R Code Sample

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October 20, 2018

Frivolities

How many Magic booster packs would I have to buy to collect the entire set? That is a coupon collectors problem with a pretty simple approximation:

$$E[n] = n \log n + \gamma n + \frac{1}{2}$$

where n is the number of items in the entire collection.

```
coupon <- function(n) {
  gamma <- 0.5772156649
  return(n*log(n) + gamma*n + 1/2)
}

ceiling(coupon(280)/10)
```

```
## [1] 174
```

Thats interesting. I would have to buy 174 ten card booster packs. Those are roughly $7 a piece. $1218?!

Important stuff

How many trials do I need to repeat in order to find one false positive?

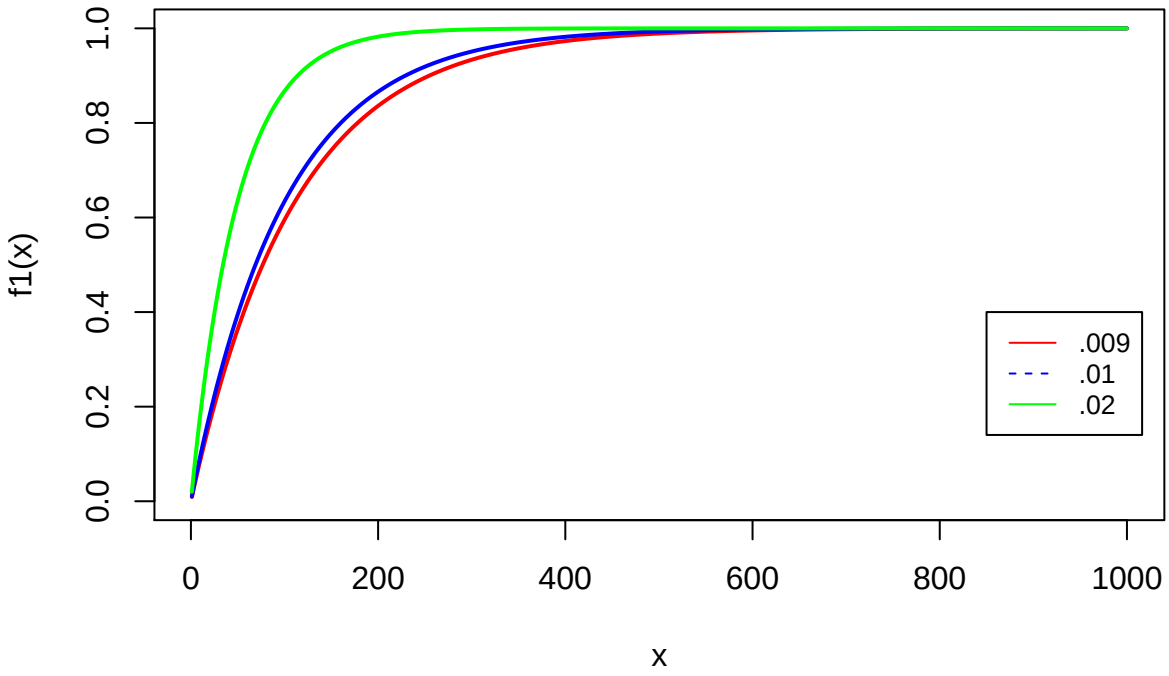
$$P(error) = e$$

$$P(noerror) = 1 - e$$

$$P(AtLeast1Error) = 1 - (1 - e)^m$$

I'll write a closure so it returns a function where we can tune the error-rate.

```
p.test <- function(e) {
  function(m) {
    1 - (1-e)^m
  }
}

f1 <- p.test(.009)
f2 <- p.test(.01)
f3 <- p.test(.02)

x <- seq(1,1000)

plot(x,f1(x),col='red', type='l', lwd='2', ylim=c(0,1))
lines(x, f2(x), col='blue', type='l', lwd='2')
lines(x, f3(x), col='green', type='l', lwd='2')
legend(850,0.4, legend=c('.009','.01','.02'),col=c('red','blue','green'), lty=1:2, cex=0.8)
```



The lower the error rate the longer it takes. That makes sense.

```
which(f1(x) >= .99)[1]
```

```
## [1] 510
```

```
which(f2(x) >= .99)[1]
```

```
## [1] 459
```

```
which(f3(x) >= .99)[1]
```

```
## [1] 228
```

For the respective error rates, .009, .01, .02, we should expect (I'm rounding up here) 510, 459, and 228 patients before our first error occurs.

R does not have a multivariate normal in the standard library. That makes sense because its super simple to implement without too much fuss.

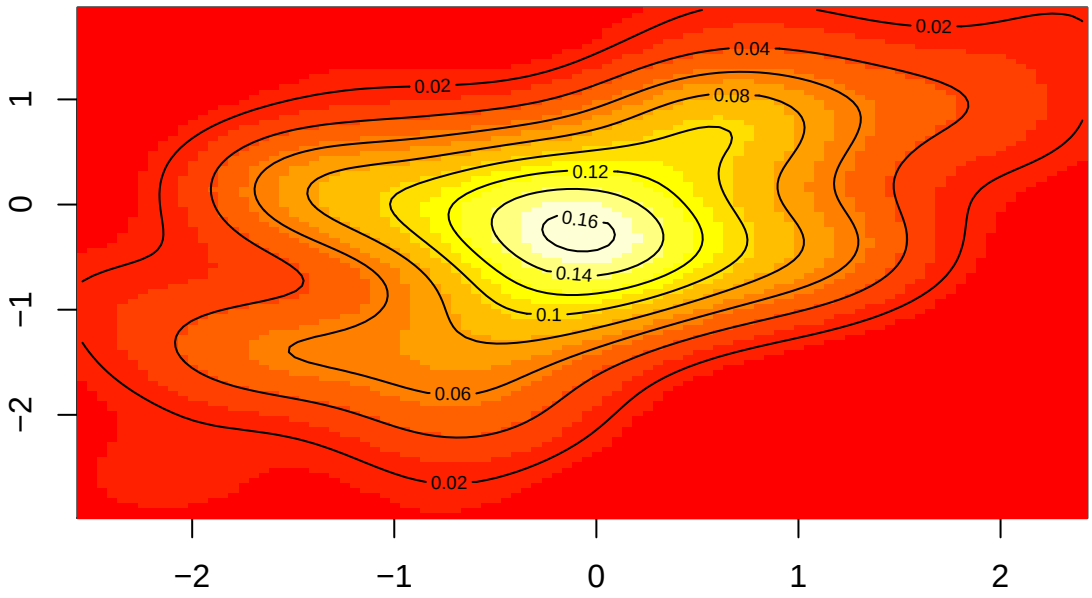
I'll do it here.

```
mnorm <- function(mu, sigma)
{
  function(n) {
    mu1 <- mu[1]

    mu2 <- mu[2]

    sigma1 <- Sigma[1,1]
```

```
    sigma2 <- Sigma[2,2]

    C <- Sigma[1,2]

    rho <- C/(sigma1*sigma2)

    Z.1 <- rnorm(n)

    Z.2 <- rnorm(n)

    X1 <- sigma1*Z.1 + mu1

    X2 <- rho*sigma2*Z.1 + sigma2*sqrt(1-rho^2)*Z.2 + mu2

    return(cbind(X1,X2))
  }
}
```

Again, this is a closure. I setup the function with a given mean and standard deviation/correlation matrix. Then we get a function back and tell it how many random variates we want. The result is returned as a two column matrix.

```
library(MASS)

mu = c(0,0)

Sigma = matrix(c(1,.5,.5,1),2)

my.mvnorm <- mnorm(mu,Sigma)

Z <- my.mvnorm(100)

den <- kde2d(x=Z[,1],y=Z[,2], n=100)

image(den)

contour(den, add=TRUE)
```



That looks pretty good.

Survival Times

As per our discussion what follows is a demonstration of my coding and presentation skills using R. I decided to execute some simple analysis of breast cancer patients. The data contains cases from a study conducted between 1958 and 1970 at the University of Chicago's Billings Hospital on the survival of patients who had undergone surgery for breast cancer.

```
df <- read.csv('haberman.data', col.names = c('age', 'operation', 'nodes', 'status'))

head(df)
```

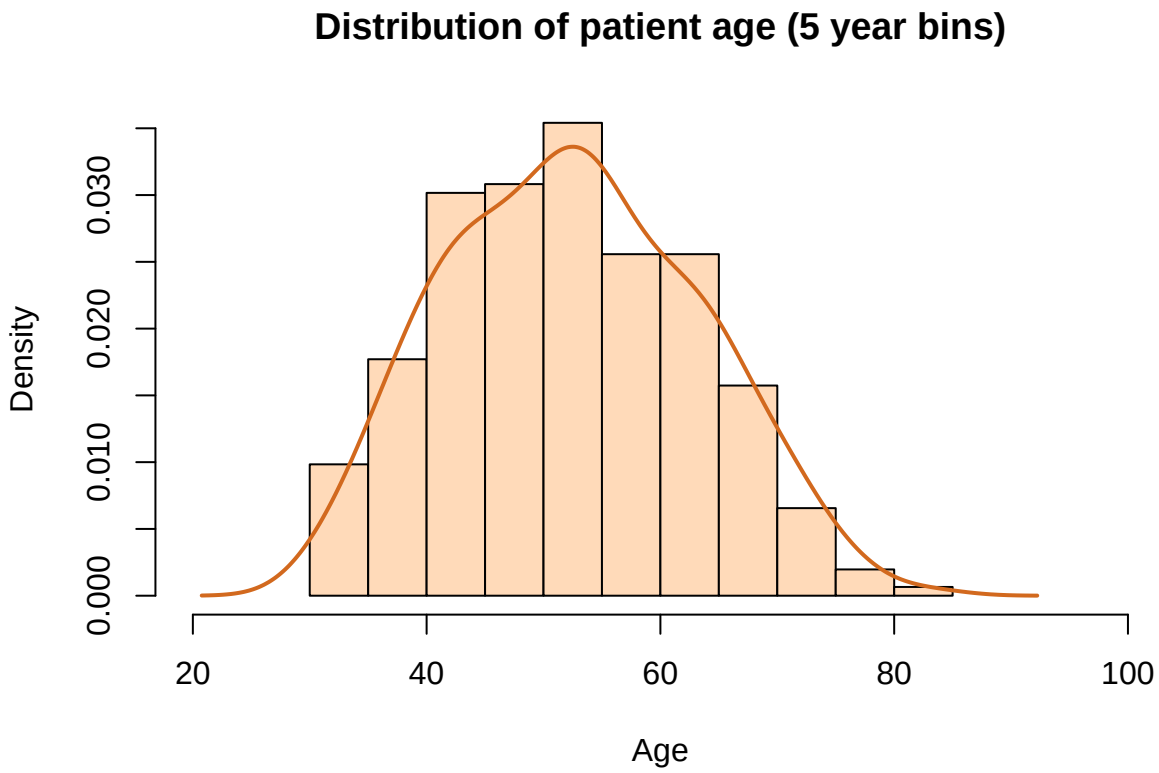
```
##   age operation nodes status
## 1  30        62     3      1
## 2  30        65     0      1
## 3  31        59     2      1
## 4  31        65     4      1
## 5  33        58    10      1
## 6  33        60     0      1
```

Columns are labeled age, year of operation, the number of nodes (cancerous/benign) and whether or not the patient survived for up to 5 years following surgery. If the patient passed then the label changes to 2. The study contains 306 patients from various age groups ranging from 20 to 80.

Lets take a quick look at the distribution of ages in our population.

```
hist(df$age,
     main = 'Distribution of patient age (5 year bins)',
```

```
     prob = TRUE,
     xlim=c(20,100),
     xlab = 'Age',
     col='peachpuff')

lines(density(df$age),
      col='chocolate',
      lwd=2)
```



Lets fit a proportional hazard model and see what the hazard rate looks like across a couple covariates.

```
my.coxph <- coxph(Surv(age, status) ~ operation + nodes, data=df)

summary(my.coxph)
```

```
## Call:
## coxph(formula = Surv(age, status) ~ operation + nodes, data = df)
##
##   n= 305, number of events= 81
##
##               coef exp(coef) se(coef)      z Pr(>|z|)
## operation -0.02801   0.97238  0.03474 -0.806     0.42
## nodes      0.05517   1.05672  0.01009  5.469 4.52e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##           exp(coef) exp(-coef) lower .95 upper .95
```

```
## operation    0.9724     1.0284    0.9084     1.041
## nodes        1.0567     0.9463    1.0360     1.078
##
## Concordance= 0.631  (se = 0.037 )
## Rsquare= 0.069   (max possible= 0.917 )
## Likelihood ratio test= 21.81  on 2 df,   p=1.833e-05
## Wald test            = 30.08  on 2 df,   p=2.932e-07
## Score (logrank) test = 32.88  on 2 df,   p=7.237e-08
```

```
exp(coef(my.coxph))
```

```
## operation     nodes
## 0.9723756 1.0567217
```

Patients with a higher number of nodes increased their hazard rate by 1.05. This means for every one unit increase in the count of nodes causes a multiple of 1.05 of hazard rate, or simply a 5% increase. Operations, however, decrease the hazard rate by 0.97 times. But, I wonder; what does that really mean? Does that mean that each year surgery is improving positive outcomes? I'm not certain. Further, the p-value seems to indicate the coefficient is insignificant. Lets see what the model says without the operations column.

```
my.coxph <- coxph(Surv(age, status) ~ nodes, data=df)

summary(my.coxph)
```

```
## Call:
## coxph(formula = Surv(age, status) ~ nodes, data = df)
##
##   n= 305, number of events= 81
##
##          coef exp(coef) se(coef)     z Pr(>|z|)
## nodes 0.05462   1.05614  0.01005 5.437 5.42e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##       exp(coef) exp(-coef) lower .95 upper .95
## nodes     1.056     0.9468     1.036     1.077
##
## Concordance= 0.657  (se = 0.035 )
## Rsquare= 0.067   (max possible= 0.917 )
## Likelihood ratio test= 21.16  on 1 df,   p=4.217e-06
## Wald test            = 29.56  on 1 df,   p=5.424e-08
## Score (logrank) test = 32.35  on 1 df,   p=1.288e-08
```

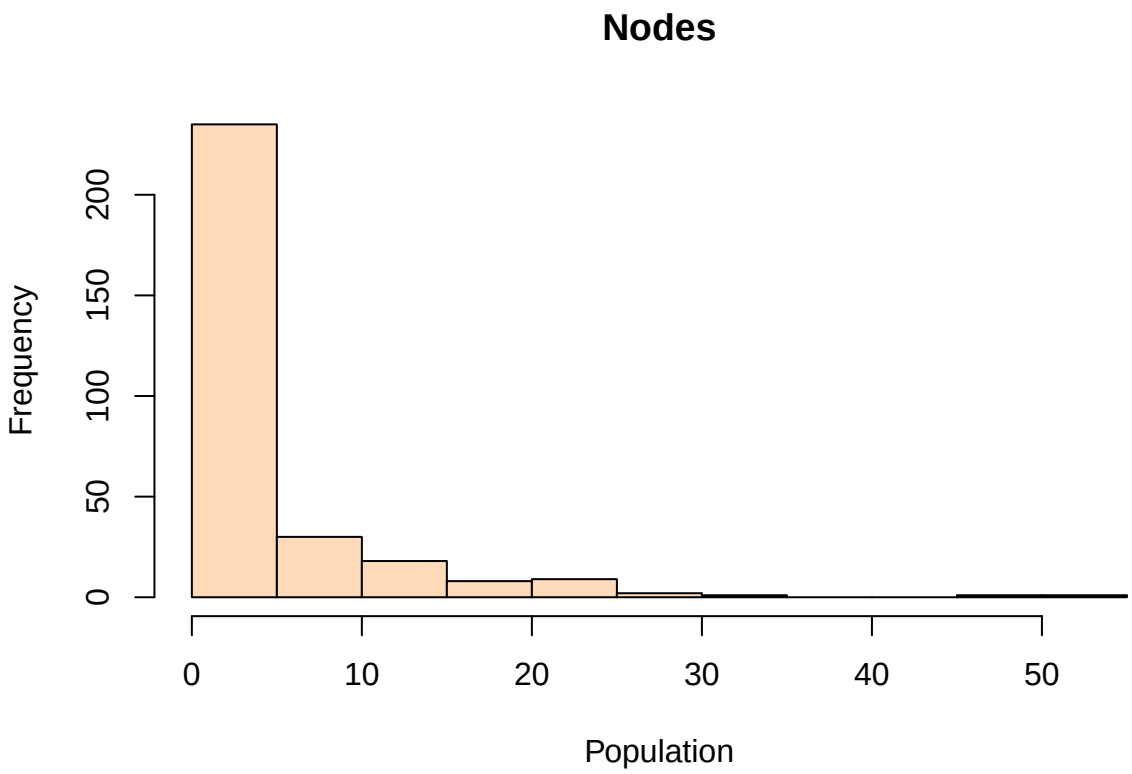
```
exp(coef(my.coxph))
```

```
##    nodes
## 1.056141
```

The goodness of fit tests remain by and large the same as does the concordance. This leads me to believe that the model may be used without the surgery column to no real negative effect. I'll omit operations further for clarity.

Here is the distribution of nodes.

```
hist(df$nodes, col='peachpuff', xlab = 'Population', main='Nodes')
```



The majority of the mass is placed around 0-5 nodes with a long tail. There appear to be a few outliers with high node counts.

I'm curious what an accelerated failure time model looks like.

```
my.surv <- survreg(Surv(age, status) ~ nodes, data=df, dist='loglog')

summary(my.surv)
```

```
##
## Call:
## survreg(formula = Surv(age, status) ~ nodes, data = df, dist = "loglog")
##               Value Std. Error      z         p
## (Intercept)  4.2575    0.02754 154.58  0.00e+00
## nodes       -0.0103    0.00226  -4.54  5.63e-06
## Log(scale)  -1.9721    0.08588 -22.96 1.09e-116
##
## Scale= 0.139
##
## Log logistic distribution
## Loglik(model)= -394.9   Loglik(intercept only)= -405.2
##  Chisq= 20.61 on 1 degrees of freedom, p= 5.6e-06
## Number of Newton-Raphson Iterations: 4
## n= 305
```

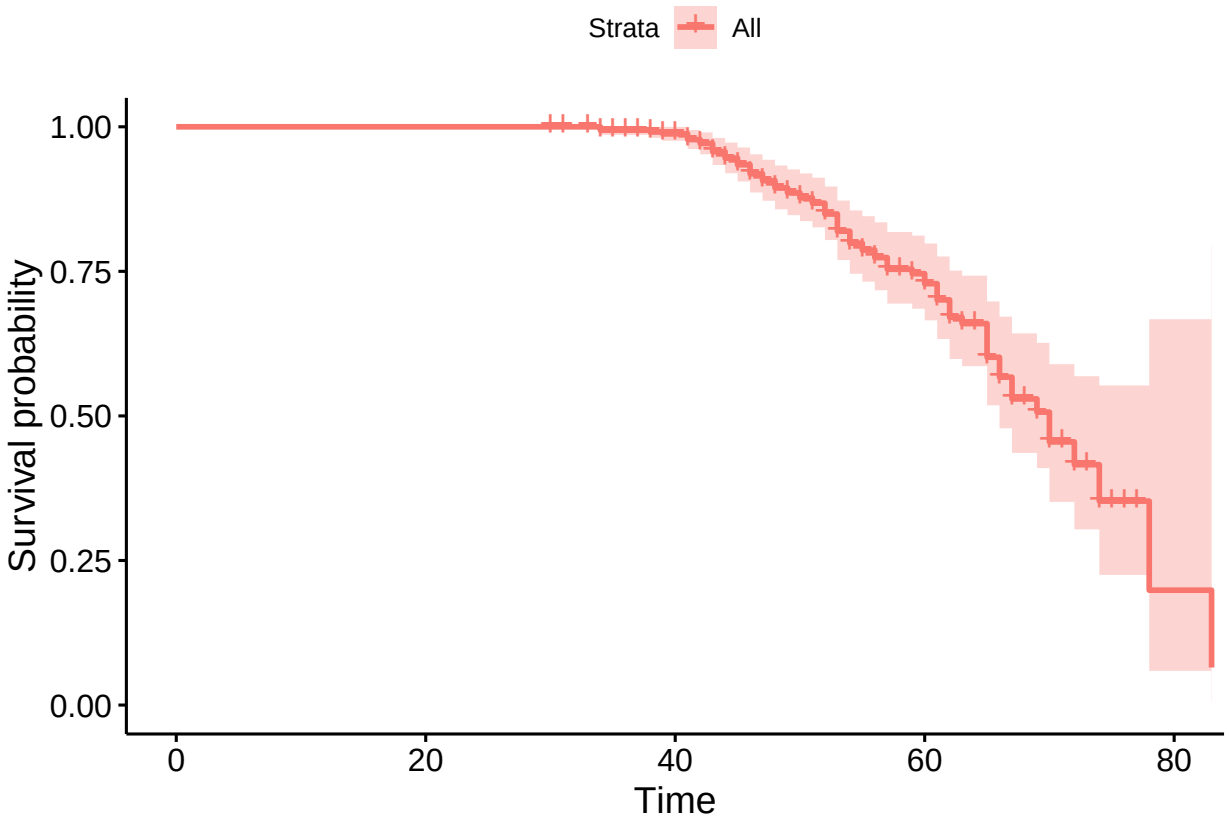
```
exp(coef(my.surv))
```

```
## (Intercept)       nodes
##  70.6342824   0.9897753
```

Nodes cause an increase in failure rate. This is consistent. The rate causes a shortening of survival times by 0.98.

Lets take a look at the survival plot.

```
ggsurvplot(survfit(my.coxph), data=df)
```



The crosses represent an event and the colored band is the confidence. As the size of the population drops due to fewer members of a particular age group the confidence interval widens. At about the age of 40 is when survivability begins to drop.

Conclusion

I have presented several methods of survival analysis as well as several frivolities which are of interest but no real consequence. Thank you for your time and I look forward to the chance to work with UCSF further.

References

Dua, D. and Karra Taniskidou, E. (2017). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.

Data.gov. (2018). Accidents. Version 1. [Coal Miner Accidents]. Location: https://catalog.data.gov/dataset/accident-injuries/resource/37ce36bb-b38c-480f-893f-ca33fa5589d9. Department of Labor.