In [7]:
```
import numpy as np
```

In [8]:
```
import pandas as pd
```

In [12]:
```
car = pd.read_excel("mileage_new.xls")
```

In [13]:
```
car
```

Out[13]:

	mpg	cyl	disp	hp	wt	acc	modyr	origin	name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino
...	...	...	...	...	...	...	...	...	...
387	27.0	4	140.0	86	2790	15.6	82	1	ford mustang gl
388	44.0	4	97.0	52	2130	24.6	82	2	vw pickup
389	32.0	4	135.0	84	2295	11.6	82	1	dodge rampage
390	28.0	4	120.0	79	2625	18.6	82	1	ford ranger
391	31.0	4	119.0	82	2720	19.4	82	1	chevy s-10

392 rows × 9 columns

In [15]:
```
car.head()
```

Out[15]:

	mpg	cyl	disp	hp	wt	acc	modyr	origin	name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino

In [19]:
```
car.tail()
```

Out[19]:

	mpg	cyl	disp	hp	wt	acc	modyr	origin	name
387	27.0	4	140.0	86	2790	15.6	82	1	ford mustang gl
388	44.0	4	97.0	52	2130	24.6	82	2	vw pickup
389	32.0	4	135.0	84	2295	11.6	82	1	dodge rampage
390	28.0	4	120.0	79	2625	18.6	82	1	ford ranger
391	31.0	4	119.0	82	2720	19.4	82	1	chevy s-10

In [20]:
```
car.describe()
```

Out[20]:

	mpg	cyl	disp	hp	wt	acc	modyr	origin
count	392.000000	392.000000	392.000000	392.000000	392.000000	392.000000	392.000000	392.000000
mean	23.445918	5.471939	194.411990	104.469388	2977.584184	15.541327	75.979592	1.576531
std	7.805007	1.705783	104.644004	38.491160	849.402560	2.758864	3.683737	0.805518
min	9.000000	3.000000	68.000000	46.000000	1613.000000	8.000000	70.000000	1.000000
25%	17.000000	4.000000	105.000000	75.000000	2225.250000	13.775000	73.000000	1.000000
50%	22.750000	4.000000	151.000000	93.500000	2803.500000	15.500000	76.000000	1.000000
75%	29.000000	8.000000	275.750000	126.000000	3614.750000	17.025000	79.000000	2.000000
max	46.600000	8.000000	455.000000	230.000000	5140.000000	24.800000	82.000000	3.000000

In [21]:
```
car.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 392 entries, 0 to 391
Data columns (total 9 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   mpg     392 non-null    float64
 1   cyl     392 non-null    int64  
 2   disp    392 non-null    float64
 3   hp      392 non-null    int64  
 4   wt      392 non-null    int64  
 5   acc     392 non-null    float64
 6   modyr   392 non-null    int64  
 7   origin  392 non-null    int64  
 8   name    392 non-null    object 
dtypes: float64(3), int64(5), object(1)
memory usage: 27.7+ KB
```

In [29]:
```
car.isnull().sum()
```

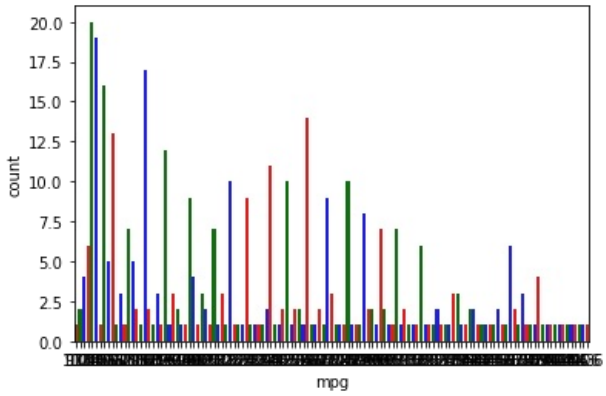
Out[29]:
```
mpg       0
cyl       0
disp      0
hp        0
wt        0
acc       0
modyr     0
origin    0
name      0
dtype: int64
```

In [30]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

In [33]:
```
carmilage = sns.load_dataset("mpg")
```

In [40]:
```
sns.countplot(x="mpg",  data=carmileage, palette=['red', 'green', 'blue'])
```

Out[40]:
```
<AxesSubplot:xlabel='mpg', ylabel='count'>
```



In [51]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [53]:
```
car.head()
```

