Predicting Animal Class Based on Physical and Behavioral Traits

Final Project: Technical Report

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Introduction

Background and Motivation

Taxonomic classification is foundational to biological sciences, allowing for the systematic study of species. This project delves into whether physical and behavioral traits, such as the presence of hair, feathers, or fins, can effectively predict an animal's classification type (i.e., *Mammals*, *Reptiles*, *Birds*, etc.). The analysis contains a dataset of 101 animals, focusing on building a model that could aid in educational or ecological applications.

Data Overview

This dataset includes:

Predictor variables: 15 binary categorical variables (i.e., *hair*, *milk*, *feathers*, etc.) and one numeric variable (*legs*).

Research Objective

We want to determine whether multinomial logistic regression can accurately classify animals into distinct classes based on observable traits, while addressing limitations, like class imbalance and multicollinearity.

Exploratory Analysis

Data Summary

Class Distribution: Drastic class imbalance lies in our dataset, with there being 41 *Mammals* and 20 *Birds*. These two classes dominate the rest in the dataset, with only having 5 *Reptiles*, 4 *Amphibians*, and 8 *Bugs*. There are more than twice the number of *Mammals* than *Birds*, and a whopping four times the number of *Birds* to *Reptiles*, indicating how much of a misrepresentation there is within this dataset.

Numeric Variable (*legs*): Mean = 2.84, Standard Deviation = 2.67,

Minimum = 0 (0 legs for *dolphins*), Maximum = 8 (8 legs for *octopuses*)

Binary Variables:

- Common: ~ 82% have a backbone and ~79% breathe air
- Rare: Only ~ 8% are venomous, while ~ 13% are domesticated

Key Visualizations and Insights

1. **Class Distribution:**

- *Mammals* and *Birds* make up ~ 60% of the dataset! *Reptiles* and *Amphibians* are underrepresented, which poses the risk of poor model performance for these classes.

2. **Leg Count by Class:**
   - *Mammals* predominantly have 4 legs, with few exceptions, such as *dolphins* (0 legs) and *humans* (2 legs).
   - *Reptiles* and *Invertebrates* exhibit high variability. For example, *snakes* have 0 legs, compared to *octopuses* having 8 legs.

3. **Correlation Matrix Heatmap:**
   - **Strong Positive Correlations:** *hair* and *milk* (r = 0.92, *mammals*), *fins* and *aquatic* (r = 0.85, *fish*).
   - **Strong Negative Correlations:** *hair* and *feathers* (r = -0.89, **mutually exclusive** traits, i.e., Having hair does **NOT** depend on having feathers; No association/correlation).
   - **Multicollinearity:** High correlation between *hair* and *milk* caused us to remove one to avoid redundancy, allowing us to consider classification as the optimal model for this dataset.

Regression Analysis

Using a multinomial logistic regression model, the analysis aimed to predict animal classes based on their physical and behavioral traits. The results indicate that specific characteristics strongly differentiate animal classes. Trait-Class Determinism suggests that some traits essentially define an animal's class. For instance, feathers almost exclusively indicate birds, while the ability to produce milk strongly identifies mammals. These deterministic traits result in extreme coefficient magnitudes, leading to instability as the logistic regression model attempts to assign very large or very small probabilities based on a single dominant predictor.

The analysis also revealed large standard errors associated with some predictors, suggesting the possibility of multicollinearity or a limited number of data points for certain trait-class combinations. Multicollinearity occurs when many animal traits are biologically interconnected; for instance, one trait's presence often implies another's presence or absence. For example, animals that have feathers usually also lay eggs and can fly. When such correlated traits are simultaneously included in the analysis, the coefficients can become inflated, unstable, and difficult to interpret. The significant magnitudes of the coefficients for predictors like venomous and feathers highlight their considerable power in distinguishing between different classes.

Although the model fits well, indicated by low residual deviance, caution is necessary due to potential violations of regression assumptions. The repeated appearance of significant coefficient magnitudes for traits like venomous and feathers emphasizes their discriminative power. However, the analysis revealed large standard errors accompanying some predictors, reinforcing the likelihood of multicollinearity or limited data points for specific trait-class combinations.

A classification tree analysis was conducted to address this, achieving a high classification accuracy of approximately 88%. This method provided clear and intuitive decision paths, effectively categorizing animals into their respective classes based on key distinguishing traits. The tree demonstrates that perfect separation or quasi-perfect separation occurs when specific characteristics—such as "feathers," "milk," or "fins"—are so definitive for specific animal classes that the model can classify them with complete accuracy.

In contrast, logistic regression faces significant challenges in such situations. The model attempts to fit coefficients that become infinitely large to represent perfect predictability, leading to instability and unreliable estimates. However, the classification tree successfully identifies animal classes based on key traits, achieving perfect separation for Mammals (milk), Birds (feathers), and Fish (fins). This indicates that these traits are definitive for classification within the dataset.

The tree is highly interpretable, but it may be prone to overfitting due to deterministic paths that might not generalize well to new data. Additionally, Amphibians and Bugs are not represented in the analysis, suggesting that the current set of traits was insufficient to establish clear decision paths for these classes. This implies that further refinement or additional features may be necessary for improved classification of these underrepresented groups.

Conclusion

The analysis demonstrated that multinomial logistic regression and classification trees are effective in predicting animal classes based on physical and behavioral traits. Key features, such as feathers, milk, and fins, played a crucial role in determining class membership, effectively categorizing birds, mammals, and fish, respectively. This resulted in perfect separation within the classification tree, leading to high accuracy but also raising concerns about overfitting.

In the logistic regression model, traits such as venomousness and feathers exhibited large coefficients, highlighting their predictive power. However, significant standard errors indicated issues with multicollinearity and sparse representation for certain classes, which inflated coefficients and diminished interpretability. Although the model fit was good, these problems suggested violations of the regression assumptions.

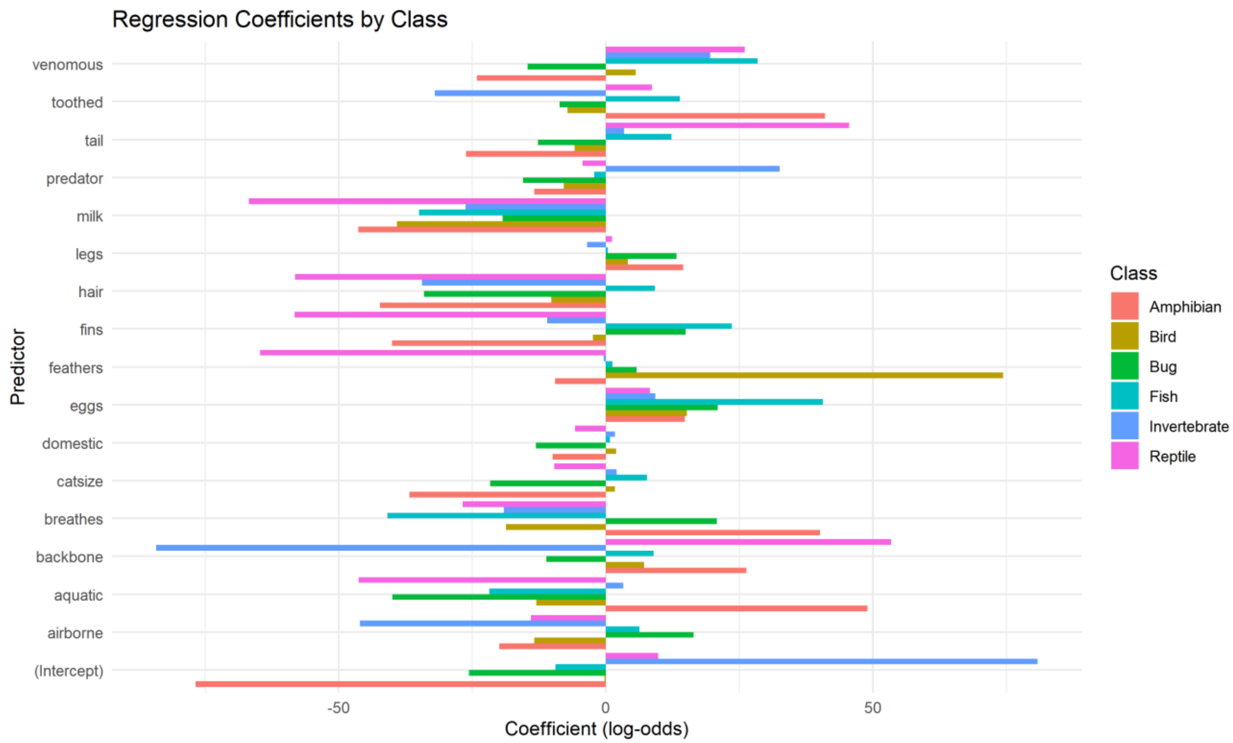
To improve the model, it would be beneficial to incorporate regularization methods to address multicollinearity, use cross-validation to assess generalizability, and, most importantly, expand datasets to better represent under classified groups. These enhancements would contribute to greater model stability and predictive reliability.

References and Appendix

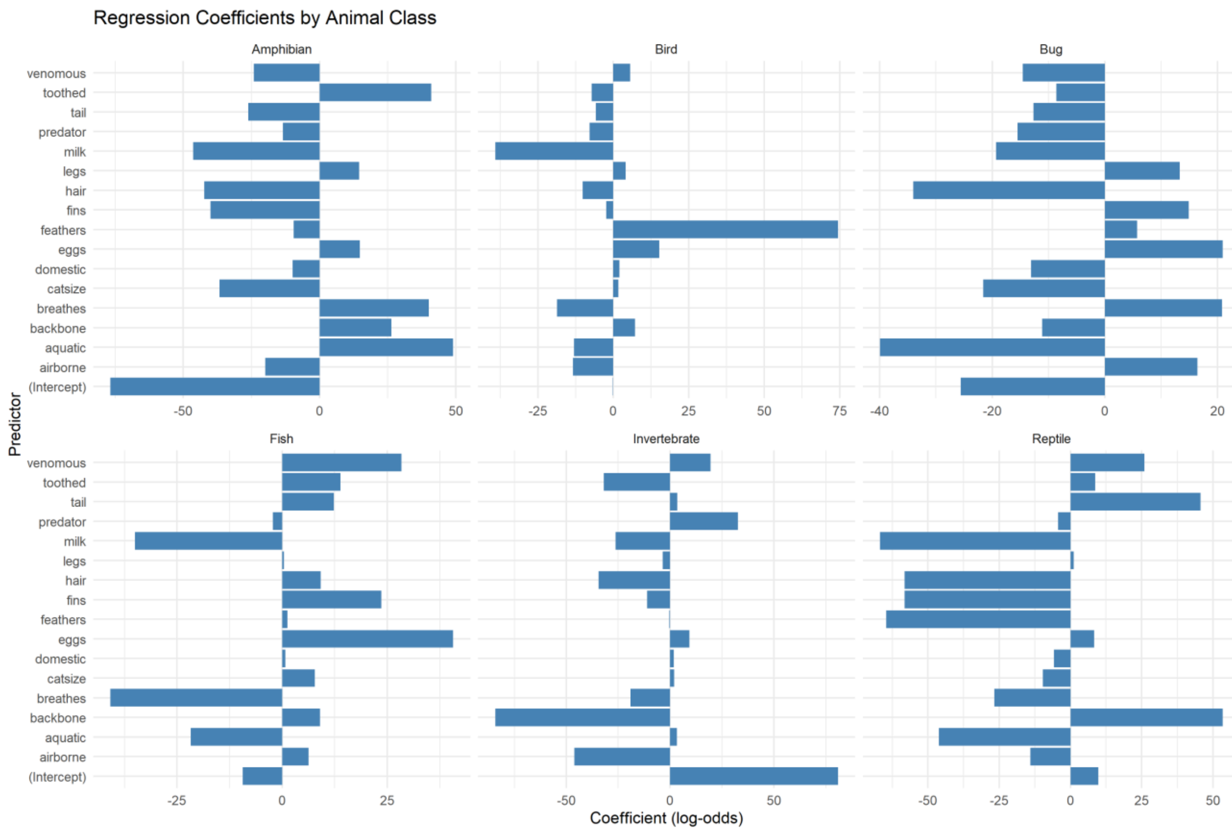
Class	Predictor	Coefficient	SE	Z	P_Value
Bird	(Intercept)	-0.21	15188.12	0	1
Bird	hair	-10.184	217.983	0.045	0.96411
Bird	feathers	74.382	5853.024	-0.002	0.9984
Bird	eggs	15.222	16475.43	-0.005	0.99601
Bird	milk	-39.088	15485.66	-0.002	0.9984
Bird	airborne	-13.372	512.642	0.158	0.87446
Bird	aquatic	-12.973	0	#NAME?	0
Bird	predator	-7.83	67.96	-0.856	0.392
Bird	toothed	-7.126	5853.631	0.002	0.9984
Bird	backbone	7.204	9666.978	-0.004	0.99681
Bird	breathes	-18.642	2850.87	-0.012	0.99043
Bird	venomous	5.596	0	#NAME?	0
Bird	fins	-2.367	15188.12	0.005	0.99601
Bird	legs	4.114	0	#NAME?	0
Bird	tail	-5.838	0.723	1.766	0.0774
Bird	domestic	1.974	25173.1	0	1
Bird	catsize	1.713	17193.3	0	1
Reptile	(Intercept)	9.822	0.012	-33	0
Reptile	hair	-58.144	15188.12	0.001	0.9992
Reptile	feathers	-64.705	3.287	2.52	0.01174
Reptile	eggs	8.282	4382.892	0.009	0.99282
Reptile	milk	-66.788	26142.3	0.001	0.9992
Reptile	airborne	-14.027	15169.64	0.001	0.9992
Reptile	aquatic	-46.201	0.012	772.833	0
Reptile	predator	-4.337	0	#NAME?	0
Reptile	toothed	8.699	67.96	-0.983	0.32561
Reptile	backbone	53.46	3344.539	-0.01	0.99202
Reptile	breathes	-26.744	9666.978	-0.005	0.99601
Reptile	venomous	26.009	0.684	-28.232	0
Reptile	fins	-58.218	0	#NAME?	0
Reptile	legs	1.164	15188.11	-0.001	0.9992
Reptile	tail	45.611	0	#NAME?	0
Reptile	domestic	-5.761	2860.091	0.002	0.9984
Reptile	catsize	-9.634	25173.1	-0.001	0.9992
Fish	(Intercept)	-9.396	14353.27	0.001	0.9992
Fish	hair	9.214	0	#NAME?	0

Fish	feathers	1.277	25173.12	-0.001	0.9992
Fish	eggs	40.676	0	#NAME?	0
Fish	milk	-34.972	1793.625	-0.012	0.99043
Fish	airborne	6.316	39802.92	0.001	0.9992
Fish	aquatic	-21.751	0	#NAME?	0
Fish	predator	-2.173	0.012	274.167	0
Fish	toothed	13.844	291.955	-0.027	0.97846
Fish	backbone	9.001	150.895	-0.029	0.97686
Fish	breathes	-40.831	1923.873	-0.001	0.9992
Fish	venomous	28.427	14929.16	-0.001	0.9992
Fish	fins	23.584	369.397	-0.042	0.9665
Fish	legs	0.414	512.642	0.064	0.94897
Fish	tail	12.333	0	#NAME?	0
Fish	domestic	0.776	71.246	0.122	0.9029
Fish	catsize	7.759	1569.446	0.009	0.99282
Amphibian	(Intercept)	-76.728	9663.691	0.004	0.99681
Amphibian	hair	-42.233	0.684	-12.573	0
Amphibian	feathers	-9.508	0	#NAME?	0
Amphibian	eggs	14.787	15188.12	0	1
Amphibian	milk	-46.33	71.246	0.75	0.45325
Amphibian	airborne	-19.914	3343.841	0.003	0.99761
Amphibian	aquatic	49.017	15509.47	0.002	0.9984
Amphibian	predator	-13.398	17193.87	-0.001	0.9992
Amphibian	toothed	41.024	0.012	-7014.67	0
Amphibian	backbone	26.317	15188.12	-0.001	0.9992
Amphibian	breathes	40.137	217.983	-0.123	0.90211
Amphibian	venomous	-24.146	5853.024	-0.007	0.99441
Amphibian	fins	-40.011	16475.43	0.002	0.9984
Amphibian	legs	14.517	15485.66	0.001	0.9992
Amphibian	tail	-26.134	512.643	-0.037	0.97049
Amphibian	domestic	-9.921	0	Inf	0
Amphibian	catsize	-36.724	146.737	0.177	0.85951
Bug	(Intercept)	-25.612	2851.409	0.01	0.99202
Bug	hair	-34.037	0	#NAME?	0
Bug	feathers	5.761	2574.776	-0.006	0.99521
Bug	eggs	20.959	512.631	0.038	0.96969
Bug	milk	-19.311	0	#NAME?	0
Bug	airborne	16.449	0	#NAME?	0
Bug	aquatic	-39.905	18.532	1.273	0.20302

Bug	predator	-15.466	0	#NAME?	0
Bug	toothed	-8.6	0	Inf	0
Bug	backbone	-11.133	0	#NAME?	0
Bug	breathes	20.846	30376.24	0	1
Bug	venomous	-14.593	1455.265	0.001	0.9992
Bug	fins	14.936	28713.87	0	1
Bug	legs	13.295	17489.29	0.001	0.9992
Bug	tail	-12.654	25354.33	0.001	0.9992
Bug	domestic	-13.084	4101.066	-0.001	0.9992
Bug	catsize	-21.609	15188.12	0	1
Invertebrate	(Intercept)	80.814	217.983	0.209	0.83445
Invertebrate	hair	-34.387	3343.841	0.004	0.99681
Invertebrate	feathers	-0.396	104929.7	0	1
Invertebrate	eggs	9.274	17499.2	-0.001	0.9992
Invertebrate	milk	-26.24	512.643	0.007	0.99441
Invertebrate	airborne	-46.031	0.003	658	0
Invertebrate	aquatic	3.29	0.103	-55.932	0
Invertebrate	predator	32.603	3878.984	0	1
Invertebrate	toothed	-31.985	89420.59	0	1
Invertebrate	backbone	-84.176	3146.945	-0.004	0.99681
Invertebrate	breathes	-19.051	0	Inf	0
Invertebrate	venomous	19.544	0.731	2.343	0.01913
Invertebrate	fins	-10.99	0.013	-741.077	0
Invertebrate	legs	-3.474	3332.041	0.002	0.9984
Invertebrate	tail	3.439	14631.21	-0.003	0.99761
Invertebrate	domestic	1.768	0	#NAME?	0
Invertebrate	catsize	2.015	0.012	167.917	0



Regression Coefficients by Class
venomous
toothed
tail
predator
milk
legs
hair
fins
feathers
eggs
domestic
catsize
breathes
backbone
aquatic
airborne
(Intercept)
Predictor
-50
0
50
Coefficient (log-odds)
Class
Amphibian
Bird
Bug
Fish
Invertebrate
Reptile



Regression Coefficients by Animal Class
Amphibian
Bird
Bug
Fish
Invertebrate
Reptile
venomous
toothed
tail
predator
milk
legs
hair
fins
feathers
eggs
domestic
catsize
breathes
backbone
aquatic
airborne
(Intercept)
Predictor
-50
0
50
-25
0
25
50
75
-40
-20
0
20
-25
0
25
-50
0
50
-50
-25
0
25
50
Coefficient (log-odds)

“Can we predict an animal’s class (mammal, bird, etc.) based on its physical and behavioral traits?”

```
# Define correct column names (based on zoo.names)
col_names <- c(
  "animal_name", "hair", "feathers", "eggs", "milk", "airborne", "aquatic", "predator",
  "toothed", "backbone", "breathes", "venomous", "fins", "legs", "tail",
  "domestic", "catsize", "class_type"
)

# Read data with headers assigned manually
zoo <- read.csv("zoo.data", header = FALSE, col.names = col_names)

# Convert class_type to a factor with labels
zoo$class_type <- factor(zoo$class_type,
                         levels = 1:7,
                         labels = c("Mammal", "Bird", "Reptile", "Fish", "Amphibian", "Bug", "In
vertebrate"))

# Summary
summary(zoo)
```

```
##  animal_name             hair          feathers          eggs
##  Length:101         Min.   :0.0000   Min.   :0.000   Min.   :0.0000
##  Class :character   1st Qu.:0.0000   1st Qu.:0.000   1st Qu.:0.0000
##  Mode  :character   Median :0.0000   Median :0.000   Median :1.0000
##                     Mean   :0.4257   Mean   :0.198   Mean   :0.5842
##                     3rd Qu.:1.0000   3rd Qu.:0.000   3rd Qu.:1.0000
##                     Max.   :1.0000   Max.   :1.000   Max.   :1.0000
##
##       milk           airborne          aquatic          predator
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :0.0000   Median :0.0000   Median :0.0000   Median :1.0000
##  Mean   :0.4059   Mean   :0.2376   Mean   :0.3564   Mean   :0.5545
##  3rd Qu.:1.0000   3rd Qu.:0.0000   3rd Qu.:1.0000   3rd Qu.:1.0000
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
##
##     toothed         backbone         breathes         venomous
##  Min.   :0.000   Min.   :0.0000   Min.   :0.0000   Min.   :0.00000
##  1st Qu.:0.000   1st Qu.:1.0000   1st Qu.:1.0000   1st Qu.:0.00000
##  Median :1.000   Median :1.0000   Median :1.0000   Median :0.00000
##  Mean   :0.604   Mean   :0.8218   Mean   :0.7921   Mean   :0.07921
##  3rd Qu.:1.000   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:0.00000
##  Max.   :1.000   Max.   :1.0000   Max.   :1.0000   Max.   :1.00000
##
##       fins             legs            tail           domestic
##  Min.   :0.0000   Min.   :0.000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:2.000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :0.0000   Median :4.000   Median :1.0000   Median :0.0000
##  Mean   :0.1683   Mean   :2.842   Mean   :0.7426   Mean   :0.1287
##  3rd Qu.:0.0000   3rd Qu.:4.000   3rd Qu.:1.0000   3rd Qu.:0.0000
##  Max.   :1.0000   Max.   :8.000   Max.   :1.0000   Max.   :1.0000
##
##     catsize             class_type
##  Min.   :0.0000   Mammal      :41
##  1st Qu.:0.0000   Bird        :20
##  Median :0.0000   Reptile     : 5
##  Mean   :0.4356   Fish        :13
##  3rd Qu.:1.0000   Amphibian   : 4
##  Max.   :1.0000   Bug         : 8
##                   Invertebrate:10
```

```
print("Frequency of each class")
```

```
## [1] "Frequency of each class"
```

