

Contents

0. Load dataset and library on workspace.

```
library(palmerpenguins) # for data
library(dplyr) # for data-handling
library(corrplot) # for correlation plot
library(GGally) # for parallel coordinate plot
library(e1071) # for svm
```

```
data(penguins) # load pre-processed penguins
```

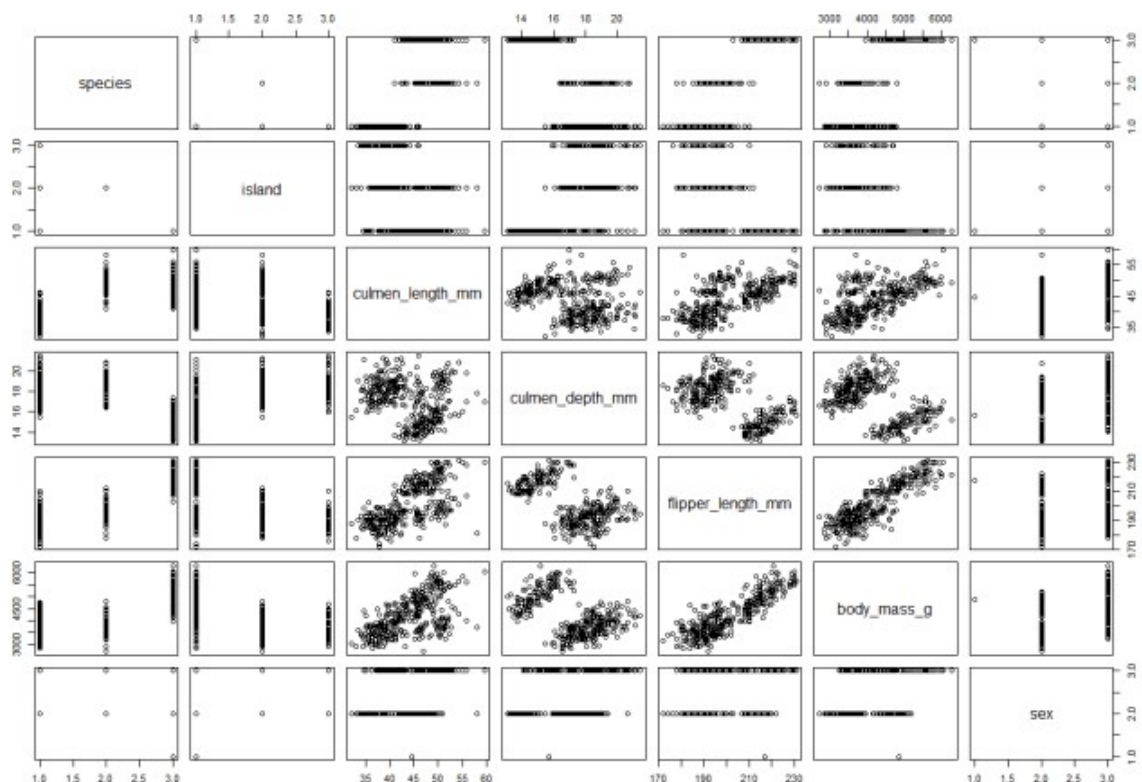
palmerpenguins have 2 data penguins, penguins_raw , and as you can see from their name, penguins is pre-processed data.

1. See the summary and plot of Dataset

```
summary(penguins)
plot(penguins)
```

```
> summary(penguins)
  species      island culmen_length_mm culmen_depth_mm flipper_length_mm body_mass_g
Length:344   Length:344      Min.   :32.10      Min.   :13.10      Min.   :172.0      Min.   :2700
Class:character Class:character 1st Qu.:39.23      1st Qu.:15.60      1st Qu.:190.0      1st Qu.:3550
Mode :character  Mode :character Median :44.45      Median :17.30      Median :197.0      Median :4050
Mean  :43.92      Mean  :17.15      Mean  :200.9      Mean  :4202
3rd Qu.:48.50      3rd Qu.:18.70      3rd Qu.:213.0      3rd Qu.:4750
Max.  :59.60      Max.  :21.50      Max.  :231.0      Max.  :6300
NA's  :2          NA's  :2          NA's  :2          NA's  :2

 sex
Length:344
Class:character
Mode :character
```



It seems species , island and sex is categorical features.
and remaining for numerical features.

