

# Computer Assignment 8 - Multiple Testing with Jelly Beans

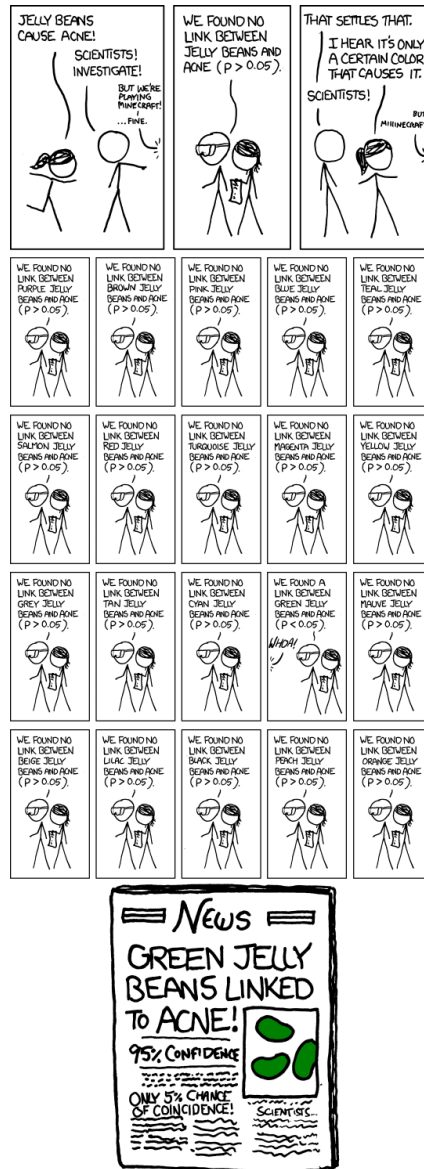
**Machine Learning, Spring 2020**

*YOUR NAME*

We will begin by reiterating a point made earlier in the semester about testing multiple hypotheses. Often, scientists in the field are looking for associations that seem unlikely to occur by chance. The issue with this is if one looks at enough associations then an association is bound to occur by chance rather than by genuine causality. Recall the metaphor about a needle in a haystack: finding a needle in a haystack might be amazing, but if you had checked 1000 haystacks perhaps this is less amazing. . .

## **The Problem with P-values?**

To get an idea of what we are about to simulate, consider the following comic.



Consider the set up of this experiment. You have a bunch of people with or without acne and you further know whether or not they have eaten a jelly bean of a particular color. We can easily simulate this in R:

```
# DON'T EDIT THIS CODE
set.seed(13)
has_acne = rbinom(100, 1, 0.4)
ate_red_jb = rbinom(100, 1, 0.6)
our_data = data.frame(HasAcne = has_acne, AteRedJB = ate_red_jb)
head(our_data)
```

```
##   HasAcne AteRedJB
## 1      1      0
## 2      0      0
## 3      0      0
## 4      0      0
## 5      1      1
## 6      0      1
```

```
summary(our_data)
```

```
##      HasAcne      AteRedJB
##  Min.    :0.00   Min.    :0.00
## 1st Qu.:0.00   1st Qu.:0.00
##  Median :0.00   Median :1.00
##   Mean  :0.37   Mean    :0.58
## 3rd Qu.:1.00   3rd Qu.:1.00
##   Max.  :1.00   Max.    :1.00
```

Here is our simple random sample of 100 people in which we know their acne and red-jelly-bean-eating status. It is significant, and indeed quite important, to note that each of these variables were generated **randomly and independently** of one another. Therefore, we know something that researchers in the field do not normally know: that in this case red-jelly-bean-eating should have **no effect** on the acne of an individual. Let's show this using one of our logistic regression models.

```
m1 <- glm(HasAcne ~ AteRedJB, data = our_data, family = binomial('logit'))
summary(m1)
```

```
##
## Call:
## glm(formula = HasAcne ~ AteRedJB, family = binomial("logit"),
##      data = our_data)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.0620  -1.0620  -0.8203   1.2974   1.5829
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.9163     0.3416  -2.683  0.0073 **
## AteRedJB       0.6387     0.4324   1.477  0.1397
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 131.79  on 99  degrees of freedom
## Residual deviance: 129.55  on 98  degrees of freedom
## AIC: 133.55
##
## Number of Fisher Scoring iterations: 4
```

Examine the **Coefficients** section, specifically the column **Pr(>|z|)**, which is the column of p-values. Here we see the p-value derived using the test  $H_0 : \beta_i = 0$  where  $i \in \{0, 1\}$  and  $\beta_0, \beta_1$  are the coefficients for the **Intercept** and our **AteRedJB** variable, respectively. Notice that we got what we expected! The p-value for the test  $H_0 : \beta_1 = 0$  was above our usual 0.05 threshold so we therefore **fail to reject** the statement that red-jelly-bean-eating is not significant.

This is all well and good! Statistics works!

