

Assignment-13- [KNN] - ZOO

```
In [114]: 1 #KNN Classification
2 import pandas as pd
3 import numpy as np
4 from sklearn.model_selection import KFold
5 from sklearn.model_selection import cross_val_score
6 from sklearn.neighbors import KNeighborsClassifier
7 from sklearn.model_selection import GridSearchCV
8 from sklearn.metrics import accuracy_score
9 import matplotlib.pyplot as plt
10 import seaborn as sns
11 import warnings
12 warnings.filterwarnings('ignore')
```

```
In [115]: 1 zoo = pd.read_csv('Zoo.csv')
```

```
In [116]: 1 zoo
```

Out[116]:

	animal name	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes	venomous	fins	legs	tail	domestic	catsize	type
0	aardvark	1	0	0	1	0	0	1	1	1	1	0	0	4	0	0	1	1
1	antelope	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0	1	1
2	bass	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0	0	4
3	bear	1	0	0	1	0	0	1	1	1	1	0	0	4	0	0	1	1
4	boar	1	0	0	1	0	0	1	1	1	1	0	0	4	1	0	1	1
...
96	wallaby	1	0	0	1	0	0	0	1	1	1	0	0	2	1	0	1	1
97	wasp	1	0	1	0	1	0	0	0	0	1	1	0	6	0	0	0	6
98	wolf	1	0	0	1	0	0	1	1	1	1	0	0	4	1	0	1	1
99	worm	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	7
100	wren	0	1	1	0	1	0	0	0	1	1	0	0	2	1	0	0	2

101 rows × 18 columns

```
In [117]: 1 zoo.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 101 entries, 0 to 100
Data columns (total 18 columns):
#   Column      Non-Null Count  Dtype
---  ---
0   animal name  101 non-null    object
1   hair         101 non-null    int64
2   feathers     101 non-null    int64
3   eggs         101 non-null    int64
4   milk         101 non-null    int64
5   airborne     101 non-null    int64
6   aquatic      101 non-null    int64
7   predator     101 non-null    int64
8   toothed      101 non-null    int64
9   backbone     101 non-null    int64
10  breathes     101 non-null    int64
11  venomous     101 non-null    int64
12  fins         101 non-null    int64
13  legs         101 non-null    int64
14  tail         101 non-null    int64
15  domestic     101 non-null    int64
16  catsize      101 non-null    int64
17  type         101 non-null    int64
dtypes: int64(17), object(1)
memory usage: 14.3+ KB
```

In [118]:

1 zoo.describe()

Out[118]:

	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes	venomous	fins	
count	101.000000	101.000000	101.000000	101.000000	101.000000	101.000000	101.000000	101.000000	101.000000	101.000000	101.000000	101.000000	101.000000
mean	0.425743	0.198020	0.584158	0.405941	0.237624	0.356436	0.554455	0.603960	0.821782	0.792079	0.079208	0.168317	2.84
std	0.496921	0.400495	0.495325	0.493522	0.427750	0.481335	0.499505	0.491512	0.384605	0.407844	0.271410	0.376013	2.03
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	1.000000	0.000000	0.000000	2.00
50%	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	1.000000	1.000000	1.000000	1.000000	0.000000	0.000000	4.00
75%	1.000000	0.000000	1.000000	1.000000	0.000000	1.000000	1.000000	1.000000	1.000000	1.000000	0.000000	0.000000	4.00
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	8.00

In [119]:

1 zoo['animal name'].value_counts()

Out[119]:

frog2

2

pony

1

sealion

1

seal

1

seahorse

1

..

gorilla

1

goat

1

gnat

1

girl

1

wren

1

Name: animal name, Length: 100, dtype: int64

In [120]:

1 #Check if there are duplicates in animal_name
2 duplicates = zoo['animal name'].value_counts()
3 duplicates[duplicates > 1]

Out[120]:

frog2

2

Name: animal name, dtype: int64

In [121]:

1 frog = zoo[zoo['animal name'] == 'frog']
2 frog

Out[121]:

	animal name	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes	venomous	fins	legs	tail	domestic	catsize	type
25	frog	0	0	1	0	0	1	1	1	1	1	0	0	4	0	0	0	5
26	frog	0	0	1	0	0	1	1	1	1	1	1	0	4	0	0	0	5

In [122]:

1 # Observation : find that one frog is venomous and another one is not
2 #change the venomous one into frog2 to separate 2kinds of frog
3 zoo['animal name'][(zoo['venomous'] == 1)& (zoo['animal name'] == 'frog')] = "frog2"

In [123]:

1 zoo['venomous'].value_counts()

Out[123]:

0

93

1

8

Name: venomous, dtype: int64

In [124]: 1 zoo.head(27)

Out[124]:

	animal name	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes	venomous	fins	legs	tail	domestic	catsize	type
0	aardvark	1	0	0	1	0	0	1	1	1	1	0	0	4	0	0	1	1
1	antelope	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0	1	1
2	bass	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0	0	4
3	bear	1	0	0	1	0	0	1	1	1	1	0	0	4	0	0	1	1
4	boar	1	0	0	1	0	0	1	1	1	1	0	0	4	1	0	1	1
5	buffalo	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0	1	1
6	calf	1	0	0	1	0	0	0	1	1	1	0	0	4	1	1	1	1
7	carp	0	0	1	0	0	1	0	1	1	0	0	1	0	1	1	0	4
8	catfish	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0	0	4
9	cavy	1	0	0	1	0	0	0	1	1	1	0	0	4	0	1	0	1
10	cheetah	1	0	0	1	0	0	1	1	1	1	0	0	4	1	0	1	1
11	chicken	0	1	1	0	1	0	0	0	1	1	0	0	2	1	1	0	2
12	chub	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0	0	4
13	clam	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	7
14	crab	0	0	1	0	0	1	1	0	0	0	0	0	4	0	0	0	7
15	crayfish	0	0	1	0	0	1	1	0	0	0	0	0	6	0	0	0	7
16	crow	0	1	1	0	1	0	1	0	1	1	0	0	2	1	0	0	2
17	deer	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0	1	1
18	dogfish	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0	1	4
19	dolphin	0	0	0	1	0	1	1	1	1	1	0	1	0	1	0	1	1
20	dove	0	1	1	0	1	0	0	0	1	1	0	0	2	1	1	0	2
21	duck	0	1	1	0	1	1	0	0	1	1	0	0	2	1	0	0	2
22	elephant	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0	1	1
23	flamingo	0	1	1	0	1	0	0	0	1	1	0	0	2	1	0	1	2
24	flea	0	0	1	0	0	0	0	0	0	1	0	0	6	0	0	0	6
25	frog	0	0	1	0	0	1	1	1	1	1	0	0	4	0	0	0	5
26	frog2	0	0	1	0	0	1	1	1	1	1	1	0	4	0	0	0	5

In [125]: 1 #Finding unique value of hair
 2 color_list = [("red" if i == 1 else "blue" if i == 0 else "yellow") for i in zoo.hair]
 3 unique_color = list(set(color_list))
 4 unique_color

Out[125]: ['red', 'blue']

```

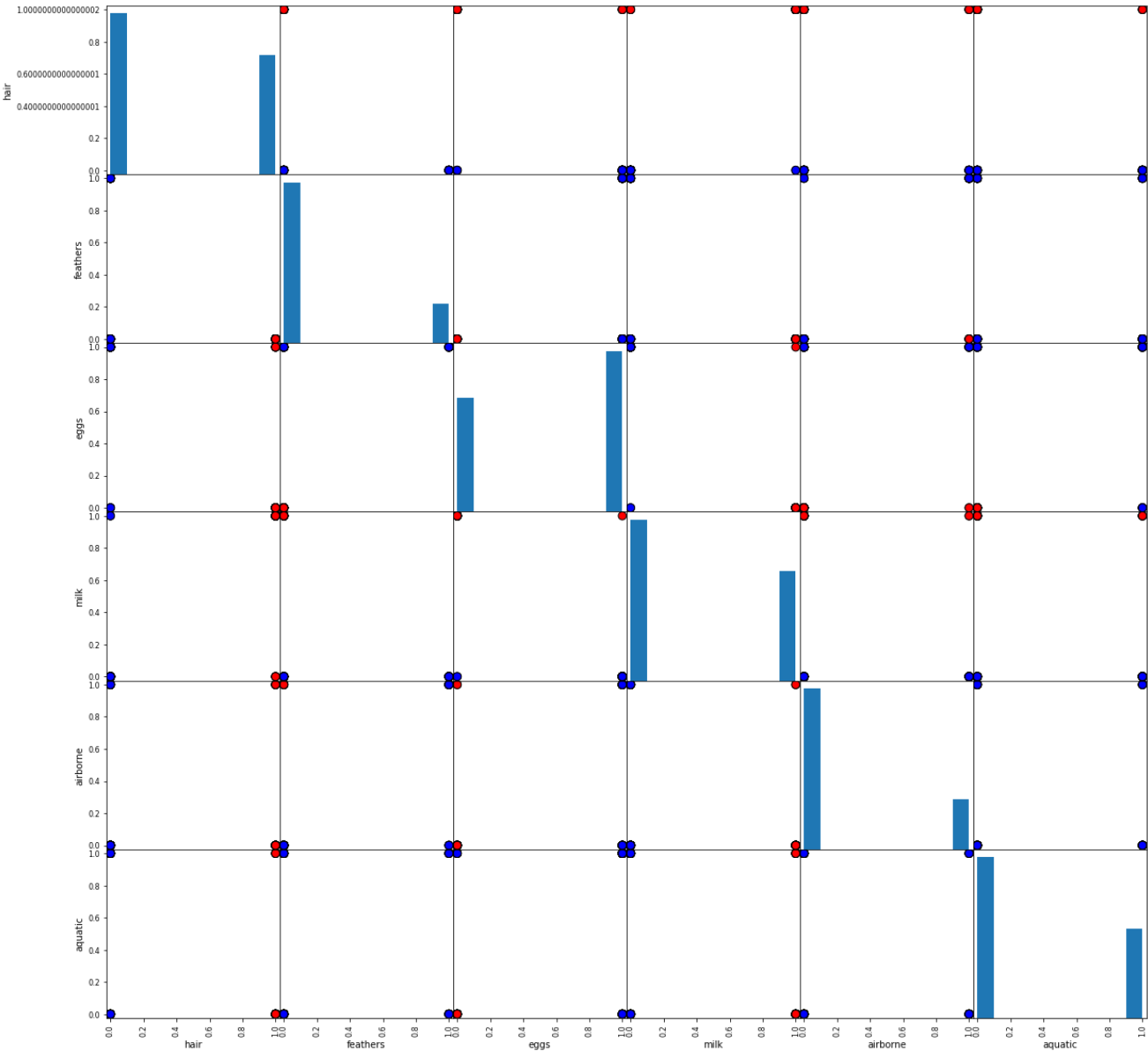
In [126]: 1 # Scatter matrix to observe relationship between every column attributes
          2 pd.plotting.scatter_matrix(zoo.iloc[:,7],
          3                               c=color_list,
          4                               figsize= [20,20],
          5                               diagonal = 'hist',
          6                               alpha=1,
          7                               s = 300,
          8                               marker = '.',
          9                               edgecolor= 'black')

```

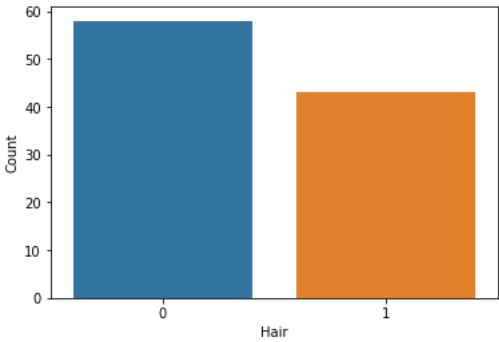
```

Out[126]: array([[<AxesSubplot:xlabel='hair', ylabel='hair'>,
                  <AxesSubplot:xlabel='feathers', ylabel='hair'>,
                  <AxesSubplot:xlabel='eggs', ylabel='hair'>,
                  <AxesSubplot:xlabel='milk', ylabel='hair'>,
                  <AxesSubplot:xlabel='airborne', ylabel='hair'>,
                  <AxesSubplot:xlabel='aquatic', ylabel='hair'>],
                [<AxesSubplot:xlabel='hair', ylabel='feathers'>,
                  <AxesSubplot:xlabel='feathers', ylabel='feathers'>,
                  <AxesSubplot:xlabel='eggs', ylabel='feathers'>,
                  <AxesSubplot:xlabel='milk', ylabel='feathers'>,
                  <AxesSubplot:xlabel='airborne', ylabel='feathers'>,
                  <AxesSubplot:xlabel='aquatic', ylabel='feathers'>],
                [<AxesSubplot:xlabel='hair', ylabel='eggs'>,
                  <AxesSubplot:xlabel='feathers', ylabel='eggs'>,
                  <AxesSubplot:xlabel='eggs', ylabel='eggs'>,
                  <AxesSubplot:xlabel='milk', ylabel='eggs'>,
                  <AxesSubplot:xlabel='airborne', ylabel='eggs'>,
                  <AxesSubplot:xlabel='aquatic', ylabel='eggs'>],
                [<AxesSubplot:xlabel='hair', ylabel='milk'>,
                  <AxesSubplot:xlabel='feathers', ylabel='milk'>,
                  <AxesSubplot:xlabel='eggs', ylabel='milk'>,
                  <AxesSubplot:xlabel='milk', ylabel='milk'>,
                  <AxesSubplot:xlabel='airborne', ylabel='milk'>,
                  <AxesSubplot:xlabel='aquatic', ylabel='milk'>],
                [<AxesSubplot:xlabel='hair', ylabel='airborne'>,
                  <AxesSubplot:xlabel='feathers', ylabel='airborne'>,
                  <AxesSubplot:xlabel='eggs', ylabel='airborne'>,
                  <AxesSubplot:xlabel='milk', ylabel='airborne'>,
                  <AxesSubplot:xlabel='airborne', ylabel='airborne'>,
                  <AxesSubplot:xlabel='aquatic', ylabel='airborne'>],
                [<AxesSubplot:xlabel='hair', ylabel='aquatic'>,
                  <AxesSubplot:xlabel='feathers', ylabel='aquatic'>,
                  <AxesSubplot:xlabel='eggs', ylabel='aquatic'>,
                  <AxesSubplot:xlabel='milk', ylabel='aquatic'>,
                  <AxesSubplot:xlabel='airborne', ylabel='aquatic'>,
                  <AxesSubplot:xlabel='aquatic', ylabel='aquatic'>]], dtype=object)

```



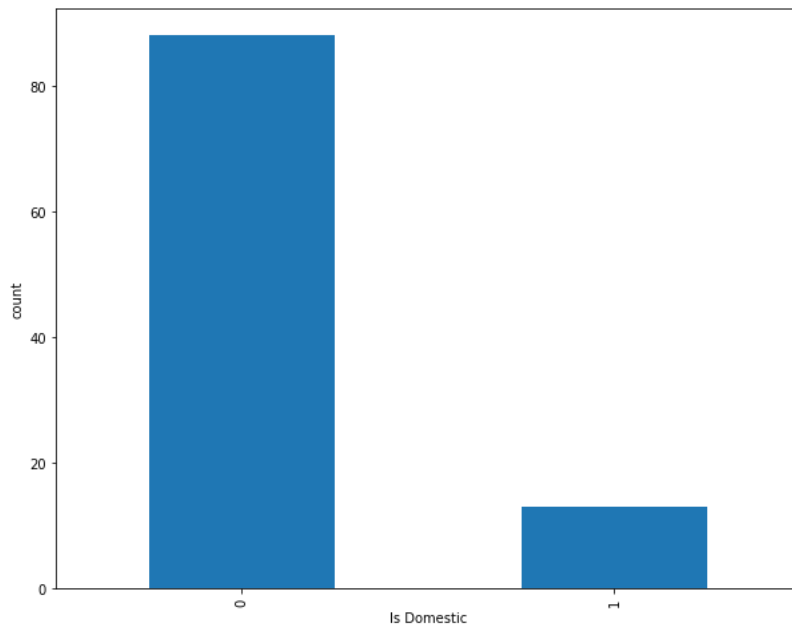
```
In [127]: 1 sns.countplot(x="hair", data=zoo)
2 plt.xlabel("Hair")
3 plt.ylabel("Count")
4 plt.show()
5 zoo.loc[:, 'hair'].value_counts()
```



```
Out[127]: 0    58
1    43
Name: hair, dtype: int64
```

```
In [128]: 1 # Let plot how many animals are domestic or not
2 plt.figure(figsize=(10,8));
3 zoo['domestic'].value_counts().plot(kind="bar");
4 plt.xlabel('Is Domestic');
5 plt.ylabel("count"),
6 plt.plot()
```

Out[128]: []



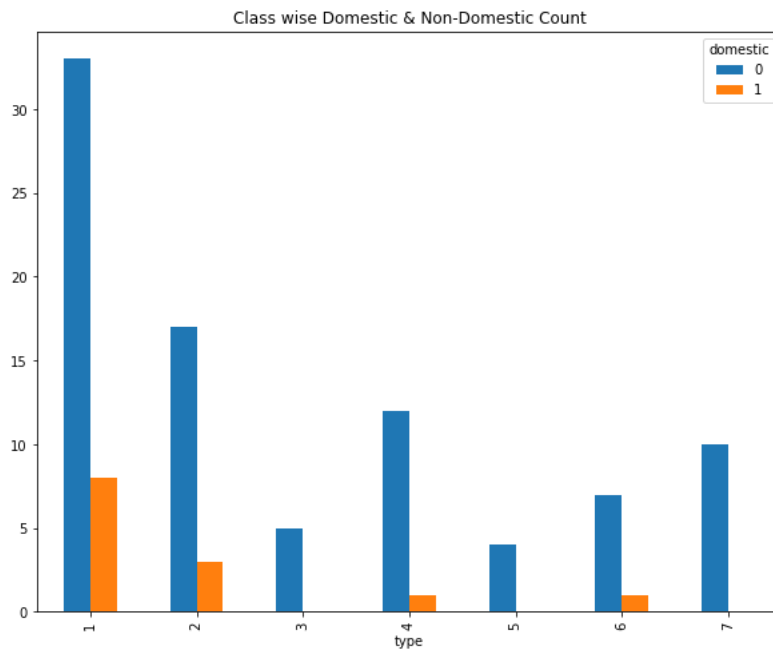
```
In [129]: 1 # So we can see mostly animals are not domestic
```

```
In [130]: 1 pd.crosstab(zoo['type'], zoo['domestic'])
```