2. Set the format of feature

```
penguins$species <- as.factor(penguins$species)
penguins$island <- as.factor(penguins$island)
```

```
penguins$sex <- as.factor(penguins$sex)
```

```
summary(penguins)
```

```
plot(penguins)
```

and see `summary` and `plot` again. note that result of `plot` is same.

```
> summary(penguins)
```

species	island	culmen_length_mm	culmen_depth_mm	flipper_length_mm	body_mass_g
Adelie :152	Biscoe :168	Min. :32.10	Min. :13.10	Min. :172.0	Min. :2700
Chinstrap: 68	Dream :124	1st Qu.:39.23	1st Qu.:15.60	1st Qu.:190.0	1st Qu.:3550
Gentoo :124	Torgersen: 52	Median :44.45	Median :17.30	Median :197.0	Median :4050
		Mean :43.92	Mean :17.15	Mean :200.9	Mean :4202
		3rd Qu.:48.50	3rd Qu.:18.70	3rd Qu.:213.0	3rd Qu.:4750
		Max. :59.60	Max. :21.50	Max. :231.0	Max. :6300
		NA's :2	NA's :2	NA's :2	NA's :2


```
sex
. : 1
FEMALE:165
MALE :168
NA's : 10
```

There's unwanted NA and . values in some features.

3. Remove not necessary datas (in this tutorial, NA)

```
penguins <- penguins %>% filter(sex == 'MALE' | sex == 'FEMALE')
```

```
summary(penguins)
```

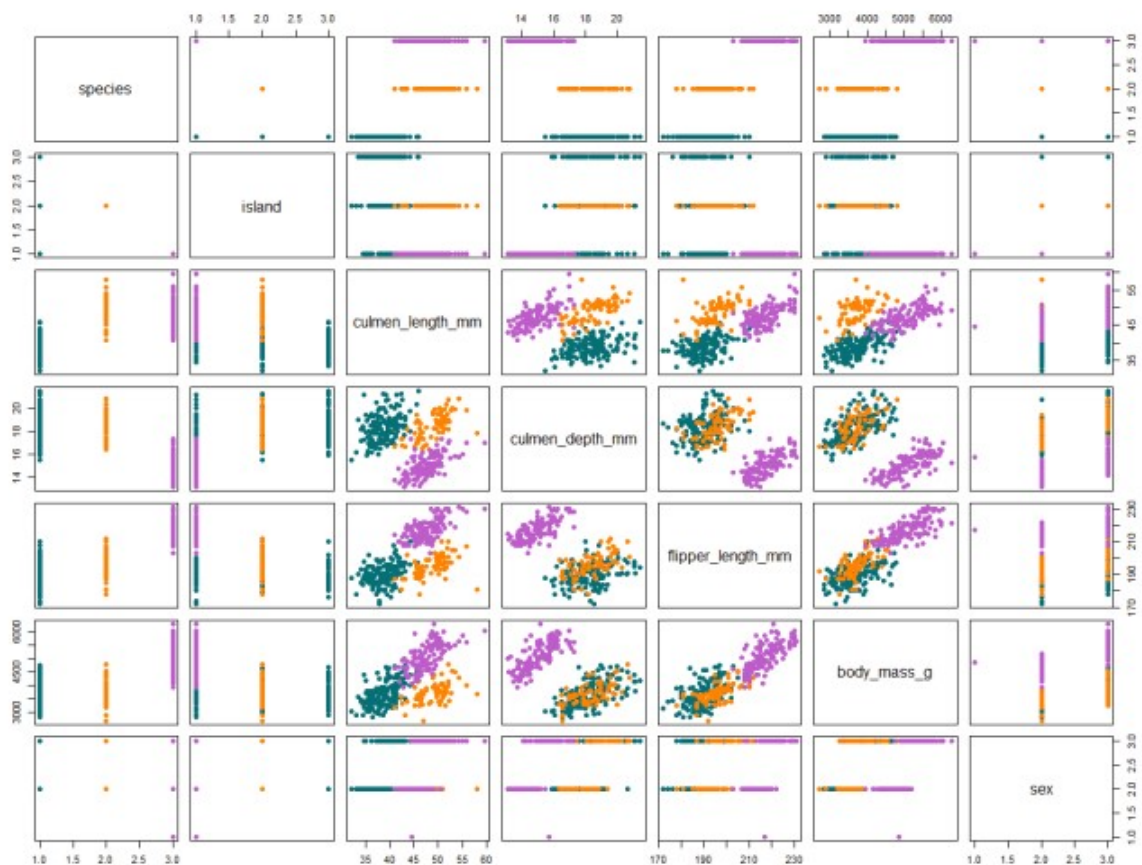
And here, I additionally defined color values for each penguins to see better plot result

```
# Green, Orange, Purple
```

```
pCol <- c('#057076', '#ff8301', '#bf5ccb')
```

```
names(pCol) <- c('Gentoo', 'Adelie', 'Chinstrap')
```

```
plot(penguins, col = pCol[penguins$species], pch = 19)
```



Now, plot results are much better to give insights.

Note that, other pre-process step may requires for different datasets.

4. See relation of categorical features

My first purpose of analysis this penguin is `species`

So, I will try to see relation between `species` and other categorical values

4-1. `species, island`

```
table(penguins$species, penguins$island)
chisq.test(table(penguins$species, penguins$island)) # meaningful difference

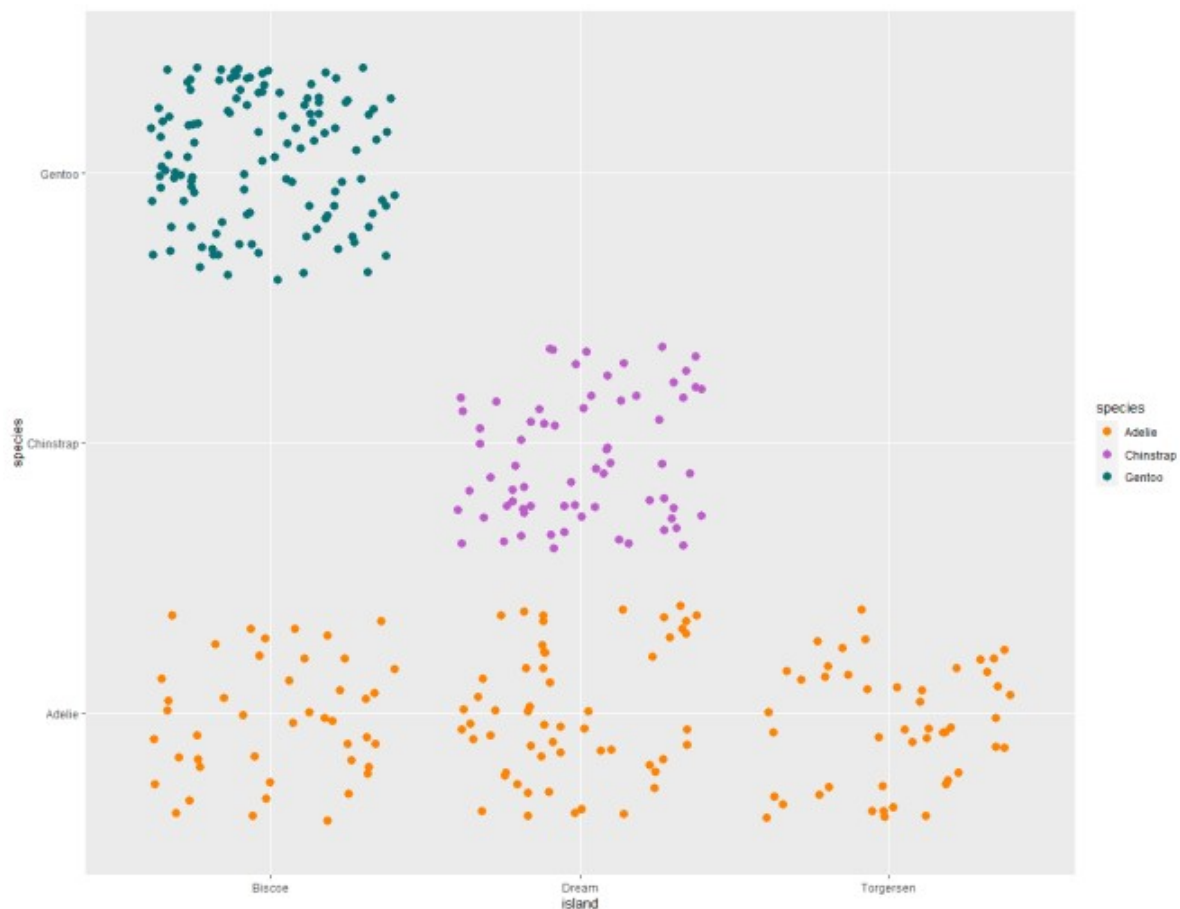
ggplot(penguins, aes(x = island, y = species, color = species)) +
  geom_jitter(size = 3) +
  scale_color_manual(values = pCol)
```

```
> table(penguins$species, penguins$island)

      Biscoe Dream Torgersen
Adelie      44      55       47
Chinstrap    0      68        0
Gentoo     119      0         0
> chisq.test(table(penguins$species, penguins$island)) # meaningful difference

      Pearson's Chi-squared test

data:  table(penguins$species, penguins$island)
X-squared = 284.59, df = 4, p-value < 2.2e-16
```



Wow, there's strong relationship between `species` and `island`

- Adelie lives in every island
- Gentoo lives in only Biscoe

– Chinstrap lives in only Dream

4-2 & 4.3.

However, species and sex or sex and island did not show any meaningful relation.

You can try following codes.

```
# species vs sex
table(penguins$sex, penguins$species)
chisq.test(table(penguins$sex, penguins$species)[-1,]) # not meaningful
difference 0.916
```

```
# sex vs island
table(penguins$sex, penguins$island) # 0.9716
chisq.test(table(penguins$sex, penguins$island)[-1,]) # not meaningful
difference 0.9716
```

5. See with numerical features

I will select numerical features.

and see correlation plot and parallel coordinate plots.

```
# Select numericals
penNumeric <- penguins %>% select(-species, -island, -sex)

# Cor-relation between numerics

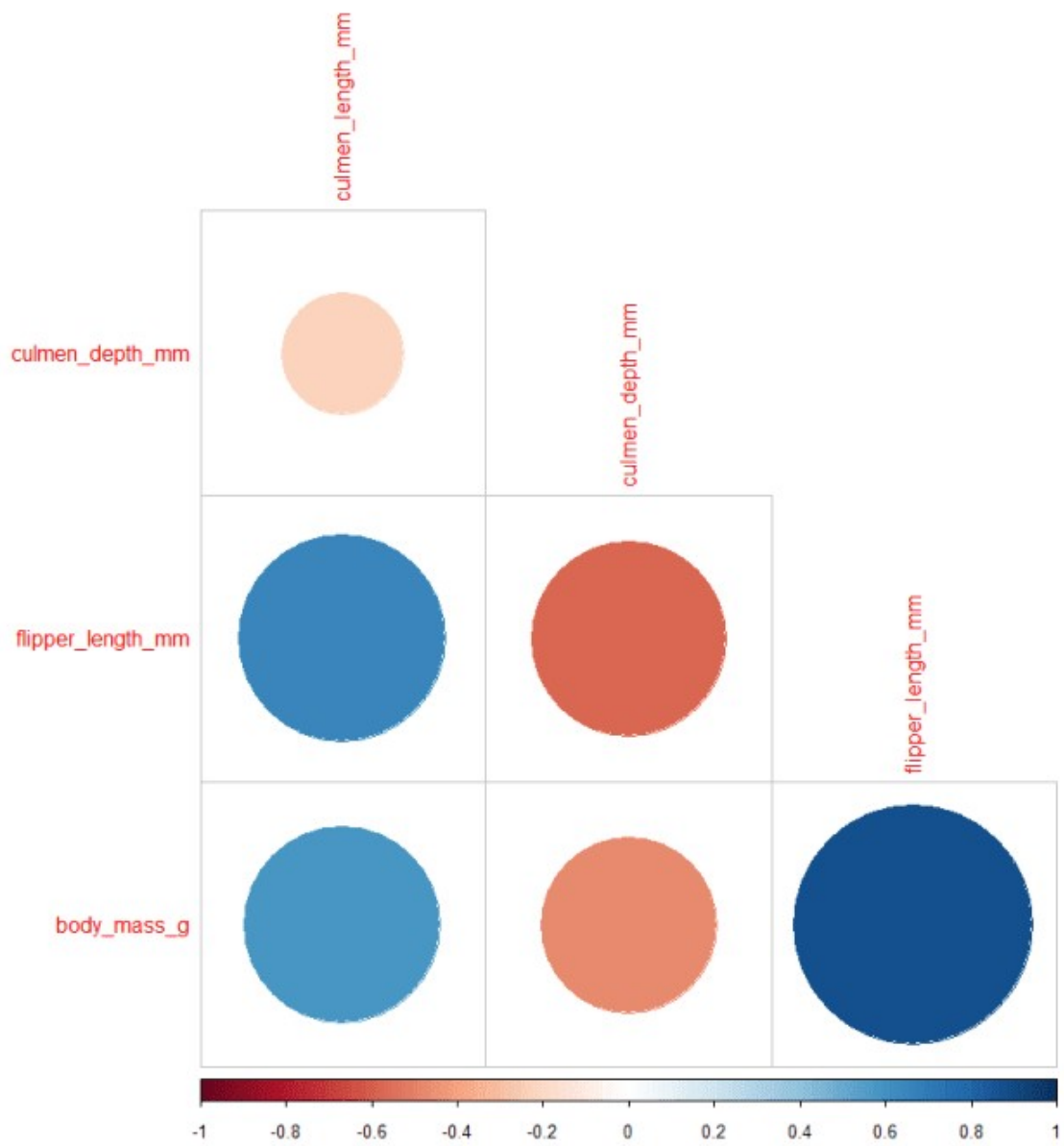
corrplot(cor(penNumeric), type = 'lower', diag = FALSE)

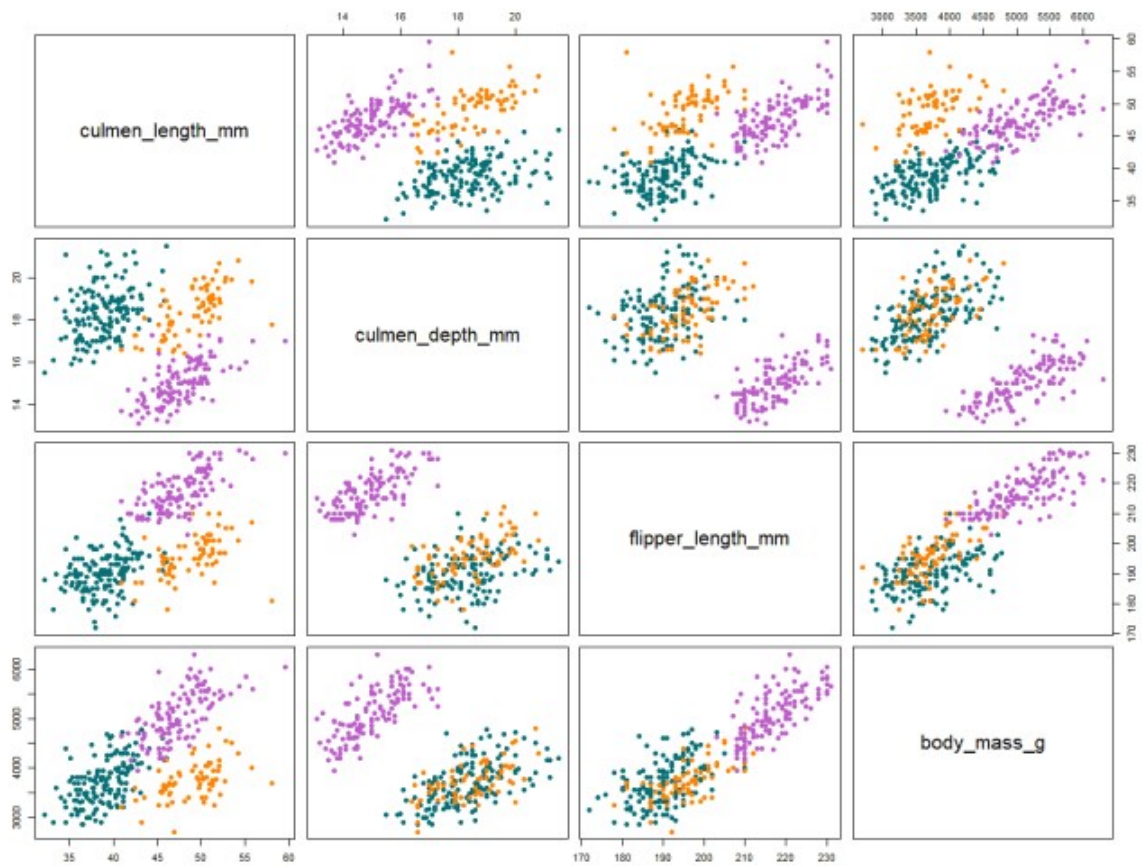
# parallel coordinate plots

ggparcoord(penguins, columns = 3:6, groupColumn = 1, order = c(4,3,5,6)) +
  scale_color_manual(values = pCol)

plot(penNumeric, col = pCol[penguins$species], pch = 19)
```

