R Notebook: K Nearest Neighbors for Zoological Classification

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Abstract

This study is concerned with categorizing wildlife by traits that could best inform a practical design of zoological display installations. The model investigated is a K-Nearest Neighbor subphylum-classifier, classifying individual animals by a typing that includes the existence or measure of various phenotypical traits. This study concerns the development and testing of a classification model that predicts mammal, bird, reptile, fish, amphibian, insect, or crustacean class of the input species. The KNN model is trained by learning which other animals or insects are of a similar subphylum type based on 16 observable phenotypical features. Each input indicates presence or magnitude of these features for a particular animal or insect.

Load Data

```
set.seed(1)
library(class)
d = read.table("zoo.DATA", sep=",", header = FALSE)
d = data.frame(d)
```

Data Conditioning

Phylogenic traits used for classification:

```
names(d) <- c("animal", "hair", "feathers", "eggs", "milk", "airborne",
"aquatic", "predator", "toothed", "backbone", "breathes", "venomous",
"fins", "legs", "tail", "domestic", "size", "type")

types <- table(d$type)
d_target <- d[, 18]
```

```
d_key <- d[, 1]
d$animal <- NULL
```

Exploratory Investigation

Inspection of the occupancy levels of the classifications (in the merged data set), indicate the necessity for cross validation. Any singularly-induced train test split in the data is unlikely to provide an adequate balance of training examples for each class. From the summary output of the data, it would appear that a very low class occupancy exists for venomous animals (at 7%), which appears as the clearest example this concern. Output classes include,

```
names(types) <- c("mammal", "bird", "reptile", "fish", "amphibian",
"insect", "crustacean")
types
```

```
##     mammal       bird    reptile       fish  amphibian     insect
##         41         20          5         13          4          8
## crustacean
##         10
```

```
summary(d)
```

```
##       hair           feathers          eggs             milk
##  Min.   :0.0000   Min.   :0.000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:0.000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :0.0000   Median :0.000   Median :1.0000   Median :0.0000
##  Mean   :0.4257   Mean   :0.198   Mean   :0.5842   Mean   :0.4059
##  3rd Qu.:1.0000   3rd Qu.:0.000   3rd Qu.:1.0000   3rd Qu.:1.0000
##  Max.   :1.0000   Max.   :1.000   Max.   :1.0000   Max.   :1.0000
##     airborne         aquatic          predator         toothed
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.000
##  Median :0.0000   Median :0.0000   Median :1.0000   Median :1.000
##  Mean   :0.2376   Mean   :0.3564   Mean   :0.5545   Mean   :0.604
##  3rd Qu.:0.0000   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.000
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.000
##     backbone         breathes         venomous            fins

##  Min.   :0.0000   Min.   :0.0000   Min.   :0.00000   Min.   :0.0000

##  1st Qu.:1.0000   1st Qu.:1.0000   1st Qu.:0.00000   1st Qu.:0.0000
```

```
##  Median :1.0000   Median :1.0000   Median :0.00000   Median :0.0000

##  Mean   :0.8218   Mean   :0.7921   Mean   :0.07921   Mean   :0.1683

##  3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:0.00000   3rd Qu.:0.0000

##  Max.   :1.0000   Max.   :1.0000   Max.   :1.00000   Max.   :1.0000

##       legs            tail           domestic           size
##  Min.   :0.000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:2.000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :4.000   Median :1.0000   Median :0.0000   Median :0.0000
##  Mean   :2.842   Mean   :0.7426   Mean   :0.1287   Mean   :0.4356
##  3rd Qu.:4.000   3rd Qu.:1.0000   3rd Qu.:0.0000   3rd Qu.:1.0000
##  Max.   :8.000   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
##       type
##  Min.   :1.000
##  1st Qu.:1.000
##  Median :2.000
##  Mean   :2.832
##  3rd Qu.:4.000
##  Max.   :7.000

str(d)

## 'data.frame':    101 obs. of  17 variables:
##  $ hair    : int  1 1 0 1 1 1 1 0 0 1 ...
##  $ feathers: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ eggs    : int  0 0 1 0 0 0 0 1 1 0 ...
##  $ milk    : int  1 1 0 1 1 1 1 0 0 1 ...
##  $ airborne: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ aquatic : int  0 0 1 0 0 0 0 1 1 0 ...
##  $ predator: int  1 0 1 1 1 0 0 0 1 0 ...
##  $ toothed : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ backbone: int  1 1 1 1 1 1 1 1 1 1 ...
##  $ breathes: int  1 1 0 1 1 1 1 0 0 1 ...
##  $ venomous: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ fins    : int  0 0 1 0 0 0 0 1 1 0 ...
##  $ legs    : int  4 4 0 4 4 4 4 0 0 4 ...
##  $ tail    : int  0 1 1 0 1 1 1 1 1 0 ...
##  $ domestic: int  0 0 0 0 0 0 1 1 0 1 ...
##  $ size    : int  1 1 0 1 1 1 1 0 0 0 ...
##  $ type    : int  1 1 4 1 1 1 1 4 4 1 ...
```

Training

The threshold neighbor-size (k), for membership is set to the square root of the number of predictors, plus a constant that assigns it to the nearest odd number. A KNN Model is formed from the data using Leave One Out Cross Validation.

```
k = sqrt(17) + 1
m1 <- knn.cv(d, d_target, k, prob = TRUE)
prediction <- m1

cmat <- table(d_target,prediction)
acc <- (sum(diag(cmat)) / length(d_target)) * 100
print(acc)
```

```
## [1] 90.09901
```

Confusion Matrix

```
data.frame(types)
```

```
##         Var1 Freq
## 1     mammal   41
## 2       bird   20
## 3    reptile    5
## 4       fish   13
## 5  amphibian    4
## 6     insect    8
## 7 crustacean   10
```

```
cmat
```

```
##         prediction
## d_target  1  2  3  4  5  6  7
##        1 41  0  0  0  0  0  0
##        2  0 20  0  0  0  0  0
##        3  0  1  0  3  1  0  0
##        4  0  0  0 13  0  0  0
##        5  0  0  0  0  4  0  0
##        6  0  0  0  0  0  8  0
##        7  0  0  0  2  1  2  5
```

Accuracy (%)

```
acc
```

```
## [1] 90.09901
```

Discussion

Classification accuracy of the LOOCV-trained knn model indicates that 90% accuracy is to be generally expected by applying this model to out-of-sample data. However, from an inspection of the confusion matrix output, it appears that there is generally a 0% accuracy for the identification of reptiles and crustaceans. It is unclear if the low-performance of class outputs is due to there being a limited amount of data on hand, or if poor class separation of the two types is the cause. Overall, this model appears to be a robust predictor for all classes excluding reptiles and crustaceans. This classifier can be of pragmatic use for classifying various animal and insect into subphylum, providing a record of observable phylogenic traits is available for each instance.

Conclusion

It would appear that subphylum is a practical level of species categorization, and is an attainable training pattern for the K Nearest Neighbors algorithm.