM00041923	TEJGAON, BG	71	72.0	73.000000	-0.027397	
	1990- 03-08	BGM00041923	TEJGAON, BG	72	81.0	73.000000	-0.013699	
	1990- 03-11	BGM00041923	TEJGAON, BG	81	69.0	74.666667	0.084821	
	1990- 03-12	BGM00041923	TEJGAON, BG	69	70.0	74.000000	-0.067568	
	1990- 03-13	BGM00041923	TEJGAON, BG	70	79.0	73.333333	-0.045455	
	1990- 03-16	BGM00041923	TEJGAON, BG	79	87.0	72.666667	0.087156	
	1990- 03-17	BGM00041923	TEJGAON, BG	87	83.0	78.666667	0.105932	
	4							<b>•</b>

predictions["diff"].round().value\_counts().sort\_index() / predictions.shape[0]



#### count

diff 0.0 0.166702 1.0 0.303018 2.0 0.239291 3.0 0.144334 4.0 0.074066 5.0 0.035451 6.0 0.018569 0.008019 7.0 8.0 0.004220 9.0 0.002532 0.001688 10.0 11.0 0.000422 **12.0** 0.000633 13.0 0.000422 16.0 0.000211 17.0 0.000211 19.0 0.000211

dtype: float64

mean\_squared\_error(predictions["actual"], predictions["prediction"])

**→** 6.638035649016272

predictions.sort\_values("diff", ascending=False)



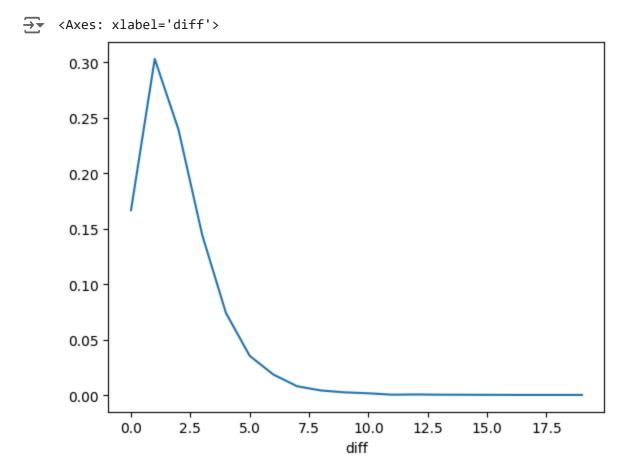
	actual	prediction	diff
DATE			
2022-01-01	87.0	68.479289	18.520711
2019-01-13	85.0	67.595650	17.404350
2014-02-03	79.0	62.828462	16.171538
2014-02-02	58.0	70.868049	12.868049
2021-01-18	78.0	65.223965	12.776035
2024-08-07	85.0	85.002833	0.002833
2023-01-12	63.0	63.002649	0.002649
2007-12-07	69.0	69.001455	0.001455
2009-06-05	85.0	85.001127	0.001127
2023-11-23	75.0	75.000713	0.000713

4739 rows × 3 columns

weather.loc["1990-03-07": "1990-03-17"]

•		station	name	tavg	target	rolling_3_tavg	<pre>rolling_3_tavg_pct</pre>	rollin
	DATE							
	1990- 03-07	BGM00041923	TEJGAON, BG	71	72.0	73.000000	-0.027397	
	1990- 03-08	BGM00041923	TEJGAON, BG	72	81.0	73.000000	-0.013699	
	1990- 03-11	BGM00041923	TEJGAON, BG	81	69.0	74.666667	0.084821	
	1990- 03-12	BGM00041923	TEJGAON, BG	69	70.0	74.000000	-0.067568	
	1990- 03-13	BGM00041923	TEJGAON, BG	70	79.0	73.333333	-0.045455	
	1990- 03-16	BGM00041923	TEJGAON, BG	79	87.0	72.666667	0.087156	
	1990- 03-17	BGM00041923	TEJGAON, BG	87	83.0	78.666667	0.105932	
	4							

(predictions["diff"].round().value\_counts().sort\_index() / predictions.shape[0]).plot()



predictions