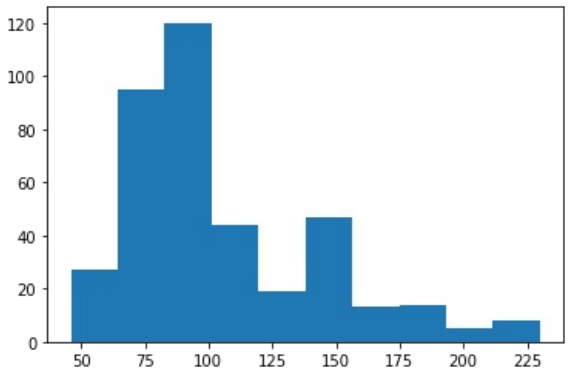
Out[53]:

	mpg	cyl	disp	hp	wt	acc	modyr	origin	name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu

1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino

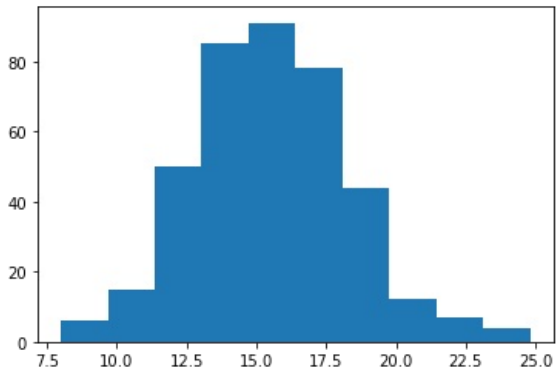
In [54]:
```
plt.hist(car['hp'])
```

Out[54]:
```
(array([ 27.,  95., 120.,  44.,  19.,  47.,  13.,  14.,   5.,   8.]),
 array([ 46. ,  64.4,  82.8, 101.2, 119.6, 138. , 156.4, 174.8, 193.2,
        211.6, 230. ]),
 <BarContainer object of 10 artists>)
```



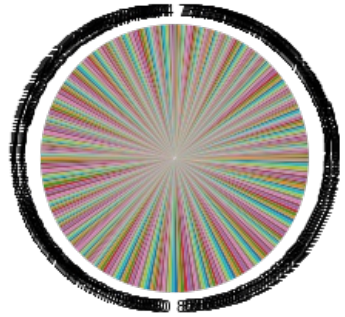
In [55]:
```
plt.hist(car['acc'])
```

Out[55]:
```
(array([ 6., 15., 50., 85., 91., 78., 44., 12.,  7.,  4.]),
 array([ 8.  ,  9.68, 11.36, 13.04, 14.72, 16.4 , 18.08, 19.76, 21.44,
        23.12, 24.8 ]),
 <BarContainer object of 10 artists>)
```



In [61]:
```
plt.pie(car['mpg'], labels=car['modyr'])
plt.show
```

Out[61]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [67]:
```
car=pd.read_excel('mileage_new.xls')
matrix=car.corr()
```

In [68]:
```
car
```

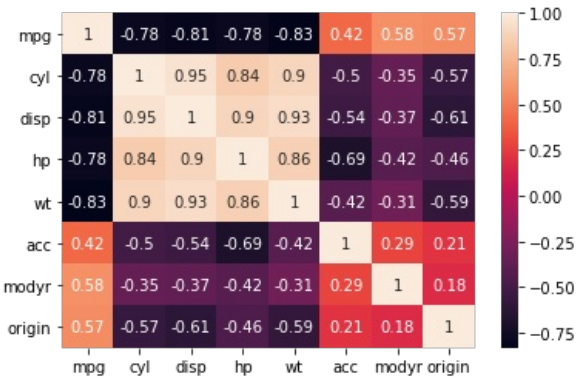
Out[68]:

	mpg	cyl	disp	hp	wt	acc	modyr	origin	name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino
...	...	...	...	...	...	...	...	...	...
387	27.0	4	140.0	86	2790	15.6	82	1	ford mustang gl
388	44.0	4	97.0	52	2130	24.6	82	2	vw pickup
389	32.0	4	135.0	84	2295	11.6	82	1	dodge rampage
390	28.0	4	120.0	79	2625	18.6	82	1	ford ranger
391	31.0	4	119.0	82	2720	19.4	82	1	chevy s-10

