

Type *Markdown* and LaTeX:  $\alpha^2$

```
In [15]: import pandas as pd
import numpy as np
df=pd.DataFrame(np.random.randn(5,3),index=['a','c','e','f','h'],columns=['one','two','three'])
print(df)
```

	one	two	three
a	-1.417411	-0.366846	-1.947782
c	-1.688598	0.795150	-1.598514
e	-0.057151	0.188724	-0.549276
f	-0.778126	-0.391546	0.237263
h	1.493284	-0.469932	-0.742576

```
In [16]: df=df.reindex(['a','b','c','d','e','f','g','h'])
print(df)
```

	one	two	three
a	-1.417411	-0.366846	-1.947782
b	NaN	NaN	NaN
c	-1.688598	0.795150	-1.598514
d	NaN	NaN	NaN
e	-0.057151	0.188724	-0.549276
f	-0.778126	-0.391546	0.237263
g	NaN	NaN	NaN
h	1.493284	-0.469932	-0.742576

```
In [17]: print(df.dropna())
```

	one	two	three
a	-1.417411	-0.366846	-1.947782
c	-1.688598	0.795150	-1.598514
e	-0.057151	0.188724	-0.549276
f	-0.778126	-0.391546	0.237263
h	1.493284	-0.469932	-0.742576

```
In [18]: b=df
print(df)
```

	one	two	three
a	-1.417411	-0.366846	-1.947782
b	NaN	NaN	NaN
c	-1.688598	0.795150	-1.598514
d	NaN	NaN	NaN
e	-0.057151	0.188724	-0.549276
f	-0.778126	-0.391546	0.237263
g	NaN	NaN	NaN
h	1.493284	-0.469932	-0.742576

```
In [19]: df2=b  
print(b)
```

	one	two	three
a	-1.417411	-0.366846	-1.947782
b	NaN	NaN	NaN
c	-1.688598	0.795150	-1.598514
d	NaN	NaN	NaN
e	-0.057151	0.188724	-0.549276
f	-0.778126	-0.391546	0.237263
g	NaN	NaN	NaN
h	1.493284	-0.469932	-0.742576

```
In [20]: print(df2.fillna(method='pad'))
```

	one	two	three
a	-1.417411	-0.366846	-1.947782
b	-1.417411	-0.366846	-1.947782
c	-1.688598	0.795150	-1.598514
d	-1.688598	0.795150	-1.598514
e	-0.057151	0.188724	-0.549276
f	-0.778126	-0.391546	0.237263
g	-0.778126	-0.391546	0.237263
h	1.493284	-0.469932	-0.742576

```
In [22]: df4=df2  
print(df4.fillna(method='bfill'))
```

	one	two	three
a	-1.417411	-0.366846	-1.947782
b	-1.688598	0.795150	-1.598514
c	-1.688598	0.795150	-1.598514
d	-0.057151	0.188724	-0.549276
e	-0.057151	0.188724	-0.549276
f	-0.778126	-0.391546	0.237263
g	1.493284	-0.469932	-0.742576
h	1.493284	-0.469932	-0.742576

```
In [23]: print(df['one'].notnull())
```

a	True
b	False
c	True
d	False
e	True
f	True
g	False
h	True

Name: one, dtype: bool

In [24]: `print(df['one'].isnull())`

```
a    False
b     True
c    False
d     True
e    False
f    False
g     True
h    False
Name: one, dtype: bool
```

In [25]: `a1=pd.DataFrame([[ 'ajay',18],[ 'arun',19],[ 'ashwin',21]],columns=[ 'name', 'age'])`  
`print(a1)`

```
   name  age
0  ajay   18
1  arun   19
2 ashwin  21
```

In [26]: `print(a1.replace({18:15,19:17,21:20}))`

```
   name  age
0  ajay   15
1  arun   17
2 ashwin  20
```

In [6]: `import pandas as pd`  
`import numpy as np`  
`a1=pd.DataFrame([[ 'lion',300],[ 'leopard',190],[ 'tiger',211],[ 'lion',298],[ 'tiger',255]])`  
`print(a1)`

```
   animal  speed
0    lion    300
1 leopard    190
2   tiger    211
3    lion    298
4   tiger    255
```

