Question 1

Prepare a model for glass classification using KNN

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import seaborn as sns
from sklearn.metrics import classification_report, accuracy_score
from sklearn.model_selection import cross_val_score
```

In [2]:
```
df = pd.read_csv('glass.csv')
df
```

Out[2]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
0	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.00	0.0	1
1	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.00	0.0	1
2	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.00	0.0	1
3	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.00	0.0	1
4	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.00	0.0	1
...	...	...	...	...	...	...	...	...	...	...
209	1.51623	14.14	0.00	2.88	72.61	0.08	9.18	1.06	0.0	7
210	1.51685	14.92	0.00	1.99	73.06	0.00	8.40	1.59	0.0	7
211	1.52065	14.36	0.00	2.02	73.42	0.00	8.44	1.64	0.0	7
212	1.51651	14.38	0.00	1.94	73.61	0.00	8.48	1.57	0.0	7
213	1.51711	14.23	0.00	2.08	73.36	0.00	8.62	1.67	0.0	7

214 rows × 10 columns

In [4]:
```
df.head()
```

Out[4]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
0	1.52101	13.64	4.49	1.10	71.78	0.06	8.75	0.0	0.0	1
1	1.51761	13.89	3.60	1.36	72.73	0.48	7.83	0.0	0.0	1
2	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.0	0.0	1
3	1.51766	13.21	3.69	1.29	72.61	0.57	8.22	0.0	0.0	1
4	1.51742	13.27	3.62	1.24	73.08	0.55	8.07	0.0	0.0	1

In [5]:
```
df.count()
```

Out[5]:
```
RI      214
Na      214
Mg      214
Al      214
Si      214
K       214
Ca      214
Ba      214
Fe      214
Type    214
dtype: int64
```

In [6]:
```
df.shape
```

Out[6]:
```
(214, 10)
```

In [7]:
```
df.tail()
```

Out[7]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
209	1.51623	14.14	0.0	2.88	72.61	0.08	9.18	1.06	0.0	7
210	1.51685	14.92	0.0	1.99	73.06	0.00	8.40	1.59	0.0	7
211	1.52065	14.36	0.0	2.02	73.42	0.00	8.44	1.64	0.0	7
212	1.51651	14.38	0.0	1.94	73.61	0.00	8.48	1.57	0.0	7
213	1.51711	14.23	0.0	2.08	73.36	0.00	8.62	1.67	0.0	7

In [9]:
```
df.value_counts()
```

Out[9]:
```
RI       Na     Mg    Al    Si     K     Ca     Ba    Fe    Type
1.52213  14.21  3.82  0.47  71.77  0.11  9.57   0.00  0.00  1       2
1.51115  17.38  0.00  0.34  75.41  0.00  6.65   0.00  0.00  6       1
1.51848  13.64  3.87  1.27  71.96  0.54  8.32   0.00  0.32  2       1
1.51831  14.39  0.00  1.82  72.86  1.41  6.47   2.88  0.00  7       1
1.51832  13.33  3.34  1.54  72.14  0.56  8.99   0.00  0.00  3       1
                                                                  ..
1.51707  13.48  3.48  1.71  72.52  0.62  7.99   0.00  0.00  2       1
1.51708  13.72  3.68  1.81  72.06  0.64  7.88   0.00  0.00  2       1
1.51709  13.00  3.47  1.79  72.72  0.66  8.18   0.00  0.00  2       1
1.51711  12.89  3.62  1.57  72.96  0.61  8.11   0.00  0.00  2       1
1.53393  12.30  0.00  1.00  70.16  0.12  16.19  0.00  0.24  2       1
Length: 213, dtype: int64
```

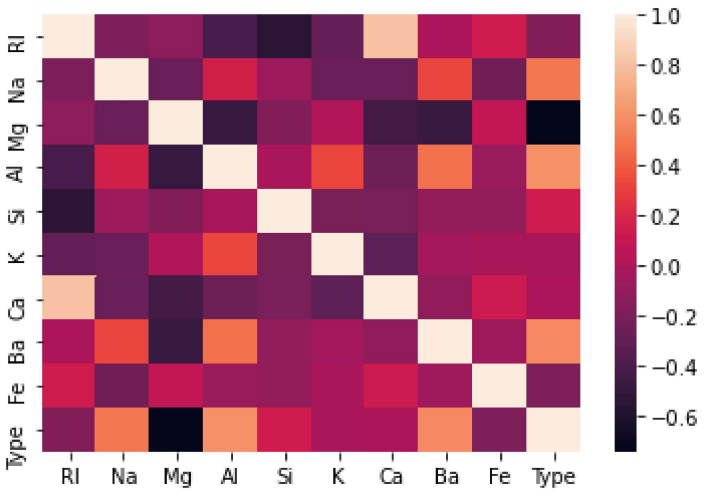
In [10]:
```
# value count for glass types
df.Type.value_counts()
```

Out[10]:
```
2    76
1    70
7    29
3    17
5    13
6     9
Name: Type, dtype: int64
```

Data exploration and visualizaion

In [12]:
```
# correlation matrix
cor = df.corr()
sns.heatmap(cor)
```

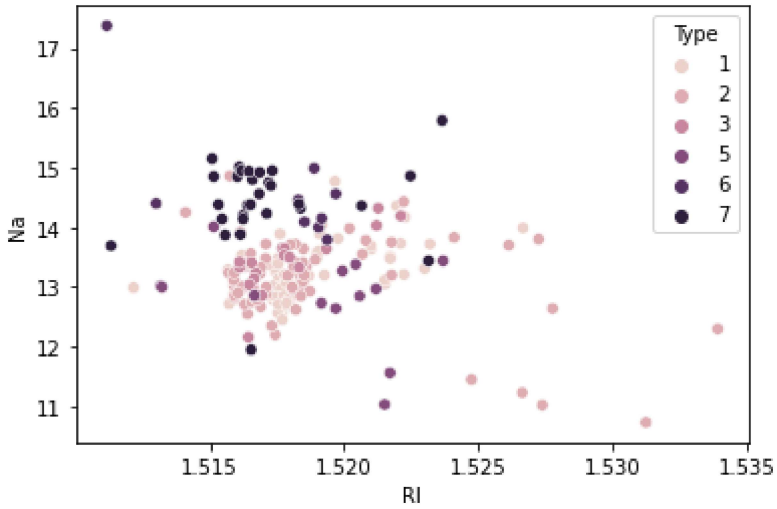
Out[12]:
```
<AxesSubplot:>
```



In [13]:
```
# Scatter plot of two features, and pairwise plot
sns.scatterplot(df['RI'],df['Na'],hue=df['Type'])
```

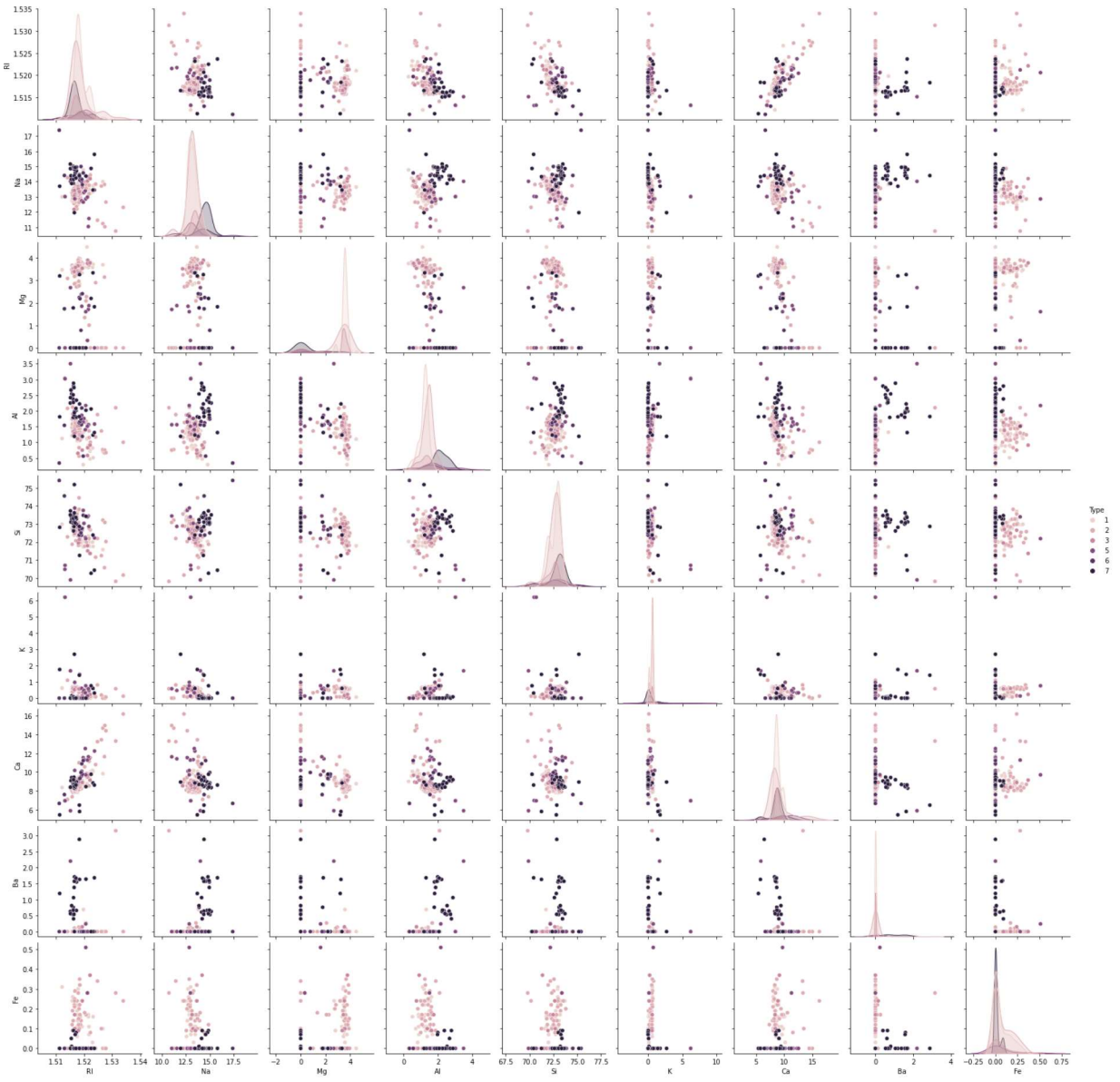
```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
ning: Pass the following variables as keyword args: x, y. From version 0.12, th
e only valid positional argument will be `data`, and passing other arguments wi
thout an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[13]: <AxesSubplot:xlabel='RI', ylabel='Na'>



In [14]:
```
#pairwise plot of all the features
sns.pairplot(df,hue='Type')
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:306: UserWa
rning: Dataset has 0 variance; skipping density estimate.
  warnings.warn(msg, UserWarning)
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:306: UserWa
rning: Dataset has 0 variance; skipping density estimate.
  warnings.warn(msg, UserWarning)
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:306: UserWa
rning: Dataset has 0 variance; skipping density estimate.
  warnings.warn(msg, UserWarning)
```



In [15]:
```
scaler = StandardScaler()
```

In [16]:
```
scaler.fit(df.drop('Type',axis=1))
```

Out[16]:
```
StandardScaler()
```

In [17]:
```
StandardScaler(copy=True, with_mean=True, with_std=True)
```

Out[17]:
```
StandardScaler()
```

In [18]:
```
#perform transformation
scaled_features = scaler.transform(df.drop('Type',axis=1))
scaled_features
```

Out[18]:
```
array([[ 0.87286765,  0.28495326,  1.25463857, ..., -0.14576634,
        -0.35287683, -0.5864509 ],
       [-0.24933347,  0.59181718,  0.63616803, ..., -0.79373376,
        -0.35287683, -0.5864509 ],
       [-0.72131806,  0.14993314,  0.60142249, ..., -0.82894938,
        -0.35287683, -0.5864509 ],
       ...,
       [ 0.75404635,  1.16872135, -1.86551055, ..., -0.36410319,
         2.95320036, -0.5864509 ],
       [-0.61239854,  1.19327046, -1.86551055, ..., -0.33593069,
         2.81208731, -0.5864509 ],
       [-0.41436305,  1.00915211, -1.86551055, ..., -0.23732695,
         3.01367739, -0.5864509 ]])
```

In [19]:
```
df_feat = pd.DataFrame(scaled_features,columns=df.columns[:-1])
df_feat.head()
```

Out[19]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe
0	0.872868	0.284953	1.254639	-0.692442	-1.127082	-0.671705	-0.145766	-0.352877	-0.586451
1	-0.249333	0.591817	0.636168	-0.170460	0.102319	-0.026213	-0.793734	-0.352877	-0.586451
2	-0.721318	0.149933	0.601422	0.190912	0.438787	-0.164533	-0.828949	-0.352877	-0.586451
3	-0.232831	-0.242853	0.698710	-0.310994	-0.052974	0.112107	-0.519052	-0.352877	-0.586451
4	-0.312045	-0.169205	0.650066	-0.411375	0.555256	0.081369	-0.624699	-0.352877	-0.586451

Applying KNN

In [20]:
```
dff = df_feat.drop(['Ca','K'],axis=1) #Removing features - Ca and K
X_train,X_test,y_train,y_test  = train_test_split(dff,df['Type'],test_size=0.3,ra
#setting random state ensures split is same eveytime, so that the results are com
```

In [21]:
```
knn = KNeighborsClassifier(n_neighbors=4,metric='manhattan')
```

In [22]:
```
knn.fit(X_train,y_train)
```

Out[22]:
```
KNeighborsClassifier(metric='manhattan', n_neighbors=4)
```

In [23]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='manhattan',
                     metric_params=None, n_jobs=None, n_neighbors=4, p=2,
                     weights='uniform')
```

Out[23]:
```
KNeighborsClassifier(metric='manhattan', n_neighbors=4)
```

In [25]:
```
y_pred = knn.predict(X_test)
```

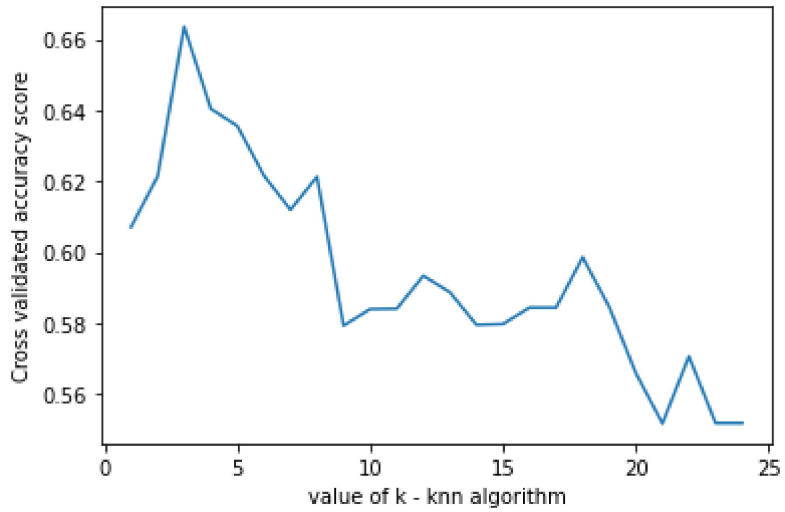
In [26]:
```
print(classification_report(y_test,y_pred))
```

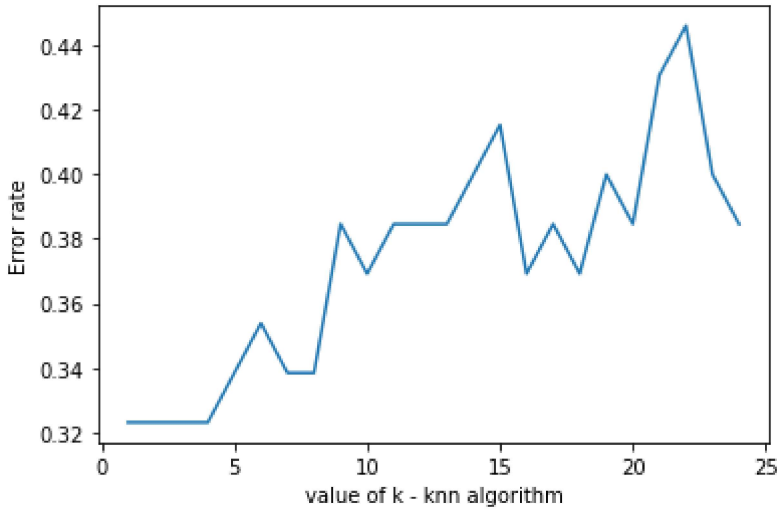
```
              precision    recall  f1-score   support

           1       0.69      0.90      0.78        20
           2       0.85      0.65      0.74        26
           3       0.00      0.00      0.00         3
           5       0.25      1.00      0.40         1
           6       0.50      0.50      0.50         2
           7       1.00      0.85      0.92        13

    accuracy                           0.74        65
   macro avg       0.55      0.65      0.56        65
weighted avg       0.77      0.74      0.74        65
```

In [27]:
```
accuracy_score(y_test,y_pred)
```

Out[27]:
```
0.7384615384615385
```

In [28]:
```
k_range = range(1,25)
k_scores = []
error_rate =[]
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    #kscores - accuracy
    scores = cross_val_score(knn,dff,df['Type'],cv=5,scoring='accuracy')
    k_scores.append(scores.mean())

    #error rate
    knn.fit(X_train,y_train)
    y_pred = knn.predict(X_test)
    error_rate.append(np.mean(y_pred!=y_test))

#plot k vs accuracy
plt.plot(k_range,k_scores)
plt.xlabel('value of k - knn algorithm')
plt.ylabel('Cross validated accuracy score')
plt.show()

#plot k vs error rate
plt.plot(k_range,error_rate)
plt.xlabel('value of k - knn algorithm')
plt.ylabel('Error rate')
plt.show()
```





Question 2

Implement a KNN model to classify the animals in to categorie

In [29]:
```
zoo = pd.read_csv('Zoo.csv')
zoo
```

Out[29]:

	animal name	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes
0	aardvark	1	0	0	1	0	0	1	1	1	1
1	antelope	1	0	0	1	0	0	0	1	1	1
2	bass	0	0	1	0	0	1	1	1	1	0
3	bear	1	0	0	1	0	0	1	1	1	1
4	boar	1	0	0	1	0	0	1	1	1	1
...	...	...	...	...	...	...	...	...	...	...	...
96	wallaby	1	0	0	1	0	0	0	1	1	1
97	wasp	1	0	1	0	1	0	0	0	0	1
98	wolf	1	0	0	1	0	0	1	1	1	1
99	worm	0	0	1	0	0	0	0	0	0	1
100	wren	0	1	1	0	1	0	0	0	1	1

101 rows × 18 columns

In [30]:
```
zoo.head()
```

Out[30]:

	animal name	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes
0	aardvark	1	0	0	1	0	0	1	1	1	1
1	antelope	1	0	0	1	0	0	0	1	1	1
2	bass	0	0	1	0	0	1	1	1	1	0
3	bear	1	0	0	1	0	0	1	1	1	1
4	boar	1	0	0	1	0	0	1	1	1	1

In [31]:
```
zoo.tail()
```

Out[31]:

	animal name	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes
96	wallaby	1	0	0	1	0	0	0	1	1	1
97	wasp	1	0	1	0	1	0	0	0	0	1
98	wolf	1	0	0	1	0	0	1	1	1	1
99	worm	0	0	1	0	0	0	0	0	0	1
100	wren	0	1	1	0	1	0	0	0	1	1

In [32]:
```
# value count for glass types
zoo.type.value_counts()
```

Out[32]:
```
1    41
2    20
4    13
7    10
6     8
3     5
5     4
Name: type, dtype: int64
```

In [34]:
```
zoo.shape
```

Out[34]:
```
(101, 18)
```

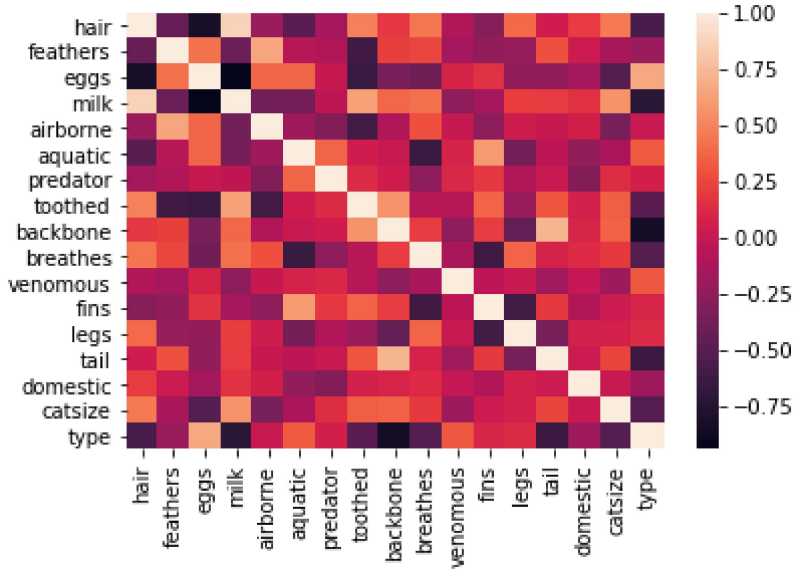
In [36]:
```
zoo.count()
```

Out[36]:
```
animal name    101
hair           101
feathers       101
eggs           101
milk           101
airborne       101
aquatic        101
predator       101
toothed        101
backbone       101
breathes       101
venomous       101
fins           101
legs           101
tail           101
domestic       101
catsize        101
type           101
dtype: int64
```

Data exploration and visualizaion

In [37]:
```
# correlation matrix
cor = zoo.corr()
sns.heatmap(cor)
```

Out[37]: <AxesSubplot:>



In [38]:
```
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 [39]:
```
zoo.describe()
```

Out[39]:

	hair	feathers	eggs	milk	airborne	aquatic	predator	
count	101.000000	101.000000	101.000000	101.000000	101.000000	101.000000	101.000000	101
mean	0.425743	0.198020	0.584158	0.405941	0.237624	0.356436	0.554455	0
std	0.496921	0.400495	0.495325	0.493522	0.427750	0.481335	0.499505	0
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0
50%	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	1.000000	1
75%	1.000000	0.000000	1.000000	1.000000	0.000000	1.000000	1.000000	1
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1

In [40]:
```
zoo.drop("animal name",axis=1,inplace=True)
```

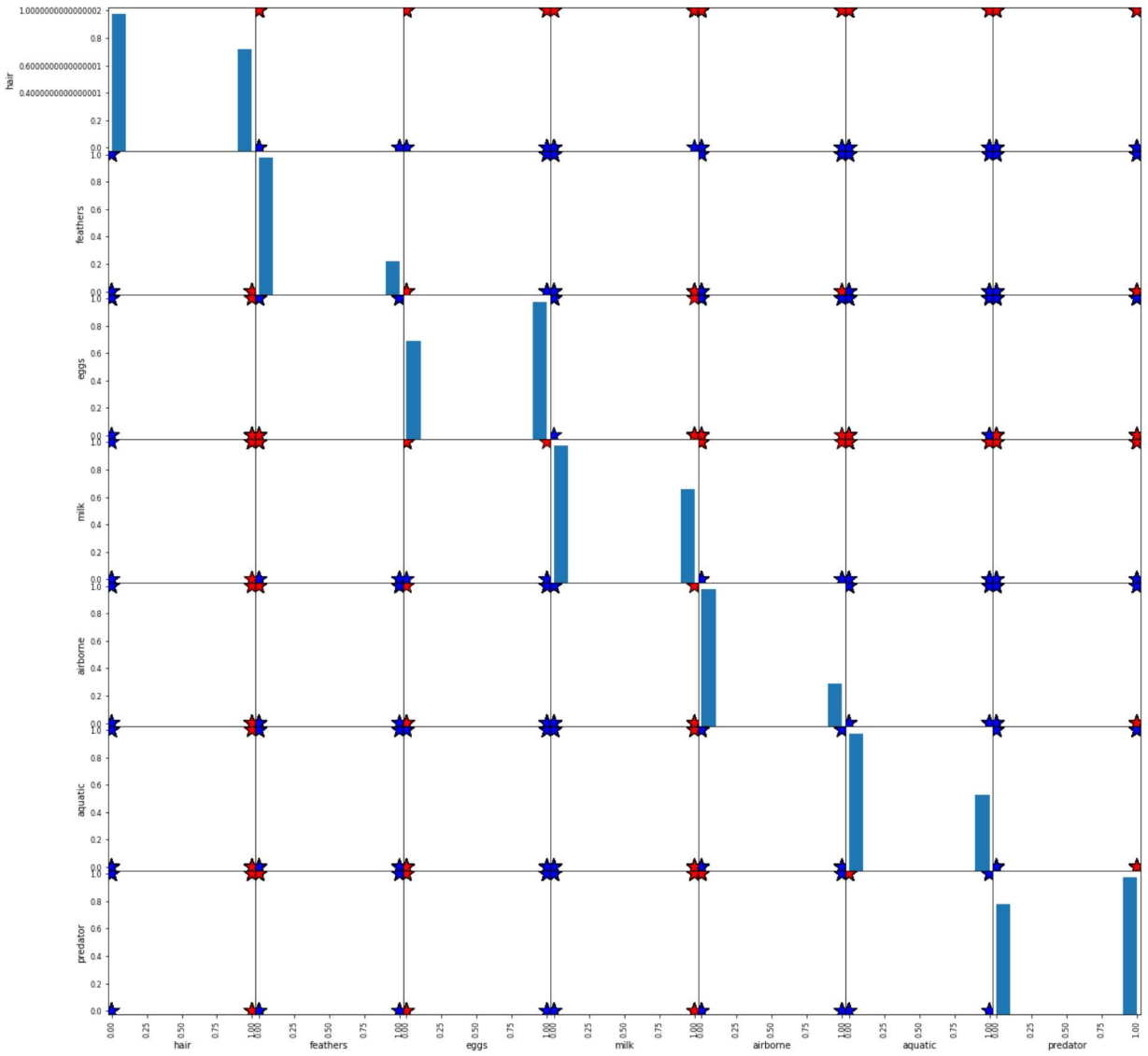
In [41]:
```
color_list = [("red" if i ==1 else "blue" if i ==0 else "yellow" ) for i in zoo.h
```

In [42]:
```
# With this set function we find unique values in a list...
unique_list = list(set(color_list))
unique_list
```

Out[42]:
```
['red', 'blue']
```

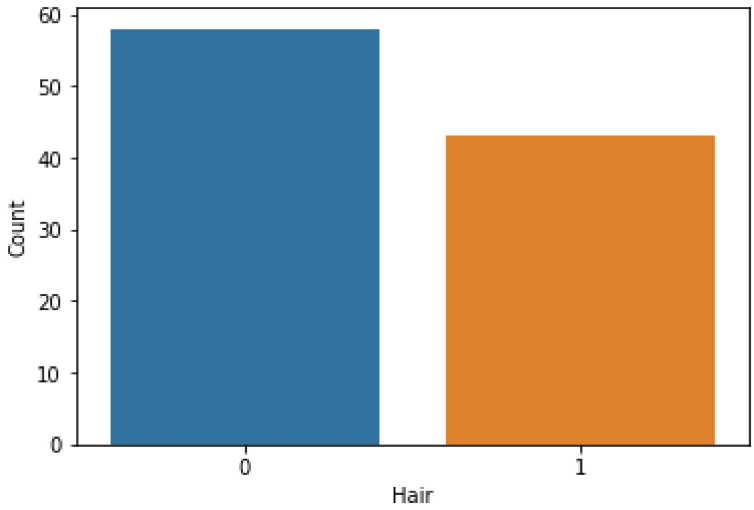
Plotting scatter matrix

In [43]:
```
pd.plotting.scatter_matrix(zoo.iloc[:,:7],
                                        c=color_list,
                                        figsize= [20,20],
                                        diagonal='hist',
                                        alpha=1,
                                        s = 300,
                                        marker = '*',
                                        edgecolor= "black")
plt.show()
```



Visualizing has hair or not ?

In [44]:
```
sns.countplot(x="hair", data=zoo)
plt.xlabel("Hair")
plt.ylabel("Count")
plt.show()
zoo.loc[:,'hair'].value_counts()
```



Out[44]:
```
0    58
1    43
Name: hair, dtype: int64
```

KNN

In [45]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors = 1)
x,y = zoo.loc[:,zoo.columns != 'hair'], zoo.loc[:,'hair']
knn.fit(x,y)
prediction = knn.predict(x)
print("Prediction = ",prediction)
```

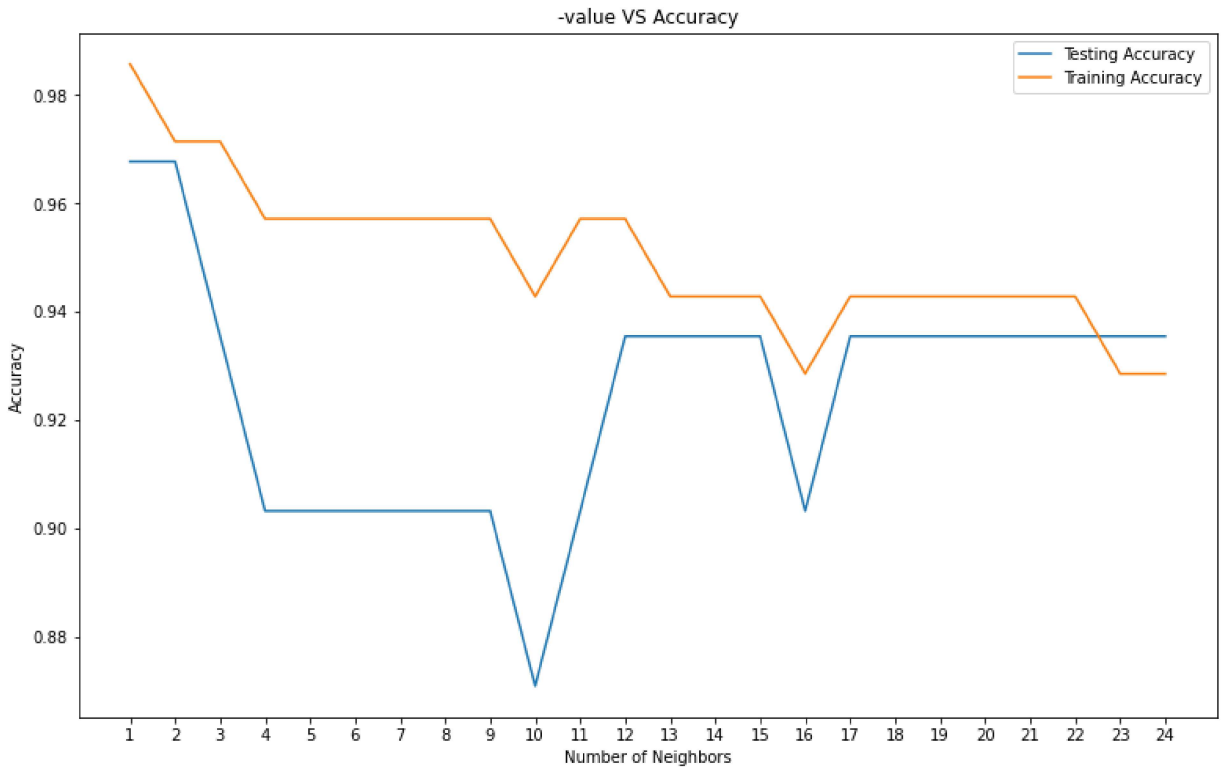
```
Prediction =  [1 1 0 1 1 1 1 0 0 1 1 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 1 1 1 0 1
1 0 0 1 1
 0 0 1 0 0 0 0 1 1 0 1 1 1 1 0 0 0 1 1 0 0 0 0 0 0 0 1 1 1 0 1 1 1 1 0 0 0
 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 1 0 1 1 1 0 0]
```

Train Test Split

In [46]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_state
knn = KNeighborsClassifier(n_neighbors = 1)
x,y = zoo.loc[:,zoo.columns != 'hair'], zoo.loc[:,'hair']
knn.fit(x_train,y_train)
prediction = knn.predict(x_test)
print('With KNN (K=1) accuracy is: ',knn.score(x_test,y_test)) # accuracy
```

```
With KNN (K=1) accuracy is:  0.967741935483871
```

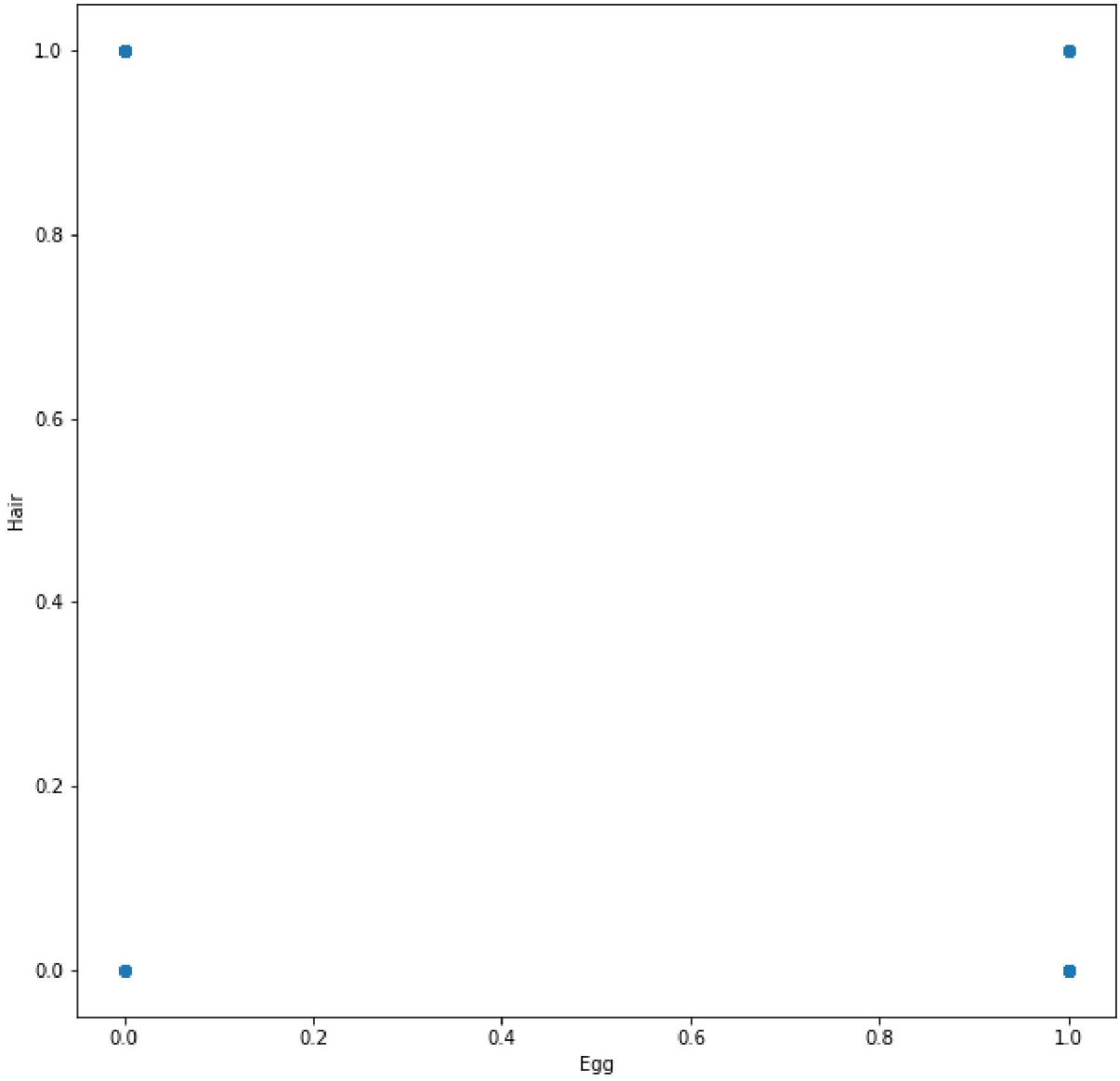
In [47]:
```
k_values = np.arange(1,25)
train_accuracy = []
test_accuracy = []

for i, k in enumerate(k_values):
    # k from 1 to 25(exclude)
    knn = KNeighborsClassifier(n_neighbors=k)
    # Fit with knn
    knn.fit(x_train,y_train)
    #train accuracy
    train_accuracy.append(knn.score(x_train, y_train))
    # test accuracy
    test_accuracy.append(knn.score(x_test, y_test))

    # Plot
plt.figure(figsize=[13,8])
plt.plot(k_values, test_accuracy, label = 'Testing Accuracy')
plt.plot(k_values, train_accuracy, label = 'Training Accuracy')
plt.legend()
plt.title('-value VS Accuracy')
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.xticks(k_values)
plt.savefig('graph.png')
plt.show()
print("Best accuracy is {} with K = {}".format(np.max(test_accuracy),1+test_accur
```




```
Best accuracy is 0.967741935483871 with K = 1
```

Visualizing Eggs and Hair on Scatter

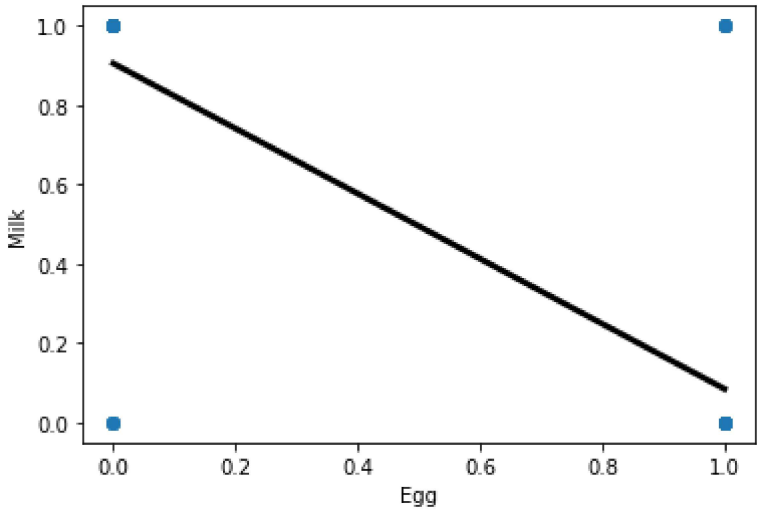
In [48]:
```
x = np.array(zoo.loc[:,"eggs"]).reshape(-1,1)
y = np.array(zoo.loc[:,'hair']).reshape(-1,1)

plt.figure(figsize=[10,10])
plt.scatter(x=x,y=y)
plt.xlabel('Egg')
plt.ylabel('Hair')
plt.show()
```



Linear Regression

In [49]:
```
# Plotting regression line and scatter
from sklearn.linear_model import LinearRegression
regression = LinearRegression()

predict_space = np.linspace(min(x),max(x)).reshape(-1,1)
regression.fit(x,y)
predicted = regression.predict(predict_space)

print("R^2 Score: ",regression.score(x,y))

plt.plot(predict_space, predicted, color='black', linewidth=3)
plt.scatter(x=x,y=y)
plt.xlabel('Egg')
plt.ylabel('Milk')
plt.show()
```

```
R^2 Score:  0.6681125904754137
```



Cross Validation

In [51]:
```
from sklearn.model_selection import cross_val_score
regression = LinearRegression()
k=5
cv_result = cross_val_score(regression,x,y,cv=k)
print("CV Scores: ",cv_result)
print("CV Average: ",np.sum(cv_result)/k)
```

```
CV Scores:  [0.80171562 0.61914032 0.79243817 0.24939434 0.76176534]
CV Average:  0.6448907578047475
```

Ridge

In [52]:
```
from sklearn.linear_model import Ridge
x_train,x_test,y_train,y_test = train_test_split(x,y,random_state = 2, test_size
ridge = Ridge(alpha= 0.001,normalize = True)
ridge.fit(x_train,y_train)
ridge_predict = ridge.predict(x_test)
print("Ridge Score: ",ridge.score(x_test,y_test))
```

```
Ridge Score:  0.930239727992853
```

Lasso

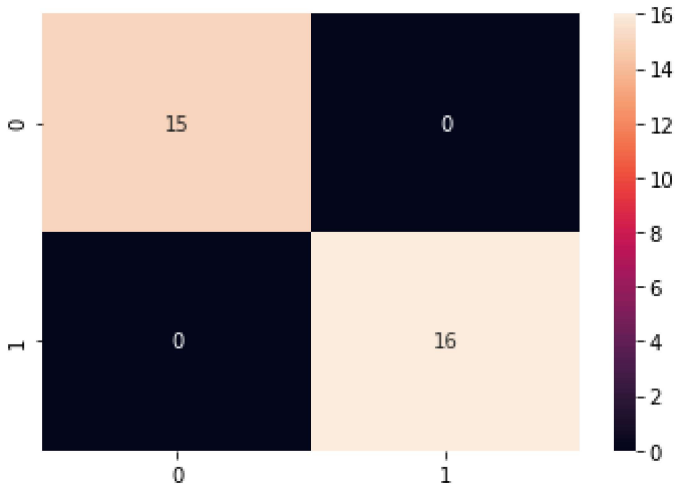
In [53]:
```
from sklearn.linear_model import Lasso
x = np.array(zoo.loc[:,['eggs','airborne','fins','legs',"hair","type"]])
x_train,x_test,y_train,y_test = train_test_split(x,y,random_state = 3, test_size
lasso = Lasso(alpha = 0.0001, normalize = True)
lasso.fit(x_train,y_train)
ridge_predict = lasso.predict(x_test)
print('Lasso score: ',lasso.score(x_test,y_test))
print('Lasso coefficients: ',lasso.coef_)
```

```
Lasso score:  0.9999970989932222
Lasso coefficients:  [-0.         -0.         -0.          0.          0.998301
54 -0.        ]
```

In [54]:
```
from sklearn.metrics import classification_report,confusion_matrix
from sklearn.ensemble import RandomForestClassifier
x,y = zoo.loc[:,zoo.columns != "hair"], zoo.loc[:,"hair"]
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_state
rf = RandomForestClassifier(random_state = 4)
rf.fit(x_train,y_train)
y_pred = rf.predict(x_test)
cm = confusion_matrix(y_test,y_pred)
print("Confisuon Matrix: \n",cm)
print("Classification Report: \n",classification_report(y_test,y_pred))
```

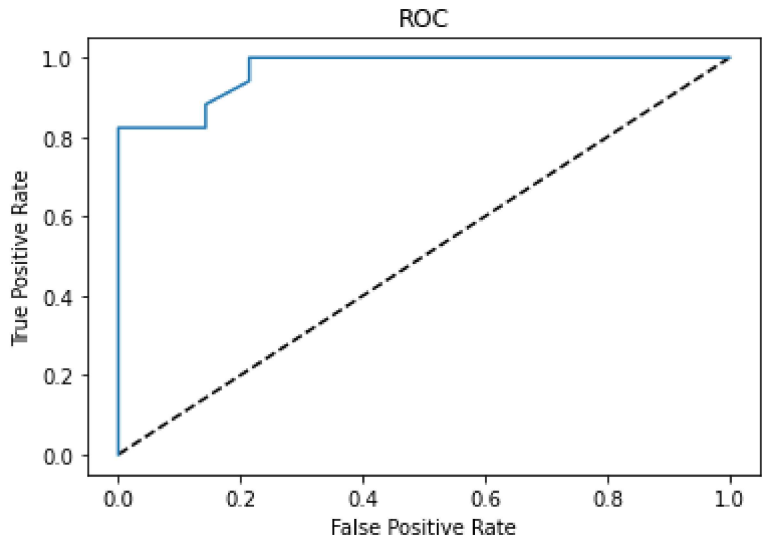
```
Confisuon Matrix:
 [[15  0]
 [ 0 16]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        15
           1       1.00      1.00      1.00        16

    accuracy                           1.00        31
   macro avg       1.00      1.00      1.00        31
weighted avg       1.00      1.00      1.00        31
```

In [55]:
```
sns.heatmap(cm,annot=True,fmt="d")
plt.show()
```



Logistic Regression

In [56]:
```
from sklearn.metrics import roc_curve
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report
#hair = 1 no = 0
x,y = zoo.loc[:,(zoo.columns != 'hair')], zoo.loc[:,'hair']
x_train,x_test,y_train,y_test = train_test_split(x, y, test_size = 0.3, random_st
logreg = LogisticRegression()
logreg.fit(x_train,y_train)
y_pred_prob = logreg.predict_proba(x_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
# Plot ROC curve
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC')
plt.show()
```



In [57]:
```
# grid search cross validation with 1 hyperparameter
from sklearn.model_selection import GridSearchCV
grid = {'n_neighbors': np.arange(1,50)}
knn = KNeighborsClassifier()
knn_cv = GridSearchCV(knn, grid, cv=3) # GridSearchCV
knn_cv.fit(x,y)# Fit

# Print hyperparameter
print("Tuned hyperparameter k: {}".format(knn_cv.best_params_))
print("Best score: {}".format(knn_cv.best_score_))
```

```
Tuned hyperparameter k: {'n_neighbors': 1}
Best score: 0.9402852049910874
```

In [58]:
```
# grid search cross validation with 2 hyperparameter
# 1. hyperparameter is C:logistic regression regularization parameter
# 2. penalty l1 or l2
# Hyperparameter grid
param_grid = {'C': np.logspace(-3, 3, 7), 'penalty': ['l1', 'l2']}
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size = 0.3,random_st
logreg = LogisticRegression()
logreg_cv = GridSearchCV(logreg,param_grid,cv=3)
logreg_cv.fit(x_train,y_train)

# Print the optimal parameters and best score
print("Tuned hyperparameters : {}".format(logreg_cv.best_params_))
print("Best Accuracy: {}".format(logreg_cv.best_score_))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection\_validatio
n.py:610: FitFailedWarning: Estimator fit failed. The score on this train-tes
t partition for these parameters will be set to nan. Details:
Traceback (most recent call last):
  File "C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection\_v
alidation.py", line 593, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_logi
stic.py", line 1306, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
  File "C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_logi
stic.py", line 443, in _check_solver
    raise ValueError("Solver %s supports only 'l2' or 'none' penalties, "
ValueError: Solver lbfgs supports only 'l2' or 'none' penalties, got l1 penal
ty.

  warnings.warn("Estimator fit failed. The score on this train-test"
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection\_validatio
n.py:610: FitFailedWarning: Estimator fit failed. The score on this train-tes
```