392 rows × 9 columns

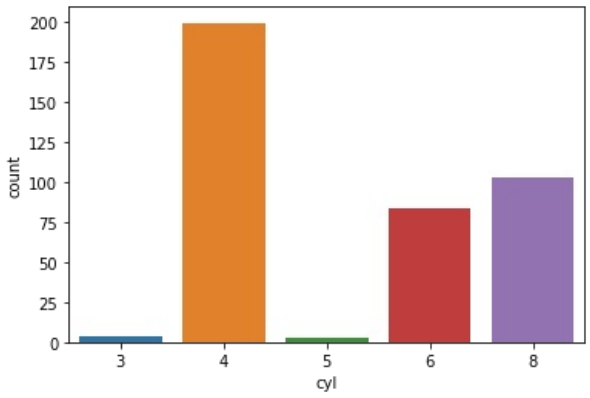
In [69]:
```
sns.heatmap(matrix, annot=True)
```

Out[69]: <AxesSubplot:>



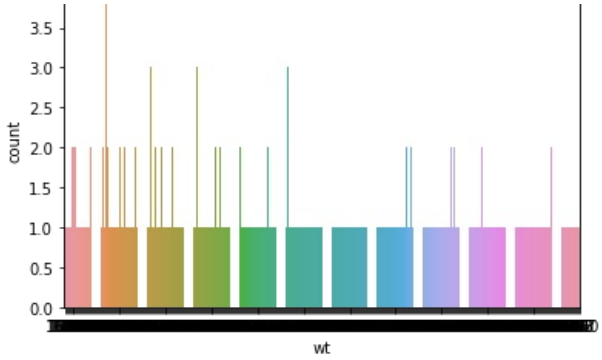
In [71]:
```
sns.countplot(x="cyl", data=carmileage)
```

Out[71]: <AxesSubplot:xlabel='cyl', ylabel='count'>



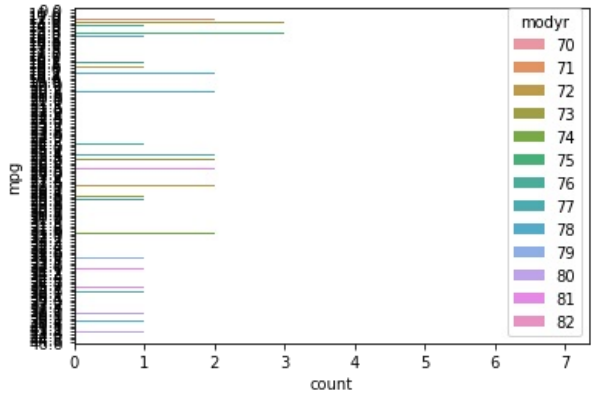
In [72]:
```
sns.countplot(x="wt", data=carmileage)
```

Out[72]: <AxesSubplot:xlabel='wt', ylabel='count'>



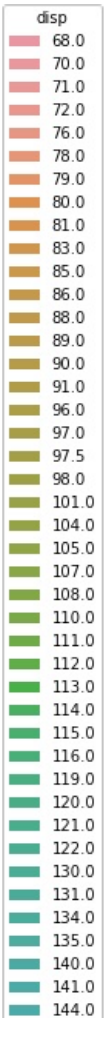
In [74]:
```
sns.countplot(y="mpg", hue="modyr", data=carmileage)
```

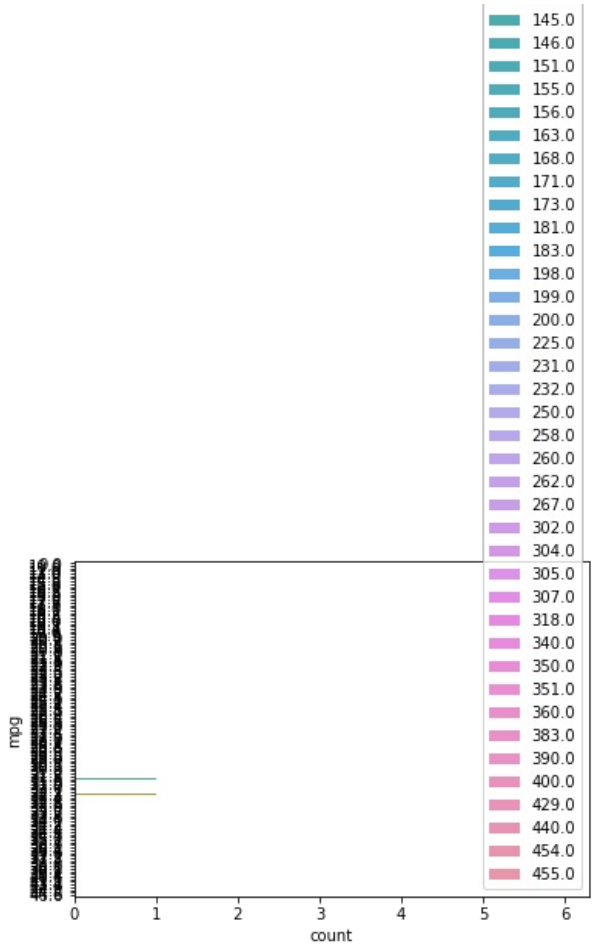
Out[74]: <AxesSubplot:xlabel='count', ylabel='mpg'>



