Modeling research topics in movement ecology

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IBC - 2020

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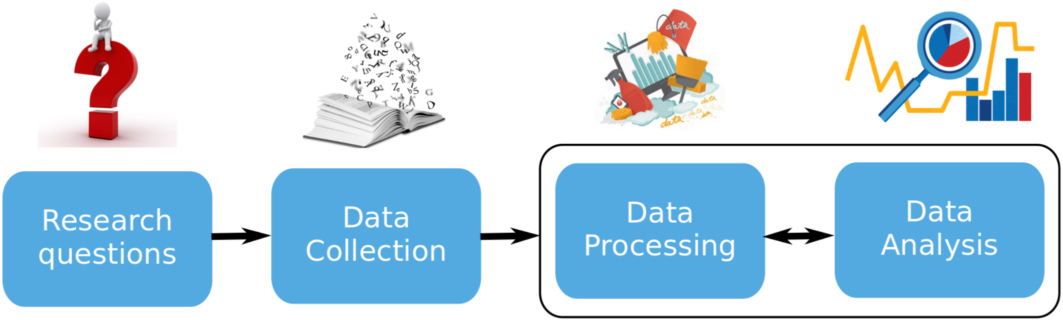
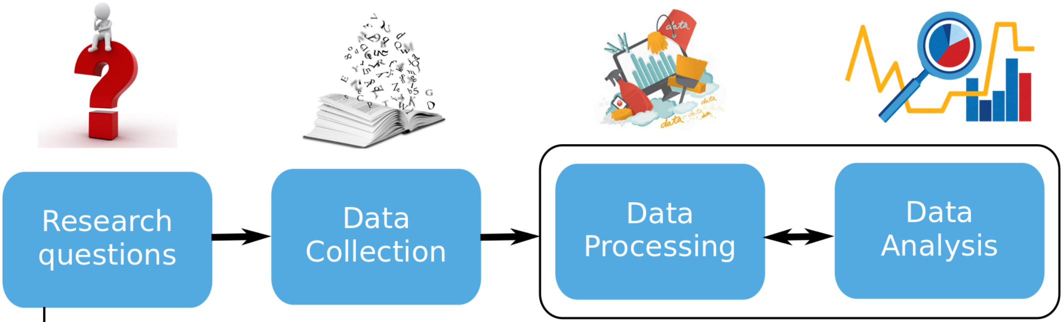
Text analysis workflow



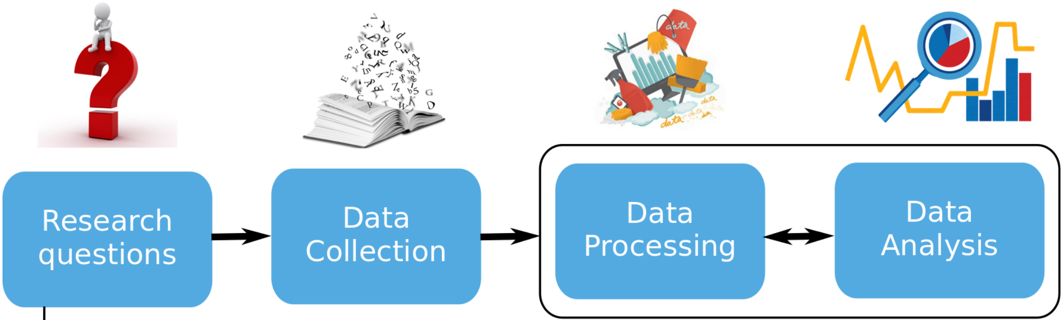
Text analysis workflow: movement ecology



- which topics?
- statistical methods?
- software?
- ⋮

in the last decade

Text analysis workflow: movement ecology



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Text analysis workflow: movement ecology

Research questions → Data Collection → Data Processing ↔ Data Analysis

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Data Processing:
- remove redundant words
- standard English (BrE or AmE)
- lemmatize
- filter out words appearing once

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Data Analysis → Topic Modeling

Topic modeling

Why attend IBC?

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Scientific community

- Community
- Network
- People
- Meeting
- Social

Knowledge

- Learn
- Teach
- Development
- Understand
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Topic modeling

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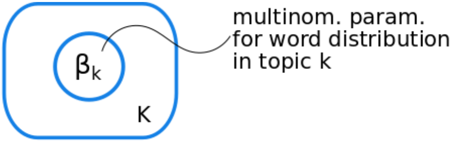

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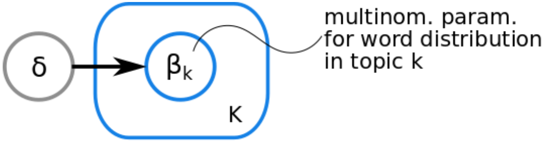

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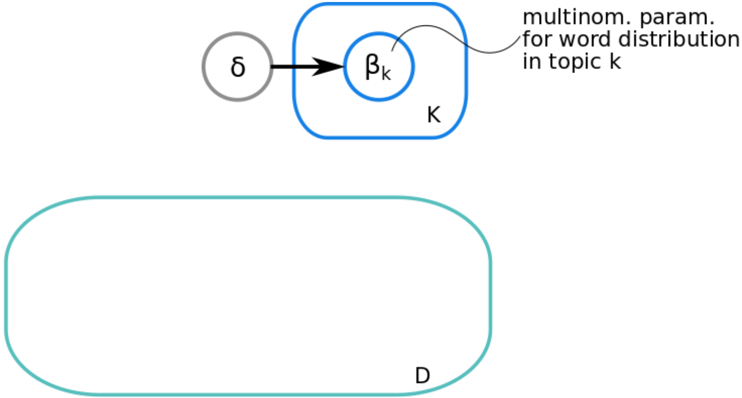
- Each document $\mathbf{d} \in \{1, ..., \mathbf{D}\}$ is composed by a mixture of topics, drawn from a multinomial distribution with parameter θ, which is drawn from a Dirichlet distribution with parameter α.



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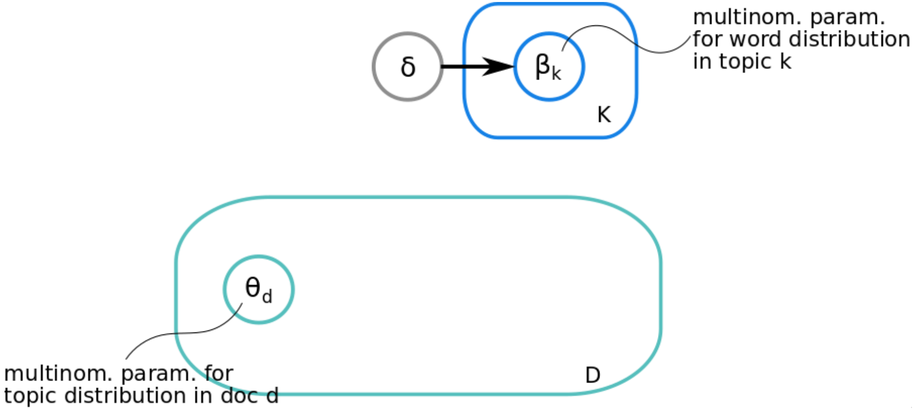

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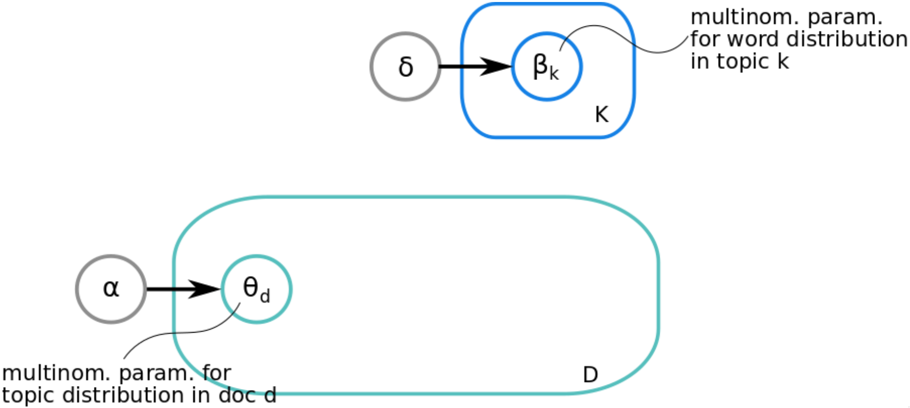

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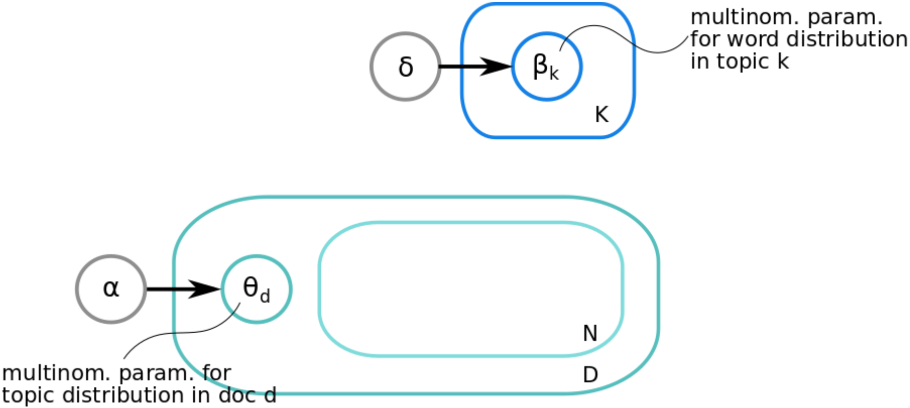
- For each word $\mathbf{w}$ in document $\mathbf{d}$, first a hidden topic $\mathbf{z}$ is selected from the multinomial distribution with parameter θ.



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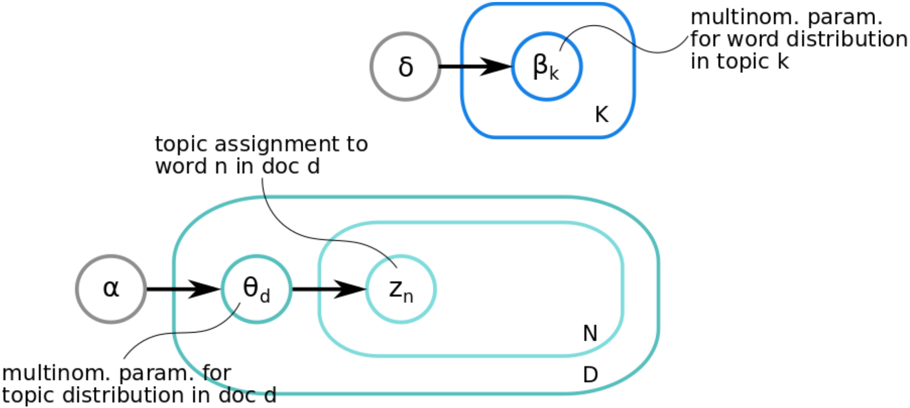

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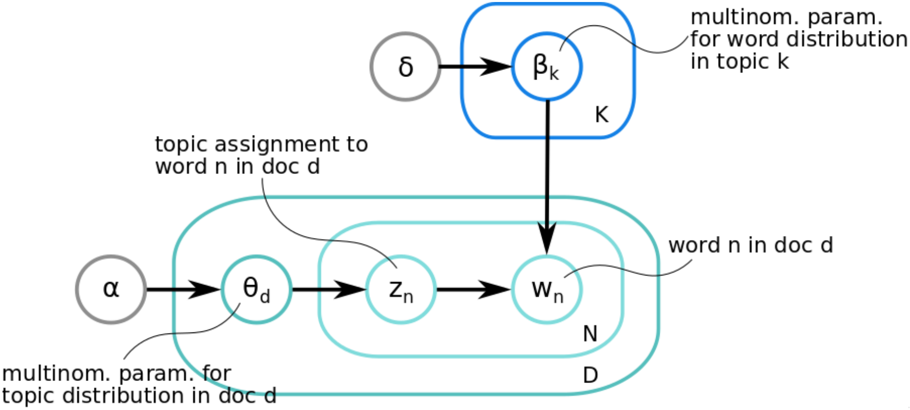
- For each word $\mathbf{w}$ in document $\mathbf{d}$, first a hidden topic $\mathbf{z}$ is selected from the multinomial distribution with parameter θ.
- From the selected topic $\mathbf{z}$, a word is selected based on the multinomial distribution with parameter β.



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The log-likelihood of a document $\mathbf{d} = \{\mathbf{w}_1, ..., \mathbf{w}_N\}$ is

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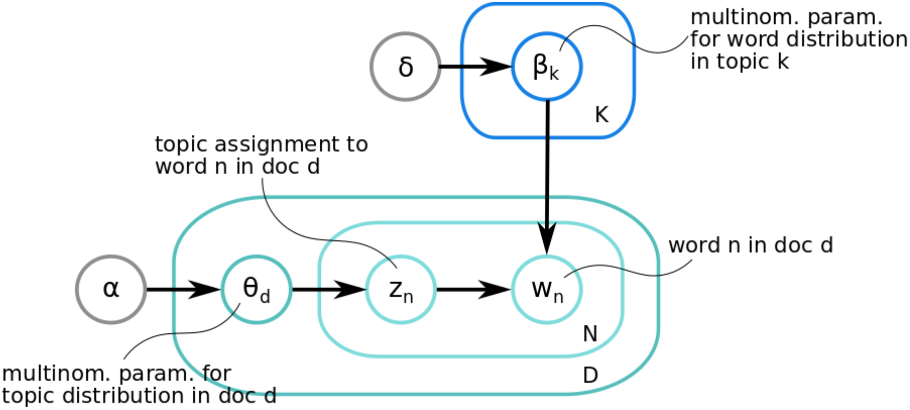

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Inference on the posterior via Variational Expectation Maximization (Blei et al. 2003; Grün and Hornik 2011); `topicmodels` R package

Assumptions:

- Exchangeability: order of words is negligible
- Topics are uncorrelated
- Number of topics is known (in this study: 15)

Topic modeling - LDA

Results - movement ecology

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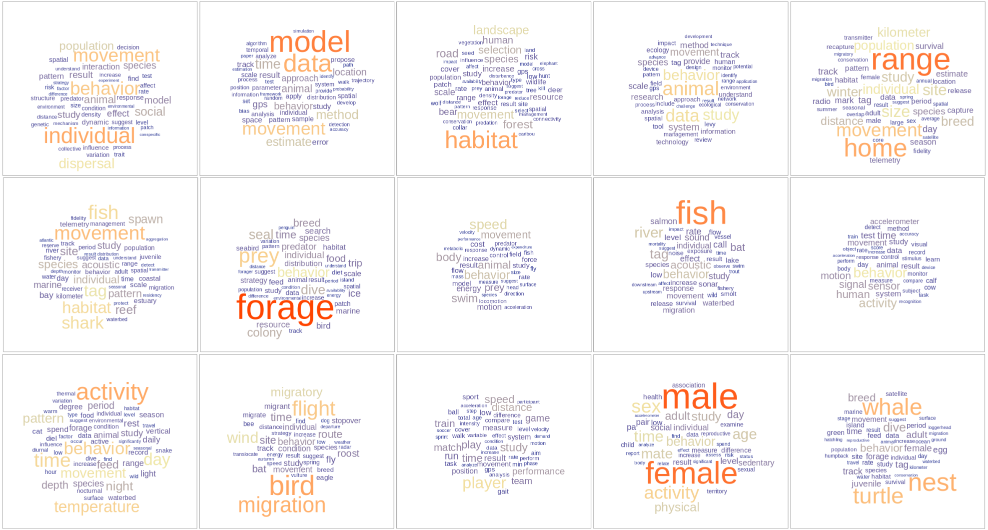

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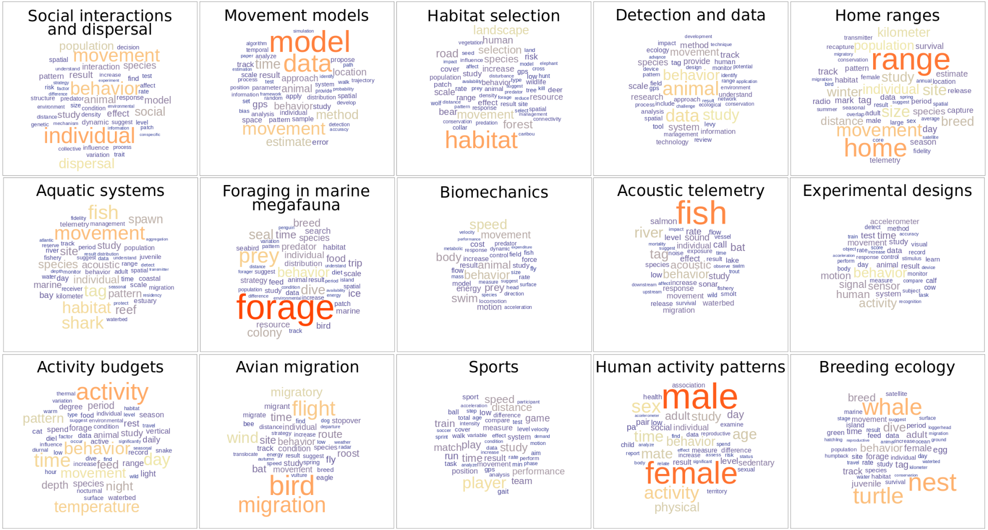

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Results - movement ecology

- $\mathbf{E}(\theta_{\mathbf{d}} \mid \mathbf{z})$: topic distribution per document
- $\sum_{\mathbf{d}} \mathbf{E}(\theta_{\mathbf{d}} \mid \mathbf{z_k})$: proxy of prevalence of each topic

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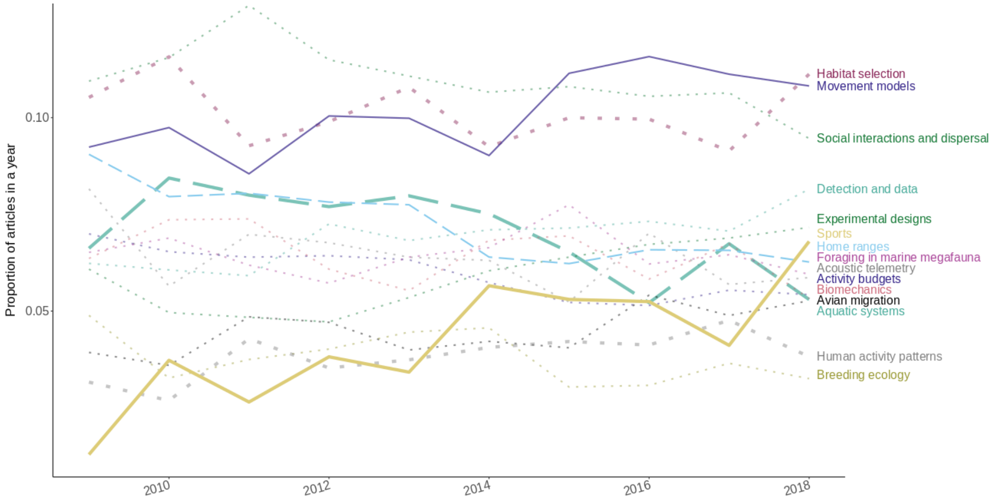

Further exploration?

- Topic evaluation: word intrusion
  - Take the highest probability words from a topic
  - Take a high-probability word from another topic and add it
  - Ask humans to identify the word that does not belong

Results shown here: Joo et al. pre-print.

References

- Blei, David M., Andrew Y. Ng, and Michael I. Jordan. 2003. ‘Latent Dirichlet Allocation.’ Journal of Machine Learning Research 3 (Jan): 993âĂŞ1022. http://jmlr.csail.mit.edu/papers/v3/blei03a.html.
- Grün, Bettina, and Kurt Hornik. 2011. ‘topicmodels: An R Package for Fitting Topic Models.’ Journal of Statistical Software 40 (13): 1âĂŞ30. https://doi.org/10.18637/jss.v040.i13.
- Joo, Rocío, Simona Picardi, Matthew E. Boone, Thomas A. Clay, Samantha C. Patrick, Vilma S. Romero-Romero and Mathieu Basille. Pre-print. ‘A decade of movement ecology’. arxiv. https://arxiv.org/abs/2006.00110.

Thanks for your attention

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