```
In [1]: import pandas as pd
```

In [2]: from sklearn.datasets import load\_breast\_cancer
 iris = load\_breast\_cancer()

In [3]: X = pd.DataFrame(iris.data, columns=['Xvar'+str(i+1)+"S" for i in range(iris.data.shape[1])])
X

Out[3]:

					1	ı		T		ı		ı	ı	ı	
	Xvar1S	Xvar2S	Xvar3S	Xvar4S	Xvar5S	Xvar6S	Xvar7S	Xvar8S	Xvar9S	Xvar10S		Xvar21S	Xvar22S	Xvar23S	Xva
0	17.990	10.38	122.80	1001.0	0.11840	0.27760	0.300100	0.147100	0.2419	0.07871		25.380	17.33	184.60	2019
1	20.570	17.77	132.90	1326.0	0.08474	0.07864	0.086900	0.070170	0.1812	0.05667		24.990	23.41	158.80	1950
2	19.690	21.25	130.00	1203.0	0.10960	0.15990	0.197400	0.127900	0.2069	0.05999		23.570	25.53	152.50	170!
3	11.420	20.38	77.58	386.1	0.14250	0.28390	0.241400	0.105200	0.2597	0.09744		14.910	26.50	98.87	567.
4	20.290	14.34	135.10	1297.0	0.10030	0.13280	0.198000	0.104300	0.1809	0.05883		22.540	16.67	152.20	157
5	12.450	15.70	82.57	477.1	0.12780	0.17000	0.157800	0.080890	0.2087	0.07613		15.470	23.75	103.40	741.
6	18.250	19.98	119.60	1040.0	0.09463	0.10900	0.112700	0.074000	0.1794	0.05742		22.880	27.66	153.20	1600
7	13.710	20.83	90.20	577.9	0.11890	0.16450	0.093660	0.059850	0.2196	0.07451	:	17.060	28.14	110.60	897.
8	13.000	21.82	87.50	519.8	0.12730	0.19320	0.185900	0.093530	0.2350	0.07389	:	15.490	30.73	106.20	739.
9	12.460	24.04	83.97	475.9	0.11860	0.23960	0.227300	0.085430	0.2030	0.08243		15.090	40.68	97.65	711.
10	16.020	23.24	102.70	797.8	0.08206	0.06669	0.032990	0.033230	0.1528	0.05697		19.190	33.88	123.80	1150
11	15.780	17.89	103.60	781.0	0.09710	0.12920	0.099540	0.066060	0.1842	0.06082		20.420	27.28	136.50	129!
12	19.170	24.80	132.40	1123.0	0.09740	0.24580	0.206500	0.111800	0.2397	0.07800		20.960	29.94	151.70	133:
13	15.850	23.95	103.70	782.7	0.08401	0.10020	0.099380	0.053640	0.1847	0.05338		16.840	27.66	112.00	876.
14	13.730	22.61	93.60	578.3	0.11310	0.22930	0.212800	0.080250	0.2069	0.07682		15.030	32.01	108.80	697.
15	14.540	27.54	96.73	658.8	0.11390	0.15950	0.163900	0.073640	0.2303	0.07077		17.460	37.13	124.10	943.
16	14.680	20.13	94.74	684.5	0.09867	0.07200	0.073950	0.052590	0.1586	0.05922		19.070	30.88	123.40	113
17	16.130	20.68	108.10	798.8	0.11700	0.20220	0.172200	0.102800	0.2164	0.07356		20.960	31.48	136.80	131
18	19.810	22.15	130.00	1260.0	0.09831	0.10270	0.147900	0.094980	0.1582	0.05395		27.320	30.88	186.80	239
19	13.540	14.36	87.46	566.3	0.09779	0.08129	0.066640	0.047810	0.1885	0.05766		15.110	19.26	99.70	711.
20	13.080	15.71	85.63	520.0	0.10750	0.12700	0.045680	0.031100	0.1967	0.06811		14.500	20.49	96.09	630.
21	9.504	12.44	60.34	273.9	0.10240	0.06492	0.029560	0.020760	0.1815	0.06905		10.230	15.66	65.13	314.
22	15.340	14.26	102.50	704.4	0.10730	0.21350	0.207700	0.097560	0.2521	0.07032		18.070	19.08	125.10	980.
23	21.160	23.04	137.20	1404.0	0.09428	0.10220	0.109700	0.086320	0.1769	0.05278		29.170	35.59	188.00	261
24	16.650	21.38	110.00	904.6	0.11210	0.14570	0.152500	0.091700	0.1995	0.06330		26.460	31.56	177.00	221
25	17.140	16.40	116.00	912.7	0.11860	0.22760	0.222900	0.140100	0.3040	0.07413		22.250	21.40	152.40	146
26	14.580	21.53	97.41	644.8	0.10540	0.18680	0.142500	0.087830	0.2252	0.06924		17.620	33.21	122.40	896.
27	18.610	20.25	122.10	1094.0	0.09440	0.10660	0.149000	0.077310	0.1697	0.05699		21.310	27.26	139.90	140:
28	15.300	25.27	102.40	732.4	0.10820	0.16970	0.168300	0.087510	0.1926	0.06540		20.270	36.71	149.30	1269
29	17.570	15.05	115.00	955.1	0.09847	0.11570	0.098750	0.079530	0.1739	0.06149		20.010	19.52	134.90	122
															ļ
539	7.691	25.44	48.34	170.4	0.08668	0.11990	0.092520	0.013640	0.2037	0.07751		8.678	31.89	54.49	223.
540	11.540	14.44	74.65	402.9	0.09984	0.11200	0.067370	0.025940	0.1818	0.06782		12.260	19.68	78.78	457.
541	14.470	24.99	95.81	656.4	0.08837	0.12300	0.100900	0.038900	0.1872	0.06341		16.220	31.73	113.50	808.
542	14.740	25.42	94.70	668.6	0.08275	0.07214	0.041050	0.030270	0.1840	0.05680		16.510	32.29	107.40	826.
	13.210	28.06	84.88	538.4	0.08671			0.032750		0.05781		14.370	37.17	92.48	629.
	13.870	20.70	89.77	584.8	0.09578	0.10180	0.036880	0.023690	0.1620	0.06688		15.050	24.75	99.17	688.
	13.620	23.23	87.19	573.2				0.024430		0.05801		15.350	29.09	97.58	729.
	10.320	16.35	65.31	324.9				0.005495		0.06201		11.250	21.77	71.12	384.
	10.260	16.58	65.85	320.8				0.024380		0.06714		10.830	22.04	71.08	357.
					2.233,1	2.23330		1102 1000			<u> </u>	12.000			
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548	9.683	19.34	61.05	285.7	0.08491	0.05030	0.023370	0.009615	0.1580	0.06235	 10.930	25.59	69.10	364.
549	10.820	24.21	68.89	361.6	0.08192	0.06602	0.015480	0.008160	0.1976	0.06328	 13.030	31.45	83.90	505.
550	10.860	21.48	68.51	360.5	0.07431	0.04227	0.000000	0.000000	0.1661	0.05948	 11.660	24.77	74.08	412.
551	11.130	22.44	71.49	378.4	0.09566	0.08194	0.048240	0.022570	0.2030	0.06552	 12.020	28.26	77.80	436.
552	12.770	29.43	81.35	507.9	0.08276	0.04234	0.019970	0.014990	0.1539	0.05637	 13.870	36.00	88.10	594.
553	9.333	21.94	59.01	264.0	0.09240	0.05605	0.039960	0.012820	0.1692	0.06576	 9.845	25.05	62.86	295.
554	12.880	28.92	82.50	514.3	0.08123	0.05824	0.061950	0.023430	0.1566	0.05708	 13.890	35.74	88.84	595.
555	10.290	27.61	65.67	321.4	0.09030	0.07658	0.059990	0.027380	0.1593	0.06127	 10.840	34.91	69.57	357.
556	10.160	19.59	64.73	311.7	0.10030	0.07504	0.005025	0.011160	0.1791	0.06331	 10.650	22.88	67.88	347.
557	9.423	27.88	59.26	271.3	0.08123	0.04971	0.000000	0.000000	0.1742	0.06059	 10.490	34.24	66.50	330.
558	14.590	22.68	96.39	657.1	0.08473	0.13300	0.102900	0.037360	0.1454	0.06147	 15.480	27.27	105.90	733.
559	11.510	23.93	74.52	403.5	0.09261	0.10210	0.111200	0.041050	0.1388	0.06570	 12.480	37.16	82.28	474.
560	14.050	27.15	91.38	600.4	0.09929	0.11260	0.044620	0.043040	0.1537	0.06171	 15.300	33.17	100.20	706.
561	11.200	29.37	70.67	386.0	0.07449	0.03558	0.000000	0.000000	0.1060	0.05502	 11.920	38.30	75.19	439.
562	15.220	30.62	103.40	716.9	0.10480	0.20870	0.255000	0.094290	0.2128	0.07152	 17.520	42.79	128.70	915.
563	20.920	25.09	143.00	1347.0	0.10990	0.22360	0.317400	0.147400	0.2149	0.06879	 24.290	29.41	179.10	1819
564	21.560	22.39	142.00	1479.0	0.11100	0.11590	0.243900	0.138900	0.1726	0.05623	 25.450	26.40	166.10	202
565	20.130	28.25	131.20	1261.0	0.09780	0.10340	0.144000	0.097910	0.1752	0.05533	 23.690	38.25	155.00	173
566	16.600	28.08	108.30	858.1	0.08455	0.10230	0.092510	0.053020	0.1590	0.05648	 18.980	34.12	126.70	112
567	20.600	29.33	140.10	1265.0	0.11780	0.27700	0.351400	0.152000	0.2397	0.07016	 25.740	39.42	184.60	182
568	7.760	24.54	47.92	181.0	0.05263	0.04362	0.000000	0.000000	0.1587	0.05884	 9.456	30.37	59.16	268.

569 rows × 30 columns

```
In [4]: Y = pd.DataFrame(iris.target, columns=['Y'])
Y.T
```

Out[4]:

	0	1	2	3	4	5	6	7	8	9	 559	560	561	562	563	564	565	566	567	568
Υ	0	0	0	0	0	0	0	0	0	0	 1	1	1	0	0	0	0	0	0	1

1 rows × 569 columns

```
In [5]: from sklearn.cross_validation import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3)
X_train.shape, X_test.shape, Y_train.shape, Y_test.shape
```

/data/soft/py3/lib/python3.6/site-packages/sklearn/cross\_validation.py:41: DeprecationWarning: This mod ule was deprecated in version 0.18 in favor of the model\_selection module into which all the refactored classes and functions are moved. Also note that the interface of the new CV iterators are different from that of this module. This module will be removed in 0.20.

"This module will be removed in 0.20.", DeprecationWarning)

```
Out[5]: ((398, 30), (171, 30), (398, 1), (171, 1))
```

In [6]: from sklearn import tree from sklearn import metrics import numpy as np

```
In [7]: model = tree.DecisionTreeClassifier(min_samples_leaf=50)
    model.fit(X_train, Y_train)
    with open("013.Test_DecisionTreeClassifier_var.result.dot", "w") as f:
        tree.export_graphviz(model, f)
```

```
In [8]: ! cat "013.Test DecisionTreeClassifier var.result.dot"
        digraph Tree {
        node [shape=box] ;
        0 [label="X[27] \le 0.142 \le 0.472 \le 398 \le [152, 246]"];
        1 [label="X[20] \le 15.68 \text{ngini} = 0.15 \text{nsamples} = 258 \text{nvalue} = [21, 237]"];
        0 -> 1 [labeldistance=2.5, labelangle=45, headlabel="True"];
        2 [label="X[15] <= 0.012 \\ ngini = 0.028 \\ nsamples = 208 \\ nvalue = [3, 205]"];
        1 -> 2 ;
        3 [label="gini = 0.105\nsamples = 54\nvalue = [3, 51]"];
        2 -> 3 ;
        4 [label="gini = 0.0\nsamples = 154\nvalue = [0, 154]"];
        2 -> 4 ;
        5 [label="gini = 0.461\nsamples = 50\nvalue = [18, 32]"];
        1 -> 5 ;
        6 [label="X[0] \le 16.1 \neq 0.12 \le 140 \neq 0.12 \le 140 = [131, 9]];
        0 -> 6 [labeldistance=2.5, labelangle=-45, headlabel="False"];
        7 [label="gini = 0.295\nsamples = 50\nvalue = [41, 9]"];
        6 -> 7;
        8 [label="gini = 0.0 \times = 90 \times = [90, 0]"];
        6 -> 8 ;
        }
In [9]: col = X_train.columns
        for i in range(len(model.tree_.threshold)):
            if model.tree .feature[i] == -2:
                print(model.tree_.feature[i])
            else:
                print(col[model.tree .feature[i]],model.tree .feature[i],model.tree .threshold[i], model.tree .i
        mpurity[i])
        Xvar28S 27 0.1423499882221222 0.47210929016944014
        Xvar21S 20 15.680000305175781 0.1495402920497566
        Xvar16S 15 0.012025000527501106 0.02843010355029585
        -2
        -2
        -2
        Xvar1S 0 16.099998474121094 0.12030612244897965
        -2
        -2
```

```
In [10]: rule = []
         arule = {}
         r = []
         with open("013.Test_DecisionTreeClassifier_var.result.dot", "r") as f:
              for i in f:
                  i = i.strip('\n')
                  if "digraph Tree {" in i or "node [shape=box];" in i or "}" in i:
                  elif "->" in i:
                      if "[" in i:
                          i = i[:i.find("[")]