In [7]: `a2=a1.groupby([ 'animal']).mean()`  
`print(a2)`

```
   animal  speed
leopard    190.0
lion       299.0
tiger      233.0
```

In [8]: `a2=a1.groupby([ 'animal']).sum()`  
`print(a2)`

```
   animal  speed
leopard    190
lion       598
tiger      466
```

```
In [9]: a2=a1.groupby(['animal']).count()  
print(a2)
```

```
      speed  
animal  
leopard    1  
lion       2  
tiger      2
```

```
In [10]: a2=a1.groupby(['animal']).first()  
print(a2)
```

```
      speed  
animal  
leopard  190  
lion     300  
tiger    211
```

```
In [11]: a2=a1.groupby(['animal']).last()  
print(a2)
```

```
      speed  
animal  
leopard  190  
lion     298  
tiger    255
```

```
In [2]: import datetime as d  
r=d.datetime.now()  
print(r)
```

```
2024-08-21 10:42:02.877264
```

```
In [3]: import datetime as d  
r=d.datetime.today()  
print(r)
```

```
2024-08-21 10:43:01.811434
```

```
In [5]: import datetime as d  
r1=d.datetime(2020,6,8,23,10,25,404040)  
print(r1)
```

```
2020-06-08 23:10:25.404040
```

```
In [6]: print(r1.replace(day=10))
```

```
2020-06-10 23:10:25.404040
```

```
In [7]: print(r1.replace(month=11))
```

```
2020-11-08 23:10:25.404040
```

```
In [8]: print(r1.replace(year=2004))
```

```
2004-06-08 23:10:25.404040
```

```
In [9]: print(r1.replace(day=10,month=11,year=2004))
```

2004-11-10 23:10:25.404040

```
In [10]: from datetime import date  
print(date(2004,11,10))
```

2004-11-10

```
In [11]: from datetime import date  
print(date(2004,11,10).ctime())
```

Wed Nov 10 00:00:00 2004

```
In [16]: print(r.strftime("%Y"))
```

2024

```
In [15]: print(r.strftime("%y"))
```

24

```
In [17]: print(r.strftime("%m"))
```

08

```
In [18]: print(r.strftime("%b"))
```

Aug

```
In [19]: print(r.strftime("%B"))
```

August

```
In [20]: print(r.strftime("%j"))
```

234

```
In [21]: print(r.strftime("%D"))
```

08/21/24

```
In [22]: print(r.strftime("%d"))
```

21

```
In [23]: print(r.strftime("%a"))
```

Wed

```
In [24]: print(r.strftime("%A"))
```

Wednesday

```
In [25]: print(r.strftime("%H"))
```

10

```
In [26]: print(r.strftime("%S"))
```

01

```
In [27]: print(r.strftime("%C"))
```

20

```
In [28]: print(r.strftime("%c"))
```

Wed Aug 21 10:43:01 2024

```
In [29]: print(r.strftime("%F"))
```

2024-08-21

```
In [30]: print(r.strftime("%f"))
```

811434

```
In [31]: print(r.strftime("%p"))
```

AM

```
In [32]: print(r.strftime("%x"))
```

08/21/24

```
In [33]: print(r.strftime("%X"))
```

10:43:01

```
In [34]: print(r.strftime("%r"))
```

10:43:01 AM

```
In [36]: print(r.strftime("%T"))
```

10:43:01



```
In [10]: x=iris.data
y=iris.target
print(x)
print(y)
```

```
[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]
 [5.4 3.9 1.7 0.4]
 [4.6 3.4 1.4 0.3]
 [5.  3.4 1.5 0.2]
 [4.4 2.9 1.4 0.2]
 [4.9 3.1 1.5 0.1]
 [5.4 3.7 1.5 0.2]
 [4.8 3.4 1.6 0.2]
 [4.8 3.  1.4 0.1]
 [4.3 3.  1.1 0.1]
 [5.8 4.  1.2 0.2]
 [5.7 4.4 1.5 0.4]
 [5.4 3.9 1.3 0.4]
 [5.1 3.5 1.4 0.3]
 [5.7 3.8 1.7 0.3]
 [5.  3.  1.  0.  ]
```

```
In [19]: df=pd.DataFrame(x,columns=iris.feature_names)
print(df)
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
...	...	...	...	...
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

[150 rows x 4 columns]



In [20]: `print(df.head())`

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.
2	4.9	3.0	1.4	0.
2	4.7	3.2	1.3	0.
3	4.6	3.1	1.5	0.
4	5.0	3.6	1.4	0.

In [21]: `print(df.tail())`

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

In [22]: `print(df.describe())`

	sepal length (cm)	sepal width (cm)	petal length (cm)	\
count	150.000000	150.000000	150.000000	
mean	5.843333	3.057333	3.758000	
std	0.828066	0.435866	1.765298	
min	4.300000	2.000000	1.000000	
25%	5.100000	2.800000	1.600000	
50%	5.800000	3.000000	4.350000	
75%	6.400000	3.300000	5.100000	
max	7.900000	4.400000	6.900000	

	petal width (cm)
count	150.000000
mean	1.199333
std	0.762238
min	0.100000
25%	0.300000
50%	1.300000
75%	1.800000
max	2.500000

In [24]: `print(df.min())`

```
sepal length (cm)    4.3
sepal width (cm)     2.0
petal length (cm)    1.0
petal width (cm)     0.1
dtype: float64
```

In [25]: `print(df.max())`

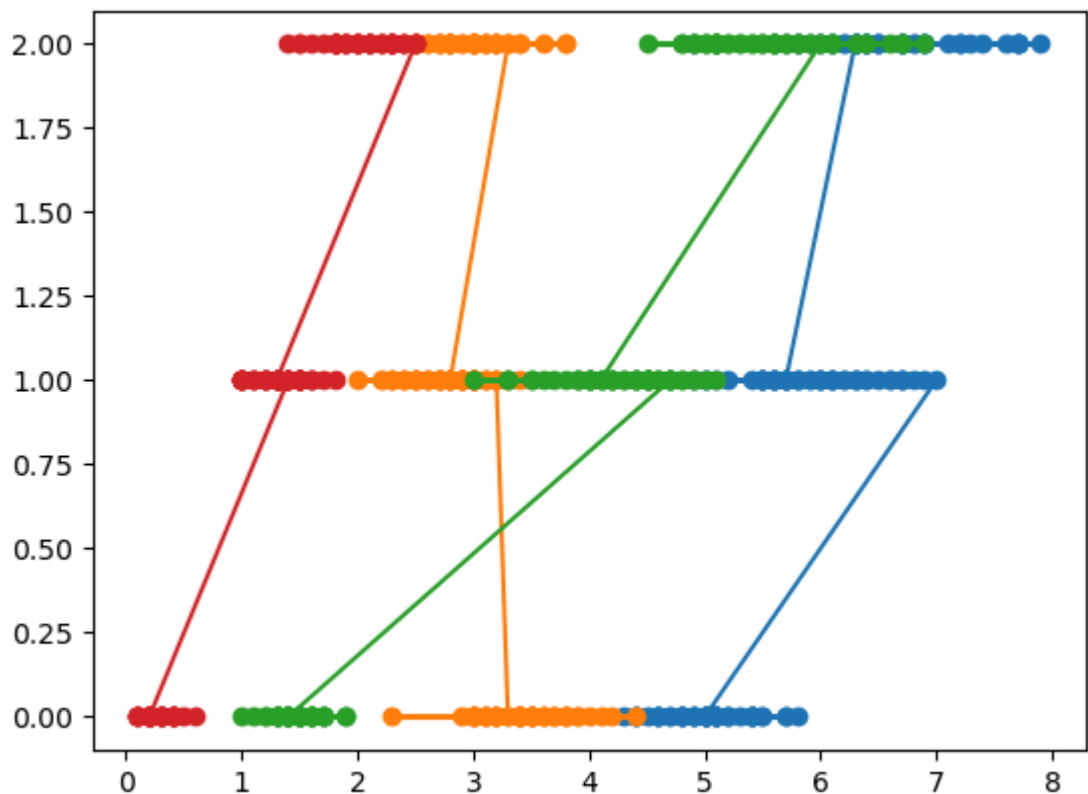
```
sepal length (cm)    7.9
sepal width (cm)     4.4
petal length (cm)    6.9
petal width (cm)     2.5
dtype: float64
```

```
In [26]: from sklearn import datasets  
import pandas as pd  
dia=datasets.load_diabetes()  
print(dia)
```

```
{'data': array([[ 0.03807591,  0.05068012,  0.06169621, ..., -0.00259226,
  0.01990749, -0.01764613],
 [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,
 -0.06833155, -0.09220405],
 [ 0.08529891,  0.05068012,  0.04445121, ..., -0.00259226,
  0.00286131, -0.02593034],
 ...,
 [ 0.04170844,  0.05068012, -0.01590626, ..., -0.01107952,
 -0.04688253,  0.01549073],
 [-0.04547248, -0.04464164,  0.03906215, ...,  0.02655962,
  0.04452873, -0.02593034],
 [-0.04547248, -0.04464164, -0.0730303 , ..., -0.03949338,
 -0.00422151,  0.00306441]]), 'target': array([151.,  75., 141., 20
 6., 135.,  97., 138.,  63., 110., 310., 101.,
 69., 179., 185., 118., 171., 166., 144.,  97., 168.,  68.,  49.,
 68., 245., 184., 202., 137.,  85., 131., 283., 129.,  59., 341.,
 87.,  65., 102., 265., 276., 252.,  90., 100.,  55.,  61.,  92.,
259.,  53., 190., 142.,  75., 142., 155., 225.,  59., 104., 182.,
128.,  52.,  37., 170., 170.,  61., 144.,  52., 128.,  71., 163.,
150.,  97., 160., 178.,  48., 270., 202., 111.,  85.,  42., 170.,
200., 252., 113., 143.,  51.,  52., 210.,  65., 141.,  55., 134.,
 42., 111.,  98., 164.,  48.,  96.,  90., 162., 150., 279.,  92.,
 83., 128., 102., 302., 198.,  95.,  53., 134., 144., 232.,  81.,
104.,  59., 246., 297., 258., 229., 275., 281., 179., 200., 200.,
173., 180.,  84., 121., 161.,  99., 109., 115., 268., 274., 158.,
107.,  83., 103., 272.,  85., 280., 336., 281., 118., 317., 235.,
 60., 174., 259., 178., 128.,  96., 126., 288.,  88., 292.,  71.,
197., 186.,  25.,  84.,  96., 195.,  53., 217., 172., 131., 214.,
 59.,  70., 220., 268., 152.,  47.,  74., 295., 101., 151., 127.,
237., 225.,  81., 151., 107.,  64., 138., 185., 265., 101., 137.,
143., 141.,  79., 292., 178.,  91., 116.,  86., 122.,  72., 129.,
142.,  90., 158.,  39., 196., 222., 277.,  99., 196., 202., 155.,
 77., 191.,  70.,  73.,  49.,  65., 263., 248., 296., 214., 185.,
 78.,  93., 252., 150.,  77., 208.,  77., 108., 160.,  53., 220.,
154., 259.,  90., 246., 124.,  67.,  72., 257., 262., 275., 177.,
 71.,  47., 187., 125.,  78.,  51., 258., 215., 303., 243.,  91.,
150., 310., 153., 346.,  63.,  89.,  50.,  39., 103., 308., 116.,
145.,  74.,  45., 115., 264.,  87., 202., 127., 182., 241.,  66.,
 94., 283.,  64., 102., 200., 265.,  94., 230., 181., 156., 233.,
 60., 219.,  80.,  68., 332., 248.,  84., 200.,  55.,  85.,  89.,
 31., 129.,  83., 275.,  65., 198., 236., 253., 124.,  44., 172.,
114., 142., 109., 180., 144., 163., 147.,  97., 220., 190., 109.,
