

STA 6360, Report 4.5

Carson Slater *Baylor University*

1

Work Problem 12 on p. 82 in *BDA3*.

Poisson regression model: expand the model of Exercise 2.13(a) by assuming that the number of fatal accidents in year t follows a Poisson distribution with mean $\alpha + \beta t$. You will estimate α and β following the example of the analysis in Section 3.7.

(a)

Discuss various choices for a ‘noninformative’ prior for (α, β) . Choose one.

Choices for non-informative priors on α would include be a diffuse normal or t distribution. A uniform prior on a specified range could also work too. For example for each parameter you could specify a $\mathcal{N}(0, 1000)$ prior.

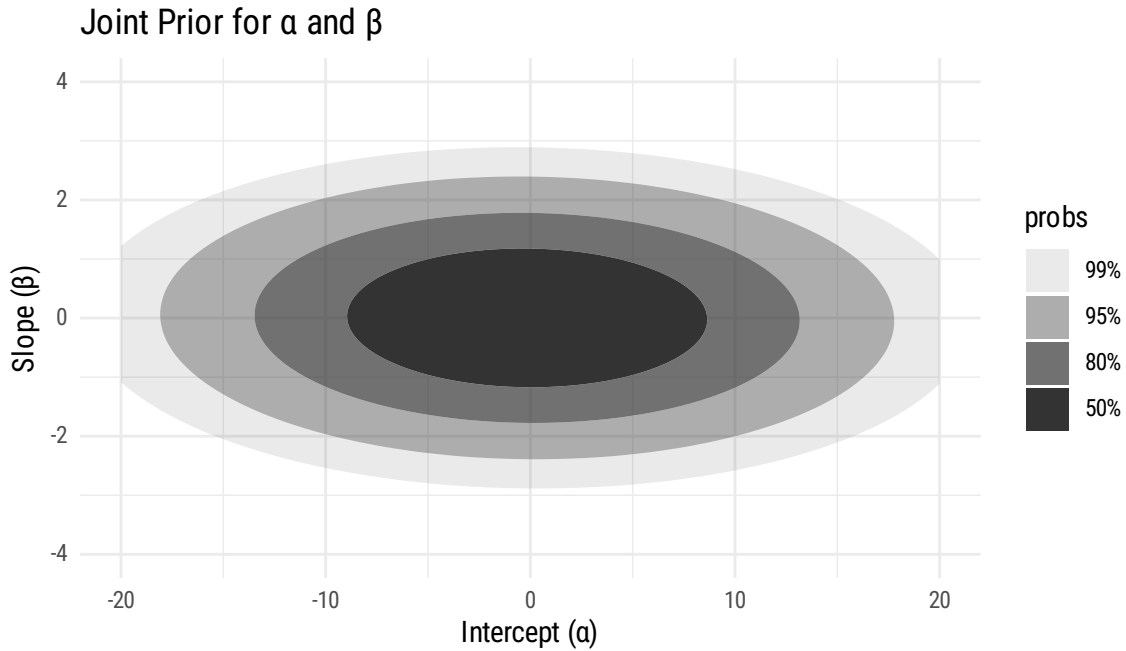
a) Discuss choices for a noninformative prior for (α, β) . Several choices for noninformative priors are:

- **Uniform prior:** $p(\alpha, \beta) \propto 1$. This assumes that all values of α and β are equally likely.
- **Independent improper priors:** $p(\alpha) \propto 1$ and $p(\beta) \propto 1$. This assumes that α and β are independent and have no prior information.
- **Jeffreys’ prior:** $p(\alpha, \beta) \propto \sqrt{|\det(I(\alpha, \beta))|}$, where $I(\alpha, \beta)$ is the Fisher information matrix. This prior is invariant under reparameterization.

(b)

Discuss what would be a realistic informative prior distribution for (α, β) . Sketch its contours and then put it aside. Do parts (c)–(h) of this problem using your noninformative prior distribution from (a).

A good informative prior would be (without using the data to elicit such a prior) would be a normal prior of the coefficients. Let’s give $\alpha \sim \mathcal{N}(0, 10)$ and $\beta \sim \mathcal{N}(0, 1)$.



(c)

The likelihood function for the Poisson regression model is:

$$L(\alpha, \beta \mid y, t) = \prod_{i=1}^n \frac{e^{-(\alpha + \beta t_i)} (\alpha + \beta t_i)^{y_i}}{y_i!}.$$

Using the uniform prior, the posterior density is proportional to the likelihood:

$$p(\alpha, \beta \mid y, t) \propto \prod_{i=1}^n e^{-(\alpha + \beta t_i)} (\alpha + \beta t_i)^{y_i}.$$

(d)

To verify that the posterior density is proper, we need to confirm that it integrates to a finite value:

$$\int \int p(\alpha, \beta \mid y, t) d\alpha d\beta < \infty.$$

Since the likelihood function is a product of Poisson densities, which are always non-negative and integrate to 1, the posterior density is proper.

(e)

Below are the estimates and the data.

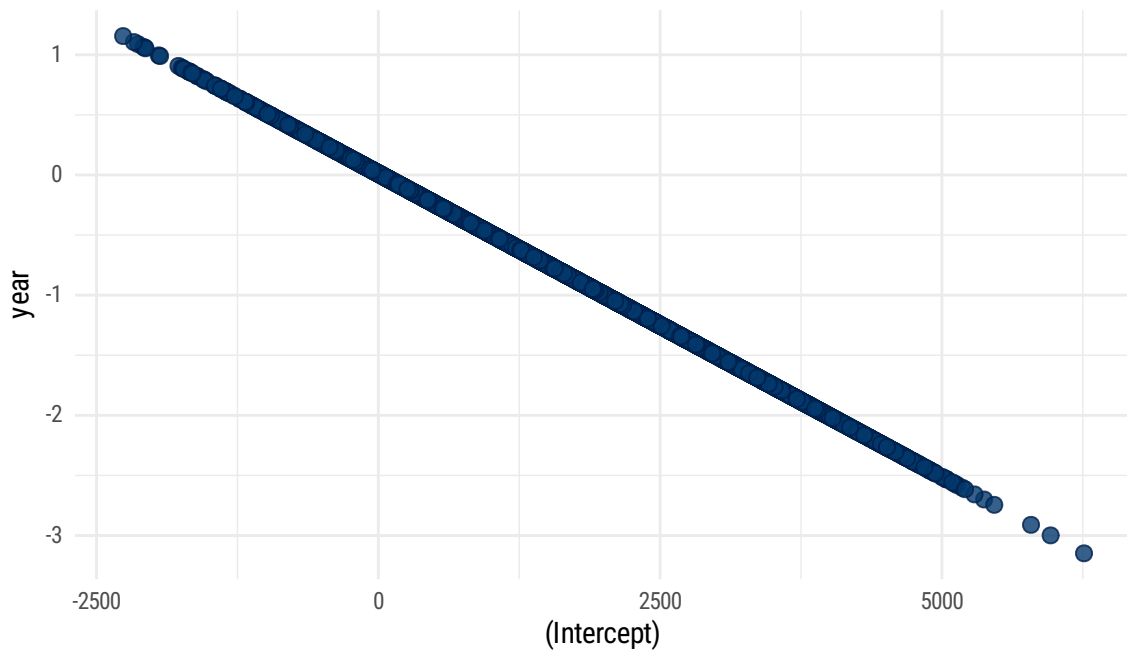
Table 1: Data for airline accidents.

Year	Fatal Accidents	Passenger Deaths	Death Rate
1976	24	734	0.19

Year	Fatal Accidents	Passenger Deaths	Death Rate
1977	25	516	0.12
1978	31	754	0.15
1979	31	877	0.16
1980	22	814	0.14
1981	21	362	0.06
1982	26	764	0.13
1983	20	809	0.13
1984	16	223	0.03
1985	22	1066	0.15

	mean	mcse	sd	10%	50%	90%	n_ eff	Rhat
(Intercept)	1906.8917109	23.6272654	1088.5175449	503.112523	1914.2483105	3312.67945	2122	1.0008621
year	-0.9507192	0.0119361	0.5495214	-	-0.9545589	-0.24175	2120	1.0008638
				1.660642				
mean_PPD	23.9948429	0.0263876	2.2096866	21.200000	23.9000000	26.80000	7012	0.9999823
log-	-	0.0213731	1.0524175	-	-	-	2425	1.0005033
posterior	34.4617194			35.768241	34.1446416	33.52503		

(f)

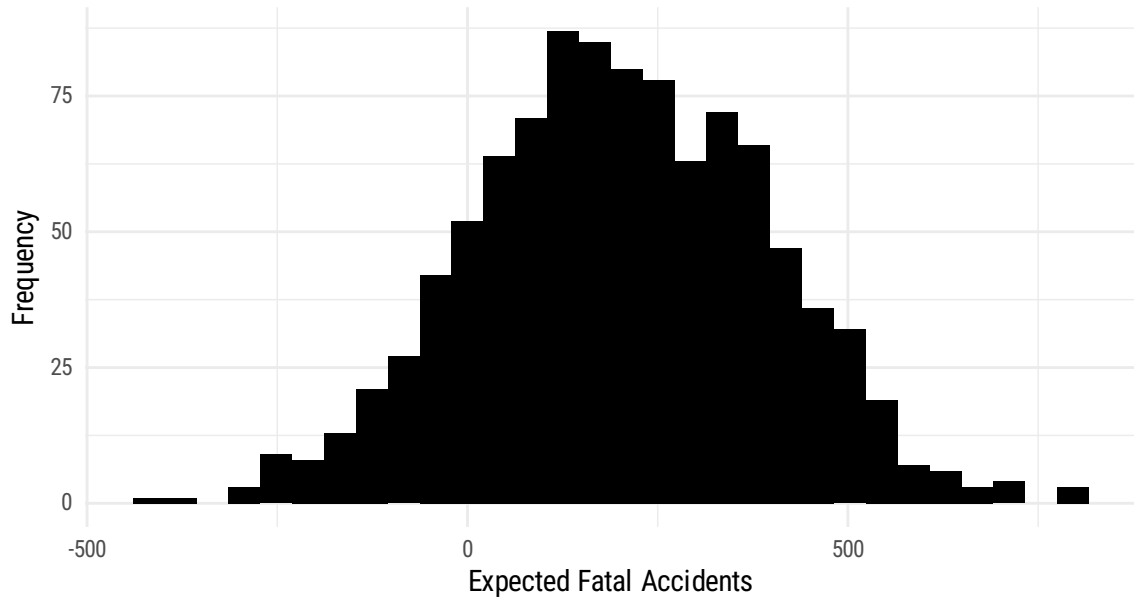


Could not figure out how to plot the posterior density using this so I used a scatter plot. It did not go well.

(g)

The left plot are intercept draws and right are coefficient draws.

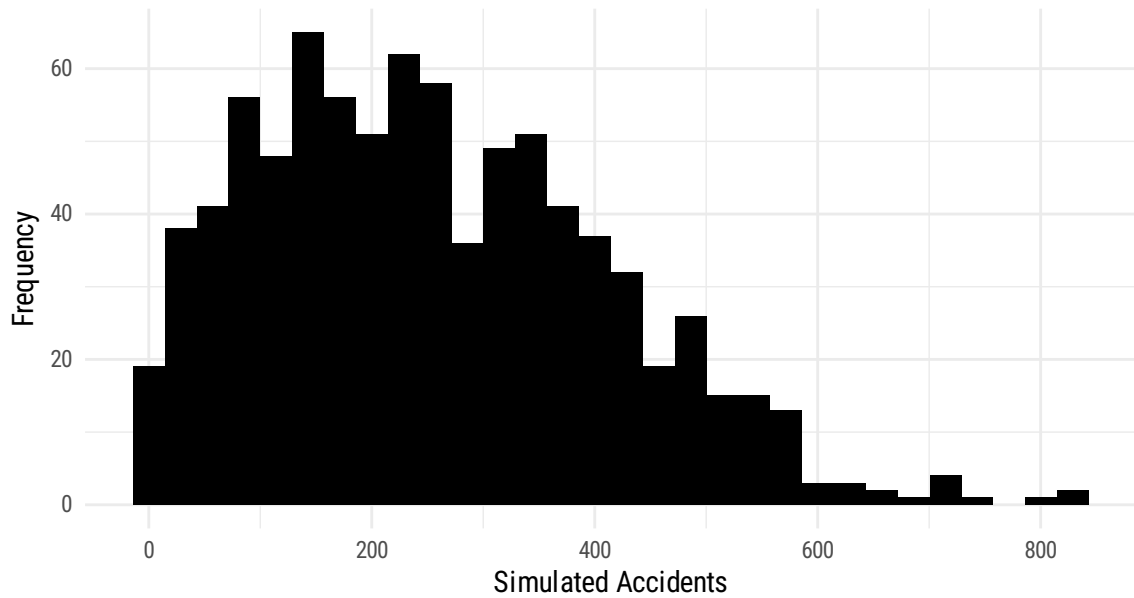
Posterior Distribution of Expected Fatal Accidents (1986)



(h)

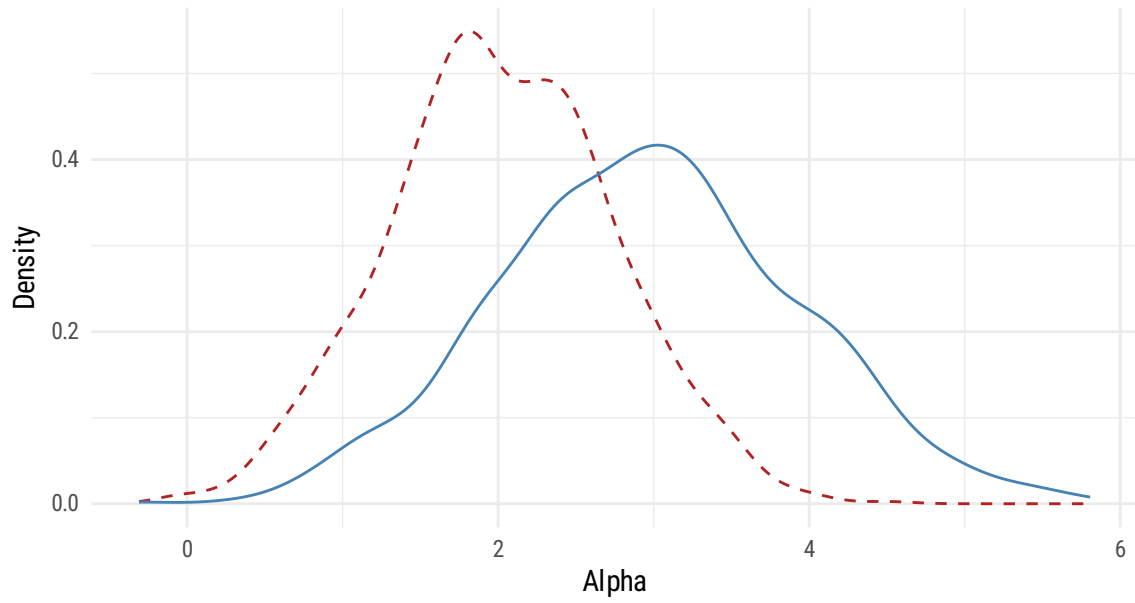
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## [1] "95% Predictive Interval: 21.1"  
## [2] "95% Predictive Interval: 574.8"
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Simulated Fatal Accidents (1986)



(i)

Comparison of Informative Prior and Posterior (Alpha)



Comparison of Informative Prior and Posterior (Beta)