                      i = i.replace(" ", "").replace(";", "")
                      [i0, i1] = i.split("->")
                      i0, i1 = int(i0), int(i1)
                      i2 = 1 if i1 == (i0 + 1) else 0
                      rule.append([i0, i1, i2])
                  else:
                      ii = i[i.find('[label="')+len('[label="'):i.find("\\n")]
                      if "gini" in ii:
                          ii = ""
                      arule[int(i.split(" ")[0])] = ii
                  if 'label="gini =' in i:
                      t0 = int(i.split(' ')[0])
                      t = i[i.find("nvalue ="):].replace(']"] ;','').replace('nvalue = [',"")
                      [t1, t2] = t.replace('\n', "").split(",")
                      t1, t2 = int(t1), int(t2)
                      r.append([t0, t1, t2, t2/(t1+t2)*100])
         print(rule, arule)
         vrule = arule
         for i, j, k in rule:
              t = arule[i]
              if k == 1:
                  pass
              else:
                  t = t.replace("<=", ">")
              if arule[j] != "":
                  vrule[j] = t + " and " + arule[j]
              else:
                  vrule[j] = t
         for i, j in vrule.items():
              n = 0
              for k in col:
                  j = j.replace("X["+str(n)+"]", k)
                  n += 1
              print(i, j)
         r = pd.DataFrame(r, columns=['No', 'G', 'B', 'B/(G+B)'])
         r.sort_values('B/(G+B)', ascending=False)
         [[0, 1, 1], [1, 2, 1], [2, 3, 1], [2, 4, 0], [1, 5, 0], [0, 6, 0], [6, 7, 1], [6, 8, 0]] {0: X[27] \leftarrow X[27]
         0.142', 1: X[20] \leftarrow 15.68', 2: X[15] \leftarrow 0.012', 3: Y[20] \leftarrow Y[20] \leftarrow Y[20] \leftarrow Y[20]
         0 Xvar28S <= 0.142</pre>
         1 Xvar28S <= 0.142 and Xvar21S <= 15.68
         2 Xvar28S <= 0.142 and Xvar21S <= 15.68 and Xvar16S <= 0.012
         3 Xvar28S <= 0.142 and Xvar21S <= 15.68 and Xvar16S <= 0.012
         4 Xvar28S > 0.142 and Xvar21S > 15.68 and Xvar16S > 0.012
         5 Xvar28S > 0.142 and Xvar21S > 15.68
         6 Xvar28S > 0.142 and Xvar1S <= 16.1
         7 Xvar28S > 0.142 and Xvar1S <= 16.1
         8 Xvar28S > 0.142 and Xvar1S > 16.1
Out[10]:
                         B/(G+B)
                G
            4
                   154 100.000000
          0 3
                       94.44444
                3
                   51
          2
            5
                   32
                       64.000000
                18
          3 7
                41
                   9
                       18.000000
          4 8
                90
                   0
                       0.000000
```

```
Out[12]: 0     0.99
     1     0.01
     Name: Y, dtype: float64

In [13]: d = pd.merge(X_train, Y_train, left_index=True, right_index=True)
     d = d.query(Q)
     pd.value_counts(d['Y'], normalize=True)

Out[13]: 0     0.986486
     1     0.013514
     Name: Y, dtype: float64

In [14]: d = pd.merge(X_test, Y_test, left_index=True, right_index=True)
     d = d.query(Q)
```

Out[14]: 0 1.0 Name: Y, dtype: float64

d = d.query(Q)

In [12]: d = pd.merge(X, Y, left\_index=True, right\_index=True)

pd.value\_counts(d['Y'], normalize=True)

pd.value\_counts(d['Y'], normalize=True)