191., 122., 230., 242., 248., 249., 192., 131., 237.,  78., 135.,
244., 199., 270., 164.,  72.,  96., 306.,  91., 214.,  95., 216.,
263., 178., 113., 200., 139., 139.,  88., 148.,  88., 243.,  71.,
 77., 109., 272.,  60.,  54., 221.,  90., 311., 281., 182., 321.,
 58., 262., 206., 233., 242., 123., 167.,  63., 197.,  71., 168.,
140., 217., 121., 235., 245.,  40.,  52., 104., 132.,  88.,  69.,
219.,  72., 201., 110.,  51., 277.,  63., 118.,  69., 273., 258.,
 43., 198., 242., 232., 175.,  93., 168., 275., 293., 281.,  72.,
140., 189., 181., 209., 136., 261., 113., 131., 174., 257.,  55.,
 84.,  42., 146., 212., 233.,  91., 111., 152., 120.,  67., 310.,
 94., 183.,  66., 173.,  72.,  49.,  64.,  48., 178., 104., 132.,
220.,  57.]), 'frame': None, 'DESCR': '.. _diabetes_dataset:\n\nDia
betes dataset\n-----\n\nTen baseline variables, age, sex, body
mass index, average blood\npressure, and six blood serum measurements were
obtained for each of n =\n442 diabetes patients, as well as the response o
f interest, a\nquantitative measure of disease progression one year after
baseline.\n\n**Data Set Characteristics:**\n\n :Number of Instances: 442
\n\n :Number of Attributes: First 10 columns are numeric predictive value
s\n\n :Target: Column 11 is a quantitative measure of disease progression
```

one year after baseline\n\n :Attribute Information:\n - age age  
in years\n - sex\n - bmi body mass index\n - bp av  
erage blood pressure\n - s1 tc, total serum cholesterol\n -  
s2 ldl, low-density lipoproteins\n - s3 hdl, high-density l  
ipoproteins\n - s4 tch, total cholesterol / HDL\n - s5  
ltg, possibly log of serum triglycerides level\n - s6 glu, blood  
sugar level\n\nNote: Each of these 10 feature variables have been mean cen  
tered and scaled by the standard deviation times the square root of `n\_sam  
ples` (i.e. the sum of squares of each column totals 1).\n\nSource URL:\n  
<https://www4.stat.ncsu.edu/~boos/var.select/diabetes.html>\n\nFor more infor  
mation see:\nBradley Efron, Trevor Hastie, Iain Johnstone and Robert Tibsh  
irani (2004) "Least Angle Regression," Annals of Statistics (with discussi  
on), 407-499.\n([https://web.stanford.edu/~hastie/Papers/LARS/LeastAngle\\_2002.pdf](https://web.stanford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf))\n', 'feature\_names': ['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3',  
's4', 's5', 's6'], 'data\_filename': 'diabetes\_data\_raw.csv.gz', 'target\_fi  
lename': 'diabetes\_target.csv.gz', 'data\_module': 'sklearn.datasets.data'}

```
In [28]: import matplotlib.pyplot
import matplotlib.pyplot as pl
pl.plot(x,y,marker='o')
pl.show()
```



```
In [29]: from sklearn import datasets  
import pandas as pd  
bc=datasets.load_breast_cancer()  
print(bc)
```

15/17

```

area (mean):                                143.5  2501.0\n    smoothness (mean):
n):                                0.053  0.163\n    compactness (mean):
0.019  0.345\n    concavity (mean):                                0.0  0.427\n
concave points (mean):                                0.0  0.201\n    symmetry (mean):
0.106  0.304\n    fractal dimension (mean):                                0.05  0.097\n
radius (standard error):                                0.112  2.873\n    texture (standard
error):                                0.36  4.885\n    perimeter (standard
error):                                0.757  21.98\n    area (standard error):                                6.802  542.2\n
smoothness (standard error):                                0.002  0.031\n    compactness (stand
ard error):                                0.002  0.135\n    concavity (standard
error):                                0.0  0.396\n    concave points (standard
error):                                0.0  0.053\n
symmetry (standard error):                                0.008  0.079\n    fractal dimension
(standard error):                                0.001  0.03\n    radius (worst):
7.93  36.04\n    texture (worst):                                12.02  49.54\n
perimeter (worst):                                50.41  251.2\n    area (worst):
185.2  4254.0\n    smoothness (worst):                                0.071  0.223\n
compactness (worst):                                0.027  1.058\n    concavity (worst):
0.0  1.252\n    concave points (worst):                                0.0  0.291\n
symmetry (worst):                                0.156  0.664\n    fractal dimension
(worst):                                0.055  0.208\n    =====
= =====\n\n    :Missing Attribute Values: None\n\n    :Class Distr
ibution: 212 - Malignant, 357 - Benign\n\n    :Creator: Dr. William H. Wo
lberg, W. Nick Street, Olvi L. Mangasarian\n\n    :Donor: Nick Street\n\n
>Date: November, 1995\n\nThis is a copy of UCI ML Breast Cancer Wisconsin
(Diagnostic) datasets.\nhttps://goo.gl/U2Uwz2\n\nFeatures are computed fro
m a digitized image of a fine needle\naspirate (FNA) of a breast mass. Th
ey describe\ncharacteristics of the cell nuclei present in the image.\n\nS
eparating plane described above was obtained using\nMultisurface Method-Tr
ee (MSM-T) [K. P. Bennett, "Decision Tree\nConstruction Via Linear Program
ming." Proceedings of the 4th\nMidwest Artificial Intelligence and Cogniti
ve Science Society,\npp. 97-101, 1992], a classification method which uses
linear\nprogramming to construct a decision tree. Relevant features\nwere
selected using an exhaustive search in the space of 1-4\nfeatures and 1-3
separating planes.\n\nThe actual linear program used to obtain the separati
ng plane\nin the 3-dimensional space is that described in:\n[K. P. Bennet
t and O. L. Mangasarian: "Robust Linear\nProgramming Discrimination of Two
Linearly Inseparable Sets",\nOptimization Methods and Software 1, 1992, 23
-34].\n\nThis database is also available through the UW CS ftp server:\n\n
ftp ftp.cs.wisc.edu\ncd math-prog/cpo-dataset/machine-learn/WDBC/\n\n.. to
pic:: References\n\n    - W.N. Street, W.H. Wolberg and O.L. Mangasarian. N
uclear feature extraction \n    for breast tumor diagnosis. IS&T/SPIE 199
3 International Symposium on \n    Electronic Imaging: Science and Techno
logy, volume 1905, pages 861-870,\n    San Jose, CA, 1993.\n    - O.L. Man
gasarian, W.N. Street and W.H. Wolberg. Breast cancer diagnosis and \n
prognosis via linear programming. Operations Research, 43(4), pages 570-57
7, \n    July-August 1995.\n    - W.H. Wolberg, W.N. Street, and O.L. Mang
asarian. Machine learning techniques\n    to diagnose breast cancer from
fine-needle aspirates. Cancer Letters 77 (1994) \n    163-171.', 'feature
_names': array(['mean radius', 'mean texture', 'mean perimeter', 'mean are
a',
    'mean smoothness', 'mean compactness', 'mean concavity',
    'mean concave points', 'mean symmetry', 'mean fractal dimension',
    'radius error', 'texture error', 'perimeter error', 'area error',
    'smoothness error', 'compactness error', 'concavity error',
    'concave points error', 'symmetry error',
    'fractal dimension error', 'worst radius', 'worst texture',
    'worst perimeter', 'worst area', 'worst smoothness',
    'worst compactness', 'worst concavity', 'worst concave points',
    'worst symmetry', 'worst fractal dimension'], dtype='<U23'), 'filen
ame': 'breast_cancer.csv', 'data_module': 'sklearn.datasets.data'}

```



In [ ]: