

Intro to linear models and generalized linear models

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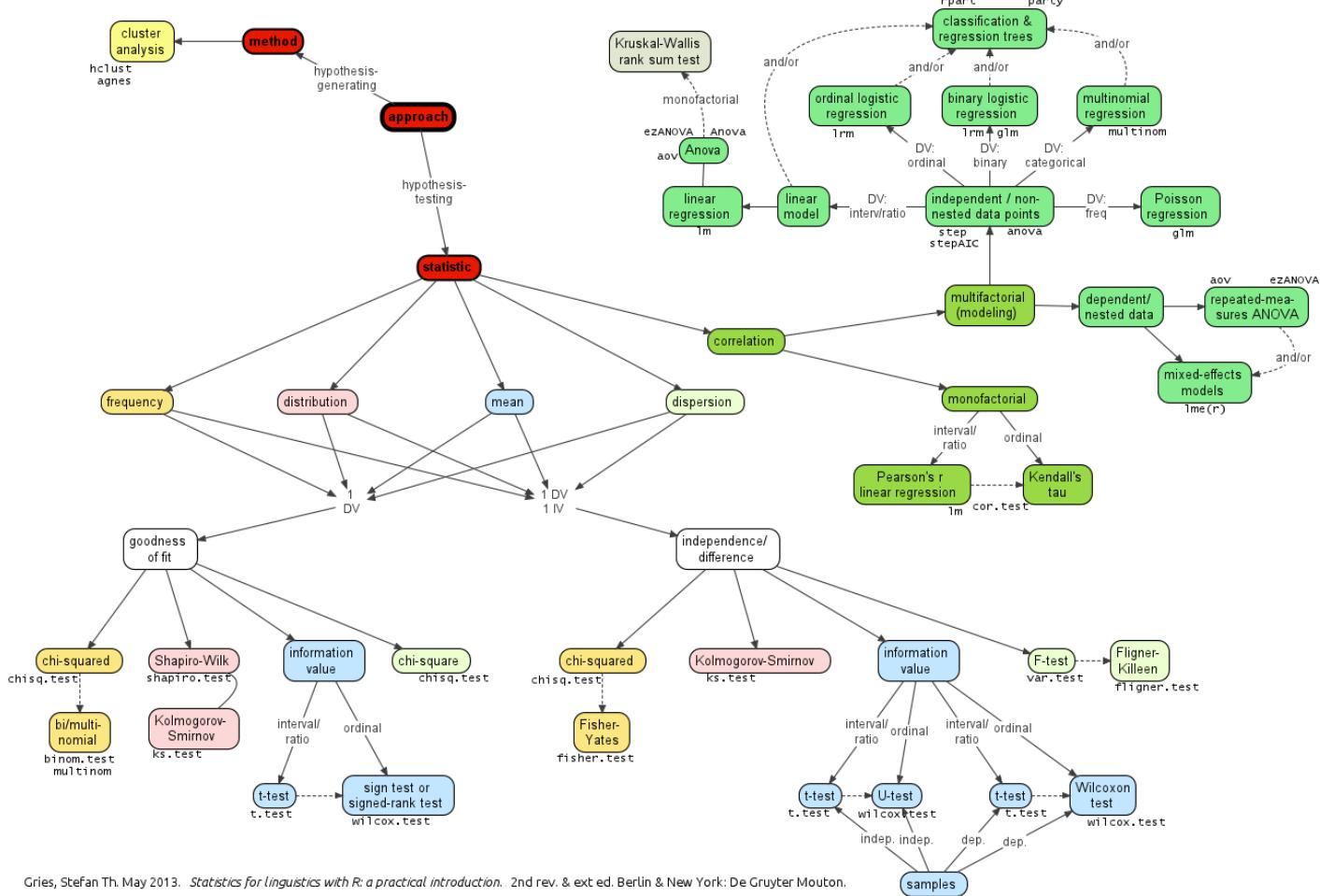
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Exercise with broom

**Linear models
101**

Intro to GLM

The messy world of statistical testing



Linear models

Simple, well-understood

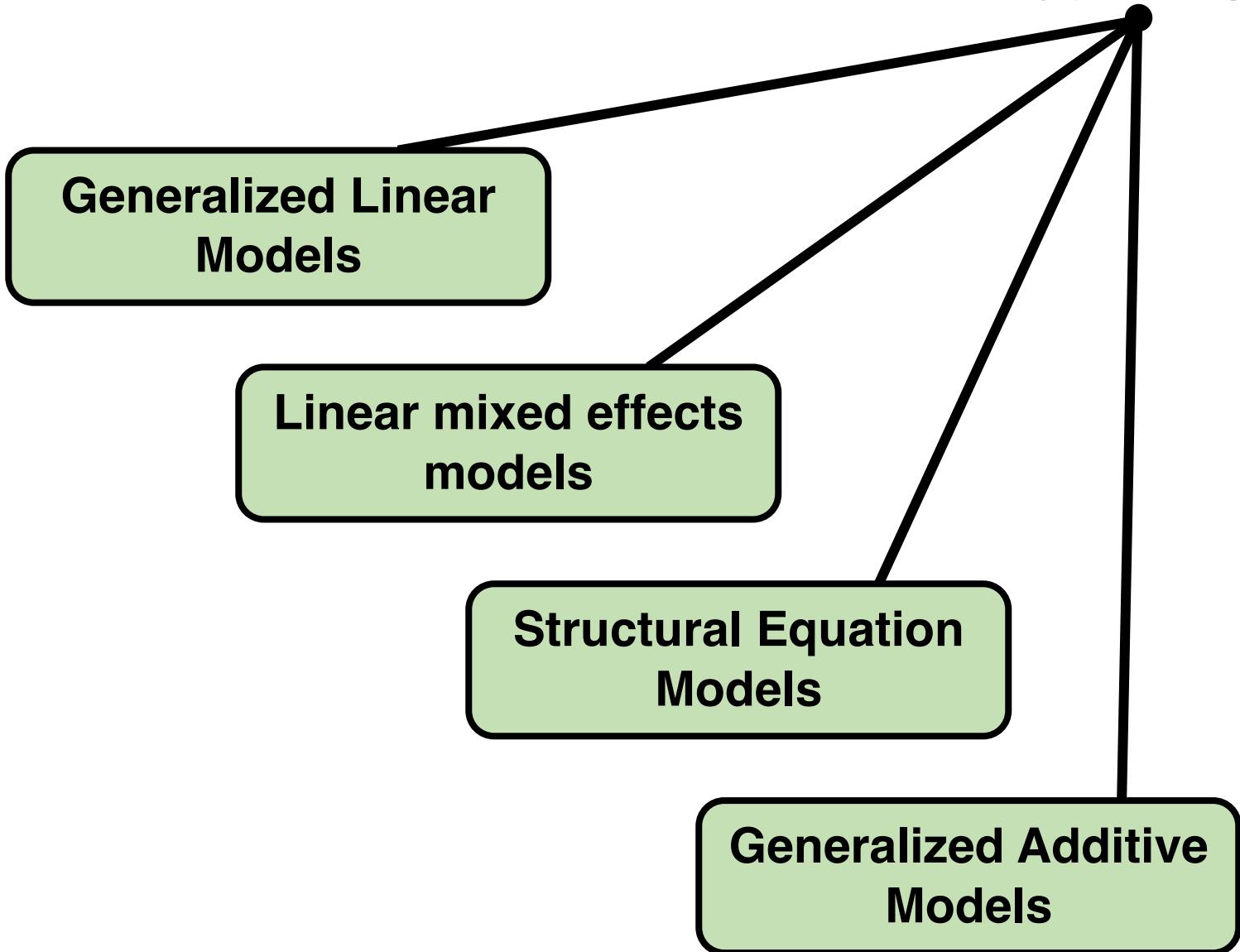
Interpretable

Good for theory-driven work

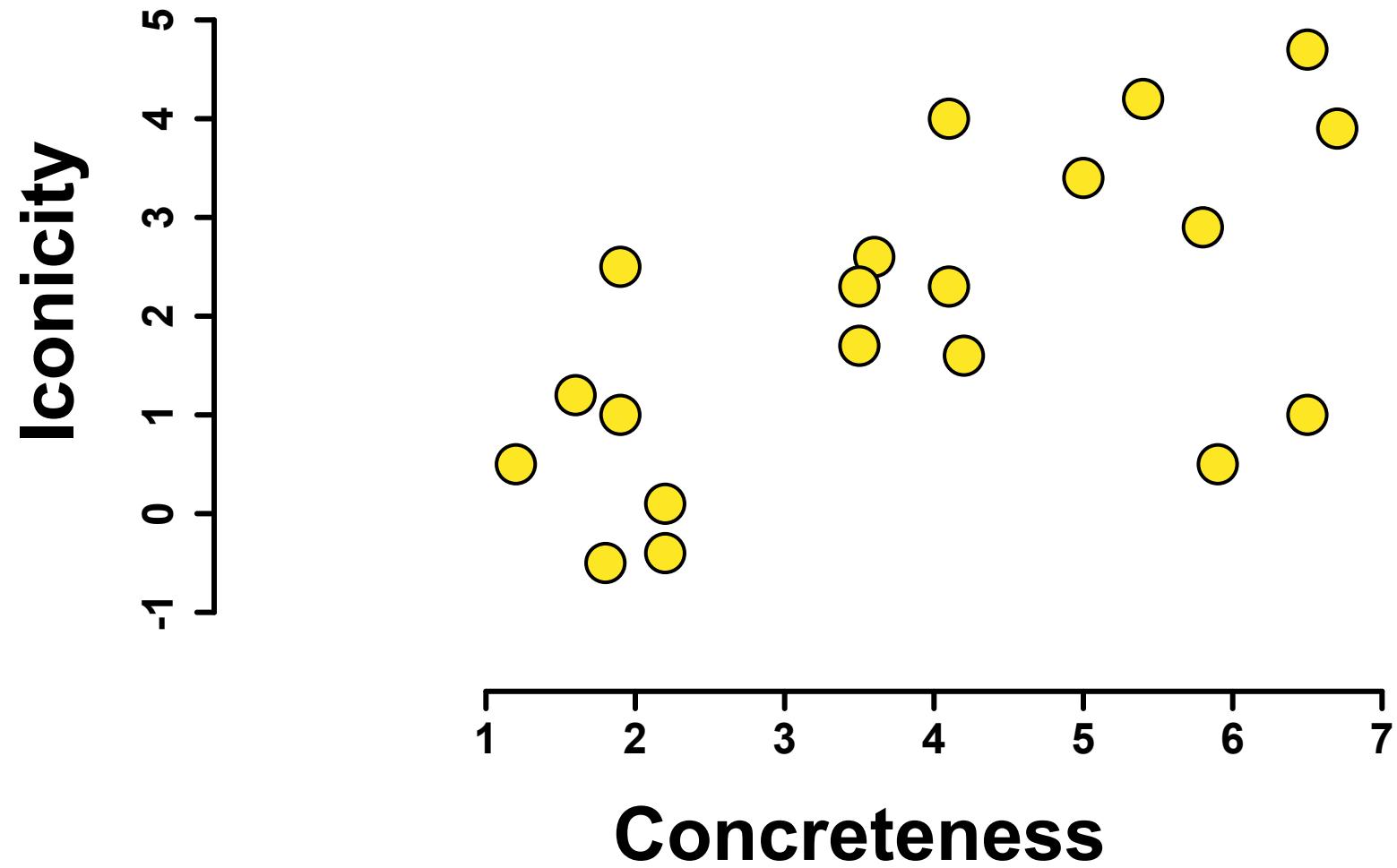
