STSB6816 Test 1 of 2023

Mathematical Statistics and Actuarial Science; University of the Free State

2023/04/20

## Time: 180 minutes; Marks: 50

# MEMORANDUM

# Instructions

* Answer all questions in a single R Markdown document. Please knit to PDF or Word at the end and submit both the PDF/Word document and the “.Rmd” file for assessment, in that order.
* Label questions clearly, as it is done on this question paper.
* All results accurate to about 3 decimal places.
* Show all derivations, formulas, code, sources, and reasoning.
* Intervals should cover 95% probability unless stated otherwise.
* No communication software, devices, or communication capable websites may be accessed prior to submission. You may not (nor even appear to) attempt to communicate or pass information to another student.

# Introduction

The data is provided at <https://ufs.blackboard.com>. **It consists of the flight times (in seconds) of paper air planes constructed and thrown by primary school learners.**

These times are assumed to follow a Gompertz distribution. You are encouraged to fit the Gompertz distribution to these times as part of this process, although other approaches will get partial credit.

The Gompertz distribution has density function

and survival function

In order to establish that you fit the distribution correctly, you are instructed first to generate a sample that you know is from a Gompertz distribution and apply your fitting approach to this simulated sample. The idea is that should you get the same parameters out that you put in, then your approach will have more credibility on the real data.

# Question 1

**1.1)** Derive the inverse survival function or inverse CDF (your choice). **[4]**

cat("$$\\begin{aligned}  
u &= \\exp\\left[-\\frac{\\alpha}{\\lambda}(\\exp(\\lambda t) - 1)\\right] \\\\  
\\log (u) &= -\\frac{\\alpha}{\\lambda}(\\exp(\\lambda t) - 1) \\\\  
1 - \\frac{\\lambda\\log (u)}{\\alpha} &= \\exp(\\lambda t) \\\\  
\\log\\left[1-\\log (u)\\lambda\\alpha^{-1}\\right]\\lambda^{-1} &= t  
\\end{aligned}$$")

NULL

**1.2)** Using the inverse survival function or inverse CDF (your choice), generate a sample of size 500 from a Gompertz(0.3, 0.1) distribution. **[4]**

[Using an established package to generate the sample instead of your own will earn 2 out of 4 marks; while using an established package in addition to your own and showing that they match within the simulation error will earn 5 out of 4 marks.]

library(tidyverse)

rGomp <- function(n = 1, lambda = 1, alpha = 1) {  
 log(1 - log(runif(n))\*lambda/alpha)/lambda  
}   
  
nsims <- 10000  
sims <- data.frame(Source = rep(c('Us', 'Them'), each = nsims),   
 Values = c(rGomp(nsims, lambda = 0.3, alpha = 0.1),   
 DescTools::rGompertz(nsims, shape = 0.3, rate = 0.1)))  
sims |> ggplot(aes(x = Values, colour = Source)) + geom\_density()



nsims <- 500  
x <- rGomp(nsims, lambda = 0.3, alpha = 0.1)

NULL

**1.3)** Fit a Gompertz distribution to the simulated times. Give parameter estimates, with uncertainty, for your fit (trace plots showing good convergence are highly recommended for simulation fits). **[11]**

Hint: As the Gompertz distribution is not one of the standard distributions in Stan, it is recommended that you add the following code to the start of your Stan model. This will allow you to sample from the Gompertz in the usual way (*i.e.* y[i] ~ Gompertz(lambda, alpha)). Alternatively, specify the full log posterior in Stan directly to the model using *target +=* and then Stan math functions. Stan’s math functions are similar to R’s math functions.

functions {  
 real Gompertz\_lpdf(real y, real lam, real a) {  
 return log(a) + lam\*y - (exp(lam\*y)-1)\*a/lam;  
 }  
}

library(rstan)  
mycores <- 3  
options(mc.cores = mycores)

// This Stan block defines a Gompertz model by Sean van der Merwe, UFS  
functions {  
 real Gompertz\_lpdf(real y, real lam, real a) {  
 return log(a) + lam\*y - (exp(lam\*y)-1)\*a/lam;  
 }  
}  
data {  
 int<lower=1> n; // number of observations  
 real<lower=0> y[n]; // observations  
}  
// The parameters of the model  
parameters {  
 real<lower=0> a; // alpha   
 real<lower=0> l; // lambda   
}  
model {  
 for (i in 1:n) {  
 y[i] ~ Gompertz(l, a);  
 }  
}

saveRDS(GompertzModel, file = 'GompertzModel.Rds')