and below are result of them.





lucky, every numeric features (even only 4) have meaningful correlation and there is trend with their combination for species (See parallel coordinate plot)

6. Give statistical work on dataset.

In this step, I usually do linear modeling or svm to predict

6.1 linear modeling

species is categorical value, so it needs to be change to **numeric value**

```
set.seed(1234)
idx <- sample(1:nrow(penguins), size = nrow(penguins)/2)

# as. numeric
speciesN <- as.numeric(penguins$species)
penguins$speciesN <- speciesN

train <- penguins[idx,]
test <- penguins[-idx,]

fm <- lm(speciesN ~ flipper_length_mm + culmen_length_mm + culmen_depth_mm +
body_mass_g, train)

summary(fm)
```

```
> summary(fm)

Call:
lm(formula = speciesN ~ flipper_length_mm + culmen_length_mm +
  culmen_depth_mm + body_mass_g, data = train)

Residuals:
    Min       1Q   Median       3Q      Max
-0.59953 -0.17149  0.00585  0.18868  0.70985

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -1.251e+00  6.097e-01  -2.051   0.0419 *
flipper_length_mm  1.538e-02  3.475e-03   4.425 1.77e-05 ***
culmen_length_mm   7.329e-02  5.116e-03  14.326 < 2e-16 ***
culmen_depth_mm  -2.012e-01  1.281e-02 -15.709 < 2e-16 ***
body_mass_g       7.626e-05  5.215e-05   1.462   0.1456
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2568 on 161 degrees of freedom
Multiple R-squared:  0.9203,    Adjusted R-squared:  0.9183
F-statistic: 464.6 on 4 and 161 DF,  p-value: < 2.2e-16
```

It shows that, body_mass_g is not meaningful feature as seen in plot above (it may explain gentoo, but not other penguins)

To predict, I used this code. however, numeric predict generate **not complete value** (like 2.123 instead of 2) so I added rounding step.

```
predRes <- round(predict(fm, test))
predRes[which(predRes>3)] <- 3
predRes <- sort(names(pCol))[predRes]

test$predRes <- predRes
ggplot(test, aes(x = species, y = predRes, color = species))+
```

```
geom_jitter(size = 3) +
scale_color_manual(values = pCol)

table(test$predRes, test$species)
```

```
> table(test$predRes, test$species)
```

	Adelie	Chinstrap	Gentoo
Adelie	67	3	0
Chinstrap	6	33	0
Gentoo	0	0	58



Accuracy of basic linear modeling is 94.6%

6-2 svm

using svm is also easy step.

```
m <- svm(species ~., train)

predRes2 <- predict(m, test)
test$predRes2 <- predRes2

ggplot(test, aes(x = species, y = predRes2, color = species)) +
  geom_jitter(size = 3) +
  scale_color_manual(values = pCol)

table(test$species, test$predRes2)
```

and below are result of this code.


```
> table(test$species, test$predRes2)
```

	Adelie	Chinstrap	Gentoo
Adelie	73	0	0
Chinstrap	0	36	0
Gentoo	0	0	58



Accuracy of `svm` is 100%. wow.