Flexible

→ Bayesian analysis

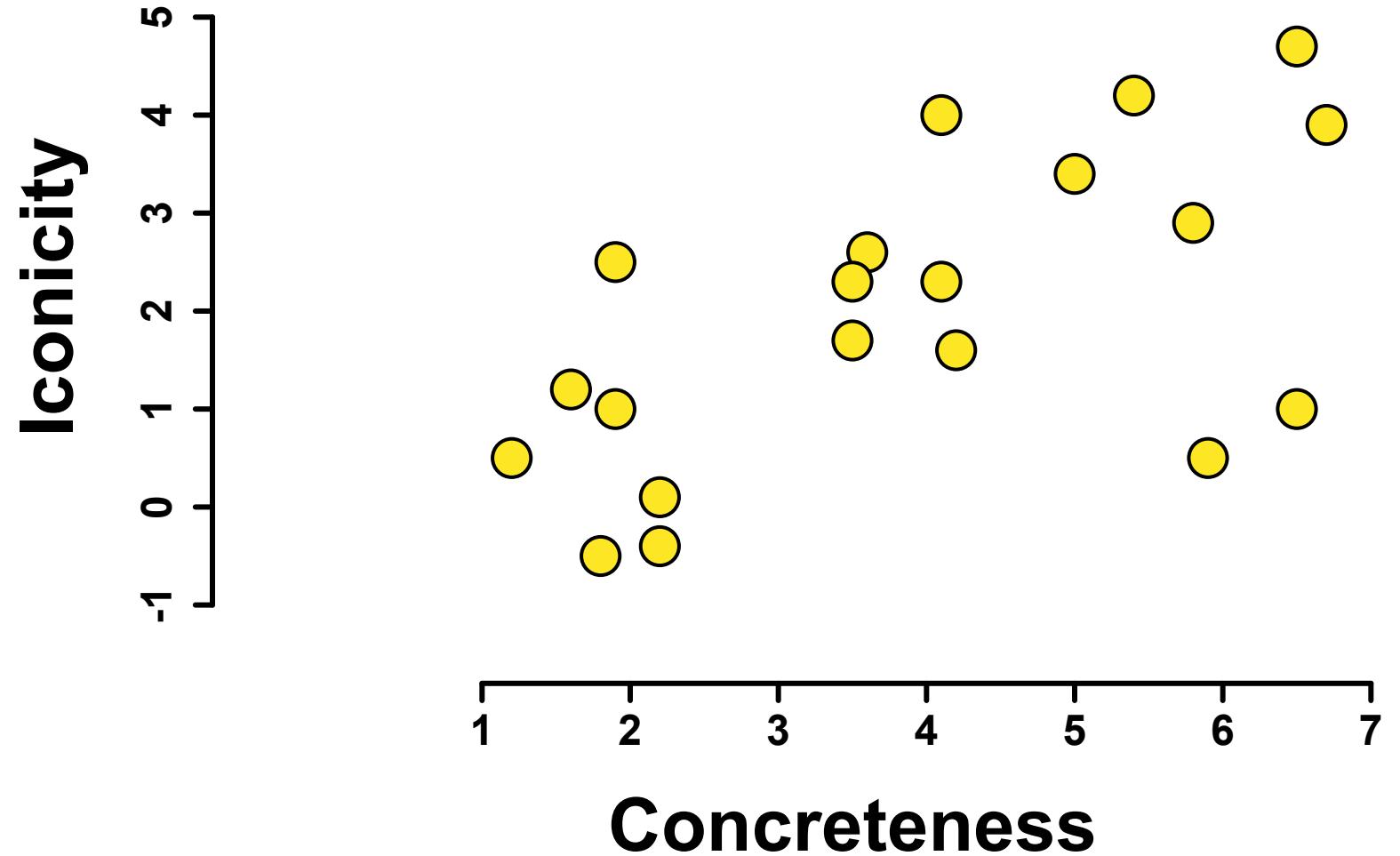
Linear models



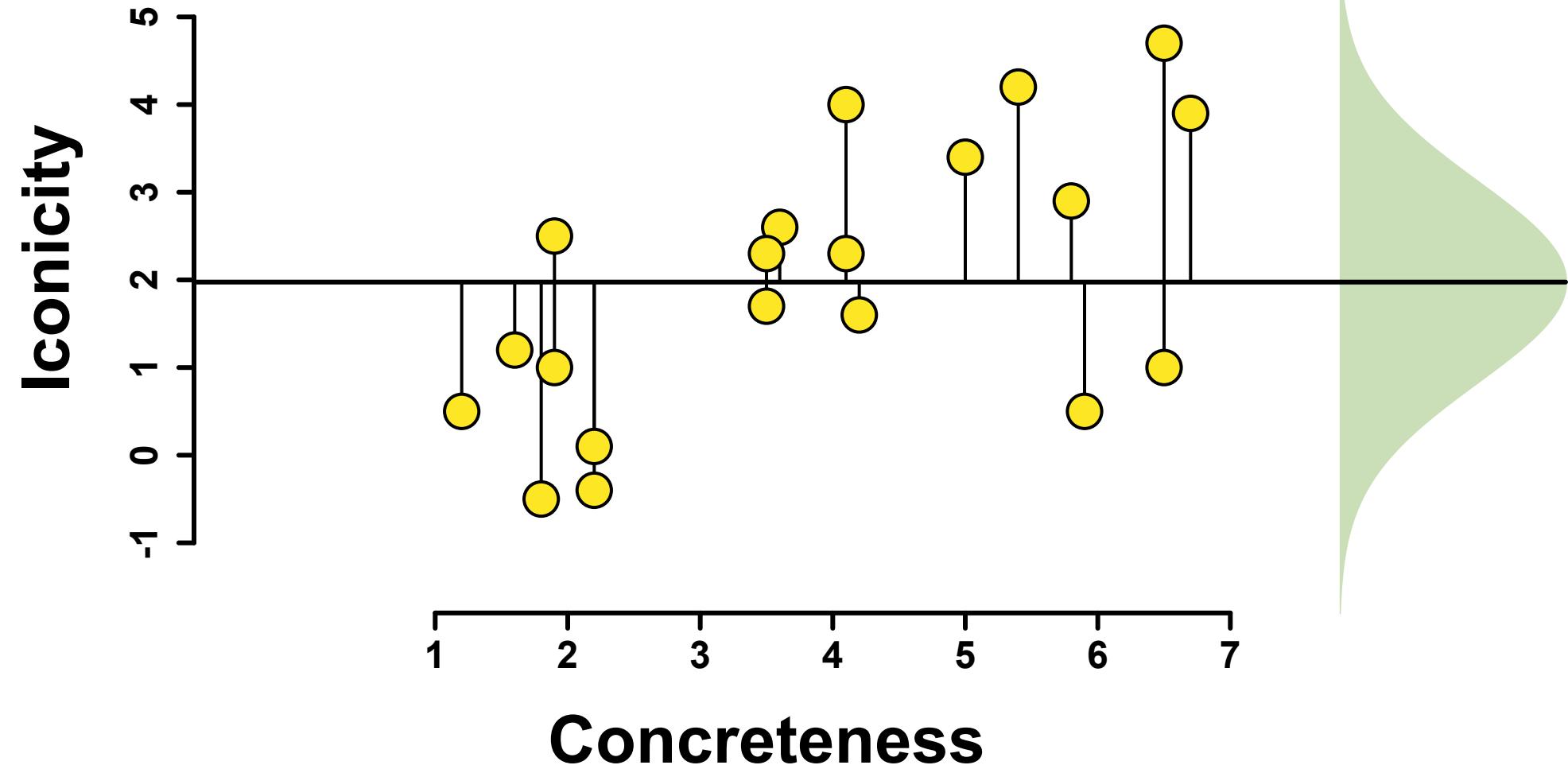




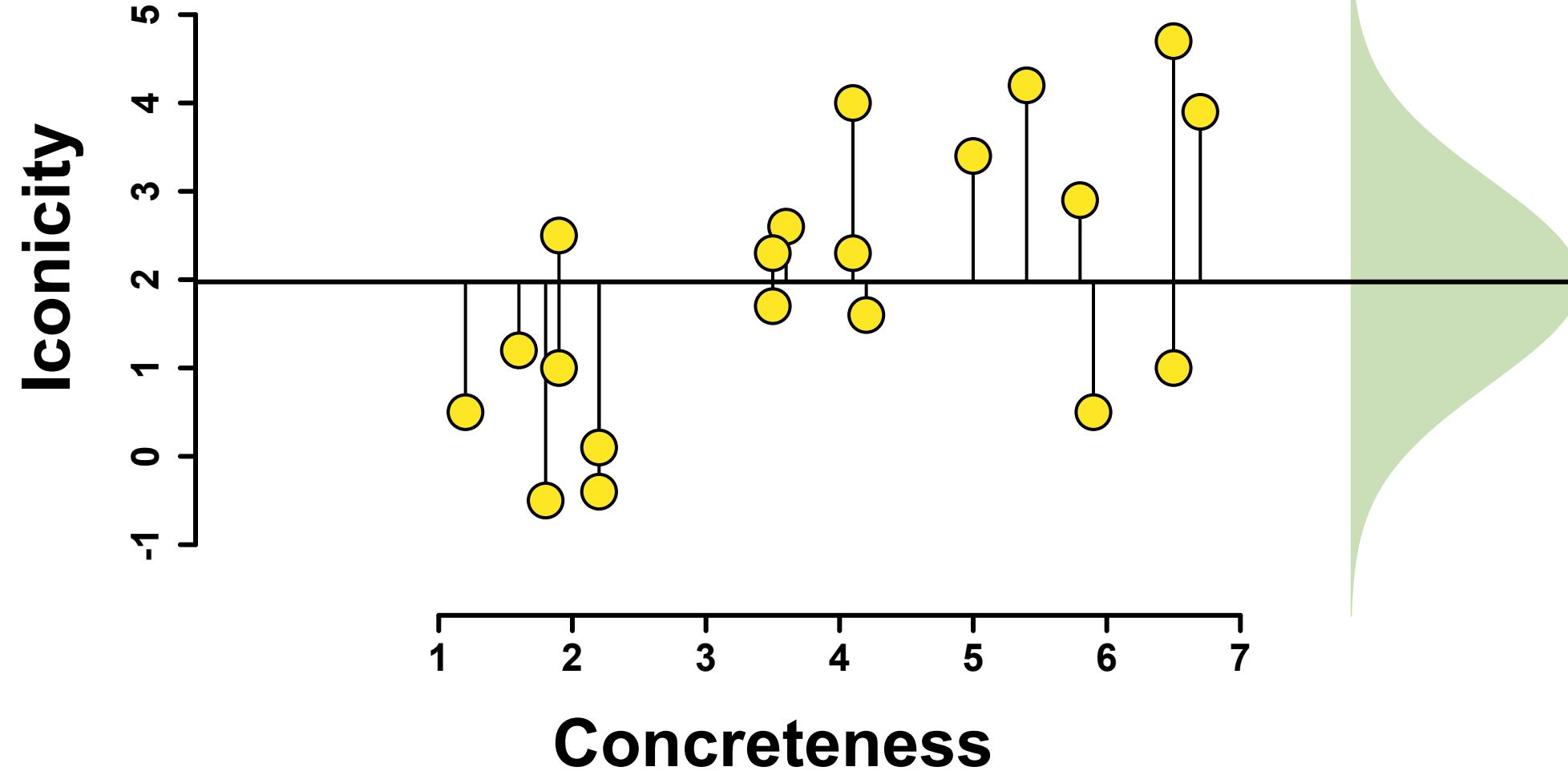
mean (Iconicity)
sd (Iconicity)



mean (Iconicity)
sd (Iconicity)

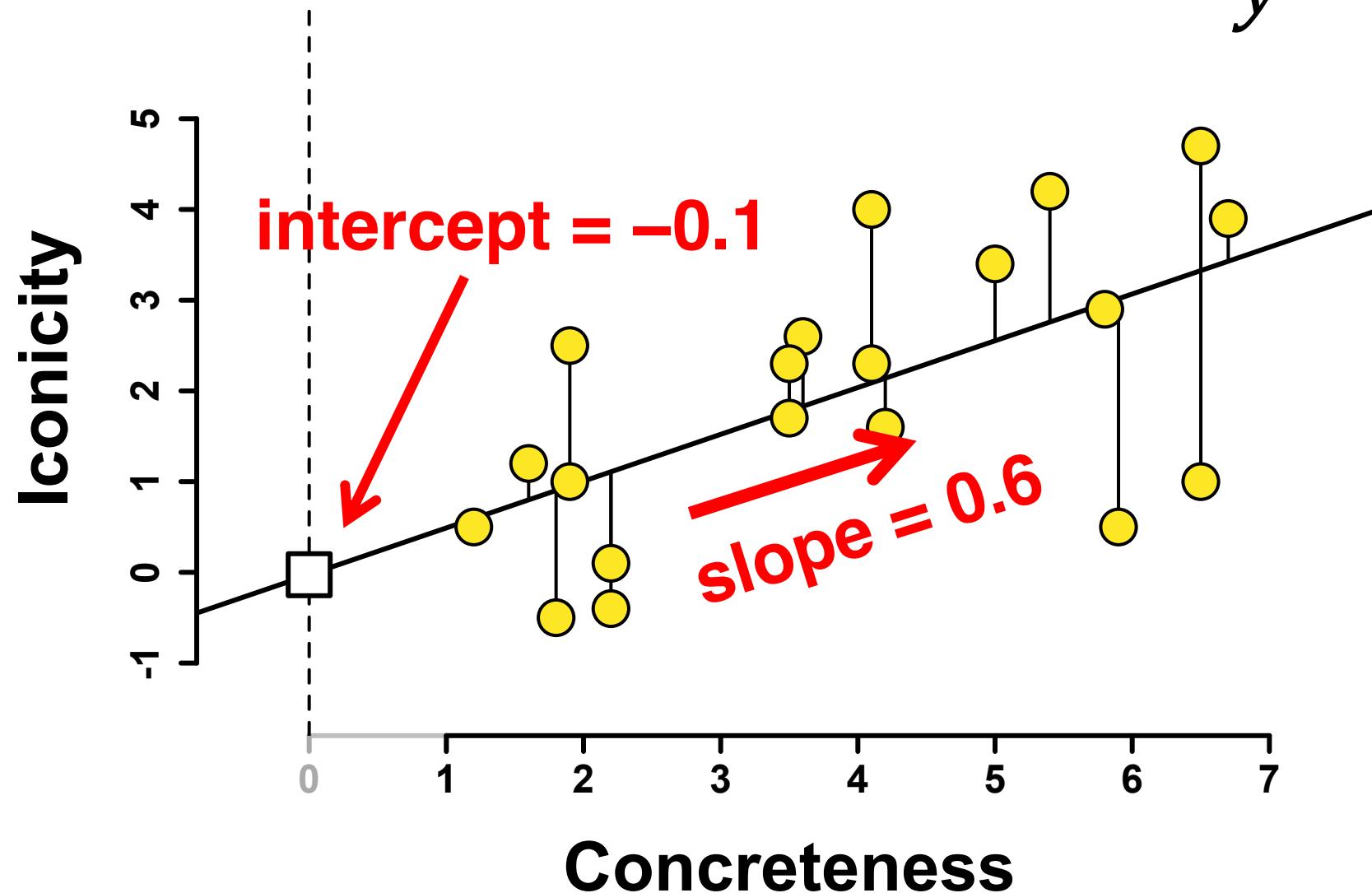


lm(Iconicity ~ 1)



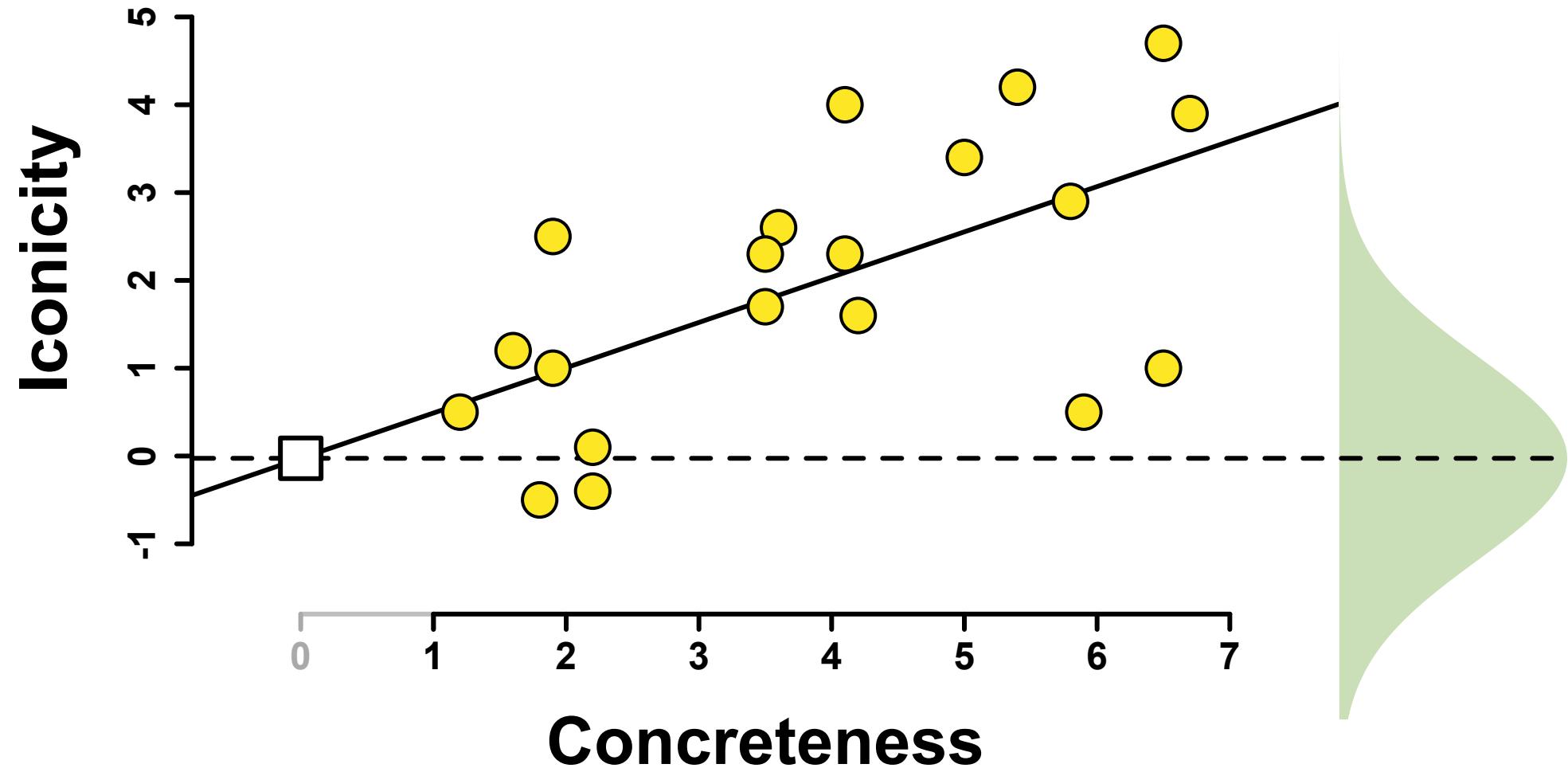
$\text{lm}(\text{Iconicity} \sim 1 + \text{Concreteness})$

$$y = b_0 + b_1 * x$$

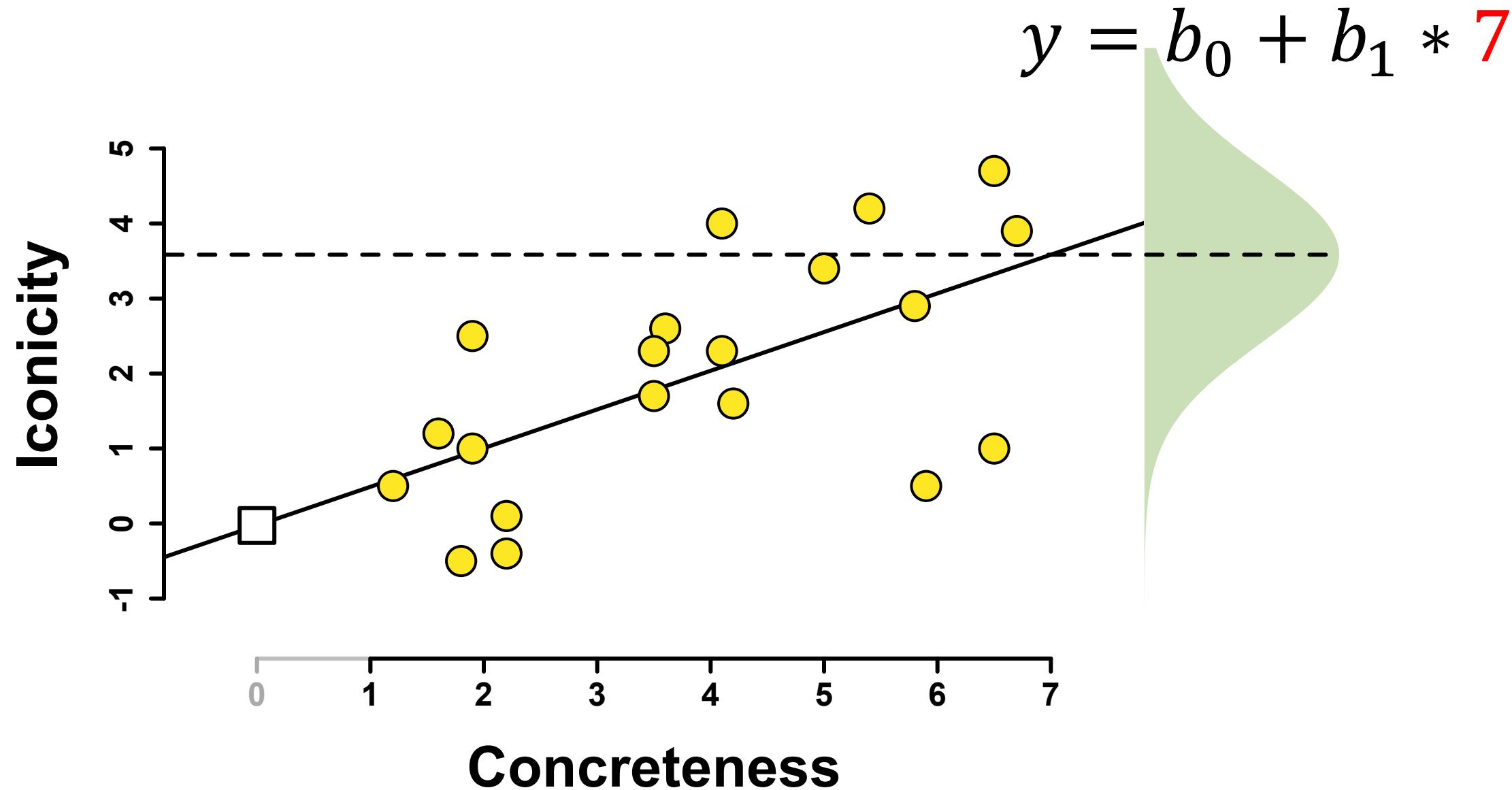


lm(Iconicity ~ Concreteness)

$$y = b_0 + b_1 * 0$$



lm(Iconicity ~ Concreteness)

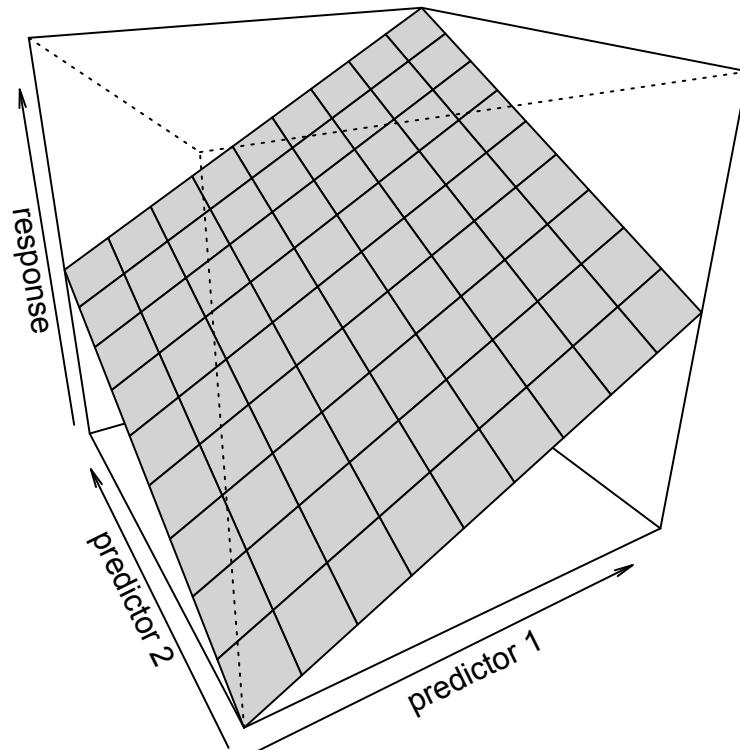


link function → **linear predictor**

$$I(\beta_0 + \beta_1 * x_i)$$


$$y_i \sim Normal(\mu_i, \sigma)$$

lm(y ~ x1 + x2)



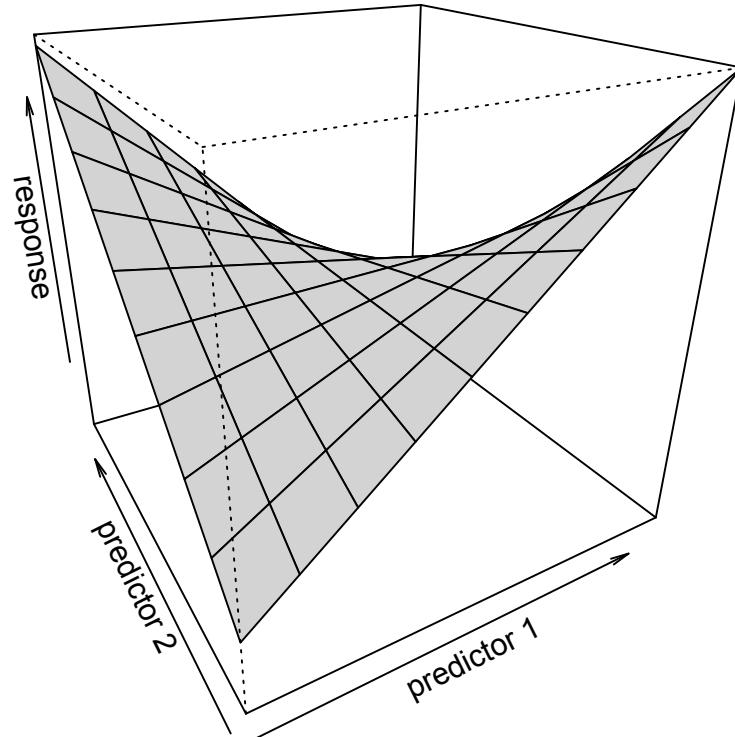
$$\beta_0 + \beta_1 x_1 + \beta_2 x_2$$



$$y \sim Normal(\mu, \sigma)$$

`lm(y ~ x1 + x2 + x1:x2)`

`lm(y ~ x1 * x2)`



$$\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 (x_1 x_2)$$



$y \sim Normal(\mu, \sigma)$

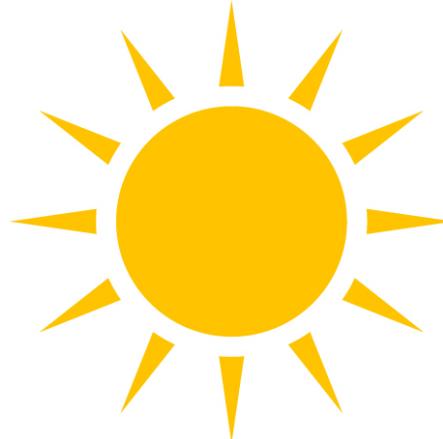
interaction term

A bit more on the concept of an interaction

$\text{lm}(\text{plant growth} \sim \text{sun exposure} * \text{water})$



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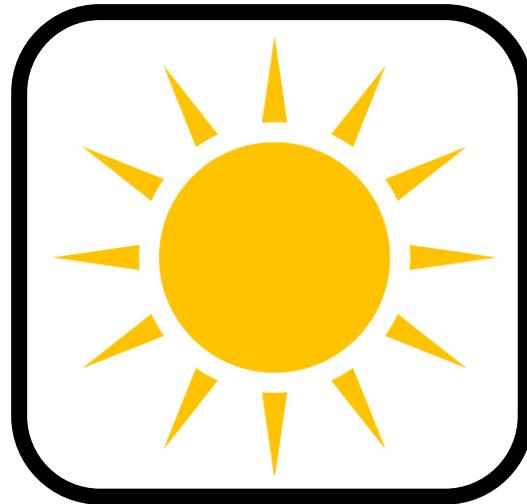
example from McElreath (2016), *Statistical Rethinking*

A bit more on the concept of an interaction

$\text{lm}(\text{plant growth} \sim \text{sun exposure} * \text{water})$



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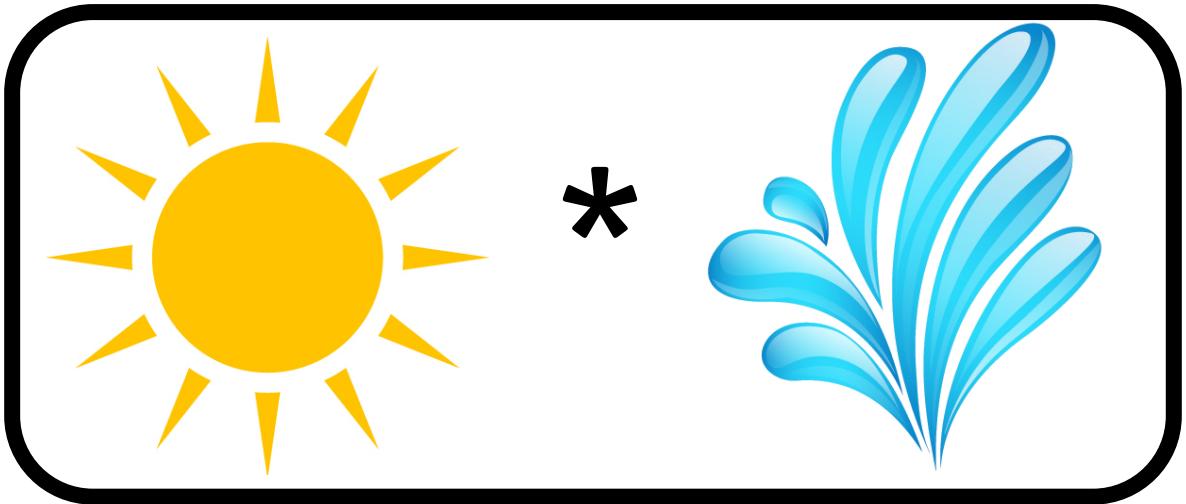
example from McElreath (2016), *Statistical Rethinking*

A bit more on the concept of an interaction

$\text{lm}(\text{plant growth} \sim \text{sun exposure} * \text{water})$



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example from McElreath (2016), *Statistical Rethinking*

Exercise with broom

**Linear models
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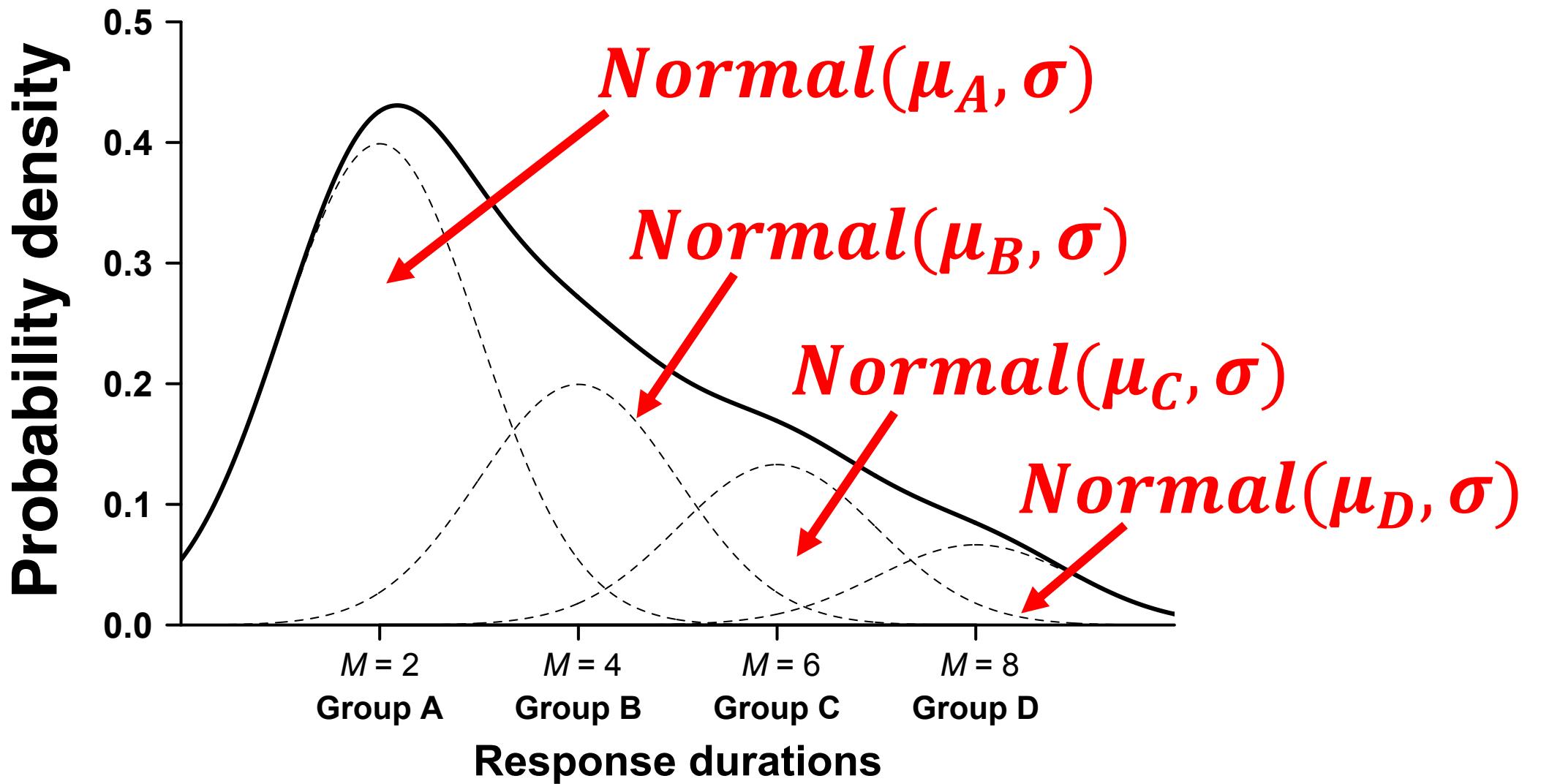
Intro to GLM



Exercise with broom

**Linear models
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Intro to GLM



link function → **linear predictor**

$$I(\beta_0 + \beta_1 * x_i)$$


$$y_i \sim Normal(\mu_i, \sigma)$$

```
glm(y ~ x, family = ...)
```

family = poisson

**Poisson distribution
for count data**

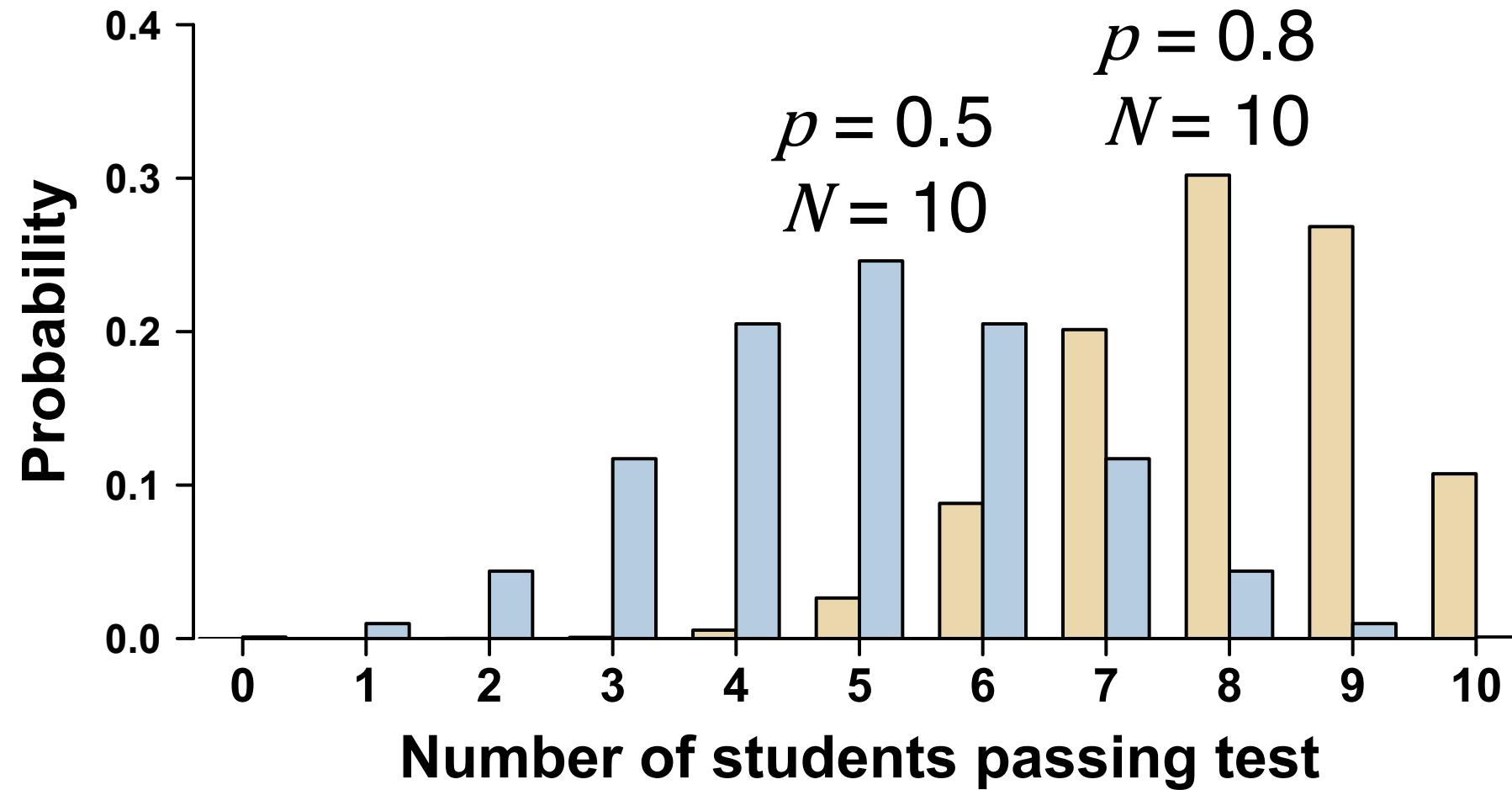
family = binomial

**Bernoulli distribution
for binary data**

$$y_i \sim Zaphod(\theta_i)$$

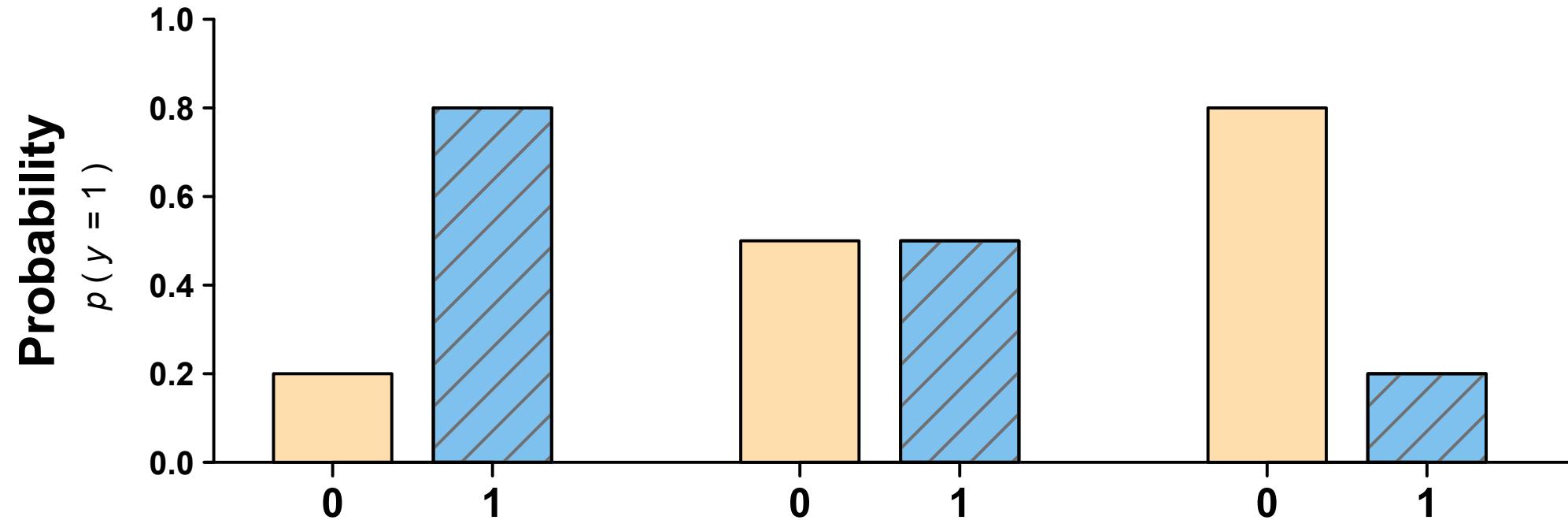
The binomial distribution

two parameters:
 p, N



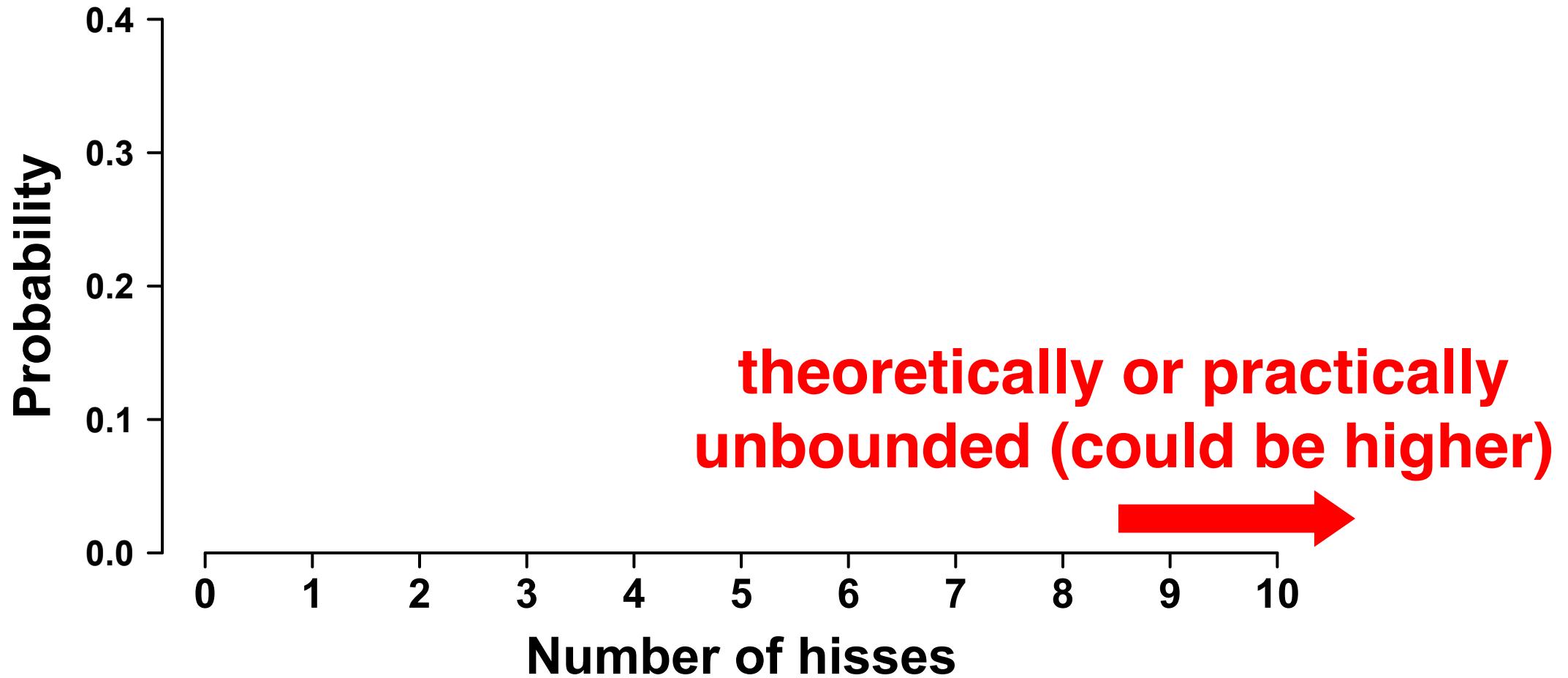
fix N to 1

The Bernoulli distribution



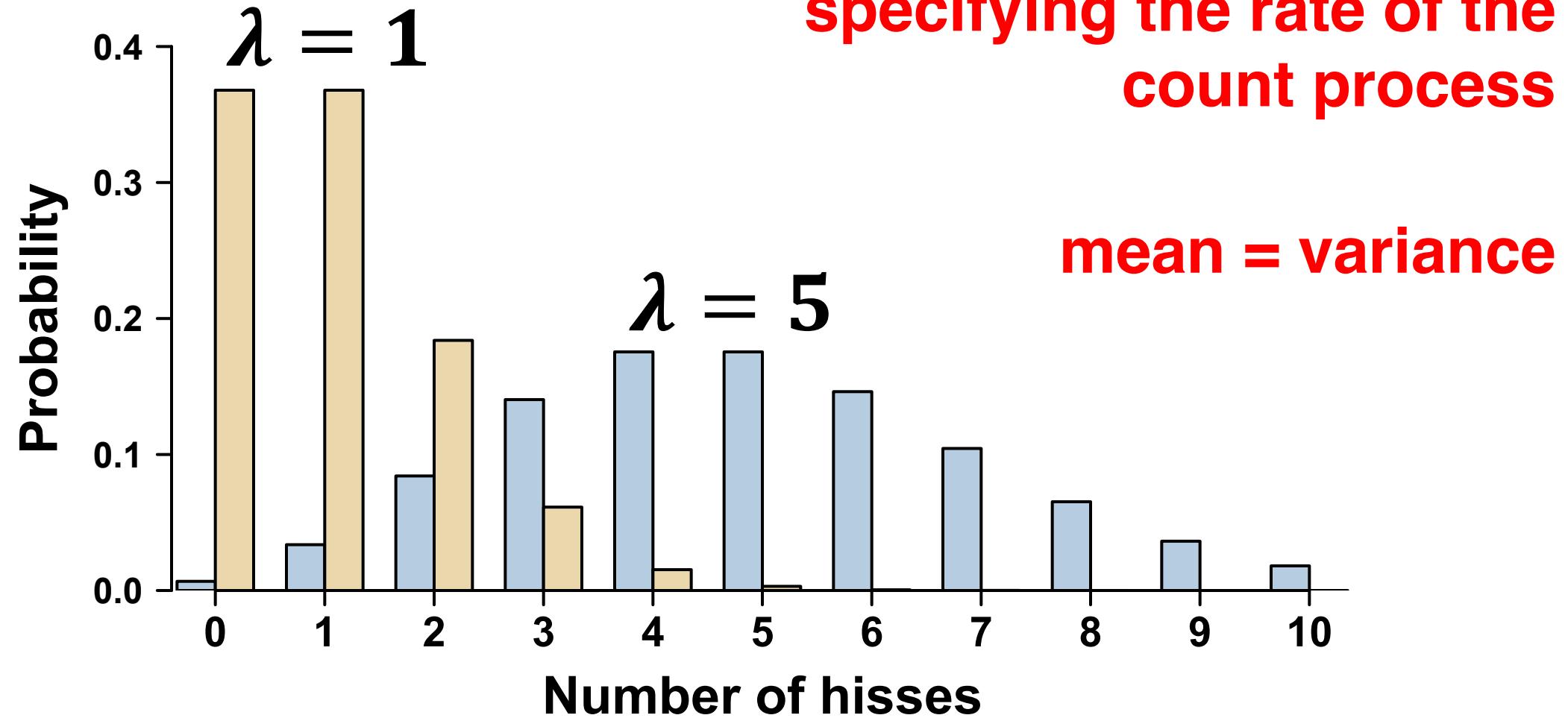
one parameter: p , specifying the probability of occurrence

The Poisson distribution



The Poisson distribution

one parameter: λ ,
specifying the rate of the
count process



Poisson regression

$$\beta_0 + \beta_1 * x_i$$

↓

$$y_i \sim Poisson(\lambda_i)$$