Out[130]:

	domestic	
	0	1
type		
1	33	8
2	17	3
3	5	0
4	12	1
5	4	0
6	7	1
7	10	0

```
In [131]: 1 # Lets see species wise domestic and non-domestic animals
2 pd.crosstab(zoo['type'], zoo['domestic']).plot(kind="bar", figsize=(10,8), title="Class wise Domestic & Non-Domestic Count")
3 plt.plot();
```



```
In [132]: 1 # Lets see how many animals provides us milk
2 zoo['milk'].value_counts()
```

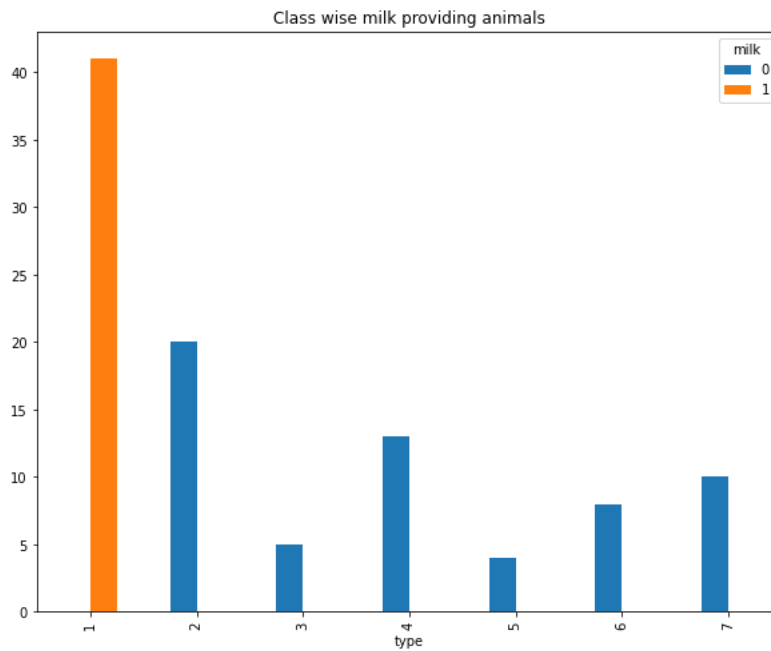
```
Out[132]: 0    60
1     41
Name: milk, dtype: int64
```

```
In [133]: 1 # So there are 41 animals in the list which provides us milk. Lets see to which category they belongs
```

```
In [134]: 1 pd.crosstab(zoo['type'], zoo['milk'])
```

```
Out[134]: milk  0  1
type
1    0  41
2    20  0
3     5  0
4    13  0
5     4  0
6     8  0
7    10  0
```

```
In [135]: 1 pd.crosstab(zoo['type'], zoo['milk']).plot(kind="bar", figsize=(10, 8), title="Class wise milk providing animals")
          2 plt.plot();
```



```
In [136]: 1 # Lets see how many animals live under water. i.e aquatic
          2 # Lets find out all aquatic animals.
          3 zoo.aquatic.value_counts() #only 36 aquatic animals are there.
          4 # Lets see there class.
```

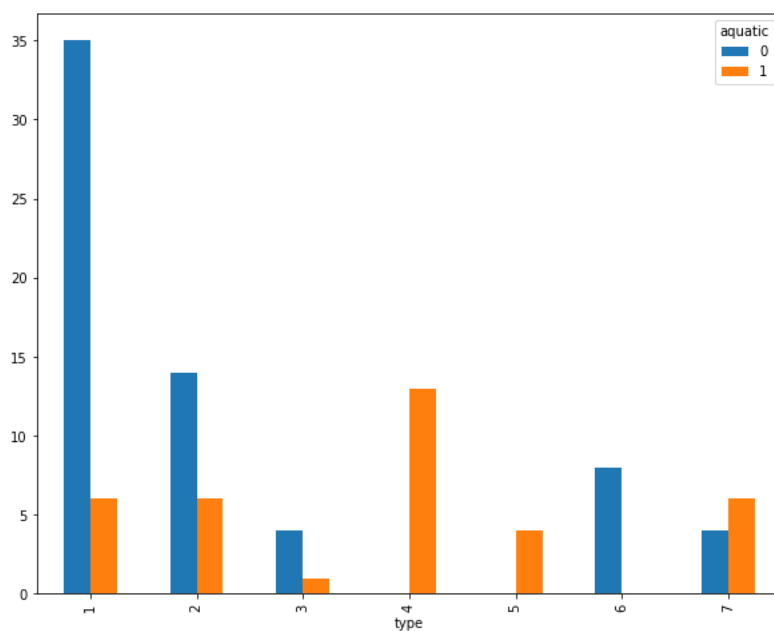
```
Out[136]: 0    65
          1    36
          Name: aquatic, dtype: int64
```

```
In [137]: 1 zoo[zoo['aquatic']==1].type.value_counts()
```

```
Out[137]: 4    13
          7     6
          1     6
          2     6
          5     4
          3     1
          Name: type, dtype: int64
```



```
In [138]: 1 pd.crosstab(zoo['type'], zoo['aquatic']).plot(kind="bar", figsize=(10,8));
```

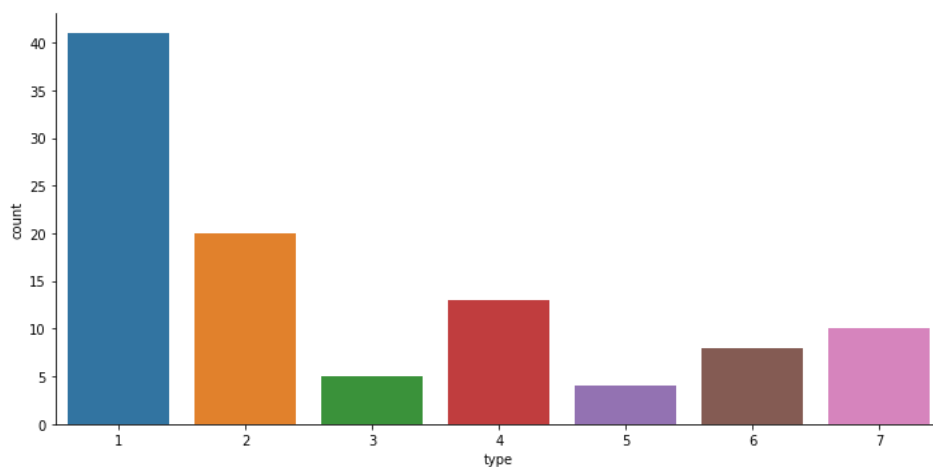


```
In [139]: 1 # finding unique value of class type
2 type_list = [i for i in zoo.type]
3 unique_type = list(set(type_list))
4 unique_type
```

```
Out[139]: [1, 2, 3, 4, 5, 6, 7]
```

```
In [140]: 1 # use seaborn to plot the count of each 7 class_type
2 sns.factorplot('type', data=zoo, kind="count",size = 5,aspect = 2)
```

```
Out[140]: <seaborn.axisgrid.FacetGrid at 0x1cbdee87340>
```



In [141]:

1 zoo

Out[141]:

	animal name	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes	venomous	fins	legs	tail	domestic	catsize	type
0	aardvark	1	0	0	1	0	0	1	1	1	1	0	0	4	0	0	1	1
1	antelope	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0	1	1
2	bass	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0	0	4
3	bear	1	0	0	1	0	0	1	1	1	1	0	0	4	0	0	1	1
4	boar	1	0	0	1	0	0	1	1	1	1	0	0	4	1	0	1	1
...
96	wallaby	1	0	0	1	0	0	0	1	1	1	0	0	2	1	0	1	1
97	wasp	1	0	1	0	1	0	0	0	0	1	1	0	6	0	0	0	6
98	wolf	1	0	0	1	0	0	1	1	1	1	0	0	4	1	0	1	1
99	worm	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	7
100	wren	0	1	1	0	1	0	0	0	1	1	0	0	2	1	0	0	2

101 rows × 18 columns

In [142]:

1 from sklearn.model_selection import train_test_split

In [143]:

1 # split train test data into 70/30.
2 from sklearn.model_selection import train_test_split
3 X = zoo.iloc[:,1:16]
4 Y = zoo.iloc[:,16]
5 X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state=1, stratify=Y)

In [144]:

1 X_train

Out[144]:

	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes	venomous	fins	legs	tail	domestic
33	0	1	1	0	1	1	1	0	1	1	0	0	2	1	0
58	0	1	1	0	0	1	1	0	1	1	0	0	2	1	0
62	0	0	1	0	0	0	1	1	1	1	1	0	0	1	0
25	0	0	1	0	0	1	1	1	1	1	0	0	4	0	0
82	0	0	1	0	0	1	0	1	1	0	0	1	0	1	0
...
35	1	0	0	1	0	0	0	1	1	1	0	0	4	1	1
83	0	1	1	0	1	0	0	0	1	1	0	0	2	1	0
59	0	1	1	0	1	0	0	0	1	1	0	0	2	1	0
65	1	0	0	1	0	0	0	1	1	1	0	0	4	1	1
77	0	0	1	0	0	1	1	0	0	0	1	0	0	0	0

70 rows × 15 columns

In [145]: 1 X_test

```
Out[145]:
```

	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes	venomous	fins	legs	tail	domestic
55	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0
0	1	0	0	1	0	0	1	1	1	1	0	0	4	0	0
16	0	1	1	0	1	0	1	0	1	1	0	0	2	1	0
12	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0
24	0	0	1	0	0	0	0	0	0	1	0	0	6	0	0
56	0	1	1	0	0	0	0	0	1	1	0	0	2	1	0
17	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0
18	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0
13	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0
100	0	1	1	0	1	0	0	0	1	1	0	0	2	1	0
47	1	0	0	1	0	0	1	1	1	1	0	0	4	1	0
72	0	0	0	0	0	0	1	0	0	1	1	0	8	1	0
71	0	1	1	0	0	0	1	0	1	1	0	0	2	1	0
36	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0
32	1	0	0	1	0	0	0	1	1	1	0	0	2	0	0
5	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0
2	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0
86	0	0	1	0	0	1	1	1	1	0	1	1	0	1	0
14	0	0	1	0	0	1	1	0	0	0	0	0	4	0	0
97	1	0	1	0	1	0	0	0	0	1	1	0	6	0	0
30	0	0	1	0	1	0	0	0	0	1	0	0	6	0	0
41	0	1	1	0	0	0	1	0	1	1	0	0	2	1	0
27	1	0	0	1	1	0	0	1	1	1	0	0	2	1	0
80	0	0	1	0	0	0	1	1	1	1	0	0	0	1	0
60	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0
44	1	0	0	1	0	0	1	1	1	1	0	0	4	1	0
7	0	0	1	0	0	1	0	1	1	0	0	1	0	1	1
21	0	1	1	0	1	1	0	0	1	1	0	0	2	1	0
95	0	1	1	0	1	0	1	0	1	1	0	0	2	1	0
63	1	0	1	1	0	1	1	0	1	1	0	0	4	1	0
15	0	0	1	0	0	1	1	0	0	0	0	0	6	0	0

In [146]: 1 Y_train

```
Out[146]: 33 0
58 1
62 0
25 0
82 0
..
35 0
83 0
59 0
65 1
77 0
Name: catsize, Length: 70, dtype: int64
```

In [147]:

```
1 Y_test
```

Out[147]:

```
55 1
0 1
16 0
12 0
24 0
56 1
17 1
18 1
13 0
100 0
47 1
72 0
71 1
36 0
32 1
5 1
2 0
86 1
14 0
97 0
30 0
41 0
27 0
80 0
60 1
44 1
7 0
21 0
95 1
63 1
15 0
Name: catsize, dtype: int64
```

In [148]:

```
1 num_folds = 10
2 KFold = KFold(n_splits=10)
```

In [149]:

```
1 model = KNeighborsClassifier(n_neighbors=3)
2 model.fit(X_train,Y_train)
```

Out[149]: KNeighborsClassifier(n_neighbors=3)

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

In [150]:

```
1 # Predicting on test data
2 preds = model.predict(X_test) # Predicting on test data set
3 pd.Series(preds).value_counts() # getting the count of each category
```

Out[150]:

```
0 22
1 9
dtype: int64
```

In [151]:

```
1 pd.crosstab(Y_test,preds) #getting the 2 way table to understand the correct and wrong predictions
```

Out[151]:

```
col_0  0  1
catsize
0  16  1
1   6  8
```

In [152]:

```
1 # Accuracy
2 np.mean(preds==Y_test)
```

Out[152]: 0.7741935483870968

In [153]:

```
1 model.score(X_train,Y_train)
```

Out[153]: 0.8285714285714286

In [154]:

```
1 print("Accuracy",accuracy_score(Y_test,preds)*100)
```

Accuracy 77.41935483870968

```
In [155]: 1 # Use cross validation score since this is a small size dataset
          2 # Get cross validation score of K-Nearest Neighbors
```

```
In [156]: 1 result = cross_val_score(model, X, Y, cv=KFold)
```

```
In [157]: 1 print(result.mean()*100)
```

76.27272727272728

```
In [158]: 1 print(result.std()*100)
```

12.704199865197182

Grid Search for Algorithm Tuning

```
In [159]: 1 n_neighbors = np.array(range(1,40))
          2 param_grid = dict(n_neighbors=n_neighbors)
```

```
In [160]: 1 model = KNeighborsClassifier()
          2 grid = GridSearchCV(estimator=model, param_grid=param_grid)
          3 grid.fit(X, Y)
```

```
Out[160]: GridSearchCV(estimator=KNeighborsClassifier(),
                        param_grid={'n_neighbors': array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
                  18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34,
                  35, 36, 37, 38, 39])})
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

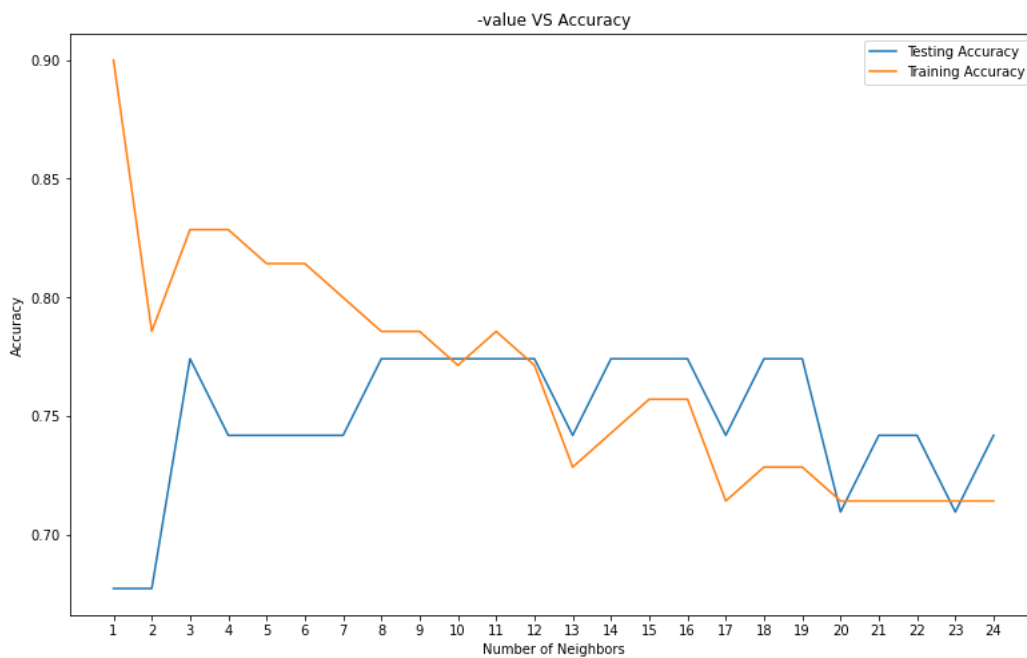
```
In [161]: 1 print(grid.best_score_)
          2 print(grid.best_params_)
```

0.790952380952381
{'n_neighbors': 5}

```

In [162]: 1 k_values = np.arange(1,25)
          2 train_accuracy = []
          3 test_accuracy = []
          4
          5 for i, k in enumerate(k_values):
          6     # k from 1 to 25(exclude)
          7     knn = KNeighborsClassifier(n_neighbors=k)
          8     # Fit with knn
          9     knn.fit(X_train,Y_train)
         10     #train accuracy
         11     train_accuracy.append(knn.score(X_train,Y_train))
         12     # test accuracy
         13     test_accuracy.append(knn.score(X_test,Y_test))
         14 # Plot
         15 plt.figure(figsize=[13,8])
         16 plt.plot(k_values, test_accuracy, label = 'Testing Accuracy')
         17 plt.plot(k_values, train_accuracy, label = 'Training Accuracy')
         18 plt.legend()
         19 plt.title('-value VS Accuracy')
         20 plt.xlabel('Number of Neighbors')
         21 plt.ylabel('Accuracy')
         22 plt.xticks(k_values)
         23 plt.savefig('graph.png')
         24 plt.show()
         25 print("Best accuracy is {} with K = {}".format(np.max(test_accuracy),1+test_accuracy.index(np.max(test_accuracy))))

```



Best accuracy is 0.7741935483870968 with K = 3

In []: 1

In []: 1