

# K-Means, PCA, and Dendrogram on the Animals with Attributes Dataset

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## K-Means, PCA, and Dendrogram on the Animals with Attributes Dataset

About the dataset: This is a small dataset that has information on about 50 animals. The animals are listed in classes.txt. For each animal, the information consists of values for 85 features: does the animal have a tail, is it slow, does it have tusks, etc. The details of the features are in the predicates.txt. The full data consists of a 50 x 85 matrix of real values, in predicate-matrix-continuous.txt. There is also a binarized version of this data, in predicate-matrix-binary.txt.

```
In [1]: %matplotlib inline
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.cluster import KMeans
from sklearn import metrics
from sklearn.decomposition import PCA
from sklearn.preprocessing import scale
from pylab import rcParams
```

## Minor Bash Scripting

```
In [3]: !wget -O data.tar.bz2 http://attributes.kyb.tuebingen.mpg.de/AwA-base.tar.bz2
```

```
# -C changes to the specified directory before unpacking (or packing).
# --strip-components removes the specified number of directories from the filenames stored in t

!mkdir data && tar xf data.tar.bz2 -C data --strip-components 1

# Looking at various text files and removing old zipped file
!ls data && rm data.tar.bz2
```

```
--2016-03-28 03:19:57-- http://attributes.kyb.tuebingen.mpg.de/AwA-base.tar.bz2
Resolving attributes.kyb.tuebingen.mpg.de (attributes.kyb.tuebingen.mpg.de)... 192.124.27.50
Connecting to attributes.kyb.tuebingen.mpg.de (attributes.kyb.tuebingen.mpg.de)|192.124.27.50|:80... co
HTTP request sent, awaiting response... 200 OK
Length: 1062822 (1.0M) [application/x-bzip2]
Saving to: 'data.tar.bz2'
```

```
data.tar.bz2          100%[=====] 1.01M  316KB/s  in 3.3s
```

```
2016-03-28 03:20:02 (316 KB/s) - 'data.tar.bz2' saved [1062822/1062822]
```

Features predicate-matrix-continuous.txt

README-attributes.txt	predicate-matrix.png
classes.txt	predicates.txt
lampert-cvpr2009.pdf	testclasses.txt
predicate-matrix-binary.txt	trainclasses.txt

Loading the real-valued array, and also the animal names into Python.

```
In [65]: samples_features = pd.read_fwf("data/predicate-matrix-continuous.txt", header=None).values
print samples_features.shape
# 50 is the number of samples n (number of animals)
# 85 is the number of features m (number of features)
```

(50, 85)

```
In [66]: classes=pd.read_fwf("data/classes.txt", header=None)[1].values
classes
```

```
Out[66]: array(['antelope', 'grizzly+bear', 'killer+whale', 'beaver', 'dalmatian',
                'persian+cat', 'horse', 'german+shepherd', 'blue+whale',
                'siamese+cat', 'skunk', 'mole', 'tiger', 'hippopotamus', 'leopard',
                'moose', 'spider+monkey', 'humpback+whale', 'elephant', 'gorilla',
                'ox', 'fox', 'sheep', 'seal', 'chimpanzee', 'hamster', 'squirrel',
                'rhinoceros', 'rabbit', 'bat', 'giraffe', 'wolf', 'chihuahua',
                'rat', 'weasel', 'otter', 'buffalo', 'zebra', 'giant+panda', 'deer',
                'bobcat', 'pig', 'lion', 'mouse', 'polar+bear', 'collie', 'walrus',
                'raccoon', 'cow', 'dolphin'], dtype=object)
```

In order to make the real-value array data (samples\_features) clearer, I put it into a pandas dataframe. Please notice how all the animals differ from each other. For example, notice how the dalmation has the column spots at 100 and the other dogs have values around 10.

```
In [67]: feature_names=pd.read_fwf("data/predicates.txt", header=None)[1].values
classes_features = pd.DataFrame(data = samples_features, columns = feature_names)
classes_features.index = classes
classes_features.loc[['german+shepherd', 'collie', 'dalmatian']]
#classes_features
```

```
Out[67]:
```

	black	white	blue	brown	gray	orange	red	yellow	\
german+shepherd	43.54	15.88	5	54.16	26.82	3.12	2.5	0.38	
collie	10.13	41.37	0	47.27	3.75	8.00	0.5	0.00	
dalmatian	69.58	73.33	0	6.39	0.00	0.00	0.0	0.00	
	patches	spots	...	water	tree	cave	fierce	timid	\
german+shepherd	48.78	11.59	...	3.75	0.00	2.5	57.44	10.00	
collie	37.00	9.09	...	0.00	0.00	0.0	5.25	43.09	
dalmatian	37.08	100.00	...	1.25	6.25	0.0	9.38	31.67	
	smart	group	solitary	nestspot	domestic				
german+shepherd	57.53	12.50	35.11	16.53	68.55				
collie	42.17	0.62	45.99	18.57	79.11				
dalmatian	53.26	24.44	29.38	11.25	72.71				

[3 rows x 85 columns]

k-means grouping of the animals into an arbitrary number (10) of clusters

```

In [57]: # Visualize the results on PCA-reduced data
reduced_data = PCA(n_components=2).fit_transform(samples_features)
kmeans = KMeans(init='k-means++', n_clusters=10, n_init=10)
kmeans.fit(reduced_data, classes)

grouping = {i:[] for i in xrange(0,10)} #dictionary comprehension

for i,animal in enumerate(classes):
    grouping[kmeans.labels_[i]].append(animal)
grouping

Out[57]: {0: ['skunk', 'mole', 'hamster', 'rabbit', 'giant+panda', 'mouse'],
1: ['antelope',
    'horse',
    'moose',
    'ox',
    'sheep',
    'giraffe',
    'zebra',
    'deer',
    'cow'],
2: ['killer+whale', 'seal', 'dolphin'],
3: ['grizzly+bear',
    'german+shepherd',
    'siamese+cat',
    'bat',
    'rat',
    'weasel',
    'lion',
    'raccoon'],
4: ['elephant', 'rhinoceros', 'buffalo', 'pig'],
5: ['beaver', 'otter', 'polar+bear'],
6: ['tiger', 'leopard', 'fox', 'wolf', 'bobcat'],
7: ['dalmatian',
    'persian+cat',
    'spider+monkey',
    'gorilla',
    'chimpanzee',
    'squirrel',
    'chihuahua',
    'collie'],
8: ['blue+whale', 'humpback+whale', 'walrus'],
9: ['hippopotamus']}

In [121]: # Step size of the mesh. Decrease to increase the quality
h = .1      # point in the mesh [x_min, m_max][y_min, y_max].

# Plot the decision boundary.
x_min, x_max = reduced_data[:, 0].min() - 10, reduced_data[:, 0].max() + 10
y_min, y_max = reduced_data[:, 1].min() - 10, reduced_data[:, 1].max() + 10
xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))

Z = kmeans.predict(np.c_[xx.ravel(), yy.ravel()])

# Put the result into a color plot

```

```

Z = Z.reshape(xx.shape)
plt.figure(1, figsize=(20, 20))
plt.clf()
plt.imshow(Z, interpolation='nearest',
           extent=(xx.min(), xx.max(), yy.min(), yy.max()),
           cmap=plt.cm.Paired,
           origin='lower')

# Plot the centroids as a white o
centroids = kmeans.cluster_centers_
plt.scatter(centroids[:, 0], centroids[:, 1],
           marker='o', s=10, linewidths=1,
           color='w', zorder=10)

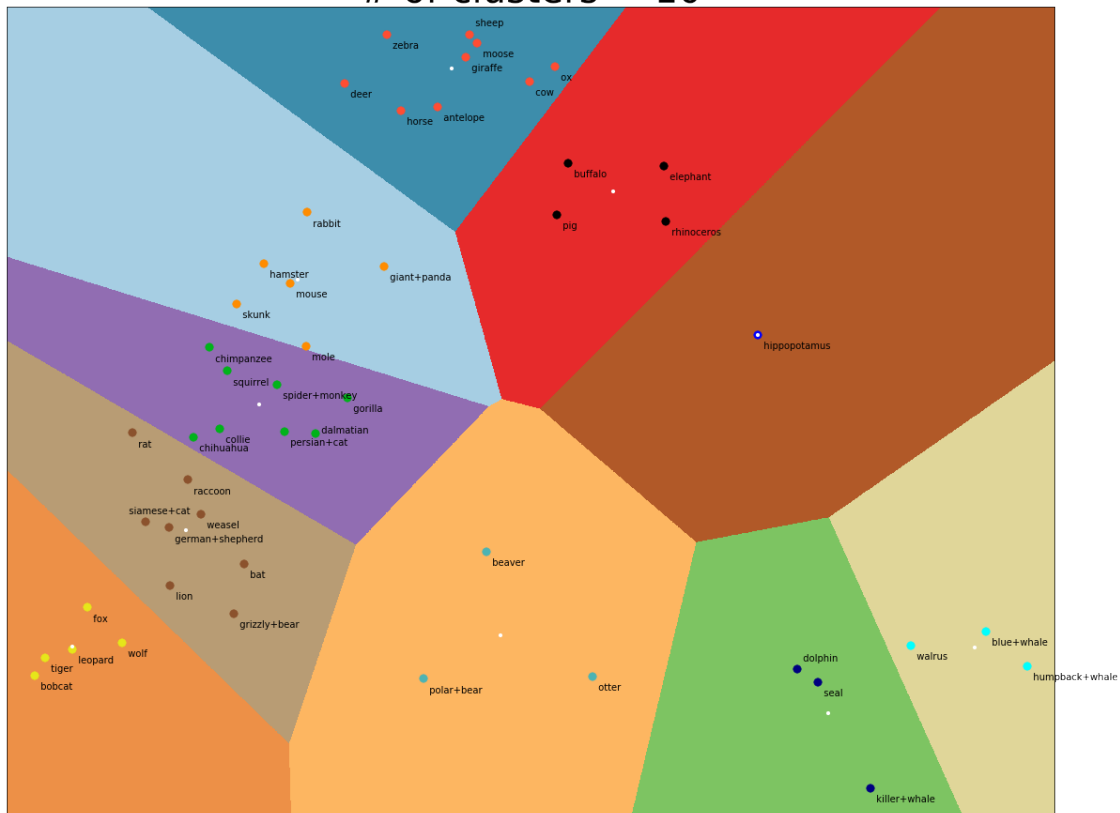
# Plot the Animals
for i, animal in enumerate(classes):
    # colors is just an array of tuples containing RGB values
    colors = [(1,.55,0),(1,.3,.2),(0,0, .5), (.545, .322, .176), (0,0, 0), (.3,.7, .7), (.9,.9, .9)]
    plt.plot(reduced_data[i, 0], reduced_data[i, 1], color = colors[kmeans.labels_[i]], marker='o')
    if animal == 'dalmatian':
        plt.annotate(' ' + animal, xy = (reduced_data[i,0], reduced_data[i, 1]), xytext = (reduced_data[i, 0] + 10, reduced_data[i, 1] + 10))
    elif animal == 'german+shepherd':
        plt.annotate(' ' + animal, xy = (reduced_data[i,0], reduced_data[i, 1]), xytext = (reduced_data[i, 0] + 10, reduced_data[i, 1] + 10))
    elif animal == 'sheep' or animal == 'dolphin':
        plt.annotate(' ' + animal, xy = (reduced_data[i,0], reduced_data[i, 1]), xytext = (reduced_data[i, 0] + 10, reduced_data[i, 1] + 10))
    elif animal == 'siamese+cat':
        plt.annotate(' ' + animal, xy = (reduced_data[i,0], reduced_data[i, 1]), xytext = (reduced_data[i, 0] + 10, reduced_data[i, 1] + 10))
    else:
        plt.annotate(' ' + animal, xy = (reduced_data[i,0], reduced_data[i, 1]), xytext = (reduced_data[i, 0] + 10, reduced_data[i, 1] + 10))

plt.title('K-means Clustering of Animals with Attributes Dataset\n # of clusters = 10 ', fontdict={'size': 16})
plt.xlim(x_min, x_max)
plt.ylim(y_min, y_max)
plt.xticks(())
plt.yticks(())
plt.savefig('images/animals_attributes.png')
plt.show()

```

## K-means Clustering of Animals with Attributes Dataset

# of clusters = 10

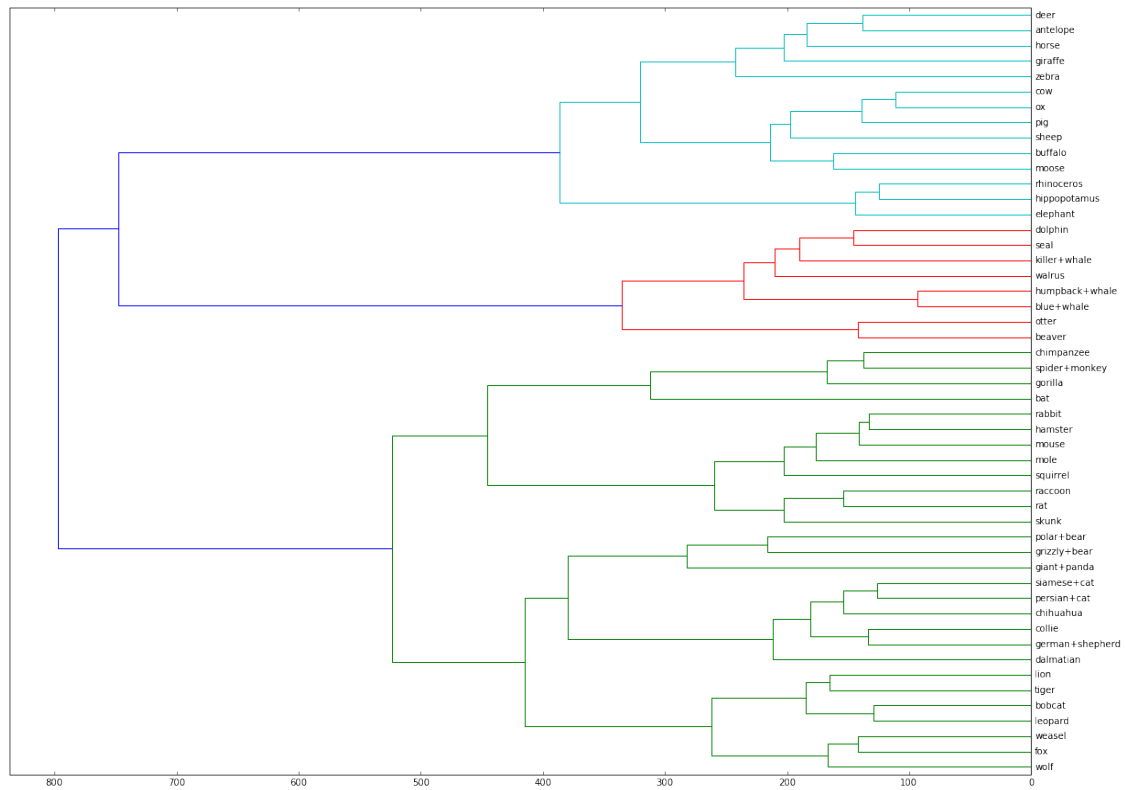


From the clustering, it is clear that the groups that are clustered together make some intuitive sense. Water dwelling creatures are grouped close together as well as other creatures such as the various types of dogs. However, more work needs to be done to group the animals better (change algorithm, increase number of clusters etc).

Hierarchical Clustering of the Data

```
In [123]: # cluster_link array (contains the hierarchical clustering information)
cluster_link = linkage(samples_features, method='ward');

dendrogram(cluster_link, orientation="right", labels=classes)
rcParams['figure.figsize']=[20,15]
```



The dendrogram seems more sensible to me since it makes more intuitive sense. The grouping of polar and grizzly bears together plus the other hierarchical relationships makes this an intriguing option

In [ ]: