Quarto

Exploration & Reference Document

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Preface (YAML Options) & Set-Up

- Default chunk options can be set under the execute section of the YAML header
 - Affects both r and python chunks!
- Under format we've also included an option df-print to specify default behavior for displaying data frames, using knitr::kable (YAML Data Frame options)
- Below I also load some packages in R and Python that are used in chunks throughout this document:

R Packages:

```
library(reticulate)
library(ggplot2)
library(magrittr)
library(palmerpenguins)
```

Python Modules

```
import seaborn as sns # violin plot, Example 3
import matplotlib.pyplot as plt # survival curves, Example 3
import numpy as np # used generally among python chunks
import pandas as pd # violin plot, Example 3
from matplotlib.ticker import ScalarFormatter
```

Misc. Quarto References

- General Quarto Reference Guide
- List of YAML document header options (PDF)
- Websites in Quarto
- RStudio
 - Can include both R and Python code via reticulate package
 - General formatting with R
 - Cell options & syntax (slightly different than normal RMD)
 - Figure generation, labelling/aliasing, calling (including multi plots)
 - Presentations (reveal.js and beamer included)
 - Advanced Writing Tips
 - * General & Technical Formatting
 - * Citations (useful to set-up Zotero, not yet completed)
- Jupyter/Python
 - I've not set-up/explored yet

Example 1 (LaTeX Writing and Equations)

Let us find the log-likelihood of a model of the form $logit(\pi_i) = \mathbf{x}_i^T \beta$, where $\pi_i = P(Y_i = 1)$ for $Y_i \sim Bernoulli(\pi_i)$. We know the likelihood function of our model:

$$L(\beta_0,\beta_1,|\mathbf{y}) = \prod_{i=1}^n \pi_i^{y_i} (1-\pi_i)^{1-y_i}$$

and the resulting log-likelihood, $\ell(\beta_0,\beta_1,|\mathbf{y})$ is:

$$\ell(\beta_0,\beta_1,|\mathbf{y}) = \sum_{i=1}^n y_i log(\pi_i) + (1-y_i) log(1-\pi_i)$$

Example 2 (Mingling Code)

Mingling Python & R

Installation

- Default/"smart" installation of miniconda using reticulate continued to fail, so I installed the miniconda package directly from GitHub (remotes::install_github("hafen/rminiconda"))
- Afterwards, used the package to install miniconda (rminiconda::install_miniconda())
- Python chunk/reticulate failed first try, but then worked second try thereafter
- Able to execute python in RStudio console by running reticulate::repl_python(), and return back to R passing exit

R

```
mean(c(0,2,3,4,6))
```

[1] 3

Python

```
np.mean([0,2,3,4,6])
```

3.0

Example 3 (Figures, ggplot, base R, seaborn, and matplotlib)

Galton-Watson Survival Curves

Base R

Note I've included only the code relevant to visualization. The code that generates the survival curves is contained in an Appendix at the end of the document.

```
legend_text <- c(expression(paste(lambda, "=0.9")),</pre>
                     expression(paste(lambda, "=1.0")),
                     expression(paste(lambda, "=1.05")),
3
                     expression(paste(lambda, "=1.1")))
   plot(109$Generation, 109$SurvProb, type="b", lty=4, col="red", lwd=2
         , x \lim = c(1, 500), y \lim = c(0, 0.7), \log = 'x'
         , xlab="Generation", ylab="Survival Probability of Infection/Process"
         , main = "Galton-Watson Survival Curves for Poisson Brancing\nWith Differing Rate Par
   lines(11$Generation, l1$SurvProb, type="b", col="green", lwd=2)
   lines(1105$Generation, 1105$SurvProb, type="b", col="skyblue", lwd=2)
   lines(l11$Generation, l11$SurvProb, type="b", col="blue", lwd=2)
   legend(x = 50, y=0.5,
          col = c("red", "green", "skyblue", "blue"),
14
          lty = rep(13, 4), pch=rep(1, 4),
15
          legend = legend_text)
16
```

Galton-Watson Survival Curves for Poisson Brancir With Differing Rate Parameters

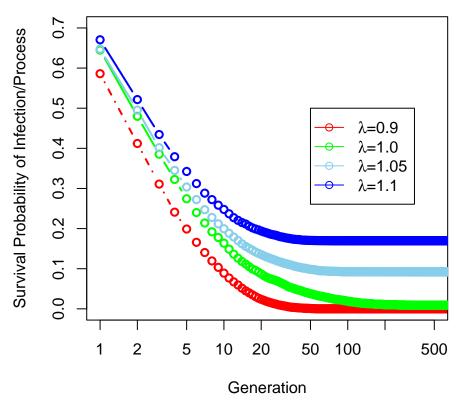


Figure 1: Galton-Watson Curve (Base R Plot)

matplotlib

We will inherit the R objects above and create the same plot using Python's matplotlib.

```
from matplotlib.ticker import ScalarFormatter
   gs_fig, gs_ax = plt.subplots()
   109plt = gs_ax.plot(r.109['Generation'], r.109['SurvProb'], '.-', color='red')
   l1plt = gs_ax.plot(r.l1['Generation'], r.l1['SurvProb'], '.-', color='green')
   1105plt = gs_ax.plot(r.1105['Generation'], r.1105['SurvProb'], '.-', color='lightblue')
   l11plt = gs_ax.plot(r.l11['Generation'], r.l11['SurvProb'], '.-', color='blue')
   axlabs = gs_ax.set(xscale='log', xlabel="Generation"
10
             , ylabel="Survival Probability"
11
             , title="Galton-Watson Survival Curves for Poisson Brancing\nWith Differing Rate
12
   leg = gs_ax.legend(['$\lambda$=0.9' , '$\lambda$=1' , '$\lambda$=1.05', '$\lambda$=1.1'])
14
15
   for axis in [gs_ax.xaxis, gs_ax.yaxis]:
16
       axlab = axis.set_major_formatter(ScalarFormatter())
17
18
   plt.show()
19
```

Galton-Watson Survival Curves for Poisson Brancing With Differing Rate Parameters

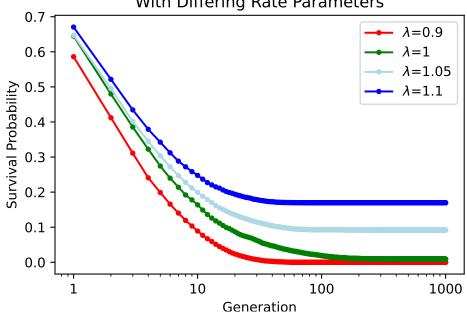


Figure 2: Galton-Watson Curve (Matplotlib Plot)

Violin Plots of Penguin Bill Length

ggplot

```
penguins %>%
ggplot(aes(x=island, y=bill_length_mm)) +
geom_violin() +
theme_minimal() +
xlab("Island") + ylab("Bill Length (mm)")
```

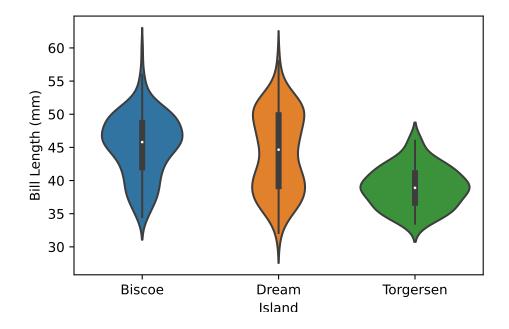


seaborn

The matplotlib code for a violin plot from a dataframe is especially ugly, so I have opted for seaborn for simplicity:

```
fig1_violin, ax1_violin = plt.subplots()
fig1_violin = sns.violinplot(x = 'island', y = 'bill_length_mm'

, data = r.penguins, ax = ax1_violin)
labs = ax1_violin.set(xlabel="Island", ylabel="Bill Length (mm)")
plt.show()
```



Example 4 (Tables)

Quarto has some wonderful point-and-click table insertion tools for Markdown tables in the Visual editor, that generates the corresponding Markdown syntax in the Source editor as well:

Table 1: GUI Generated Table (results are fabricated)

Model	Mean Bias	MSE
Left aligned	Centered	Right aligned
Logistic Regression	-0.235	1.23
Poisson Link	0.501	2.35
Firth Estimation	0.172	1.10

Below we simply call an R data frame (a preview of our penguins data set), that is displaying using knitr::kable() by default from our specified YAML options.

```
head(penguins[,c("species", "island", "bill_length_mm", "bill_depth_mm")])
```

species	island	bill_length_mm	bill_depth_mm
Adelie	Torgersen	39.1	18.7
Adelie	Torgersen	39.5	17.4
Adelie	Torgersen	40.3	18.0
Adelie	Torgersen	NA	NA
Adelie	Torgersen	36.7	19.3
Adelie	Torgersen	39.3	20.6

My knowledge of pretty Python tables is limited, but one can easily generate a table in Python and then call it from within an r chunk.

First we create the table in a chunk of Python code:

```
cases_df = pd.DataFrame({'Unit': [1, 2, 3], 'Cases_per_100k':np.random.poisson(64, 3)})
```

then call in an chunk of R code, which will again display as a kable:

```
py$cases_df
```

Unit	Cases_per_	_100k
1		46
2		66
3		60

Appendix (Survival Curve Code)

```
poisson_bp <- function(L, generations, sims){</pre>
      extinct_gen <- rep(NA, sims)</pre>
4
      for (sim in 1:sims){
        x_t \leftarrow 1 \text{ # assume one infection occurred}
        for (gen in 1:generations){
          (x_t <- sum(rpois(x_t, lambda=L)))</pre>
10
11
          if(x_t==0 & is.na(extinct_gen[sim])) extinct_gen[sim] <- gen</pre>
12
13
          if(x_t>100) {break} # escape if the population explodes, valid assumption?
        }
15
      }
16
17
      extinct_gen[is.na(extinct_gen)] <- Inf # no extinction occurred</pre>
18
19
20
      surv_prob <- c()</pre>
21
      for (i in 1:generations){
          surv_prob <- c(surv_prob, mean(extinct_gen>i))
      }
25
26
      output <- data.frame(Generation = 1:generations,</pre>
27
                              SurvProb = surv_prob)
^{28}
      return(output)
   }
32
33
```

```
nsim <- 10000
ngen <- 1000
ngen <- 1000

109 <- poisson_bp(0.9, generations = ngen, sims = nsim)
11 <- poisson_bp(1, generations = ngen, sims = nsim)
1105 <- poisson_bp(1.05, generations = ngen, sims = nsim)
111 <- poisson_bp(1.1, generations = ngen, sims = nsim)</pre>
```