

Agenda

Expanding on the
Poisson regression

1. Administrative
2. Interpreting coefficients from Poisson regressions
3. "Over-dispersed" Poisson regressions
4. Zero-inflated Poisson regressions
5. ***Hands on:***
Poisson models in R

Interpreting Poisson coefficients



$$H_i \sim \text{Pois}(\lambda_i)$$

$$\log(\lambda_i) = \alpha + \beta_M M_i + \beta_G G_i$$

$$\alpha \sim \text{Norm}(3, 1)$$

$$\beta_M \sim \text{Norm}(0, 0.5)$$

$$\beta_G \sim \text{Norm}(0, 0.3)$$

	Mean	exp(Mean)
α	0.27	1.32
β_M	1.11	3.05
β_G	-0.14	0.87

α (baseline)

∴ A student who is not a boy ($M_i = 0$) and is in grade 10 ($G_i = 0$) is predicted to play about 1.32 hours of games per week.

β_M (gender)

∴ Boys ($M_i = 1$) are expected to spend about 3.05 times more time than non-boys ($M_i = 0$) playing games.

β_G (grade)

∴ A one-year increase in grade is associated with playing 0.87 times as much. This is a decrease of 13% each year.

Over- dispersion



To illustrate, consider the simpler model with only gender as a predictor:

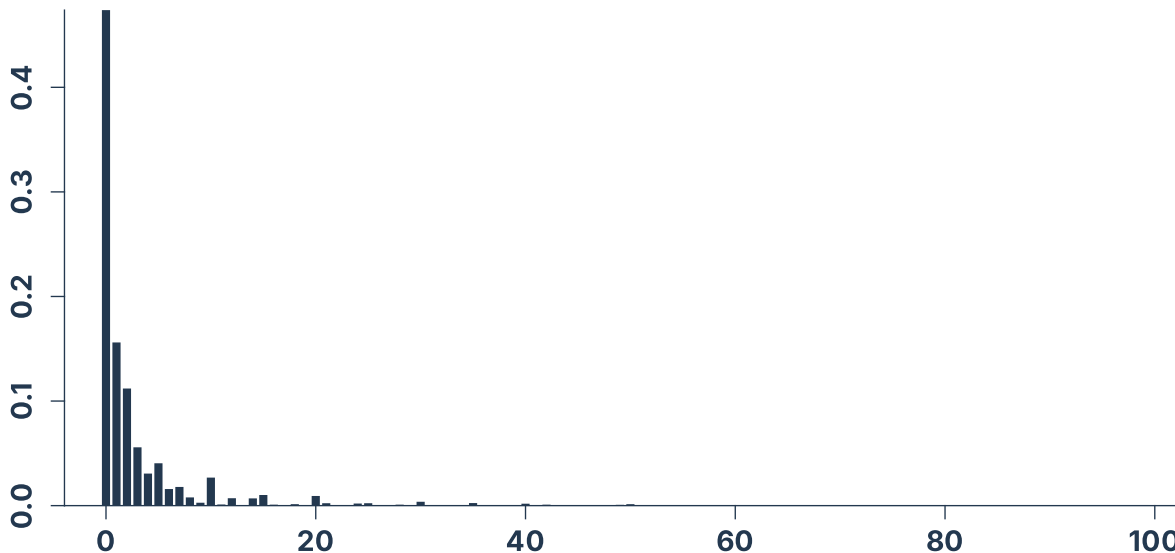
$$H_i \sim \text{Pois}(\lambda_i)$$
$$\log(\lambda_i) = \alpha + \beta M_i$$

$$\alpha \sim \text{Norm}(3, 1.0)$$

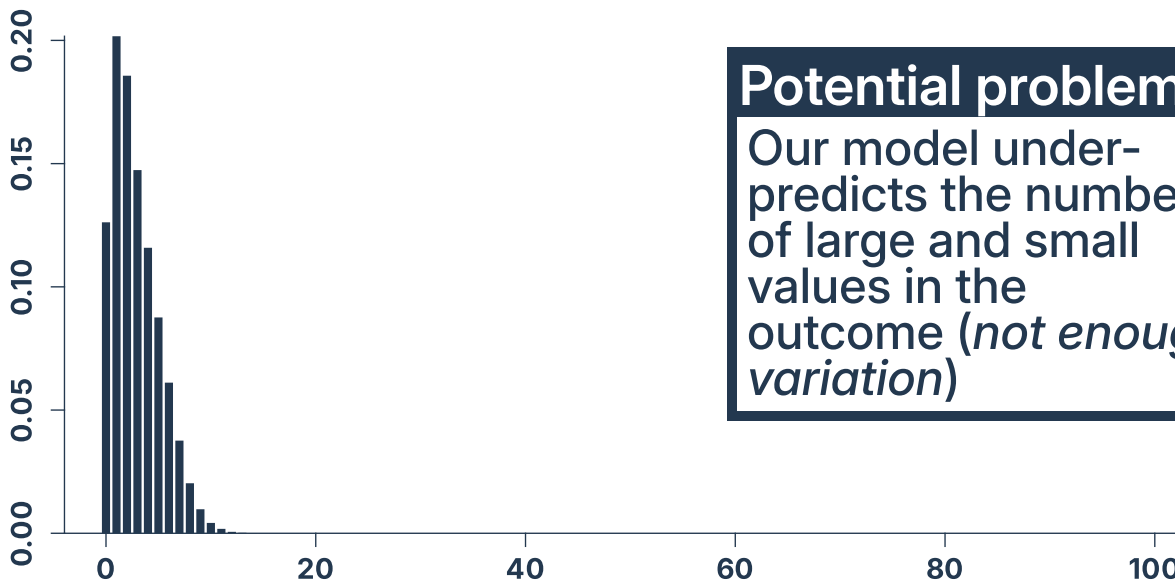
$$\beta \sim \text{Norm}(0, 0.7)$$

	Mean	exp(Mean)
α	0.38	1.46
β	1.10	3.00

Actual
distribution



Posterior
predicted
distribution
(Poisson)



Potential problem:

Our model under-predicts the number of large and small values in the outcome (*not enough variation*)

Gamma-Poisson regression:

AKA *negative binomial*
AKA *over-dispersed Poisson*

$$H_i \sim \text{Pois}(\lambda_i)$$

$$\lambda_i \sim \text{Gamma}(\mu_i, \theta)$$

$$\log(\mu_i) = \alpha + \beta M_i$$

$$\alpha \sim \text{Norm}(3, 1.0)$$

$$\beta \sim \text{Norm}(0, 0.7)$$

$$\theta \sim \text{Unif}(0, 20)$$

← Extra "dispersion" from gamma

Two students who look identical based on covariates can have different Poisson rates λ_i .

← One more prior

Gamma-Poisson regression:

$$H_i \sim \text{Pois}(\lambda_i)$$

$$\lambda_i \sim \text{Gamma}(\mu_i, \theta)$$

$$\log(\mu_i) = \alpha + \beta M_i$$

$$\alpha \sim \text{Norm}(3, 1.0)$$

$$\beta \sim \text{Norm}(0, 0.7)$$

$$\theta \sim \text{Unif}(0, 20)$$

Data story:

Student characteristics



Individual student variation



$$H_i \geq 0$$

Gamma-Poisson and negative-binomial regressions are the same:

$$H_i \sim \text{Pois}(\lambda_i)$$

$$H_i \sim \text{NegBin}(\lambda_i, \theta)$$

$$\lambda_i \sim \text{Gamma}(\mu_i, \theta)$$

$$\log(\lambda_i) = \alpha + \beta M_i$$

$$\log(\mu_i) = \alpha + \beta M_i$$

"Negative binomial regression" is
the typical terminology

$$H_i \sim \text{NegBin}(\lambda_i, \theta)$$
$$\log(\lambda_i) = \alpha + \beta M_i$$

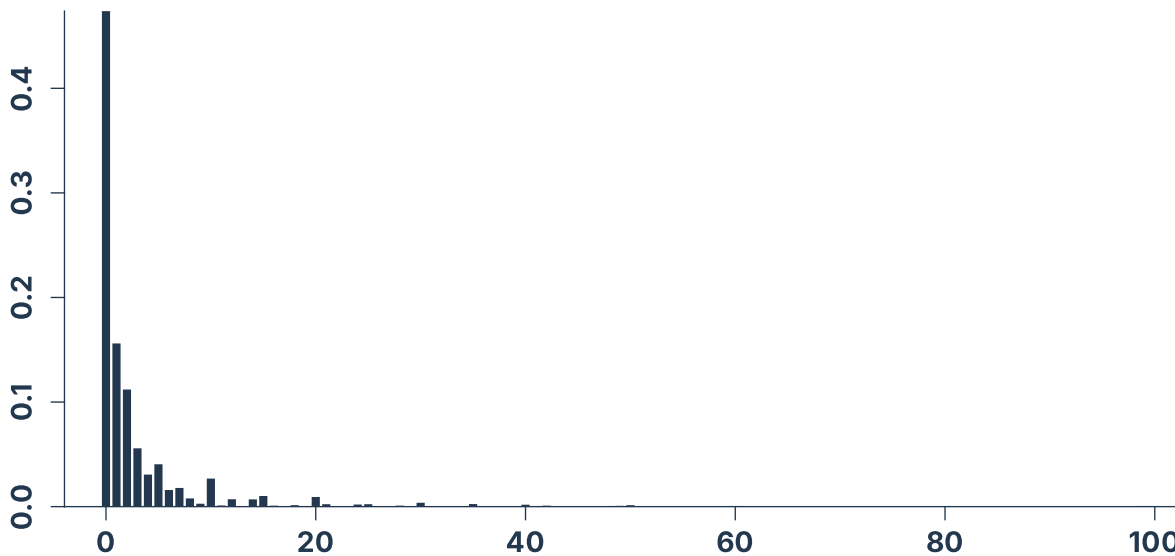
$$\alpha \sim \text{Norm}(3, 1.0)$$

$$\beta \sim \text{Norm}(0, 0.7)$$

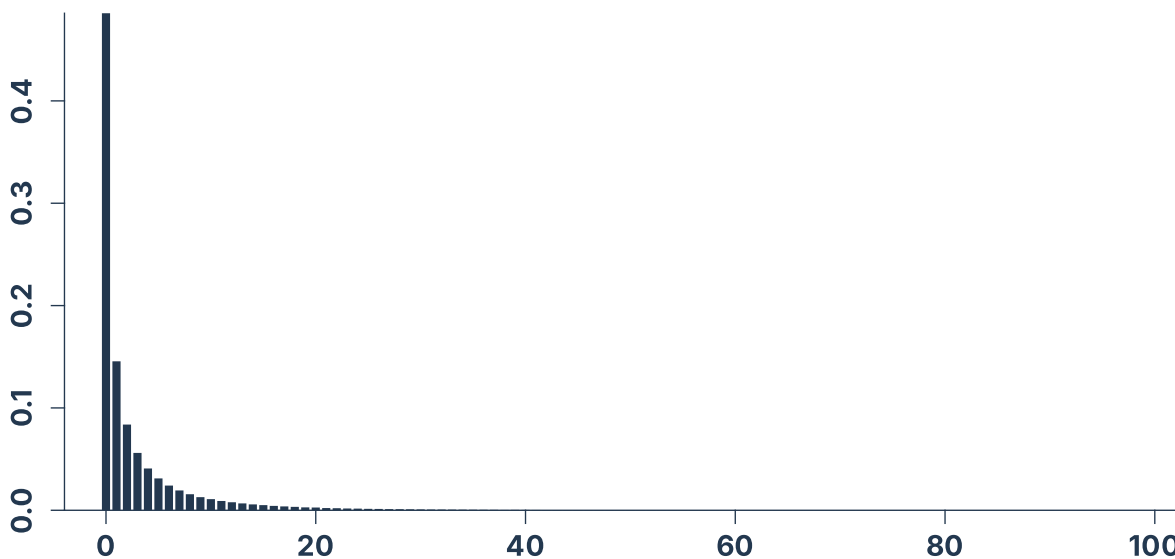
$$\theta \sim \text{Unif}(0, 20)$$

	Mean	95% CI	exp(Mean)
α	0.38	(0.32, 0.45)	1.47
β	1.09	(1.01, 1.18)	2.99
θ	0.35	(0.33, 0.37)	—

Actual
distribution



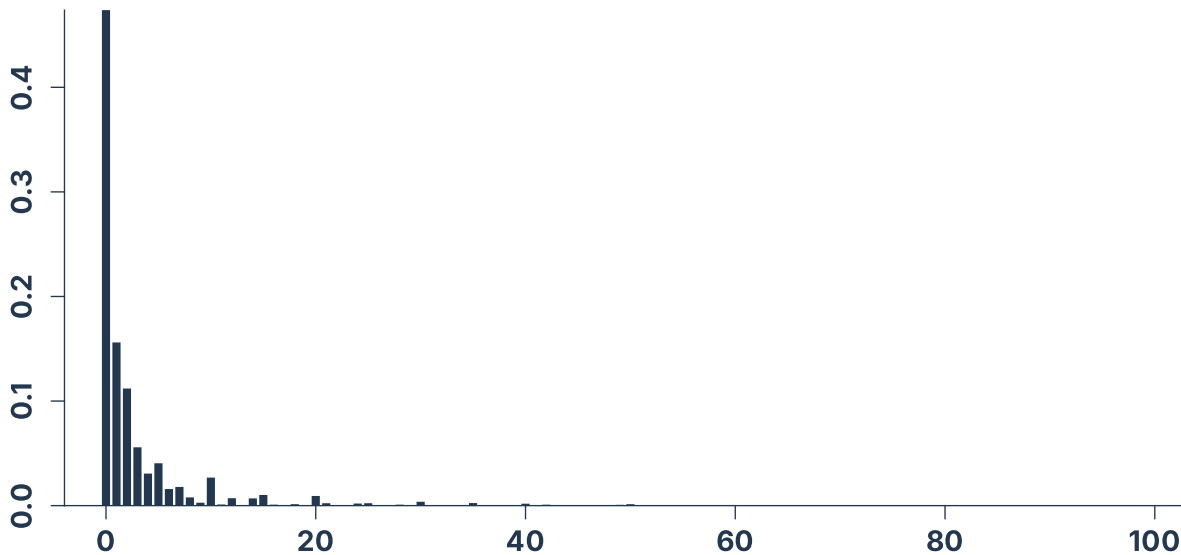
Posterior
predicted
distribution
(Gamma-
Poisson)



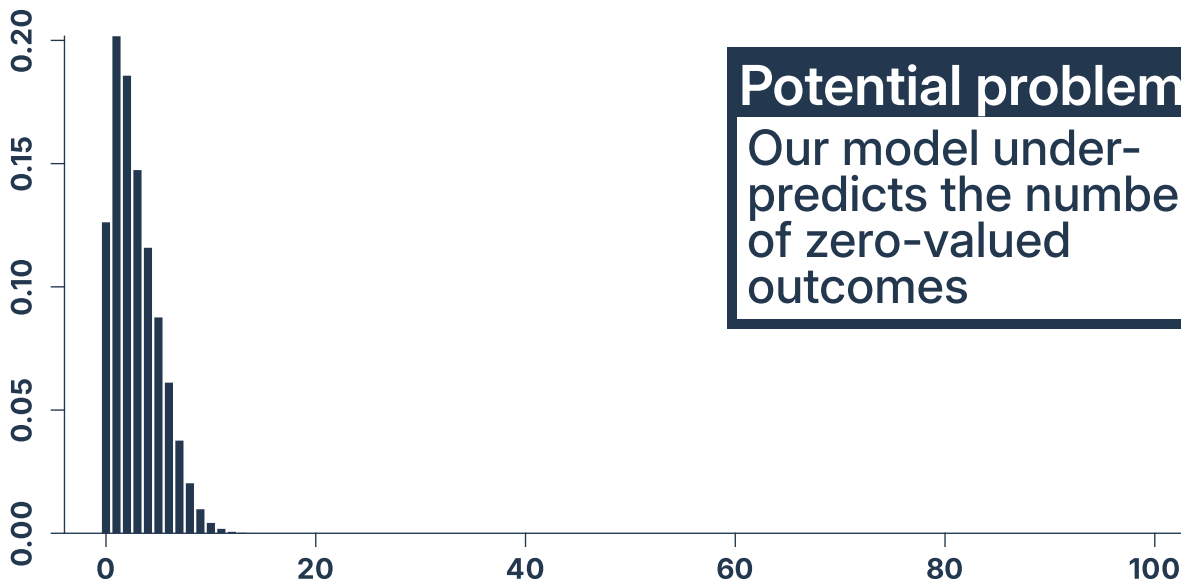
Zero inflation



Actual
distribution



Posterior
predicted
distribution
(Poisson)



Potential problem:

Our model under-predicts the number of zero-valued outcomes

Outcome variable is the result of *one of two processes*:

Either the student is structurally constrained to play zero hours per week—e.g. they do not own a game console ($C_i = 1$)

Or the student *is* able to play games and does so at a rate λ_i ($C_i = 0$)

$$H_i \begin{cases} = 0 & \text{if } C_i = 1 \\ \sim \text{Pois}(\lambda_i) & \text{if } C_i = 0 \end{cases}$$

Each student's probability of not owning a console is modeled with p_i

$$H_i \begin{cases} = 0 & \text{if } C_i = 1 \\ \sim \text{Pois}(\lambda_i) & \text{if } C_i = 0 \end{cases}$$
$$C_i = \text{Bernoulli}(p_i)$$

The probability p_i is modeled with a linear function of family income

$$H_i \begin{cases} = 0 & \text{if } C_i = 1 \\ \sim \text{Pois}(\lambda_i) & \text{if } C_i = 0 \end{cases}$$
$$C_i = \text{Bernoulli}(p_i)$$

$$\text{logit}(p_i) = \alpha_p + \beta_p W_i$$

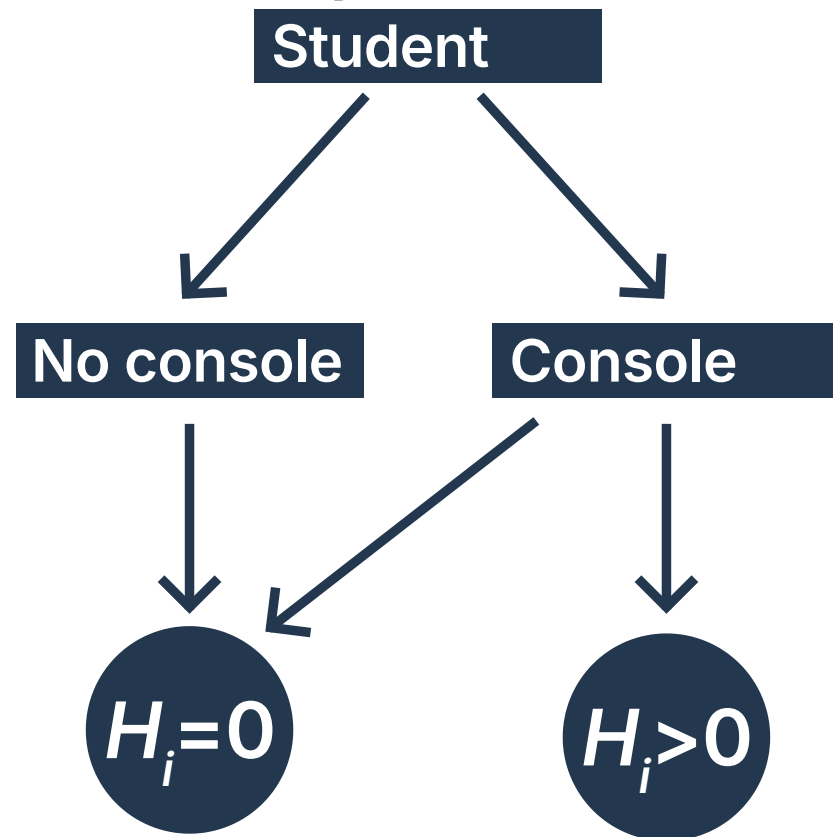
The rate λ_i is modeled with a linear function of gender

$$H_i \begin{cases} = 0 & \text{if } C_i = 1 \\ \sim \text{Pois}(\lambda_i) & \text{if } C_i = 0 \end{cases}$$
$$C_i = \text{Bernoulli}(p_i)$$

$$\text{logit}(p_i) = \alpha_p + \beta_p W_i$$

$$\log(\lambda_i) = \alpha_\lambda + \beta_\lambda M_i$$

Data story:



$$H_i \begin{cases} = 0 & \text{if } C_i = 1 \\ \sim \text{Pois}(\lambda_i) & \text{if } C_i = 0 \end{cases}$$
$$C_i = \text{Bernoulli}(p_i)$$

$$\text{logit}(p_i) = \alpha_p + \beta_p W_i$$
$$\log(\lambda_i) = \alpha_\lambda + \beta_\lambda M_i$$

$$\alpha_p \sim \text{Norm}(0, 1)$$

$$\beta_p \sim \text{Norm}(0, 2)$$

$$\alpha_\lambda \sim \text{Norm}(3, 1)$$

$$\beta_\lambda \sim \text{Norm}(0, 0.7)$$

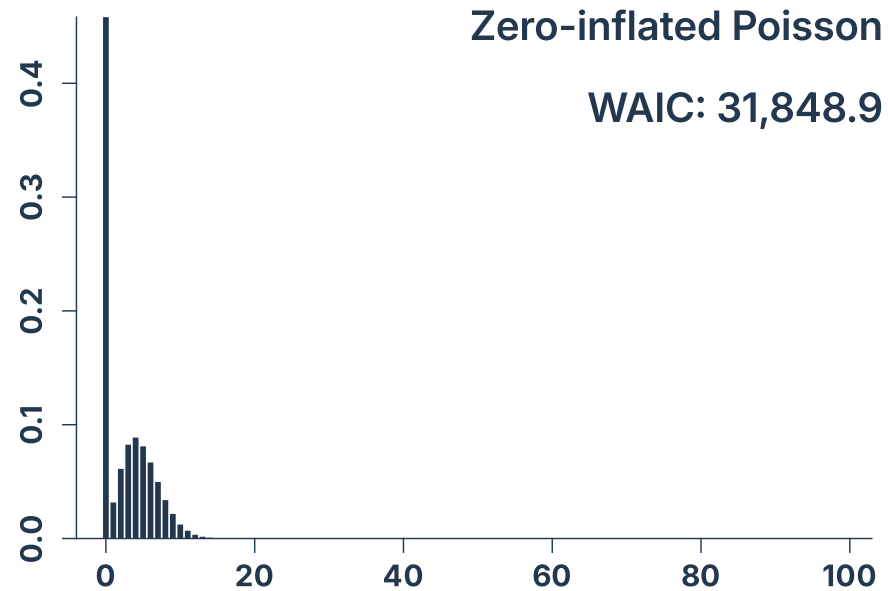
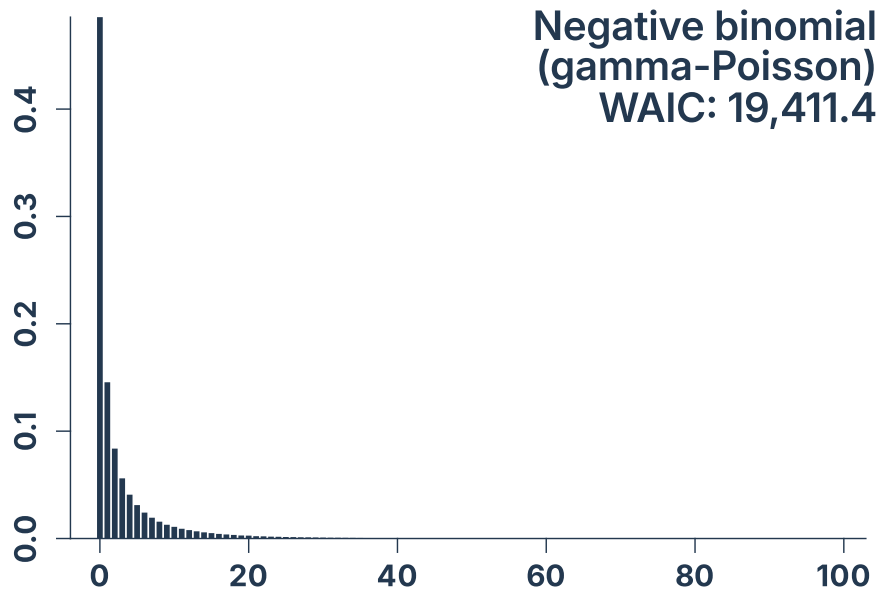
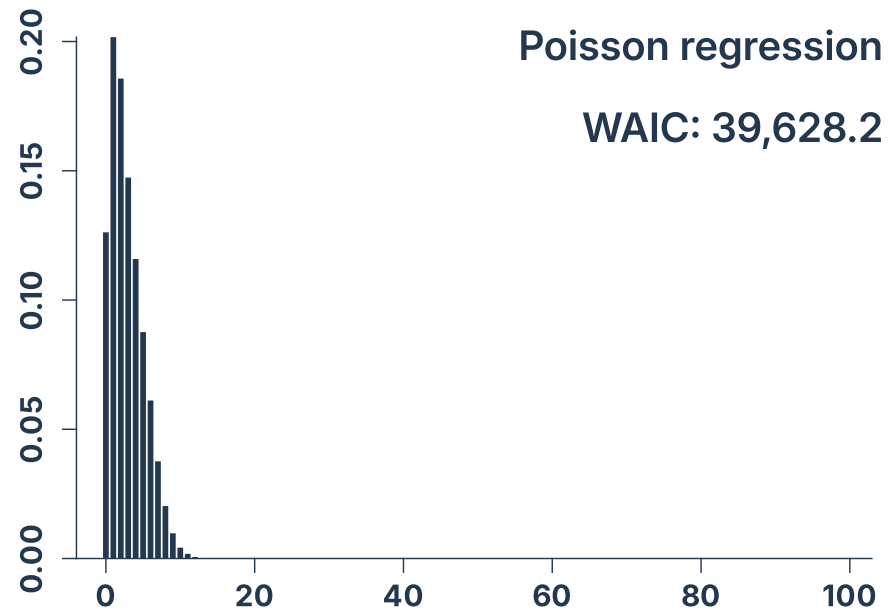
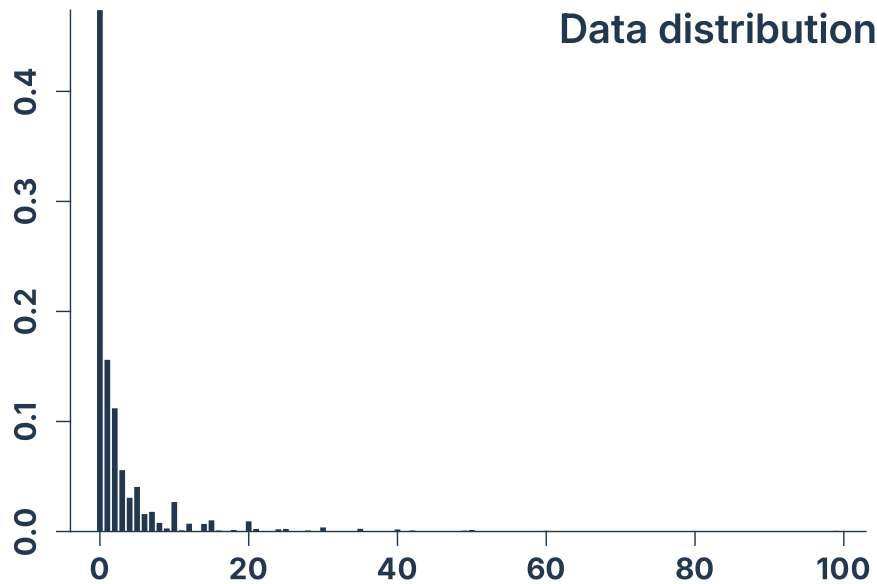
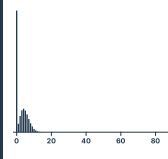


Image credit



Figures by Peter McMahan ([source code](#))



Still from [National Treasure \(2004\)](#)



Still from [Brazil \(1985\)](#)



Merchandise from [The Nightmare Before Christmas \(1993\)](#)