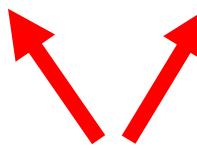
Poisson regression

$$e^{\beta_0 + \beta_1 * x_i}$$

↓

$$y_i \sim Poisson(\lambda_i)$$

$$\log(\lambda_i) = \beta_0 + \beta_1 * x_i$$


**coefficients are
in log space**

Logistic regression

$$\logit^{-1}(\beta_0 + \beta_1 * x_i) \downarrow y_i \sim \text{Bernoulli}(p_i)$$
$$\logit(p_i) = \beta_0 + \beta_1 * x_i$$

↑↑
**coefficients are
in log odd space**

Overview: some standard generalized linear models

$$I(\beta_0 + \beta_1 * x_i)$$



$$y_i \sim Normal(\mu_i, \sigma)$$

Linear regression

$$\text{logistic}(\beta_0 + \beta_1 * x_i)$$



$$y_i \sim Bernoulli(p_i)$$

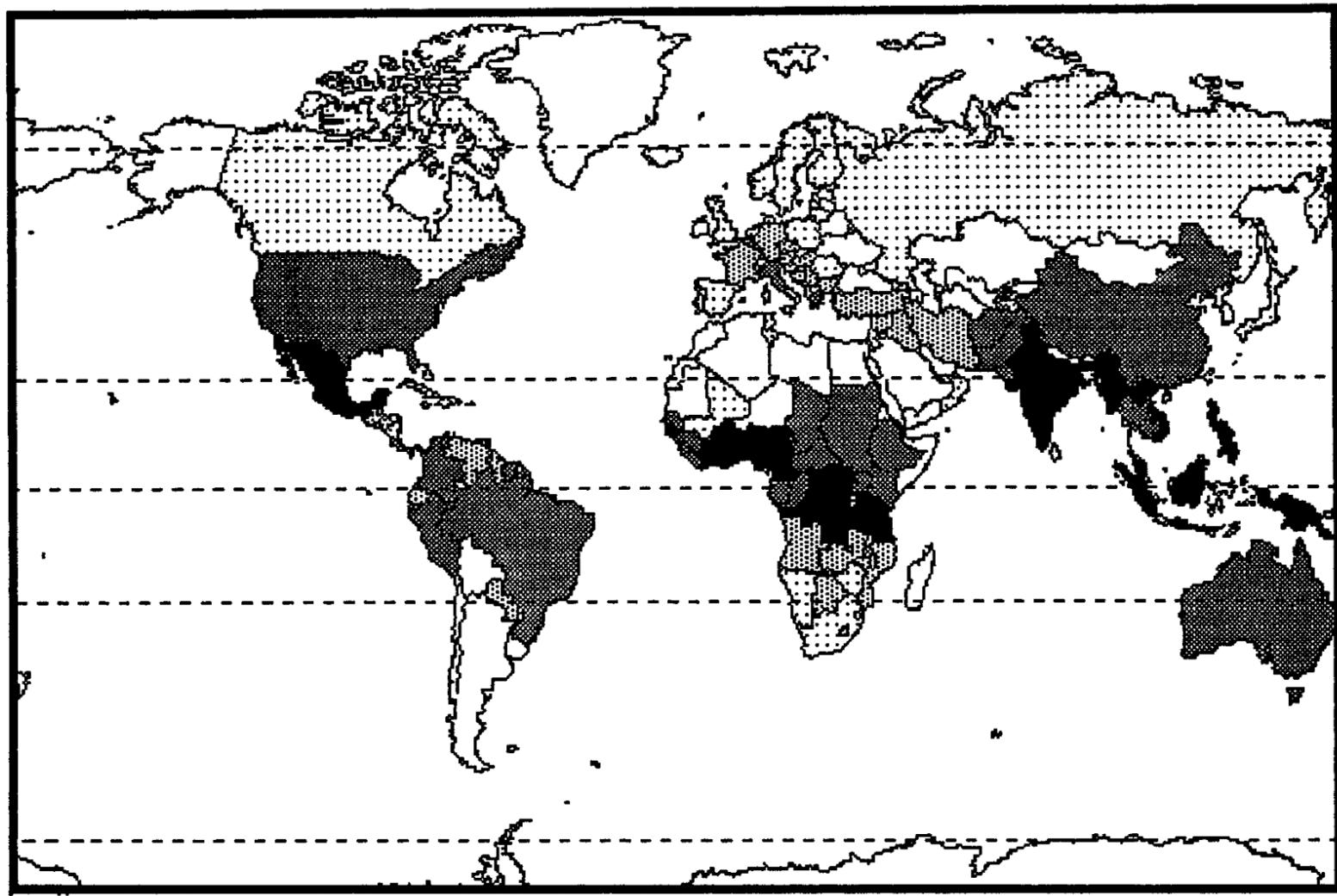
Logistic regression

$$\exp(\beta_0 + \beta_1 * x_i)$$



$$y_i \sim Poisson(\lambda_i)$$

Poisson regression



Nettle, D. (1999). *Linguistic diversity*. Oxford, UK: Oxford University Press.

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