ModelFitSims <- sampling(GompertzModel, list(n=length(x), y=x), iter = 10000, chains = mycores)

pars\_of\_interest <- c('l', 'a')  
ModelFitSims |> traceplot(pars = pars\_of\_interest)



summary(ModelFitSims, pars = pars\_of\_interest)$summary |> kable(digits = 3)

|  | mean | se\_mean | sd | 2.5% | 25% | 50% | 75% | 97.5% | n\_eff | Rhat |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| l | 0.292 | 0 | 0.020 | 0.251 | 0.279 | 0.292 | 0.306 | 0.332 | 3969.960 | 1.002 |
| a | 0.107 | 0 | 0.009 | 0.089 | 0.100 | 0.106 | 0.113 | 0.127 | 4037.109 | 1.001 |

NULL

**1.4)** For each parameter, report how many absolute standard deviations it is away from the known values used to simulate the sample. Comment on whether the values are reasonable. **[5]**

simssims <- rstan::extract(ModelFitSims)  
c(  
 lambda = abs(mean(simssims$l) - 0.3)/sd(simssims$l),  
 alpha = abs(mean(simssims$a) - 0.1)/sd(simssims$a)  
) |> round(4)

| lambda alpha   
| 0.3782 0.7115

NULL

**1.5)** Import the data set into R and explore it visually. You could use a histogram or density plot and discuss what you see. **[4]**

"STSB6816Test1Data2023.xlsx" |> openxlsx::read.xlsx("TestData") -> d

par(mar=c(5,5,1,1))  
d$Time |> hist(col = 'purple', main = '', xlab = 'Time')



NULL

**1.6)** Fit a Gompertz distribution to the observed times. Give parameter estimates, with uncertainty, for your fit. **[6]**

ModelFitData <- sampling(GompertzModel, list(n=nrow(d), y=d$Time), iter = 10000, chains = mycores)

ModelFitData |> traceplot(pars = pars\_of\_interest)



summary(ModelFitData, pars = pars\_of\_interest)$summary |> kable(digits = 3)

|  | mean | se\_mean | sd | 2.5% | 25% | 50% | 75% | 97.5% | n\_eff | Rhat |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| l | 0.157 | 0.001 | 0.036 | 0.086 | 0.134 | 0.158 | 0.182 | 0.225 | 4166.966 | 1.001 |
| a | 0.169 | 0.000 | 0.029 | 0.117 | 0.149 | 0.167 | 0.188 | 0.232 | 4077.547 | 1.001 |

NULL

**1.7)** Draw a quantile-quantile plot showing the quantiles of the observed data against the quantiles of the posterior predictive distribution of the next random throw. Comment on the quality of the fit, both the discrepancies and possible sources of discrepancies. **[7]**

datasims <- rstan::extract(ModelFitData)  
preds <- rGomp(length(datasims$l), datasims$l, datasims$a)  
qseq <- seq(0.01, 0.99, 0.02)  
plot(quantile(preds, qseq), quantile(d$Time, qseq),   
 main='Posterior Predictive QQ Plot',   
 xlab = 'Predicted Quantiles', ylab = 'Observed Quantiles',  
 col = 'darkred')  
lines(c(0,13), c(0,13), col = 'purple')



NULL

**1.8)** Consider 10 random future throws. What is the probability that the one that flies the furthest stays in the air for more than 8 seconds? **[5]**

Hint: You must predict sets of 10 throws, then check whether the longest flight time of the 10 is longer than 8 seconds. You must do this at least 1000 times and average the results to get a probability estimate.

longest <- preds |> matrix(10) |> apply(2, max)  
mean(longest > 8)

| [1] 0.5133333

NULL

**1.9)** Is your probability above sensible based on the observed data? First give an instinctive answer then calculate a bootstrap/resampling estimate using the data alone and compare. **[4]**

longest <- replicate(2000, {d$Time |> sample(10, replace = TRUE) |> max()})  
mean(longest > 8)

| [1] 0.401

NULL

## Points total

The points on the test add up to **50**