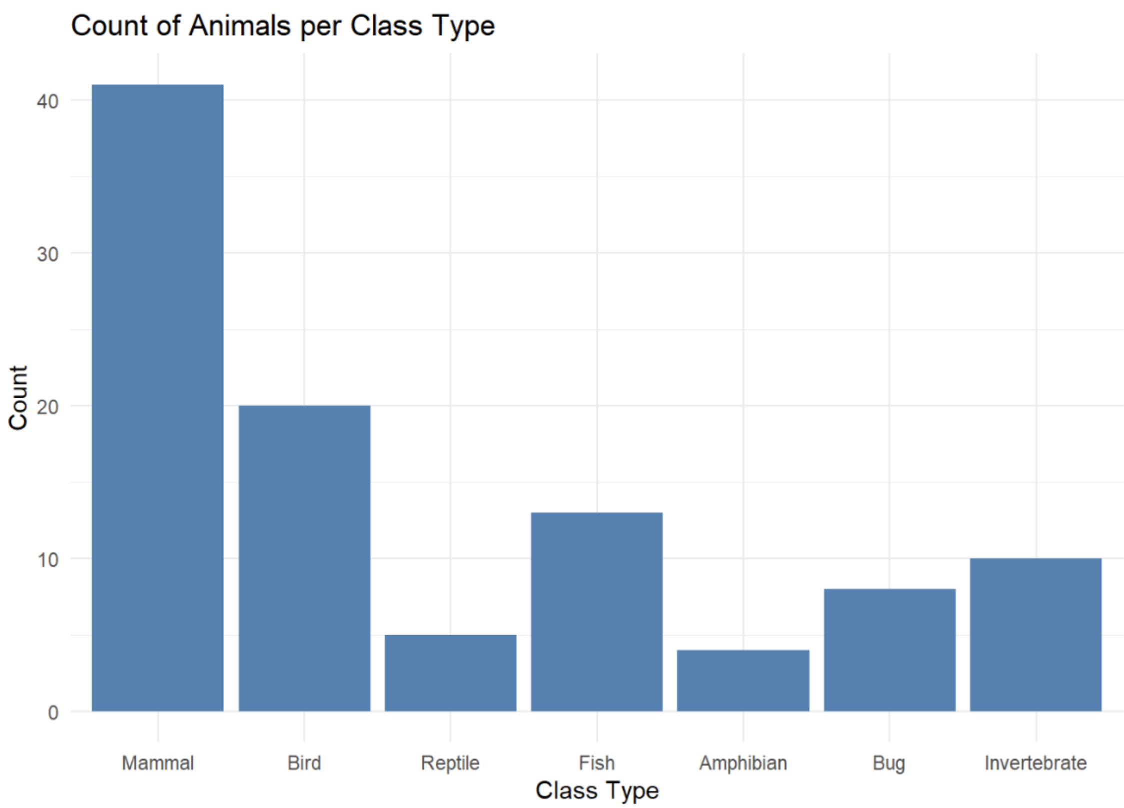
```
table(zoo$class_type)
```

```
##
##       Mammal         Bird      Reptile         Fish    Amphibian          Bug
##           41           20            5           13            4            8
## Invertebrate
##           10
```

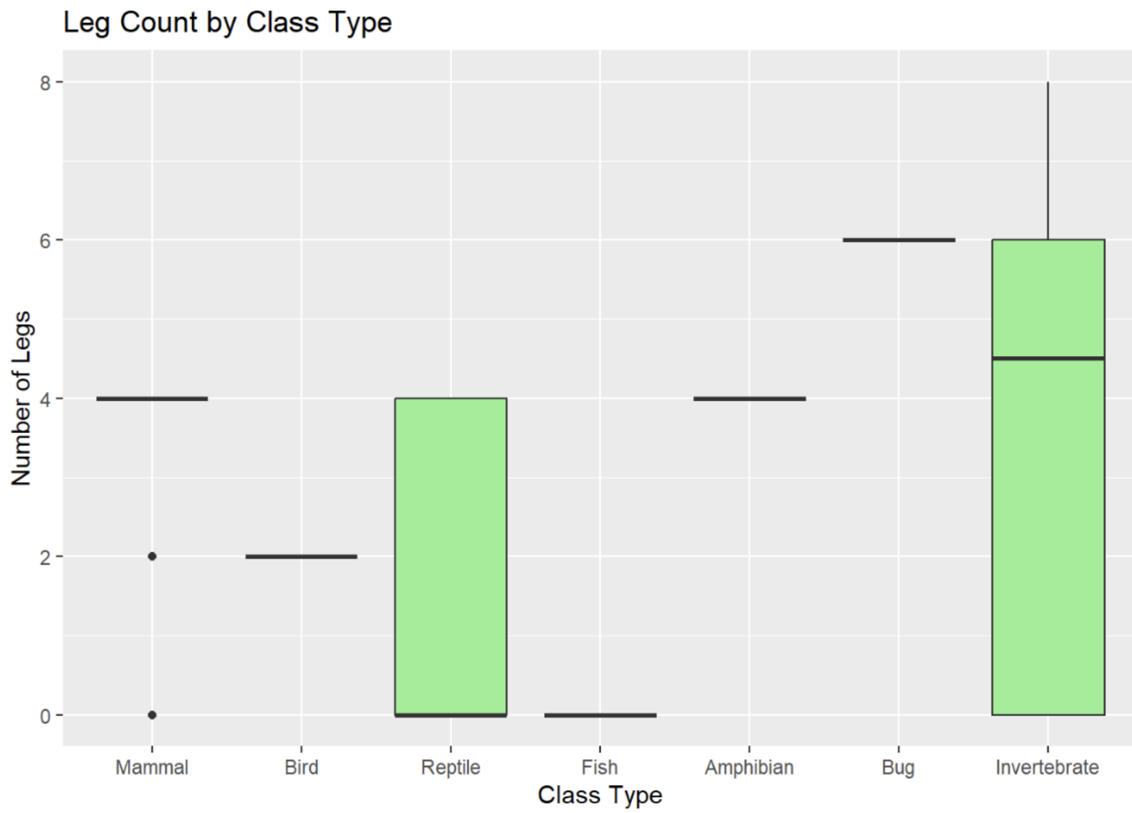
```
# Bar plot of response variable
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 4.4.3
```

```
ggplot(zoo, aes(x = class_type)) +
  geom_bar(fill = "steelblue") +
  labs(title = "Count of Animals per Class Type", x = "Class Type", y = "Count") +
  theme_minimal()
```




```
# Boxplot of legs by class
ggplot(zoo, aes(x = class_type, y = legs)) +
  geom_boxplot(fill = "lightgreen") +
  labs(title = "Leg Count by Class Type", x = "Class Type", y = "Number of Legs")
```




```
# Correlation matrix for numeric/binary columns
library(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 4.4.3
```

```
## corrplot 0.95 loaded
```

```
library(dplyr)
```

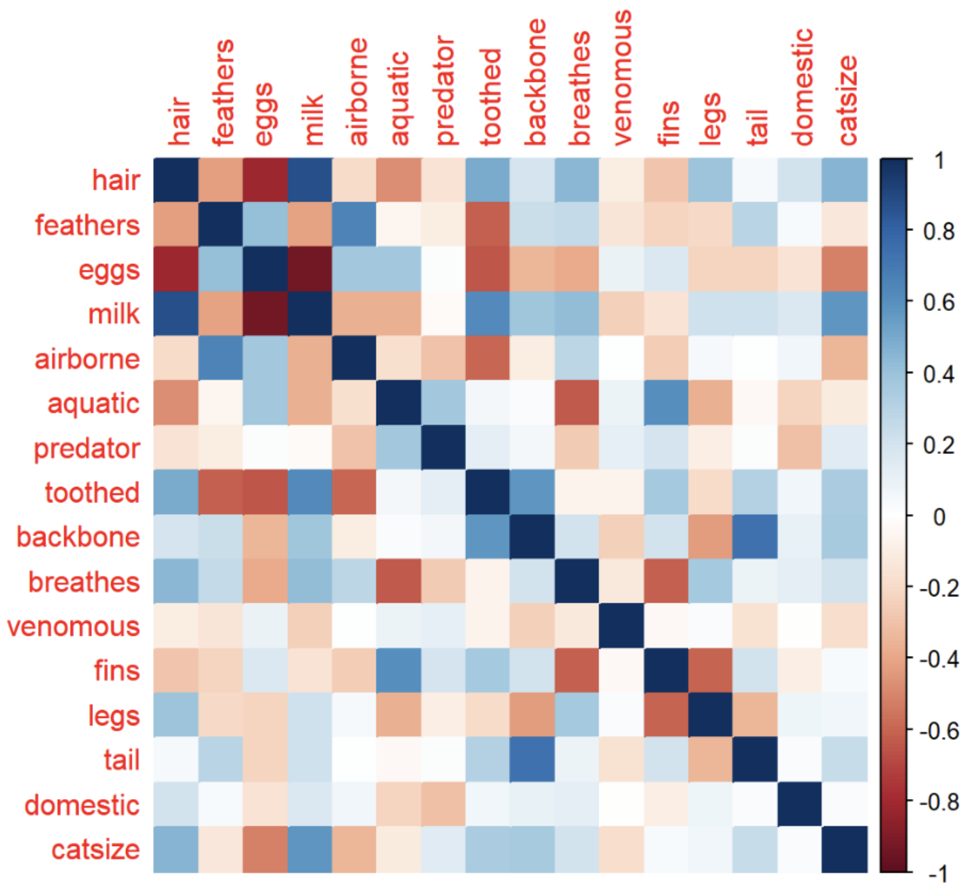
```
## Warning: package 'dplyr' was built under R version 4.4.3
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

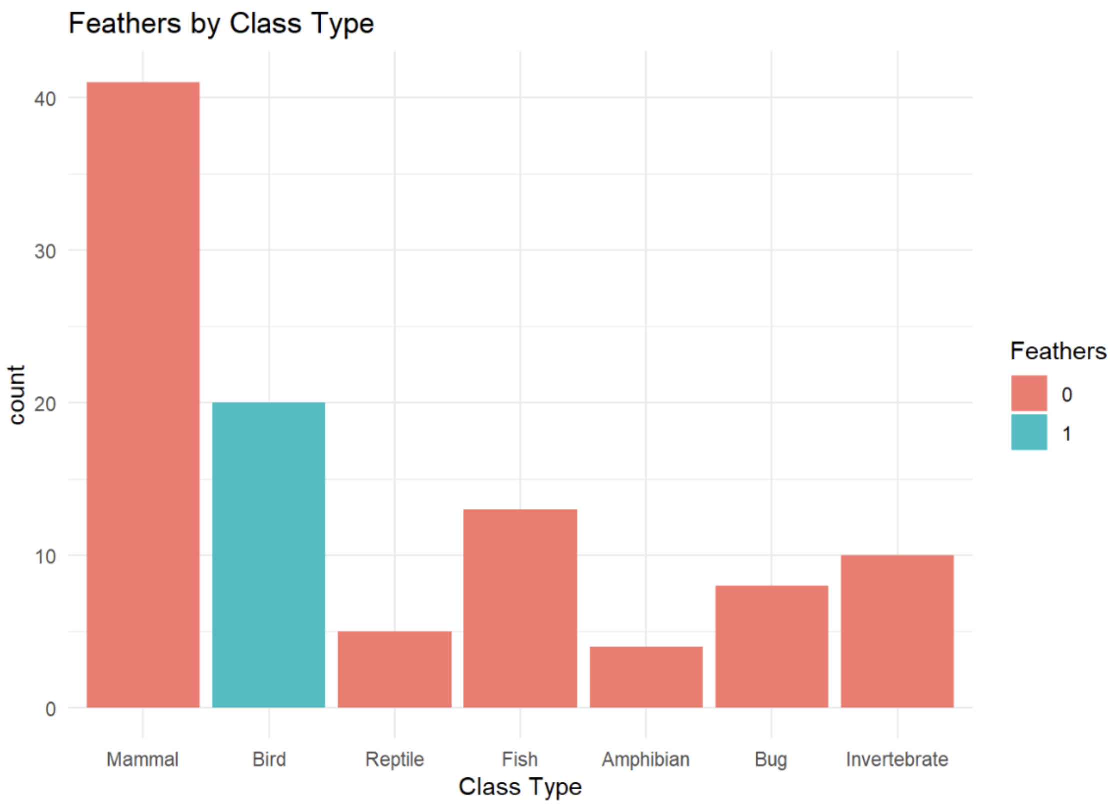
```
numeric_vars <- zoo %>% select(-animal_name, -class_type)
corrplot(cor(numeric_vars), method = "color")
```




```
print("Bar plot for a feature by class")
```

```
## [1] "Bar plot for a feature by class"
```

```
ggplot(zoo, aes(x = class_type, fill = factor(feathers))) +
  geom_bar(position = "dodge") +
  labs(title = "Feathers by Class Type", x = "Class Type", fill = "Feathers") +
  theme_minimal()
```




```
print("Bar Plot of All Binary Features")
```

```
## [1] "Bar Plot of All Binary Features"
```

```
library(tidyr)
```

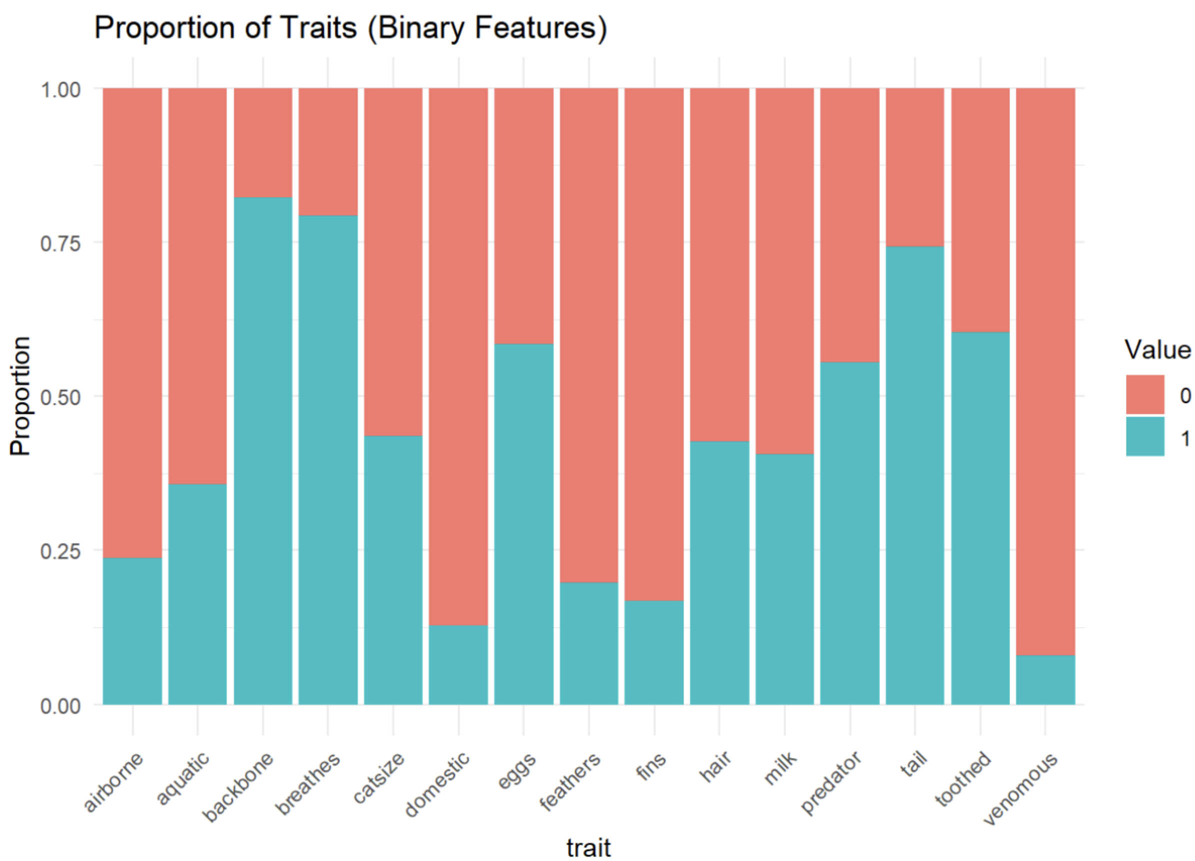
```
## Warning: package 'tidyr' was built under R version 4.4.3
```

```
library(dplyr)

binary_vars <- zoo %>%
  select(hair:catsize, -legs) %>%  # exclude animal_name, legs, class_type
  mutate(animal = zoo$animal_name)

long_binary <- pivot_longer(binary_vars, cols = -animal, names_to = "trait", values_to = "valu
e")

ggplot(long_binary, aes(x = trait, fill = factor(value))) +
  geom_bar(position = "fill") +
  labs(title = "Proportion of Traits (Binary Features)", y = "Proportion", fill = "Value") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

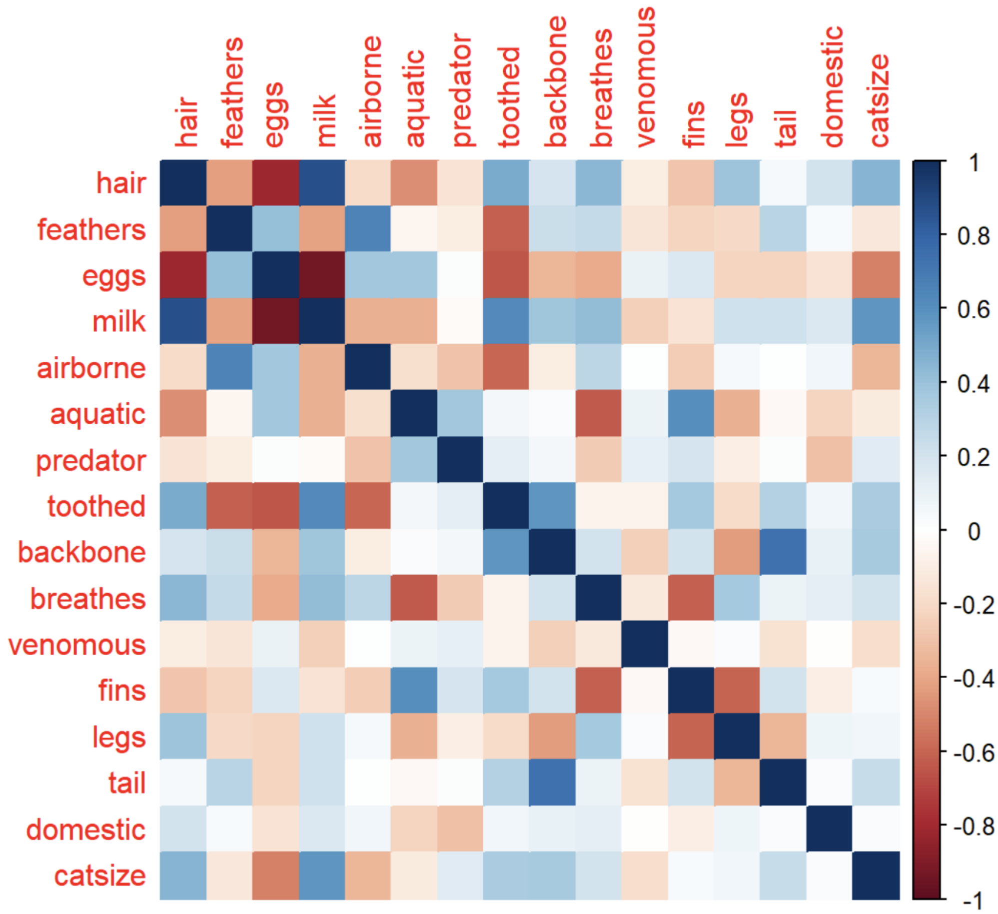


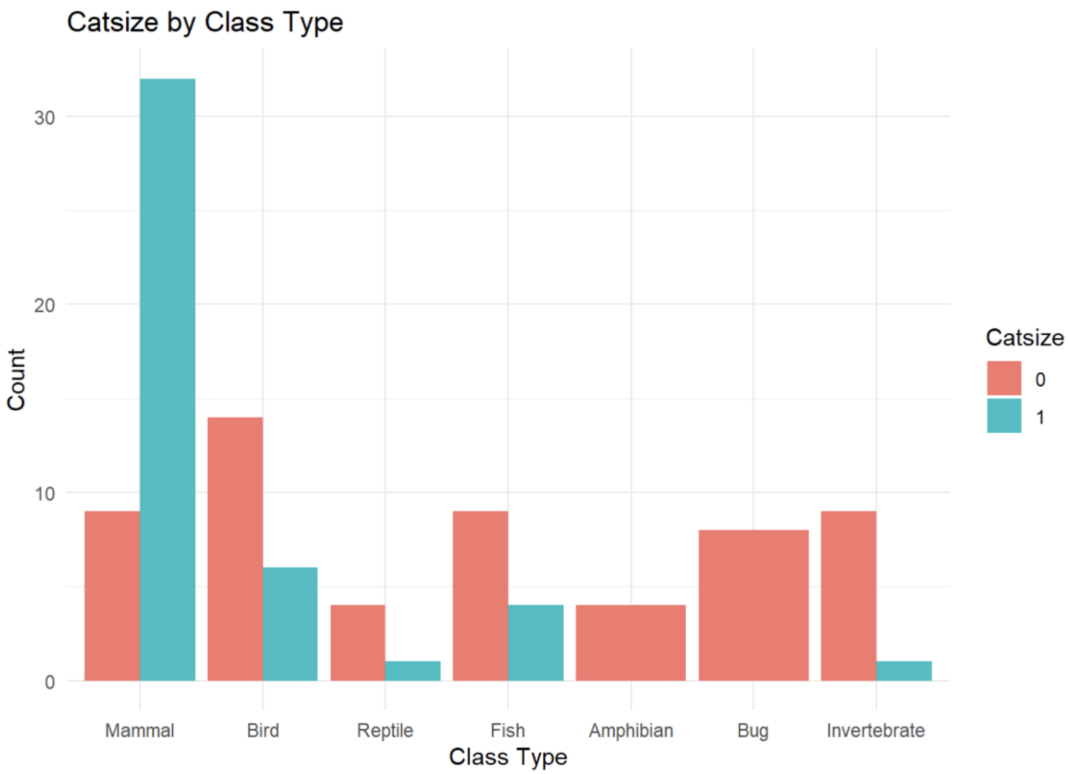

```
print("Correlation Heatmap")
```

```
## [1] "Correlation Heatmap"
```

```
library(corrplot)
library(dplyr)

numeric_vars <- zoo %>% select(-animal_name, -class_type)
cor_matrix <- cor(numeric_vars)
corrplot(cor_matrix, method = "color")
```


hair
feathers
eggs
milk
airborne
aquatic
predator
toothed
backbone
breathes
venomous
fins
legs
tail
domestic
catsize
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1



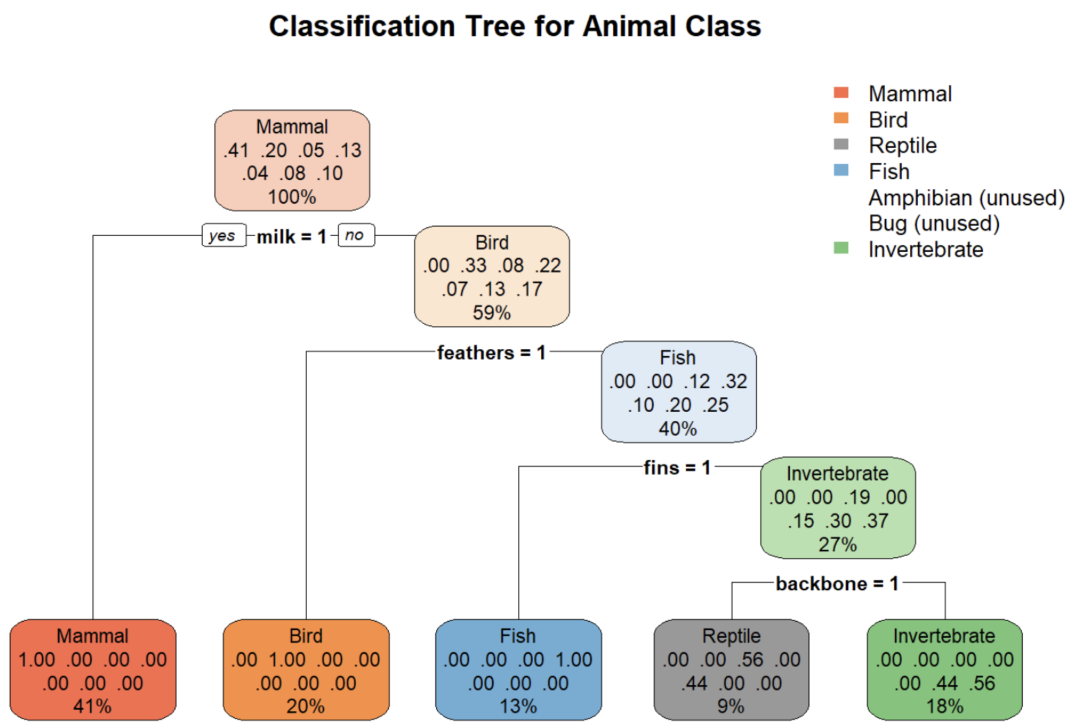
Classification tree

```
library(rpart)
library(rpart.plot)
```

```
## Warning: package 'rpart.plot' was built under R version 4.4.3
```

```
tree_model <- rpart(class_type ~ . -animal_name, data = zoo, method = "class")

rpart.plot(tree_model, type = 2, extra = 104,
           fallen.leaves = TRUE, main = "Classification Tree for Animal Class")
```




```
# training data prediction
predict_tree <- predict(tree_model, zoo, type = "class")

# Confusion matrix
cat("\n")
```

```
table(Predicted = predict_tree, Actual = zoo$class_type)
```

```
##                 Actual
## Predicted        Mammal Bird Reptile Fish Amphibian Bug Invertebrate
##   Mammal             41    0       0    0         0   0            0
##   Bird                0   20       0    0         0   0            0
##   Reptile             0    0       5    0         4   0            0
##   Fish                0    0       0   13         0   0            0
##   Amphibian           0    0       0    0         0   0            0
##   Bug                 0    0       0    0         0   0            0
##   Invertebrate        0    0       0    0         0   8           10
```

```
cat("\n")
```

```
print("Mean: ")
```

```
## [1] "Mean: "
```

```
mean(predict_tree == zoo$class_type)
```

```
## [1] 0.8811881
```

```
cat("\n")
```

```
cat("\n")
```

```
library(nnet)

# Fit multinomial logistic regression model
cat("\n")
```

```
multi_model <- multinom(class_type ~ hair + feathers + eggs + milk + airborne + aquatic + predat
or + toothed + backbone + breathes + venomous + fins + legs + tail + domestic + catsize, data =
zoo)
```

```
## # weights:  126 (102 variable)
## initial  value 196.536925
## iter  10 value 24.659968
## iter  20 value 0.191530
## iter  30 value 0.001598
## final  value 0.000066
## converged
```

```
cat("\n")
```

```
# Summary of model
cat("\n")
```

```
summary(multi_model)
```

```
## Call:
## multinom(formula = class_type ~ hair + feathers + eggs + milk +
##     airborne + aquatic + predator + toothed + backbone + breathes +
##     venomous + fins + legs + tail + domestic + catsize, data = zoo)
##
## Coefficients:
##              (Intercept)      hair    feathers      eggs      milk   airborne
## Bird          -0.2101589 -10.18368  74.3816066 15.222258 -39.08765 -13.371519
## Reptile        9.8215431 -58.14376 -64.7046422  8.282286 -66.78833 -14.027152
## Fish          -9.3964720   9.21434   1.2766138 40.676090 -34.97206   6.316331
## Amphibian    -76.7281050 -42.23348  -9.5079605 14.787060 -46.33031 -19.914495
## Bug          -25.6120056 -34.03710   5.7612443 20.959429 -19.31109  16.448537
## Invertebrate  80.8135610 -34.38730  -0.3962482  9.273720 -26.24041 -46.030510
##                 aquatic   predator    toothed   backbone  breathes   venomous
## Bird         -12.973226  -7.830139  -7.125918   7.203609 -18.64237   5.596145
## Reptile      -46.200803  -4.336674   8.698936  53.459993 -26.74356  26.008685
## Fish         -21.751250  -2.173047  13.843991   9.000926 -40.83073  28.426961
## Amphibian     49.016827 -13.398018  41.023653  26.317426  40.13652 -24.146208
## Bug          -39.904530 -15.465755  -8.600219 -11.132936  20.84639 -14.593208
## Invertebrate   3.289797  32.603088 -31.984788 -84.175781 -19.05068  19.544049
##                   fins       legs       tail    domestic    catsize
## Bird          -2.36661  4.1142203  -5.838030   1.9735580   1.713439
## Reptile      -58.21758  1.1642215  45.611221  -5.7608026  -9.634136
## Fish          23.58437  0.4139403  12.333305   0.7762755   7.759215
## Amphibian    -40.01138 14.5172396 -26.134234  -9.9206924 -36.723993
## Bug           14.93551 13.2950729 -12.654370 -13.0840970 -21.608976
## Invertebrate -10.98958 -3.4739147   3.438824   1.7678507   2.015067
##
## Std. Errors:
##              (Intercept)         hair     feathers         eggs         milk
## Bird          15188.1189 6.752125e-05 1.518812e+04 1.518812e+04 1.114525e-06
## Reptile         217.9830 6.795957e+01 4.464375e-06 3.286902e+00 6.795957e+01
## Fish           5853.0237 5.853631e+03 7.225602e-01 4.382892e+03 3.344539e+03
## Amphibian     16475.4286 9.666978e+03 2.517310e+04 2.614230e+04 9.666978e+03
## Bug           15485.6572 2.850870e+03 1.719330e+04 1.516964e+04 6.839777e-01
## Invertebrate    512.6424 4.119517e-06 1.227296e-02 1.185466e-02 4.136800e-06
##                  airborne      aquatic   predator      toothed     backbone
## Bird         1.518811e+04 2.517312e+04   291.9550 1.099773e-06 1.518812e+04
## Reptile      5.064023e-07 9.148479e-06   150.8952 7.124648e+01 7.124647e+01
## Fish         2.860091e+03 1.793625e+03  1923.8725 1.569446e+03 3.343841e+03
## Amphibian    2.517310e+04 3.980292e+04 14929.1562 9.663691e+03 1.550946e+04
## Bug          1.435327e+04 5.561084e-09   369.3970 6.839777e-01 1.719387e+04
## Invertebrate 1.266641e-10 1.169569e-02   512.6422 1.736282e-08 1.227709e-02
##               breathes     venomous         fins      legs        tail
## Bird         15188.119 8.425177e-06 4.437994e-17 30376.238  15188.1189
## Reptile        217.983 1.467366e+02 9.148569e-06  1455.265    217.9830
## Fish          5853.024 2.851409e+03 1.853203e+01 28713.873   3343.8410
## Amphibian    16475.428 7.435796e-17 3.409486e-19 17489.288 104929.6804
## Bug          15485.657 2.574776e+03 1.096644e-36 25354.329  17499.2015
## Invertebrate   512.643 5.126306e+02 1.736282e-08  4101.066    512.6428
##                  domestic      catsize
## Bird         3.383224e-03 7.309296e-01
```

```
## Reptile      1.026182e-01 1.322683e-02
## Fish         3.878984e+03 3.332041e+03
## Amphibian    8.942059e+04 1.463121e+04
## Bug          3.146945e+03 3.201599e-07
## Invertebrate 7.997172e-11 1.225516e-02
##
## Residual Deviance: 0.0001311772
## AIC: 204.0001
```

```
cat("\n")
```

```
# compute z and p values
cat("\n")
```

```
z <- summary(multi_model)$coefficients / summary(multi_model)$standard.errors
p <- 2 * (1 - pnorm(abs(z)))

# combine into table
cat("\n")
```

```
coef_table <- cbind(
  round(summary(multi_model)$coefficients,3),
  round(z, 3),
  round(p, 5)
)
print(coef_table)
```

```
##              (Intercept)    hair feathers   eggs    milk airborne aquatic
## Bird              -0.210 -10.184   74.382 15.222 -39.088  -13.372 -12.973
## Reptile            9.822 -58.144  -64.705  8.282 -66.788  -14.027 -46.201
## Fish              -9.396   9.214    1.277 40.676 -34.972    6.316 -21.751
## Amphibian        -76.728 -42.233   -9.508 14.787 -46.330  -19.914  49.017
## Bug              -25.612 -34.037    5.761 20.959 -19.311   16.449 -39.905
## Invertebrate      80.814 -34.387   -0.396  9.274 -26.240  -46.031   3.290
##              predator toothed backbone breathes venomous    fins   legs    tail
## Bird           -7.830  -7.126    7.204  -18.642    5.596  -2.367  4.114  -5.838
## Reptile        -4.337   8.699   53.460  -26.744   26.009 -58.218  1.164  45.611
## Fish           -2.173  13.844    9.001  -40.831   28.427  23.584  0.414  12.333
## Amphibian     -13.398  41.024   26.317   40.137  -24.146 -40.011 14.517 -26.134
## Bug           -15.466  -8.600  -11.133   20.846  -14.593  14.936 13.295 -12.654
## Invertebrate   32.603 -31.985  -84.176  -19.051   19.544 -10.990 -3.474   3.439
##              domestic catsize (Intercept)         hair      feathers    eggs
## Bird            1.974   1.713       0.000  -150821.876         0.005   0.001
## Reptile        -5.761  -9.634       0.045       -0.856 -14493550.453   2.520
## Fish            0.776   7.759      -0.002        0.002         1.767   0.009
## Amphibian      -9.921 -36.724      -0.005       -0.004         0.000   0.001
## Bug           -13.084 -21.609      -0.002       -0.012         0.000   0.001
## Invertebrate    1.768   2.015       0.158 -8347408.972       -32.286 782.285
##                       milk      airborne       aquatic predator       toothed
## Bird         -35071123.018 -1.000000e-03 -1.000000e-03   -0.027 -6.479447e+06
## Reptile             -0.983 -2.769962e+07 -5.050108e+06   -0.029  1.220000e-01
## Fish                -0.010  2.000000e-03 -1.200000e-02   -0.001  9.000000e-03
## Amphibian           -0.005 -1.000000e-03  1.000000e-03   -0.001  4.000000e-03
## Bug                -28.234  1.000000e-03 -7.175675e+09   -0.042 -1.257400e+01
## Invertebrate  -6343167.256 -3.634061e+11  2.812830e+02    0.064 -1.842143e+09
##               backbone breathes      venomous          fins   legs   tail
## Bird             0.000   -0.001  6.642169e+05 -5.332611e+16  0.000  0.000
## Reptile          0.750   -0.123  1.770000e-01 -6.363573e+06  0.001  0.209
## Fish             0.003   -0.007  1.000000e-02  1.273000e+00  0.000  0.004
## Amphibian        0.002    0.002 -3.247293e+17 -1.173531e+20  0.001  0.000
## Bug             -0.001    0.001 -6.000000e-03  1.361930e+37  0.001 -0.001
## Invertebrate -6856.331   -0.037  3.800000e-02 -6.329375e+08 -0.001  0.007
##                   domestic       catsize (Intercept)    hair feathers    eggs
## Bird          5.833360e+02         2.344     0.99999 0.00000  0.99609 0.99920
## Reptile      -5.613800e+01      -728.379     0.96406 0.39224  0.00000 0.01174
## Fish          0.000000e+00         0.002     0.99872 0.99874  0.07726 0.99260
## Amphibian     0.000000e+00        -0.003     0.99628 0.99651  0.99970 0.99955
## Bug          -4.000000e-03 -67494315.447     0.99868 0.99047  0.99973 0.99890
## Invertebrate  2.210595e+10       164.426     0.87474 0.00000  0.00000 0.00000
##                 milk airborne aquatic predator toothed backbone breathes
## Bird         0.00000  0.99930 0.99959  0.97860 0.00000  0.99962  0.99902
## Reptile      0.32572  0.00000 0.00000  0.97707 0.90282  0.45304  0.90236
## Fish         0.99166  0.99824 0.99032  0.99910 0.99296  0.99785  0.99443
## Amphibian    0.99618  0.99937 0.99902  0.99928 0.99661  0.99865  0.99806
## Bug          0.00000  0.99909 0.00000  0.96660 0.00000  0.99948  0.99893
## Invertebrate 0.00000  0.00000 0.00000  0.94929 0.00000  0.00000  0.97036
##              venomous    fins    legs    tail domestic catsize
## Bird          0.00000 0.00000 0.99989 0.99969  0.00000 0.01907
## Reptile       0.85931 0.00000 0.99936 0.83426  0.00000 0.00000
```

```
## Fish          0.99205 0.20315 0.99999 0.99706  0.99984 0.99814
## Amphibian     0.00000 0.00000 0.99934 0.99980  0.99991 0.99800
## Bug           0.99548 0.00000 0.99958 0.99942  0.99668 0.00000
## Invertebrate  0.96959 0.00000 0.99932 0.99465  0.00000 0.00000
```

```
#write.csv(coef_table, "Coef_table.csv")
```

```
# Extract values
coef <- round(summary(multi_model)$coefficients, 3)
se <- round(summary(multi_model)$standard.errors, 3)
z <- round(coef / se, 3)
p <- round(2 * (1 - pnorm(abs(z))), 5)

# Create labeled table
library(tibble)
```

```
## Warning: package 'tibble' was built under R version 4.4.3
```

```
library(dplyr)

coef_table <- tibble::as_tibble(coef, rownames = "Class") %>%
  pivot_longer(-Class, names_to = "Predictor", values_to = "Coefficient") %>%
  mutate(
    SE = as.vector(se),
    Z = as.vector(z),
    P_Value = as.vector(p)
  ) %>%
  relocate(Class, Predictor, Coefficient, SE, Z, P_Value)

# View in console or export
print(coef_table)
```

```
## # A tibble: 102 × 6
##    Class Predictor   Coefficient      SE        Z P_Value
##    <chr> <chr>             <dbl>   <dbl>    <dbl>   <dbl>
##  1 Bird  (Intercept)       -0.21 15188.     0       1
##  2 Bird  hair             -10.2    218.     0.045   0.964
##  3 Bird  feathers          74.4   5853.    -0.002   0.998
##  4 Bird  eggs              15.2  16475.    -0.005   0.996
##  5 Bird  milk             -39.1  15486.    -0.002   0.998
##  6 Bird  airborne         -13.4    513.     0.158   0.874
##  7 Bird  aquatic          -13.0      0   -Inf       0
##  8 Bird  predator          -7.83    68.0   -0.856   0.392
##  9 Bird  toothed           -7.13  5854.     0.002   0.998
## 10 Bird  backbone           7.20  9667.    -0.004   0.997
## # ℹ 92 more rows
```

```
# Export to CSV
#write.csv(coef_table, "Labeled_Coef_Table.csv", row.names = FALSE)
```