In [59]:
```
# get_dummies
df = pd.get_dummies(zoo)
df.head(10)
```

Out[59]:

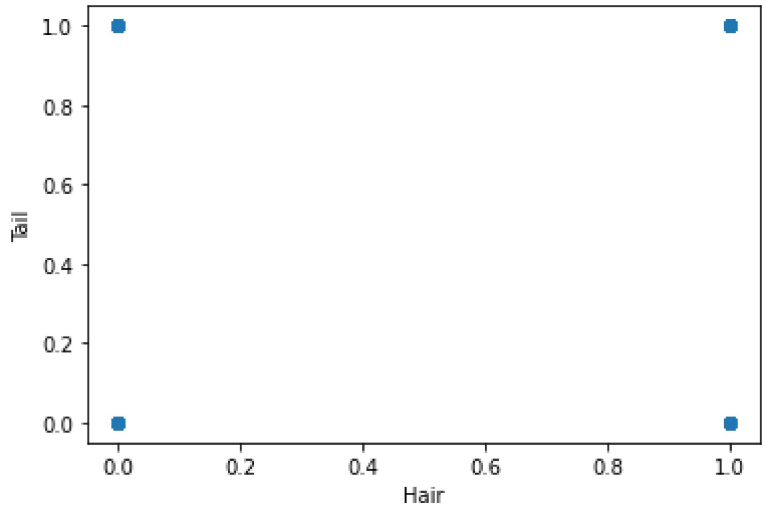
	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes	venomous
0	1	0	0	1	0	0	1	1	1	1	0
1	1	0	0	1	0	0	0	1	1	1	0
2	0	0	1	0	0	1	1	1	1	0	0
3	1	0	0	1	0	0	1	1	1	1	0
4	1	0	0	1	0	0	1	1	1	1	0
5	1	0	0	1	0	0	0	1	1	1	0
6	1	0	0	1	0	0	0	1	1	1	0
7	0	0	1	0	0	1	0	1	1	0	0
8	0	0	1	0	0	1	1	1	1	0	0
9	1	0	0	1	0	0	0	1	1	1	0

Support Vector Machine

In [60]:
```
# SVM, pre-process and pipeline
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
steps = [('scalar', StandardScaler()),
         ('SVM', SVC())]
pipeline = Pipeline(steps)
parameters = {'SVM__C':[1, 10, 100],
              'SVM__gamma':[0.1, 0.01]}
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.2,random_stat
cv = GridSearchCV(pipeline,param_grid=parameters,cv=3)
cv.fit(x_train,y_train)

y_pred = cv.predict(x_test)

print("Accuracy: {}".format(cv.score(x_test, y_test)))
print("Tuned Model Parameters: {}".format(cv.best_params_))
```

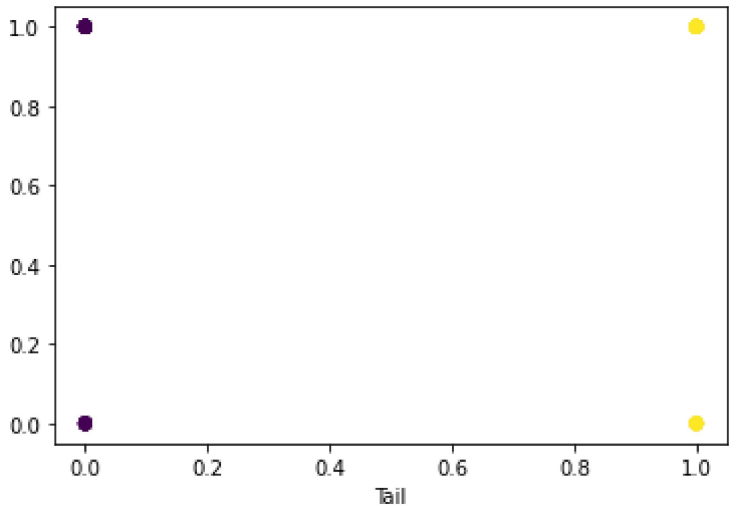
```
Accuracy: 0.9523809523809523
Tuned Model Parameters: {'SVM__C': 1, 'SVM__gamma': 0.01}
```

In [61]:
```
plt.scatter(zoo['hair'],zoo['tail'])
plt.xlabel('Hair')
plt.ylabel('Tail')
plt.show()
```



K-Means Clustering

In [62]:
```
data2 = zoo.loc[:,['tail','hair']]
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters = 2)
kmeans.fit(data2)
labels = kmeans.predict(data2)
plt.scatter(zoo['hair'],zoo['tail'],c = labels)
plt.xlabel('Hair')
plt.xlabel('Tail')
plt.show()
```



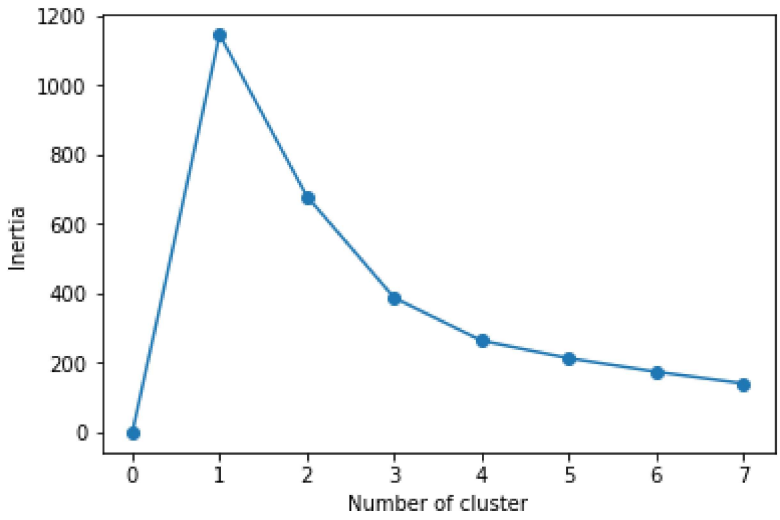
In [63]:
```
# cross tabulation table
df = pd.DataFrame({'labels':labels,"hair":zoo['hair']})
ct = pd.crosstab(df['labels'],df['hair'])
print(ct)
```

```
hair     0   1
labels
0       58   0
1        0  43
```

Inertia

In [64]:
```
inertia_list = np.empty(8)
for i in range(1,8):
    kmeans = KMeans(n_clusters=i)
    kmeans.fit(zoo)
    inertia_list[i] = kmeans.inertia_
plt.plot(range(0,8),inertia_list,'-o')
plt.xlabel('Number of cluster')
plt.ylabel('Inertia')
plt.show()
# we choose the elbow < 1
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:881: User
Warning: KMeans is known to have a memory leak on Windows with MKL, when there
are less chunks than available threads. You can avoid it by setting the environ
ment variable OMP_NUM_THREADS=1.
  warnings.warn(
```



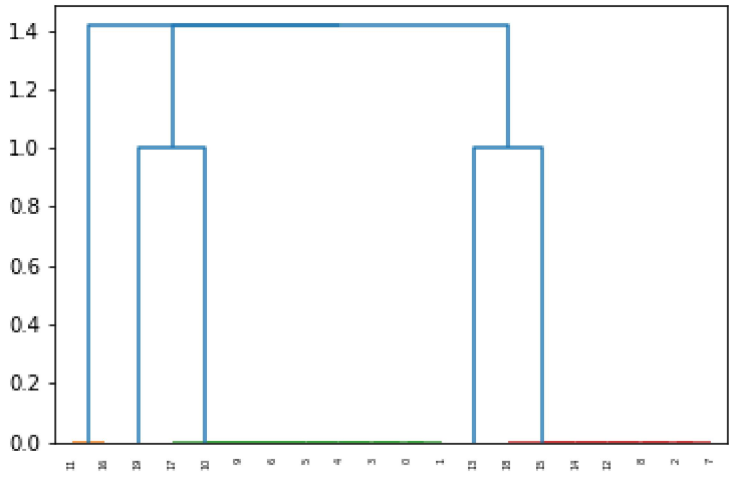
In [65]:
```
data2 = zoo.drop("hair",axis=1)
```

In [67]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
scalar = StandardScaler()
kmeans = KMeans(n_clusters = 2)
pipe = make_pipeline(scalar,kmeans)
pipe.fit(data2)
labels = pipe.predict(data2)
df = pd.DataFrame({'labels':labels,"hair":zoo['hair']})
ct = pd.crosstab(df['labels'],df['hair'])
print(ct)
```

```
hair     0   1
labels
0        2  39
1       56   4
```

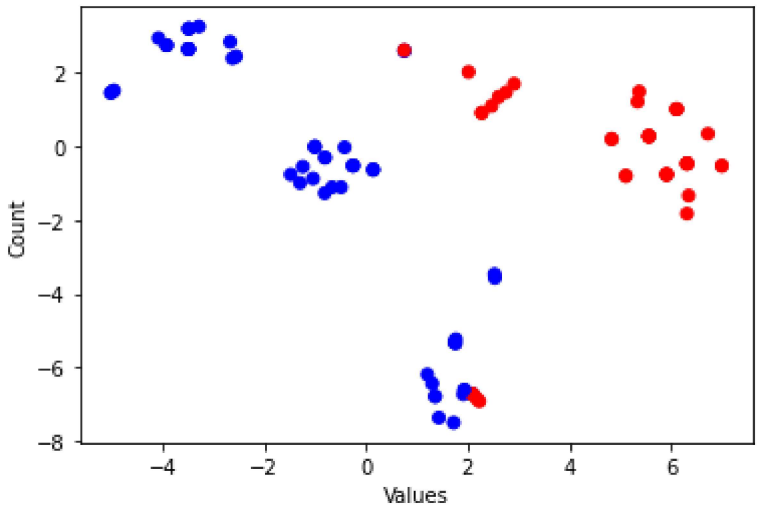
Dendogram

In [68]:
```
from scipy.cluster.hierarchy import linkage,dendrogram

merg = linkage(data2.iloc[:20,0:5],method = 'single')
dendrogram(merg, leaf_rotation = 90, leaf_font_size = 5)
plt.show()
```



t-distributed Stochastic Neighbor Embedding

In [69]:
```
from sklearn.manifold import TSNE
model = TSNE(learning_rate=100,random_state=42)
transformed = model.fit_transform(data2)
x = transformed[:,0]
y = transformed[:,1]
plt.scatter(x,y,c = color_list )
plt.xlabel('Values')
plt.ylabel('Count')
plt.show()
```

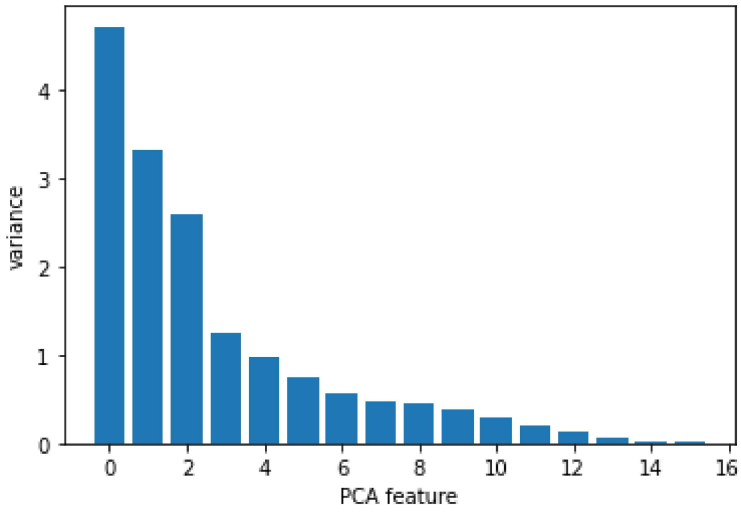


PCA

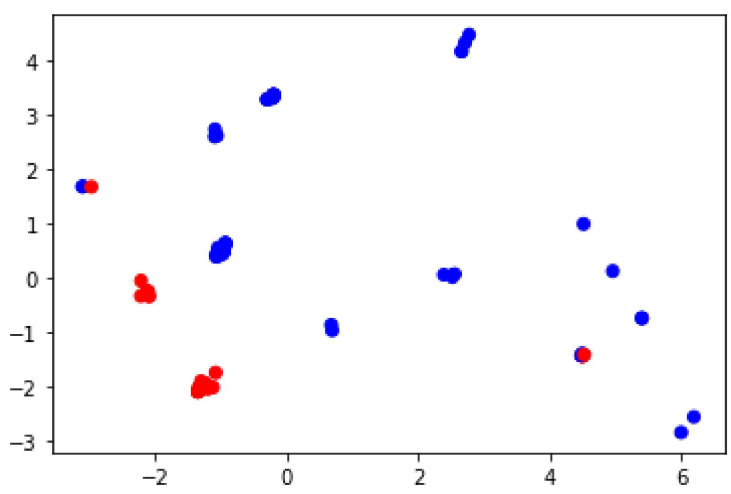
In [70]:
```
from sklearn.decomposition import PCA
model = PCA()
model.fit(data2[0:4])
transformed = model.transform(data2[0:4])
print('Principle components: ',model.components_)
```

```
Principle components:  [[ 0.00000000e+00  1.77997984e-01 -1.77997984e-01  0.000
00000e+00
   1.77997984e-01  5.75617345e-02  0.00000000e+00  0.00000000e+00
  -1.77997984e-01  0.00000000e+00  1.77997984e-01 -7.11991938e-01
   1.20436250e-01  0.00000000e+00 -1.77997984e-01  5.33993953e-01]
 [-3.88578059e-16 -7.92144437e-03  7.92144437e-03  0.00000000e+00
  -7.92144437e-03 -7.10368323e-01  0.00000000e+00  0.00000000e+00
   7.92144437e-03  0.00000000e+00 -7.92144437e-03  3.16857775e-02
   7.02446879e-01  0.00000000e+00  7.92144437e-03 -2.37643331e-02]
 [ 9.41361976e-01 -7.66453051e-02 -2.27239351e-02 -0.00000000e+00
   2.27239351e-02  1.73863535e-01 -0.00000000e+00 -0.00000000e+00
  -2.27239351e-02 -0.00000000e+00  2.27239351e-02 -9.08957403e-02
   1.73863535e-01 -0.00000000e+00 -2.27239351e-02 -1.91473622e-01]
 [-7.16711058e-02 -9.77226881e-01 -3.93907347e-02 -0.00000000e+00
   3.93907347e-02 -4.04656681e-02 -0.00000000e+00 -0.00000000e+00
  -3.93907347e-02 -0.00000000e+00  3.93907347e-02 -1.57562939e-01
  -4.04656681e-02 -0.00000000e+00 -3.93907347e-02  6.34957067e-02]]
```

In [71]:
```
# PCA variance
scaler = StandardScaler()
pca = PCA()
pipeline = make_pipeline(scaler,pca)
pipeline.fit(data2)

plt.bar(range(pca.n_components_), pca.explained_variance_)
plt.xlabel('PCA feature')
plt.ylabel('variance')
plt.show()
```



In [72]:
```
# apply PCA
pca = PCA(n_components = 2)
pca.fit(data2)
transformed = pca.transform(data2)
x = transformed[:,0]
y = transformed[:,1]
plt.scatter(x,y,c = color_list)
plt.show()
```



In [ ]: