Bayessian Regression Model

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```
###Objective
##To predict how much icecream should be kept as stock on a hot day at 35
degree centigrade, such that the probability of run out of icecream is 2.5%

#Data considered for analyses
temp   <-   c(11.9,14.2,15.2,16.4,17.2,18.1,18.5,19.4,22.1,22.6,23.4,25.1)
units   <-   c(185L,215L,332L,325L,408L,421L,406L,412L,522L,445L,544L,614L)
log_units <- log(units)
n <- length(units)
market.size <- rep(800, n)
df <- data.frame(temp,units,log_units,market.size)

# Using brms package to derive 97.5% prediction credible
interval library(brms)

## Warning: package 'brms' was built under R version 3.4.3

## Loading required package: Rcpp

## Loading required package: ggplot2

## Warning: package 'ggplot2' was built under R version 3.4.3

## Loading 'brms' package (version 2.1.0). Useful instructions
## can be found by typing help('brms'). A more detailed introduction
## to the package is available through vignette('brms_overview').
## Run theme_set(theme_default()) to use the default bayesplot theme.

library(rstan)

## Warning: package 'rstan' was built under R version 3.4.3

## Loading required package: StanHeaders

## Warning: package 'StanHeaders' was built under R version 3.4.3

## rstan (Version 2.17.3, GitRev: 2e1f913d3ca3)

## For  execution  on  a  local,  multicore  CPU  with  excess  RAM  we
recommend calling
## options(mc.cores = parallel::detectCores()).
## To avoid recompilation of unchanged Stan programs, we recommend calling
## rstan_options(auto_write = TRUE)
```

```r
# Linear Gaussian model
lin.mod <- brm(units ~ temp,data = df, family="gaussian")
```

```
## Compiling the C++ model

## Start sampling

##
## SAMPLING FOR MODEL 'gaussian brms-model' NOW (CHAIN 1).
##
## Gradient evaluation took 0.001 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
10 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.222 seconds (Warm-up)
 ##               0.117 seconds (Sampling)
 ##               0.339 seconds (Total)
 ##
 ##
## SAMPLING FOR MODEL 'gaussian brms-model' NOW (CHAIN 2).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
```

```
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.272 seconds (Warm-up)
 ##                0.097 seconds (Sampling)
 ##                0.369 seconds (Total)
 ##
 ##
## SAMPLING FOR MODEL 'gaussian brms-model' NOW (CHAIN 3).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.2 seconds (Warm-up)
 ##                0.082 seconds (Sampling)
 ##                0.282 seconds (Total)
 ##
 ##
## SAMPLING FOR MODEL 'gaussian brms-model' NOW (CHAIN 4).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
```

```
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
```

```
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.186 seconds (Warm-up)
 ##                0.111 seconds (Sampling)
 ##                0.297 seconds (Total)
```

```
# Log-transformed Linear Gaussian model
log.lin.mod <- brm(log_units ~ temp, data = df,family="gaussian")
```

```
## Compiling the C++ model
## Start sampling

##
## SAMPLING FOR MODEL 'gaussian brms-model' NOW (CHAIN 1).
##
## Gradient evaluation took 0.001 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
10 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.139 seconds (Warm-up)
 ##                0.114 seconds (Sampling)
 ##                0.253 seconds (Total)
 ##
 ##
## SAMPLING FOR MODEL 'gaussian brms-model' NOW (CHAIN 2).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
```

```
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.133 seconds (Warm-up)
##                0.126 seconds (Sampling)
##                0.259 seconds (Total)
##
##
## SAMPLING FOR MODEL 'gaussian brms-model' NOW (CHAIN 3).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.129 seconds (Warm-up)
##                0.141 seconds (Sampling)
##                0.27 seconds (Total)
##
##
## SAMPLING FOR MODEL 'gaussian brms-model' NOW (CHAIN 4).
##
## Gradient evaluation took 0 seconds
```

```
## 1000 transitions using 10 leapfrog steps per transition would take 0
```

```
seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.194 seconds (Warm-up)
##                0.158 seconds (Sampling)
##                0.352 seconds (Total)
```

```
# Poisson model
pois.mod <- brm(units ~ temp,data = df, family="poisson")
```

```
## Compiling the C++ model
## Start sampling
```

```
##
## SAMPLING FOR MODEL 'poisson brms-model' NOW (CHAIN 1).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.064 seconds (Warm-up)
```

```
##                0.057 seconds (Sampling)
##                0.121 seconds (Total)
##
##
## SAMPLING FOR MODEL 'poisson brms-model' NOW (CHAIN 2).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.054 seconds (Warm-up)
##                0.057 seconds (Sampling)
##                0.111 seconds (Total)
##
##
## SAMPLING FOR MODEL 'poisson brms-model' NOW (CHAIN 3).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
```

```
## Iteration: 2000 / 2000 [100%] (Sampling)
```

```
##
##  Elapsed Time: 0.065 seconds (Warm-up)
##                0.059 seconds (Sampling)
##                0.124 seconds (Total)
##
##
## SAMPLING FOR MODEL 'poisson brms-model' NOW (CHAIN 4).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.053 seconds (Warm-up)
##                0.052 seconds (Sampling)
##                0.105 seconds (Total)
```

```
# Binomial model
bin.mod <- brm(units | trials(market.size) ~ temp,data = df,
family="binomial")
```

```
## Compiling the C++ model
## Start sampling
```

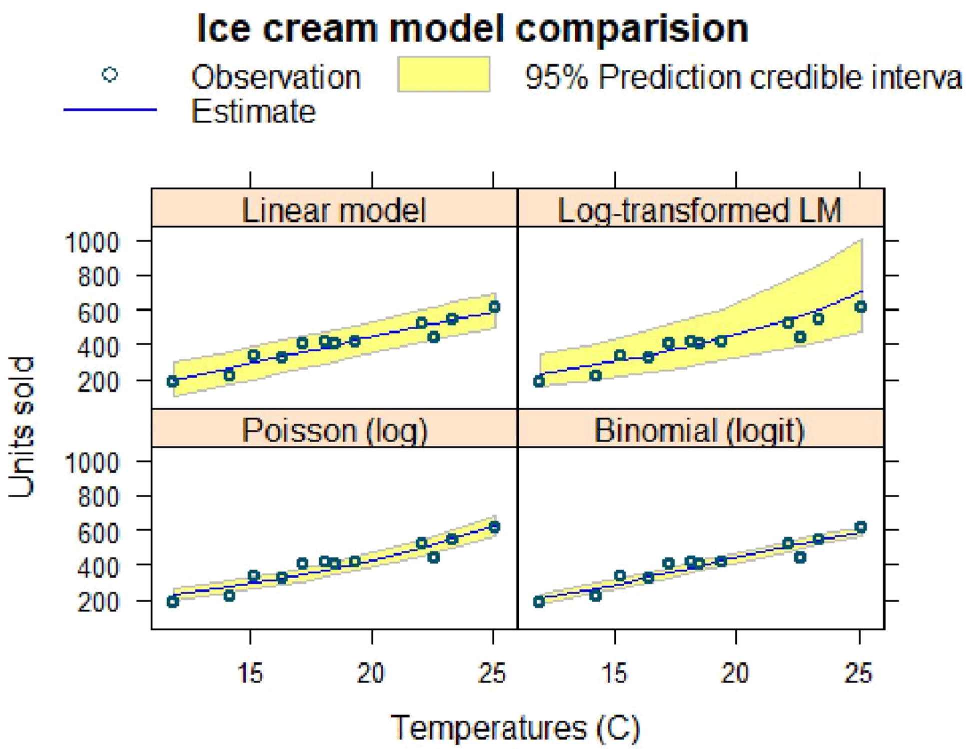
```
##
## SAMPLING FOR MODEL 'binomial brms-model' NOW (CHAIN 1).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
```

```
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.107 seconds (Warm-up)
##                0.154 seconds (Sampling)
##                0.261 seconds (Total)
##
##
## SAMPLING FOR MODEL 'binomial brms-model' NOW (CHAIN 2).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.143 seconds (Warm-up)
##                0.124 seconds (Sampling)
##                0.267 seconds (Total)
##
##
## SAMPLING FOR MODEL 'binomial brms-model' NOW (CHAIN 3).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
##
##
```

```
## Iteration:    1 / 2000 [  0%]  (Warmup)
```

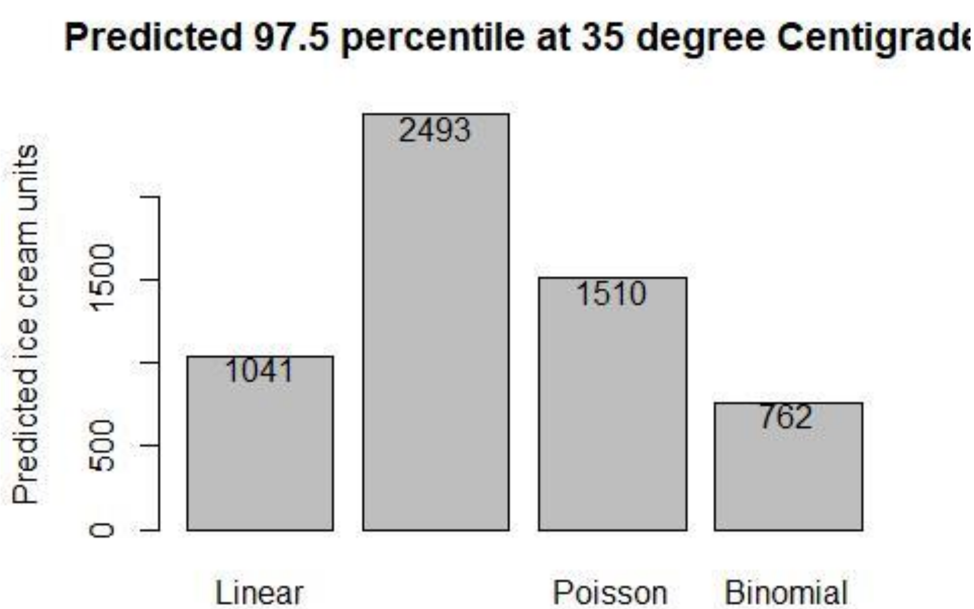
```
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.103 seconds (Warm-up)
##                0.142 seconds (Sampling)
##                0.245 seconds (Total)
##
##
## SAMPLING FOR MODEL 'binomial brms-model' NOW (CHAIN 4).
##
## Gradient evaluation took 0 seconds
## 1000 transitions using 10 leapfrog steps per transition would take
0 seconds.
## Adjust your expectations accordingly!
##
##
## Iteration:    1 / 2000 [  0%]  (Warmup)
## Iteration:  200 / 2000 [ 10%]  (Warmup)
## Iteration:  400 / 2000 [ 20%]  (Warmup)
## Iteration:  600 / 2000 [ 30%]  (Warmup)
## Iteration:  800 / 2000 [ 40%]  (Warmup)
## Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Iteration: 2000 / 2000 [100%]  (Sampling)
##
##  Elapsed Time: 0.156 seconds (Warm-up)
##                0.137 seconds (Sampling)
##                0.293 seconds (Total)

##Prediction Credible interval

modelData <- data.frame(
  Model=factor(c(rep("Linear model", 12), rep("Log-transformed LM",
12),rep("Poisson (log)",12),rep("Binomial (logit)",12)),levels=c("Linear
model","Log-transformed LM","Poisson (log)","Binomial (logit)"), ordered =
TRUE), Temperature=rep(temp, 4),Units_sold=rep(units,4),
rbind(predict(lin.mod),exp(predict(log.lin.mod) + 0.5 *
```

```r
mean(extract(log.lin.mod$fit)[["sigma"]])),predict(pois.mod),predict(bin.mod)
))

#The predict function gives access to posterior predctive statistics,
including the 97.5% prediction credible interval.Here going to combine
the output of the models into dataframe to compare the prediction
credible intervals of the four models in one chart.

library(lattice)
# Plot the data
key <- list(
  rep=FALSE, lines=list(col=c("#00526D", "blue"), type=c("p","l"), pch=1),
  text=list(lab=c("Observation","Estimate")),rectangles =
list(col=adjustcolor("yellow", alpha.f=0.5),
border="grey"),text=list(lab="95% Prediction credible interval"))
xyplot(X2.5.ile + X97.5.ile + Estimate + Units_sold ~ Temperature | Model,
       data=modelData, as.table=TRUE, main="Ice cream model
       comparision", xlab="Temperatures (C)", ylab="Units sold",
       scales=list(alternating=1), key=key,
       panel=function(x,
         y){ n <- length(x)
         k <- n/2
         upper <- y[(k/2+1):k]
         lower <- y[1:(k/2)]
         x <- x[1:(k/2)]
         panel.polygon(c(x, rev(x)), c(upper, rev(lower)),
         col = adjustcolor("yellow", alpha.f = 0.5),
         border = "grey")
         panel.lines(x, y[(k+1):(k+n/4)], col="blue")
         panel.points(x, y[(n*3/4+1):n], lwd=2, col="#00526D")
       })
```




```
#The plot displays the posterior prediction credible intervals for the four
models and it indicates over prediction of the log-transformed linear model.

## Stock to be maintained on a hot
day A <- function(samples){
  as.matrix(samples[,c("b_Intercept" ,"b_temp")])
}
x <- c(1, 35)
prob <- 0.975

#Linear model
lin.samples <- posterior_samples(lin.mod)
n <- nrow(lin.samples)
mu <- A(lin.samples) %*% x
sigma <- lin.samples[,"sigma"]
(lin.q <- quantile(rnorm(n, mu, sigma), prob))

##    97.5%
## 1040.875

#Log-transformed model
log.lin.samples <- posterior_samples(log.lin.mod)
mu <- A(log.lin.samples) %*% x
sigma <- log.lin.samples[,"sigma"]
(log.lin.q <- quantile(exp(rnorm(n, mu +  0.5*sigma^2, sigma)), prob))
```

```
##   97.5%
## 2493.38

#Poisson model
pois.samples <- posterior_samples(pois.mod)
mu <- exp(A(pois.samples) %*% x)
(pois.q <- quantile(rpois(n, mu) , prob))

##    97.5%
## 1510.025

#Binomial model
bin.samples   <-   posterior_samples(bin.mod)
inv.logit  <-  function(u)  exp(u)/(1+exp(u))
mu <- inv.logit( A(bin.samples) %*% x)
(bin.q <- quantile(rbinom(n, size = 800, mu), prob))

## 97.5%
##   762

percentiles <- c(lin.q, log.lin.q, pois.q, bin.q)

#Barplot the models with the predicted icecream units
plot_bar <- barplot(percentiles, names.arg = c("Linear", "Log-transformed",
"Poisson", "Binomial"),ylab="Predicted ice cream units", main="Predicted 97.5
percentile at 35 degree Centigrade")
text(plot_bar, percentiles-75, round(percentiles))
```



```
#The above plot displays the models and their predicted ice cream units.The
value ranges from 762 to 2506.Since the market size was set to 800, the
binomial model has a prediction of 762 units.The log normal distribution is
skewed to the right , hence has a prediction of 2506 units.The Poisson
model is similar to the log-transform linear model having an exponential
growth assumption.

##Conclusion
#It is strongly believed that if the assumption of market size is 800,
then binomial model should be considered.
```