In [82]:
```
sns.countplot(y="mpg", hue="disp", data=carmileage)
```

Out[82]: <AxesSubplot:xlabel='count', ylabel='mpg'>





In [83]:
```
import matplotlib.pyplot as plt
```

In [84]:
```
y=car["mpg"]
```

In [85]:
```
y
```

Out[85]:
```
0      18.0
1      15.0
2      18.0
3      16.0
4      17.0
       ...
387    27.0
388    44.0
389    32.0
390    28.0
391    31.0
Name: mpg, Length: 392, dtype: float64
```

In [88]:
```
x=car.loc[ :40]
```

In [89]:
```
X
```

Out[89]:

	mpg	cyl	disp	hp	wt	acc	modyr	origin	name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino
5	15.0	8	429.0	198	4341	10.0	70	1	ford galaxie 500
6	14.0	8	454.0	220	4354	9.0	70	1	chevrolet impala

7	14.0	8	440.0	215	4312	8.5	70	1	plymouth fury iii
8	14.0	8	455.0	225	4425	10.0	70	1	pontiac catalina
9	15.0	8	390.0	190	3850	8.5	70	1	amc ambassador dpl
10	15.0	8	383.0	170	3563	10.0	70	1	dodge challenger se
11	14.0	8	340.0	160	3609	8.0	70	1	plymouth 'cuda 340
12	15.0	8	400.0	150	3761	9.5	70	1	chevrolet monte carlo
13	14.0	8	455.0	225	3086	10.0	70	1	buick estate wagon (sw)
14	24.0	4	113.0	95	2372	15.0	70	3	toyota corona mark ii
15	22.0	6	198.0	95	2833	15.5	70	1	plymouth duster
16	18.0	6	199.0	97	2774	15.5	70	1	amc hornet
17	21.0	6	200.0	85	2587	16.0	70	1	ford maverick
18	27.0	4	97.0	88	2130	14.5	70	3	datsun pl510
19	26.0	4	97.0	46	1835	20.5	70	2	volkswagen 1131 deluxe sedan
20	25.0	4	110.0	87	2672	17.5	70	2	peugeot 504
21	24.0	4	107.0	90	2430	14.5	70	2	audi 100 ls
22	25.0	4	104.0	95	2375	17.5	70	2	saab 99e
23	26.0	4	121.0	113	2234	12.5	70	2	bmw 2002
24	21.0	6	199.0	90	2648	15.0	70	1	amc gremlin
25	10.0	8	360.0	215	4615	14.0	70	1	ford f250
26	10.0	8	307.0	200	4376	15.0	70	1	chevy c20
27	11.0	8	318.0	210	4382	13.5	70	1	dodge d200
28	9.0	8	304.0	193	4732	18.5	70	1	hi 1200d
29	27.0	4	97.0	88	2130	14.5	71	3	datsun pl510
30	28.0	4	140.0	90	2264	15.5	71	1	chevrolet vega 2300
31	25.0	4	113.0	95	2228	14.0	71	3	toyota corona
32	19.0	6	232.0	100	2634	13.0	71	1	amc gremlin
33	16.0	6	225.0	105	3439	15.5	71	1	plymouth satellite custom
34	17.0	6	250.0	100	3329	15.5	71	1	chevrolet chevelle malibu
35	19.0	6	250.0	88	3302	15.5	71	1	ford torino 500
36	18.0	6	232.0	100	3288	15.5	71	1	amc matador
37	14.0	8	350.0	165	4209	12.0	71	1	chevrolet impala
38	14.0	8	400.0	175	4464	11.5	71	1	pontiac catalina brougham
39	14.0	8	351.0	153	4154	13.5	71	1	ford galaxie 500
40	14.0	8	318.0	150	4096	13.0	71	1	plymouth fury iii

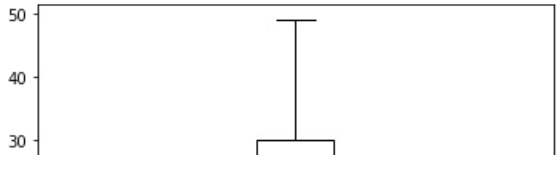
In [90]:
```
car = [1,2,3,4,5,6,7,8,9,12,14,16,19,28,26,30,35,38,40,45,49]
```

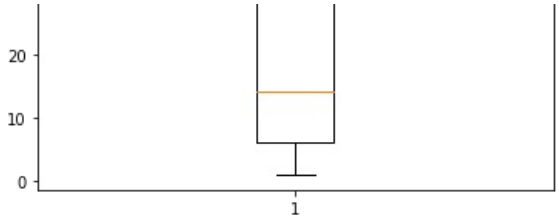
In [91]:
```
car
```

Out[91]:
```
[1, 2, 3, 4, 5, 6, 7, 8, 9, 12, 14, 16, 19, 28, 26, 30, 35, 38, 40, 45, 49]
```

In [92]:
```
plt.boxplot(car)
```

Out[92]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7fd822e9d250>,
  <matplotlib.lines.Line2D at 0x7fd822e9d5b0>],
 'caps': [<matplotlib.lines.Line2D at 0x7fd822e9d910>,
  <matplotlib.lines.Line2D at 0x7fd822e9dc70>],
 'boxes': [<matplotlib.lines.Line2D at 0x7fd822c08ee0>],
 'medians': [<matplotlib.lines.Line2D at 0x7fd822e9dfd0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7fd822ea5370>],
 'means': []}
```





In [93]:
```
from sklearn.datasets import load_iris
import pandas as pd
```

In [94]:
```
car = load_iris()
```

In [95]:
```
car
```

Out[95]:
```
{'data': array([[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],
        [5.1, 3.8, 1.5, 0.3],
        [5.4, 3.4, 1.7, 0.2],
        [5.1, 3.7, 1.5, 0.4],
        [4.6, 3.6, 1. , 0.2],
        [5.1, 3.3, 1.7, 0.5],
        [4.8, 3.4, 1.9, 0.2],
        [5. , 3. , 1.6, 0.2],
        [5. , 3.4, 1.6, 0.4],
        [5.2, 3.5, 1.5, 0.2],
        [5.2, 3.4, 1.4, 0.2],
        [4.7, 3.2, 1.6, 0.2],
        [4.8, 3.1, 1.6, 0.2],
        [5.4, 3.4, 1.5, 0.4],
        [5.2, 4.1, 1.5, 0.1],
        [5.5, 4.2, 1.4, 0.2],
        [4.9, 3.1, 1.5, 0.2],
        [5. , 3.2, 1.2, 0.2],
        [5.5, 3.5, 1.3, 0.2],
        [4.9, 3.6, 1.4, 0.1],
        [4.4, 3. , 1.3, 0.2],
        [5.1, 3.4, 1.5, 0.2],
        [5. , 3.5, 1.3, 0.3],
        [4.5, 2.3, 1.3, 0.3],
        [4.4, 3.2, 1.3, 0.2],
        [5. , 3.5, 1.6, 0.6],
        [5.1, 3.8, 1.9, 0.4],
        [4.8, 3. , 1.4, 0.3],
        [5.1, 3.8, 1.6, 0.2],
        [4.6, 3.2, 1.4, 0.2],
        [5.3, 3.7, 1.5, 0.2],
        [5. , 3.3, 1.4, 0.2],
        [7. , 3.2, 4.7, 1.4],
        [6.4, 3.2, 4.5, 1.5],
        [6.9, 3.1, 4.9, 1.5],
        [5.5, 2.3, 4. , 1.3],
        [6.5, 2.8, 4.6, 1.5],
        [5.7, 2.8, 4.5, 1.3],
        [6.3, 3.3, 4.7, 1.6],
        [4.9, 2.4, 3.3, 1. ],
        [6.6, 2.9, 4.6, 1.3],
        [5.2, 2.7, 3.9, 1.4],
        [5. , 2. , 3.5, 1. ],
        [5.9, 3. , 4.2, 1.5],
```

