

rstanarm - Exercise 4

Bayesian Inference - Lab Sessions

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Exercise 4: Poisson Regression

Poisson regression model in a dose-response study.

- A dataset about the mutagenicity on salmonella is available.
- Three plates ($j = 1, 2, 3$) are processed at each dose (x_i ; $i = 1, \dots, 6$) of quinoline (liquid organic compound) and the number of revertant colonies of Salmonella were counted y_{ij} .

Exercise: compare a simple Poisson regression model and a Poisson model with random effects in terms of goodness of fit. Suppose that we want to study the effect of quinoline both at the measurement scale and at a logarithmic scale of the type $\log(\text{quinoline} + 10)$. Start from a $\mathcal{N}(0, 10)$ prior for the β parameters and define a $\mathcal{N}(0, c)$ weakly informative prior.

Remarks:

- The Poisson model with random effects is usually assumed in order to take into account the eventual presence of overdispersion or underdispersion.
- The Poisson distribution has only one parameter ($\mathbb{E}[Y] = \mathbb{V}[Y] = \lambda$), and in fact the variance increases with the mean.

Simple Poisson Model

→ First, a simple **Poisson regression model** is considered.

Its Bayesian formulation is:

$$\begin{aligned}y_i | \mu_i &\sim \text{Poisson}(\mu_i) \\ \log(\mu_i) | \boldsymbol{\beta} &= \beta_0 + \beta_1 \log(x_i + 10) + \beta_2 x_i \\ &= \beta_0 + \beta_1 \log(\text{quinoline}_i + 10) + \beta_2 \text{quinoline}_i \\ &= \beta_0 + \beta_1 \log_quinoline_i + \beta_2 \text{quinoline}_i, \quad i = 1, \dots, n. \\ \beta_k &\sim \mathcal{N}(0, c), \quad k = 0, 1, 2;\end{aligned}$$

```
data4 <- read.csv("Data_Ex_4.csv")

mod_ex4a <- stan_glm(formula =
  colonies~quinoline+log_quinoline,
  data = data4,
  family = "poisson",
  prior = normal(0,10, autoscale=T),
  prior_intercept = normal(0,10, autoscale=T))

prior_summary(mod_ex4a)
```

```
-----
Intercept (after predictors centered)
~ normal(location = 0, scale = 10)

Coefficients
Specified prior:
~ normal(location = [0,0], scale = [10,10])
Adjusted prior:
~ normal(location = [0,0], scale = [0.027,6.091])
-----
```

```
summary(mod_ex4a)
```

```
MCMC diagnostics
```

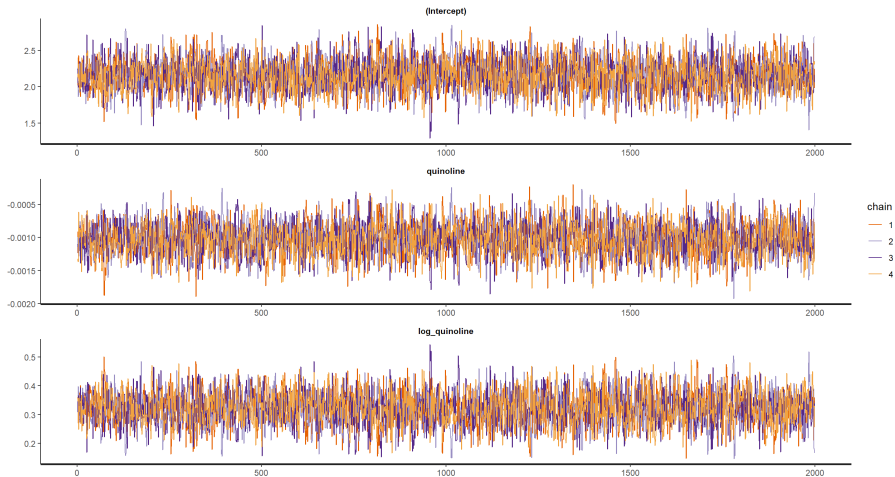
	mcse	Rhat	n_eff
(Intercept)	0.0	1.0	1711
quinoline	0.0	1.0	1669
log_quinoline	0.0	1.0	1629
mean_PPD	0.0	1.0	2750
log-posterior	0.0	1.0	1713

```
mod_ex4a<-update(mod_ex4a, iter=4000)  
summary(mod_ex4a)
```

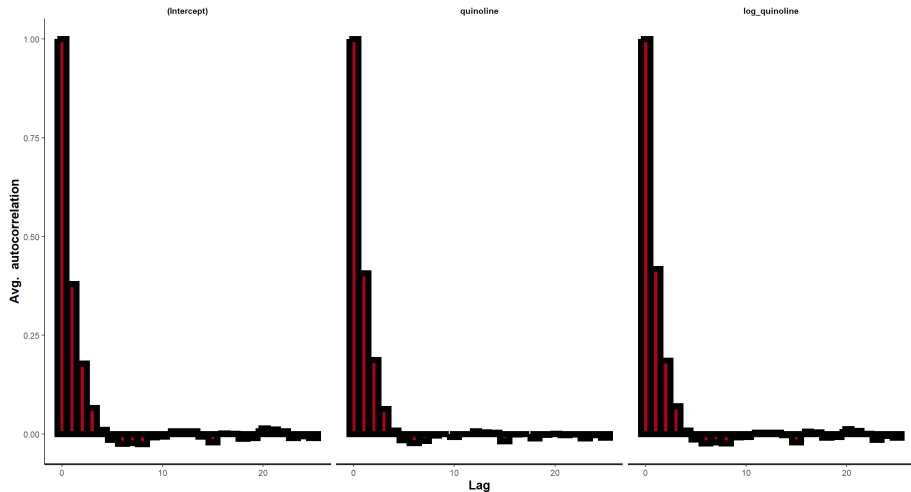
```
MCMC diagnostics
```

	mcse	Rhat	n_eff
(Intercept)	0.0	1.0	3545
quinoline	0.0	1.0	3442
log_quinoline	0.0	1.0	3395
mean_PPD	0.0	1.0	5403
log-posterior	0.0	1.0	3085

```
stan_trace(mod_ex4a, nrow=3, ncol=1)
```



