Online sellers example

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Online Sellers

- This introductory modeling example comes from the YouTube channel 3Blue1Brown, and involves comparing the positive ratings of three online sellers.

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- The research question is to infer from these data which seller has the highest probability of providing a positive buying experience.

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Exercise

Implement the model with these data and assumptions in JAGS. Which seller is better?

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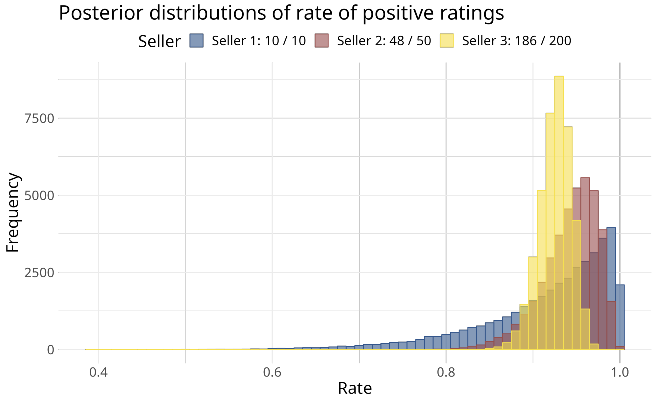
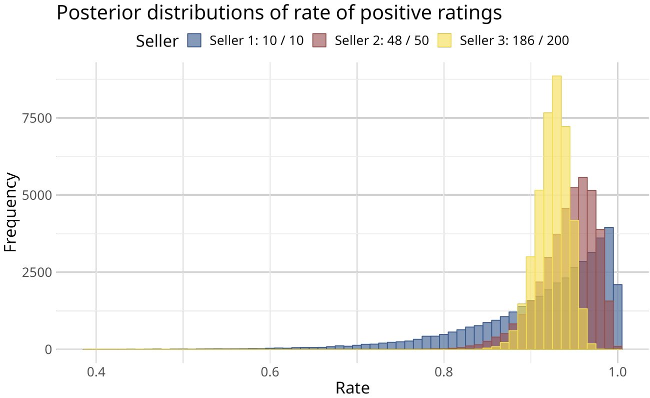
Rate Inferences

- The posterior distributions for the underlying rate of positive ratings show what values are possible, based on the data and the assumptions of the model.



Rate Inferences (Continued)

- The posterior distributions can be summarized by 95% credible intervals, which are $(0.70, 1.00)$ for Seller 1, $(0.86, 0.99)$ for Seller 2, and $(0.89, 0.96)$ for Seller 3.



Which Seller is Better?

- The posterior distributions represent everything we know about the possible underlying rates of positive reviews.

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Seller 2	0.54	–	0.70
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  - These are 0.68 for Seller 1, 0.89 for Seller 2, 0.92 for Seller 3.

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- Online sellers is a simple introductory model, but has the basic features of a parameter that controls a data-generating process, and observed data.

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- Inference about parameters represents uncertainty about their possible values, based on the available data and the assumptions of the model.