```
[6. , 2.2, 4. , 1. ],
[6.1, 2.9, 4.7, 1.4],
[5.6, 2.9, 3.6, 1.3],
[6.7, 3.1, 4.4, 1.4],
[5.6, 3. , 4.5, 1.5],
[5.8, 2.7, 4.1, 1. ],
[6.2, 2.2, 4.5, 1.5],
[5.6, 2.5, 3.9, 1.1],
[5.9, 3.2, 4.8, 1.8],
[6.1, 2.8, 4. , 1.3],
[6.3, 2.5, 4.9, 1.5],
[6.1, 2.8, 4.7, 1.2],
[6.4, 2.9, 4.3, 1.3],
[6.6, 3. , 4.4, 1.4],
[6.8, 2.8, 4.8, 1.4],
[6.7, 3. , 5. , 1.7],
[6. , 2.9, 4.5, 1.5],
[5.7, 2.6, 3.5, 1. ],
[5.5, 2.4, 3.8, 1.1],
[5.5, 2.4, 3.7, 1. ],
[5.8, 2.7, 3.9, 1.2],
[6. , 2.7, 5.1, 1.6],
[5.4, 3. , 4.5, 1.5],
[6. , 3.4, 4.5, 1.6],
[6.7, 3.1, 4.7, 1.5],
[6.3, 2.3, 4.4, 1.3],
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       [6.5, 3. , 5.2, 2. ],
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       [5.9, 3. , 5.1, 1.8]]),
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       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
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 'frame': None,
 'target_names': array(['setosa', 'versicolor', 'virginica'], dtype='<U10'),
 'DESCR': '.. _iris_dataset:\n\nIris plants dataset\n--------------------\n\n**Data Set Characteristics:**\n\n
:Number of Instances: 150 (50 in each of three classes)\n    :Number of Attributes: 4 numeric, predictive attribu
tes and the class\n    :Attribute Information:\n        - sepal length in cm\n        - sepal width in cm\n
- petal length in cm\n        - petal width in cm\n        - class:\n                - Iris-Setosa\n
- Iris-Versicolour\n                - Iris-Virginica\n                \n    :Summary Statistics:\n\n    =========
===== ==== ==== ======= ===== ====================\n                  Min  Max   Mean    SD   Class Correlation
\n    ============== ==== ==== ======= ===== ====================\n    sepal length:   4.3  7.9   5.84   0.83
0.7826\n    sepal width:    2.0  4.4   3.05   0.43   -0.4194\n    petal length:   1.0  6.9   3.76   1.76    0.949
0  (high!)\n    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)\n    ============== ==== ==== ======= =
==== ====================\n\n    :Missing Attribute Values: None\n    :Class Distribution: 33.3% for each of 3 cl
asses.\n    :Creator: R.A. Fisher\n    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)\n    :Date: July,
1988\n\nThe famous Iris database, first used by Sir R.A. Fisher. The dataset is taken\nfrom Fisher\'s paper. Note
that it\'s the same as in R, but not as in the UCI\nMachine Learning Repository, which has two wrong data points.
\n\nThis is perhaps the best known database to be found in the\npattern recognition literature.  Fisher\'s paper
is a classic in the field and\nis referenced frequently to this day.  (See Duda & Hart, for example.)  The\ndata
set contains 3 classes of 50 instances each, where each class refers to a\ntype of iris plant.  One class is line
arly separable from the other 2; the\nlatter are NOT linearly separable from each other.\n\n.. topic:: References
\n\n   - Fisher, R.A. "The use of multiple measurements in taxonomic problems"\n     Annual Eugenics, 7, Part II,
179-188 (1936); also in "Contributions to\n     Mathematical Statistics" (John Wiley, NY, 1950).\n   - Duda, R.O.
, & Hart, P.E. (1973) Pattern Classification and Scene Analysis.\n     (Q327.D83) John Wiley & Sons.  ISBN 0-471-
22361-1.  See page 218.\n   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System\n     Structur
e and Classification Rule for Recognition in Partially Exposed\n     Environments".  IEEE Transactions on Pattern
Analysis and Machine\n     Intelligence, Vol. PAMI-2, No. 1, 67-71.\n   - Gates, G.W. (1972) "The Reduced Nearest
Neighbor Rule".  IEEE Transactions\n     on Information Theory, May 1972, 431-433.\n   - See also: 1988 MLC Proce
edings, 54-64.  Cheeseman et al"s AUTOCLASS II\n     conceptual clustering system finds 3 classes in the data.\n
- Many, many more ...',
 'feature_names': ['sepal length (cm)',
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  'petal length (cm)',
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 'filename': '/opt/anaconda3/lib/python3.8/site-packages/sklearn/datasets/data/iris.csv'}
```

In [96]:
```
car.feature_names
```

Out[96]:
```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```

In [97]:
```
car.target
```

Out[97]:
```
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```

In [ ]:

In [ ]: