

# LDAVis: A Method for Visualizing and Interpreting Topics

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<http://cpsievert.github.com/slides/LDAvis>

What is a topic model?

- ▶ Topic models discover 'topics' that occur in a collection of text:
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- ▶ **Drawback:** Rare words tend to receive too high of a ranking.
- ▶ We believe that a compromise between these two measures can aid topic interpretation:

$$\text{relevance} = \lambda * p(w_i|z_j) + (1 - \lambda) * \text{lift}$$

# User study



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- ▶ We anticipate this 'optimal' value of  $\lambda$  will vary for different datasets.
- ▶ For this reason, it is nice to have an *interactive* tool that *quickly* iterates through word rankings (based on different values of  $\lambda$ ).
- ▶ The R package LDAvis makes it easy to create an interactive visualizations to aid topic interpretation.

Live demo







## Some links

- ▶ LDAvis on GitHub (see README.md) –  
<https://github.com/cpsievert/LDAvis/>
- ▶ Reach me on Twitter @cpsievert
- ▶ Thanks for coming!