## ST440/540 Applied Bayesian Analysis Lab activity for 1/22/2024

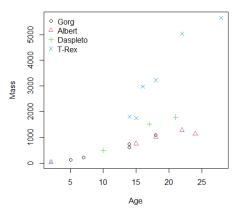
## (A) QUIZ AND HOMEWORK SOLUTIONS

A1: Download the tyrannosaurid growth curves data attached to this assignment

(a) Write a loop to compute the mean and standard deviation of the mass for each taxon. You must write a loop to get full credit. Put the results in a table and make sure the rows and columns are labelled clearly.

```
> mn <- sd <- rep(0,4)
> for(i in 1:4){
  mn[i] <- mean(mass[id==i])</pre>
+
^{+}
   sd[i] <- sd(mass[id==i])</pre>
+ }
      <- cbind(mn,sd)
> out
> rownames(out) <- taxon</pre>
> colnames(out) <- c("Mean","SD")</pre>
> round(out,1)
          Mean
                   SD
Gorg
        563.0 397.2
Albert 849.9 486.2
Daspleto 1268.3 682.6
T-Rex 2929.4 1958.0
```

(b) Make a plot of age versus mass that includes all observations but a different plotting symbol (i.e., the pch option in plot) or color for each taxon. Make sure the axes and legends are clearly labeled. plot (age, mass, pch=id, col=id, xlab="Age", ylab="Mass") legend ("topleft", taxon, pch=1:4, col=1:4, bty="n")



(c) Perform a non-Bayesian linear regression of y=log(mass) onto x=log(age) (ignoring taxon), and report and interpret the results.

There is a positive and statistically significant relationship between log age and log mass.

## **(B) DISCUSSION QUESTIONS**

(1) Select an appropriate family of distributions for the following quantities. Justify your choice.

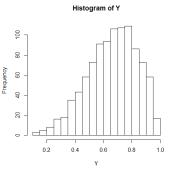
(a) The time between entering Starbucks and having your order: Exponential or gamma because time is continuous and positive.

(b) IQ scores: They are designed to be Normal(100,15<sup>2</sup>). If IQ is recorded as an integer, then a normal is still a good approximation.

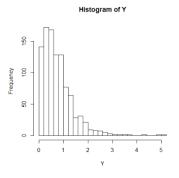
(c) Number of hurricanes in NC in 2022: Since it is a number of events (discrete) in an interval of time so it might be a Poisson random variable.

(d) Number of 100 patients in a vaccine trial that experience an adverse event: Binomial(100, p) since we have a number of success in a fixed number of trials.

(e) The data plotted in this histogram: Beta distribution because it's continuous (although a histogram makes it look discrete) between 0 and 1.



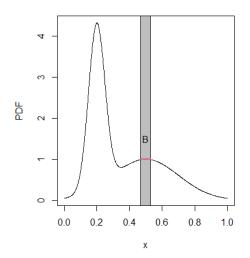
(f) The data plotted in this histogram: Chi-square or gamma distribution because its support is (0,inf) and it is continuous (though again, the histogram makes it look discrete).



(g) The data in this table: Bernoulli because the support is {0,1}.



(2) Argue that if X is a continuous random variable, then P(X=x) must be zero for any single value of x. If we consider a tiny interval like B in the plot below, then it is reasonable to assuming the PDF is constant in the interval, so P(X=x) = c for any x in B. But there are infinitely-many x's in B, and if each has probability c then the total probability in B is infinity \* c = infinity. Therefore, c must be zero.



(3) Say that 80% of cabs in the city are blue and 20% are green, and that hit-and-run witnesses can correctly identify the color of a car 90% of the time, regardless of the true color. Given that a witness claims a car is green, what is the probability that the car is truly green? What assumptions are you making in this calculation? (this problem is adapted from Thinking Fast and Slow)

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This analysis assumes green and blue cars are equally to be in a crash. Under this assumption, say
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\theta = 1 if the car is green and \theta = 0 otherwise and
        Y = 1 if the witness sees green and Y = 0 otherwise.
The problem gives P(\theta=1) = 0.2, P(\theta=0) = 0.8, P(Y=1|\theta=1) = 0.9 and P(Y=1|\theta=0) = 0.1. We want
P(\theta=1|Y=1). Bayes Theorem gives
        P(\theta=1|Y=1)
                         = P(Y=1 | \theta=1)P(\theta=1)/P(Y=1)
                         = P(Y=1|\theta=1)P(\theta=1)/[P(Y=1|\theta=0)P(\theta=0) + P(Y=1|\theta=1)P(\theta=1)]
                         = 0.9*0.2/(0.1*0.8+0.9*0.2) = 0.69.
This can also be approximated using Monte Carlo sampling,
> S <- 100000
> theta <- rbinom(S, 1, 0.2)
> prob1 <- ifelse(theta==1,0.9,0.1)</pre>
          <- rbinom(S,1,prob1)
> Y
> table(theta,Y)
      Υ
theta
            0 1
```

```
0 72225 7933
1 1962 17880
> mean(theta[Y==1])
[1] 0.6926742
```

(4) Using the fact that f(x,y) = f(x|y)f(y) and f(x,y) = f(y|x)f(x), prove Bayes' Theorem.

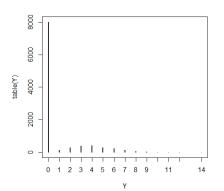
We set them equal giving f(x|y)f(y) = f(y|x)f(x), and divided by f(y) gives

f(x | y) = f(y | x)f(x)/f(y)

which proves Bayes' Theorem.

(5) If Y follows the zero-inflated Poisson (ZIP) distribution, it can be written in terms of two variables  $Y=U^*V$ , where U ~ Bernoulli(p) independent of V ~ Poisson(lambda). Here is an example with p=0.2 and lambda=4.

> U <- rbinom(10000,1,0.2)
> V <- rpois(10000,4)
> Y <- U\*V
> plot(table(Y))



```
> round(dpois(0:10,4),2) # might be helpful
[1] 0.02 0.07 0.15 0.20 0.20 0.16 0.10 0.06 0.03 0.01 0.01
```

(a) What is a real-life example of a variable that might follow this distribution? In your example, what are the interpretations of U and V?

Population of a species with a small ecological niche. U indicates that the location is conducive to the species and V is be the number of individuals in a location where the species is present.

(b) What is the probability that Y=0?

P(Y = 0) = P(U=0) + P(U=1)\*P(V=0) = 0.8 + 0.2\*0.02 = 0.804 (0.02 is from the R table above).

(c) What is the probability that Y=4?

P(Y=4) = P(U=1)\*P(V=4) = 0.2\*0.2 = 0.04.

(d) What is the probability that U=1 given Y=0?

Bayes rule says P(U=1|Y=0) = P(Y=0|U=1)\*P(U=1)/P(Y=0). We know P(Y=0|U=1) = P(V=0) = 0.02 and the prior for U is P(U=1) = 0.2. P(Y=0) is computed above to be 0.804. So P(U=1|Y=0) = 0.02\*0.20/0.804 = 0.005.

(e) What is the probability that U=1 given Y=4? If Y>0 then we know U=1, so P(U=1|Y=4) = 1.0.