

Online sellers example

Joachim Vandekerckhove and Michael Lee

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

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Two	48	50	96%
Three	186	200	93%

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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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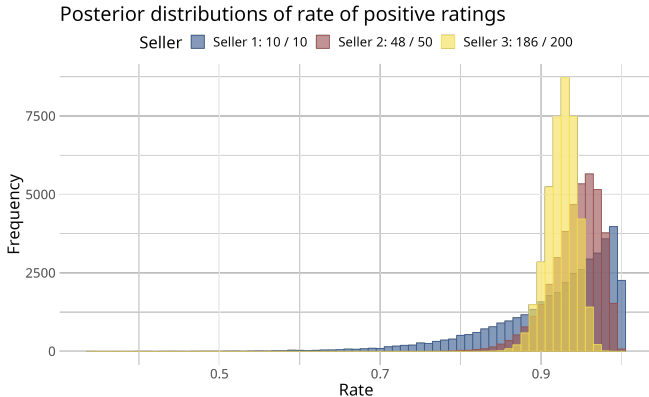
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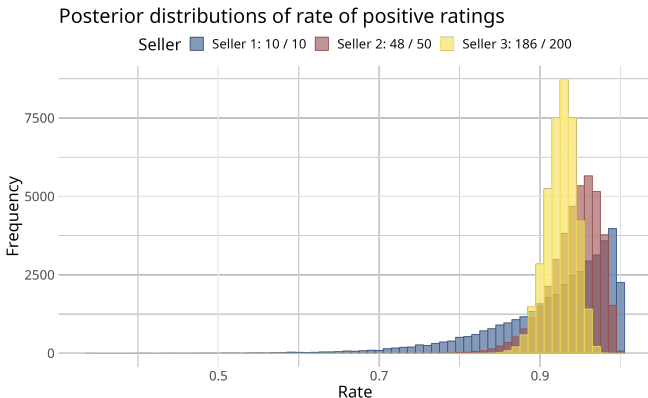
Rate Inferences

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

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Key Points

- Online sellers is a simple introductory model, but has the basic features of a parameter that controls a data-generating process, and observed data.
- Inference about parameters represents uncertainty about their possible values, based on the available data and the assumptions of the model.