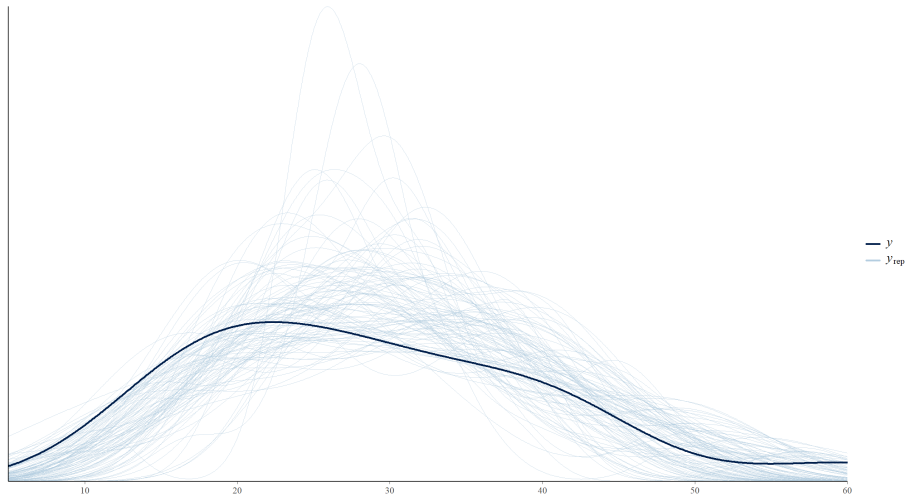
```
stan_ac(mod_ex4a)
```



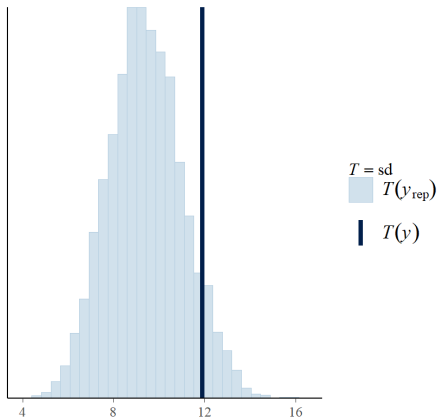
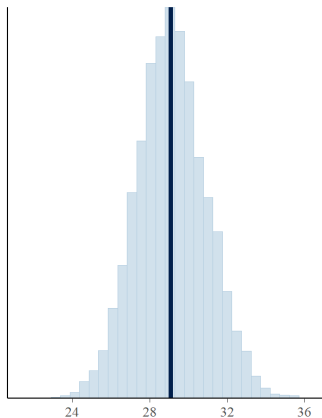
```
# Posterior checks
```

```
y_tilde4a <- posterior_predict(mod_ex4a)
```

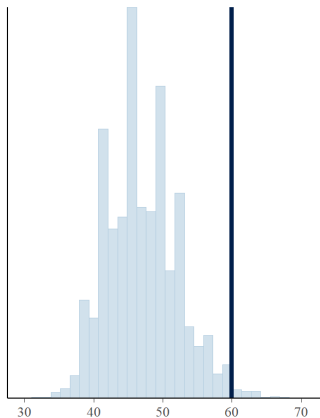
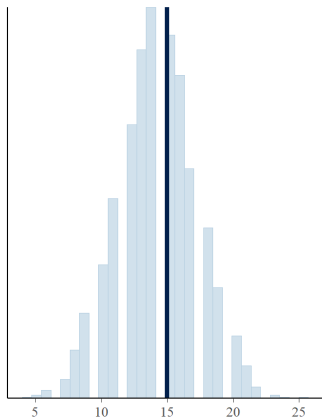
```
ppc_dens_overlay(y = data4$colonies,  
                 yrep = y_tilde4a[1100:1200,])
```




```
ppc_stat(y = data4$colonies,
         yrep = y_tilde4a, stat = "mean")
ppc_stat(y = data4$colonies,
         yrep = y_tilde4a, stat = "sd")
```



```
ppc_stat(y = data4$colonies,
         yrep = y_tilde4a, stat = "min")
ppc_stat(y = data4$colonies,
         yrep = y_tilde4a, stat = "max")
```



Poisson Regression Model with random effects

→ To take into account the eventual presence of overdispersion, the term λ_j , that is *plate-specific* is included in the linear predictor.

Likelihood:

$$y_{ij} | \mu_{ij} \sim \text{Poisson}(\mu_{ij})$$

$$\log(\mu_{ij}) | \beta, \lambda_j = \beta_0 + \beta_1 \log(x_{ij} + 10) + \beta_2 x_{ij} + \lambda_j$$

Priors:

$$\lambda_j | \sigma_\lambda^2 \sim \mathcal{N}(0, \sigma_\lambda^2), \quad j = 1, 2, 3;$$

$$\beta_k \sim \mathcal{N}(0, c), \quad k = 0, 1, 2.$$

Hyperprior:

$$\sigma_\lambda \sim \pi(\sigma_\lambda).$$

```
mod_ex4b <- stan_glmer(formula =
  colonies~quinoline+log_quinoline+(1|plate),
  data = data4,
  family = "poisson",
  prior = normal(0,10, autoscale=T),
  prior_intercept = normal(0,10, autoscale=T))

prior_summary(mod_ex4b)
```

```
Priors for model 'mod_ex4b'
-----
Intercept (after predictors centered)
~ normal(location = 0, scale = 10)

Coefficients
Specified prior:
~ normal(location = [0,0], scale = [10,10])
Adjusted prior:
~ normal(location = [0,0], scale = [0.027,6.091])

Covariance
~ decov(reg. = 1, conc. = 1, shape = 1, scale = 1)
-----
```

```
summary(mod_ex4b)
```

```
MCMC diagnostics
```

	mcse	Rhat	n_eff
(Intercept)	0.0	1.0	1312
quinoline	0.0	1.0	1819
log_quinoline	0.0	1.0	1769
b[(Intercept) plate:A]	0.0	1.0	1072
b[(Intercept) plate:B]	0.0	1.0	1059
b[(Intercept) plate:C]	0.0	1.0	1067
Sigma[plate:(Intercept),(Intercept)]	0.0	1.0	1031
mean_PPD	0.0	1.0	4138

```
mod_ex4b <- update(mod_ex4b, iter=8000)
summary(mod_ex4b)
```

```
MCMC diagnostics
```

	mcse	Rhat	n_eff
(Intercept)	0.0	1.0	4092
quinoline	0.0	1.0	8308
log_quinoline	0.0	1.0	8350
b[(Intercept) plate:A]	0.0	1.0	3723
b[(Intercept) plate:B]	0.0	1.0	3604
b[(Intercept) plate:C]	0.0	1.0	3609
Sigma[plate:(Intercept),(Intercept)]	0.0	1.0	2906
mean_PPD	0.0	1.0	16445

Warning messages:

1: There were 18 divergent transitions after warmup. See <https://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup> to find out why this is a problem and how to eliminate them.

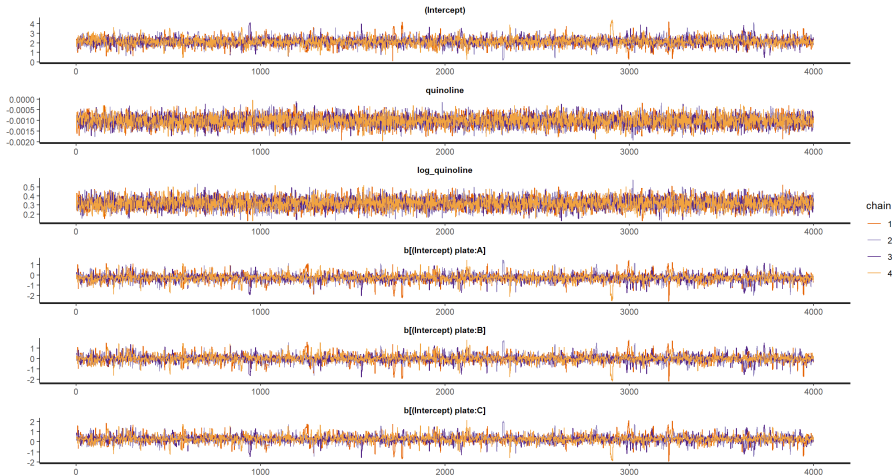
2: Examine the pairs() plot to diagnose sampling problems

- Classical warning when we work with the Poisson regression with random effects.

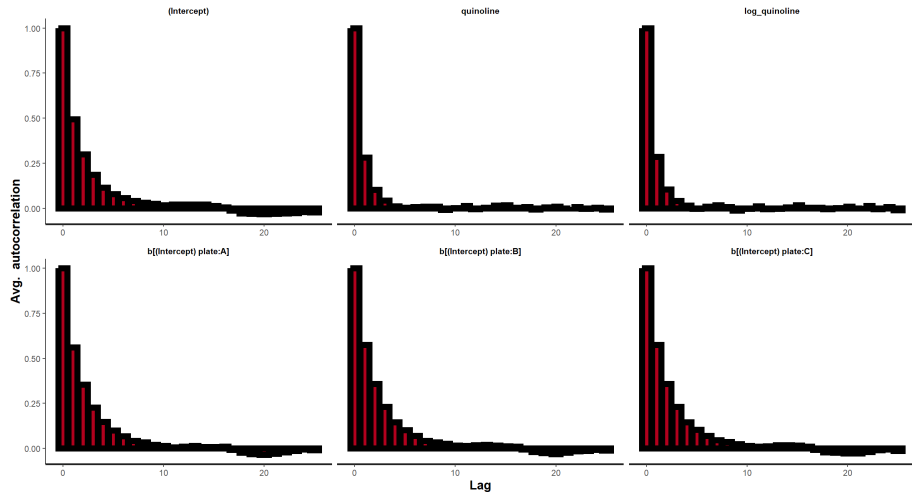
```
model <- update(model, adapt_delta=.99)
```

- `adapt_delta` is the target average proposal acceptance probability
- In general you should not need to change `adapt_delta` unless you see a warning message about divergent transitions, in which case you can increase `adapt_delta` from the default to a value closer to 1 (e.g. from 0.95 to 0.99, or from 0.99 to 0.999, etc).
- The step size used by the numerical integrator is a function of `adapt_delta` in that increasing `adapt_delta` will result in a smaller step size and fewer divergences.
- Increasing `adapt_delta` will typically result in a slower sampler, but it will always lead to a more robust sampler.

```
stan_trace(mod_ex4b, nrow=6, ncol=1)
```



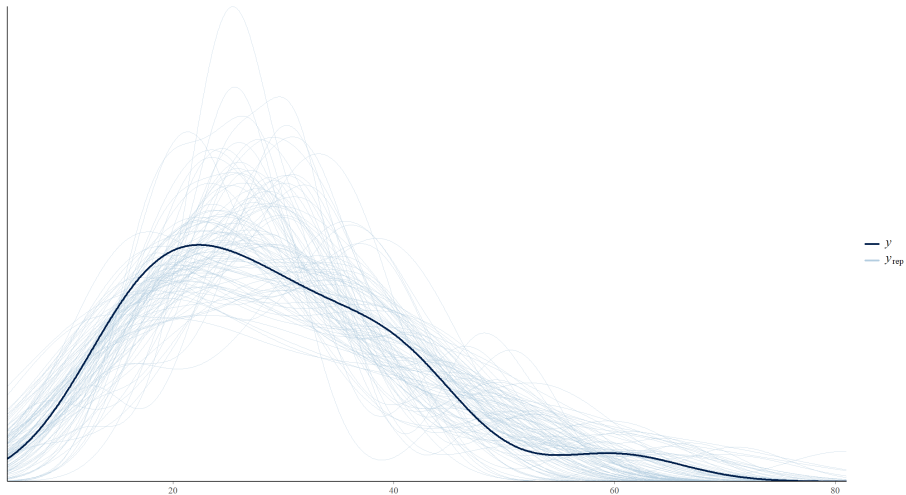
```
stan_ac(mod_ex4b)
```



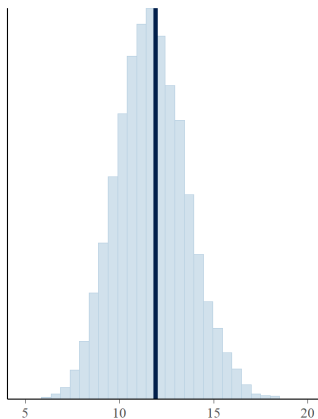
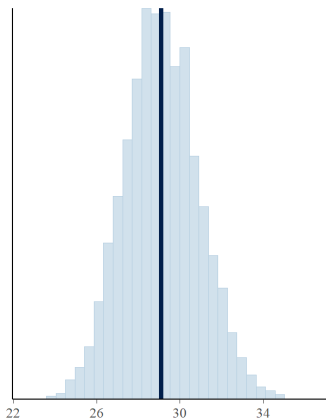

```
# Posterior checks
```

```
y_tilde4b <- posterior_predict(mod_ex4b)
```

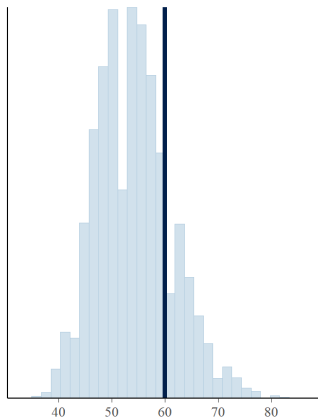
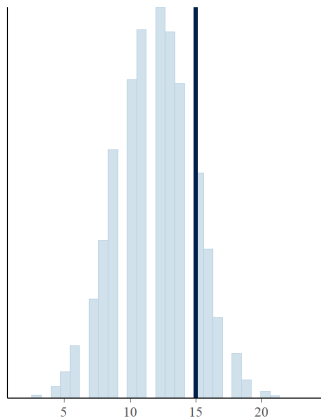
```
ppc_dens_overlay(y = data4$colonies,  
                 yrep = y_tilde4b[1100:1200,])
```



```
ppc_stat(y = data4$colonies,
         yrep = y_tilde4a, stat = "mean")
ppc_stat(y = data4$colonies,
         yrep = y_tilde4a, stat = "sd")
```



```
ppc_stat(y = data4$colonies,
         yrep = y_tilde4a, stat = "min")
ppc_stat(y = data4$colonies,
         yrep = y_tilde4a, stat = "max")
```



Suppose now that we want to use our model to perform inference on a new covariate pattern `quinoline = 500` and `plate = "A"`

```
# Generate the new dataset
data4_new <- data.frame(quinoline=500,
                        log_quinoline = log(500+10),
                        plate ="A")

# evaluation linear predictor
mu_new <- posterior_epred(mod_ex4b, newdata = data4_new)

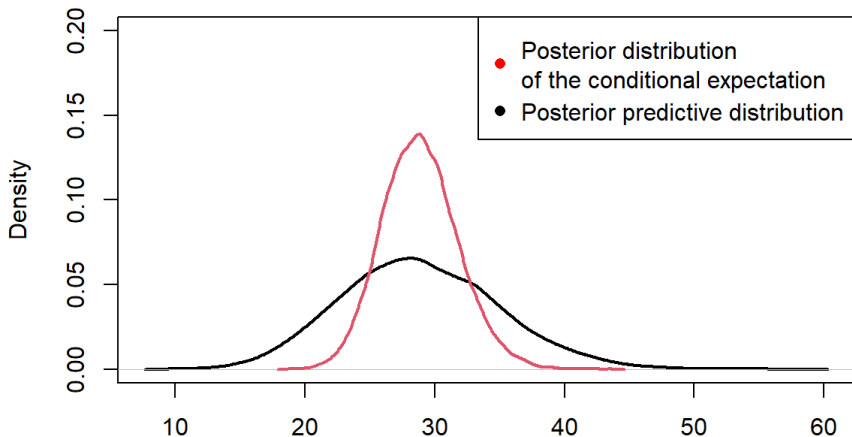
# posterior predictive distribution
y_tilde_new <- posterior_predict(mod_ex4b,
                                newdata = data4_new)
```

```
#comparison
```

```
plot(density(y_tilde_new), ylim=c(0,0.2), lwd=2)
```

```
lines(density(mu_new), col="red", lwd=2)
```

Comparison of the variability



```
mean(mu_new); sd(mu_new)
mean(y_tilde_new); sd(y_tilde_new)
```

```
> mean(mu_new);sd(mu_new)
[1] 28.85901
[1] 2.91659
> mean(y_tilde_new);sd(y_tilde_new)
[1] 28.85675
[1] 6.095023
```