But wait. What if we repeated this experiment over and over again? During each experiment we will take a new random sample of people and examine a new color of Jelly Bean. We will record whether or not the jelly-bean-eating for each new experiment is significant. Indeed,

```
# DO NOT EDIT THIS CODE
set.seed(10)
```

```

colors = c("Purple", "Brown", "Green", "Pink", "Blue", "Teal", "Salmon", "Red", "Turquoise",
           "Magenta", "Yellow", "Grey", "Tan", "Cyan", "Mauve", "Beige",
           "Lilac", "Black", "Peach", "Orange")
for(index in 1:20){
  has_acne = rbinom(100, 1, 0.4)
  ate_color_jb = rbinom(100, 1, 0.6)
  our_data = data.frame(HasAcne = has_acne, AteJB = ate_color_jb)
  fit <- glm(HasAcne ~ AteJB, data = our_data, family = binomial('logit'))
  p_value = coef(summary(fit))[, "Pr(>|z|)"][2]
  print(paste(colors[index], ": ", p_value < 0.05, sep = ""))
}

```

```

## [1] "Purple: FALSE"
## [1] "Brown: FALSE"
## [1] "Green: TRUE"
## [1] "Pink: FALSE"
## [1] "Blue: FALSE"
## [1] "Teal: FALSE"
## [1] "Salmon: FALSE"
## [1] "Red: FALSE"
## [1] "Turquoise: FALSE"
## [1] "Magenta: FALSE"
## [1] "Yellow: FALSE"
## [1] "Grey: FALSE"
## [1] "Tan: FALSE"
## [1] "Cyan: FALSE"
## [1] "Mauve: FALSE"
## [1] "Beige: FALSE"
## [1] "Lilac: FALSE"
## [1] "Black: FALSE"
## [1] "Peach: FALSE"
## [1] "Orange: FALSE"

```

So, were they right? Does eating green Jelly Beans cause acne?

## Questions

The purpose of this exercise is to introduce you to the multiple comparisons problem and thereby hopefully serve as a warning to those who want to use statistics in practice in the future. Note that since this is primarily a written exercise, complete sentences and proper grammar are expected.

1. Read pages 67-68 in Gareth James' book. Based on what is written here, and any other (credible) resource that you can find, provide a full definition of a p-value.

YOUR ANSWER HERE

2. In what situation might a p-value be inaccurate?

YOUR ANSWER HERE

3. Do green Jelly Beans cause acne? Your answer to this question should explain either why the above experiment validates your conclusion or why the above results may be misleading.

YOUR ANSWER HERE

4. If you checked 100 colors of Jelly Beans (rather than 20), how many would you expect to have a statistically significant effect on acne-having? Why?

YOUR ANSWER HERE

5. Multiple testing is actually a well-known problem in Statistics. A common solution is to do a **Bonferroni Correction**. There are many resources online on how to do this. Research the **Bonferroni Correction** and repeat the above experience using it (and using the same `set.seed()`). Discuss the results.

YOUR CODE, AND DISCUSSION, HERE

## Model Assumptions

We have spent a lot of time this semester looking at different supervised and unsupervised methods for analyzing data and performing classification. There is a saying in statistics: **every dog has its day**. This is to say that there is always a situation where a certain method will out perform all the others and will be, in a sense, the “right” method for a given problem. There is an art to picking the right tool in your toolbox for a given application, so the next few problems (on this and the next computer assignment) will try to build your intuition on when to use certain methods. There are some questions in this next exercise that are similar to previous exercises. This is to give you extra practice and to help motivate what we will try to do next week.

### The Perfect Data for LDA

Recall that in the case of LDA is we assume that the marginal class densities are both normal and have the same variance. This is, for the binary classification problem, we have that:

$$\text{Data Classified as 0} \sim \mathcal{N}(\mu_0, \Sigma), \text{Data Classified as 1} \sim \mathcal{N}(\mu_1, \Sigma).$$

```
# Make sure to install this package if you do not have it:
library(mvtnorm)
my_sigma = t(matrix(c(1:25), ncol=5)) %*% matrix(c(1:25), ncol=5)
data_0 = rmvnorm(250, mean = rep(1, times = 5), sigma = my_sigma)
data_1 = rmvnorm(250, mean = rep(-1, times = 5), sigma = my_sigma)
labels = c(rep(0, times = 250), rep(1, times = 250))
names = c("variable1", "variable2", "variable3", "variable4", "variable5", "labels")
full_data = rbind(data_0, data_1)
full_data = cbind(full_data, labels)
full_data = as.data.frame(full_data)
names(full_data) = names
```

A crucial thing to note here is that this data **fits the assumptions we made with a LDA model exactly**. The class marginals are, indeed, normal and they do, indeed, have the same variance. Let us now examine how well an LDA model does on data like this, and compare it to another one of our models.

### Questions

- 1) Fit an LDA model on this data and examine the model output. Does this output makes sense based off of our data? Print the linear discriminants (look at possible model outputs).

```
library(MASS)
YOUR CODE, AND ANALYSIS HERE
```

- 2) Split the data into a testing data set and a training data set. Build an LDA model on the training data. Use the training data again to predict the class labels and report the performance of your model. What is the error rate? (the proportion of times your model classified an observation incorrectly)

YOUR CODE, AND ANALYSIS HERE

- 3) Now predict the class labels using the testing data and report the performance of your model. What is the error rate?

YOUR CODE, AND ANALYSIS HERE

- 4) Repeat steps 2-3 using a knn model for  $k \in \{1, 5, 11\}$ . Considering only the cases where you predicted labels on your testing data, compare the error rates between the LDA model and all of the knn models.

YOUR CODE, AND ANALYSIS HERE

Note that this is a case where LDA is supposed to perform especially well. The punchline here is that if you encounter data where the class marginals seem normal with the same variance, then LDA is a *very good* choice! For our next CA we will examine what happens when the assumptions inherent to LDA are broken. That is, when LDA perhaps is not the best tool for the job.