

Unit 6: Topic Models

Florida State Summer Methods Workshop

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May 2019



An Example

Islamophobia and Media Portrayals of Muslim Women (*International Studies Quarterly*)

- **Question:** How do U.S. news media report about women's rights abroad?

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- **Data:** 35 years of reporting in the *New York Times* and *Washington Post*.
- **Method:** Topic Modeling

Today: Topic model American news coverage of women abroad

Goal: represent each article as a mixture of topics:

- Describe each topic.
- Measure proportion of each article addressing each topic.

Method: Latent Dirichlet Allocation (LDA); Structural Topic Modeling (STM)

Game Plan:

- 1) Single versus Mixed Membership models
- 2) Topic modeling intuition, output, decision points
- 3) Interpretation and applications

Key Terms:

- Mixed membership model
- Topic models
- Topic and topic proportions
- Latent Dirichlet Allocation (LDA)
- Structural Topic Modeling (STM)

Key R Packages

- `stm`

Single vs. Mixed Membership Models

Clustering

Document \rightsquigarrow One Cluster

Doc 1

Doc 2

Doc 3

\vdots

Doc N

Cluster 1

Cluster 2

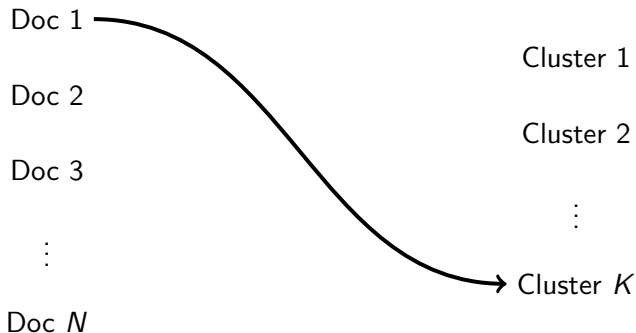
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Cluster K

Single vs. Mixed Membership Models

Clustering

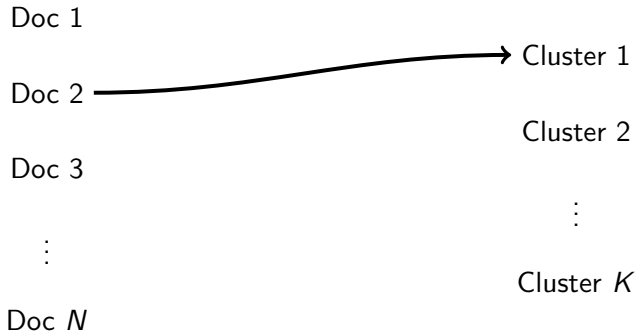
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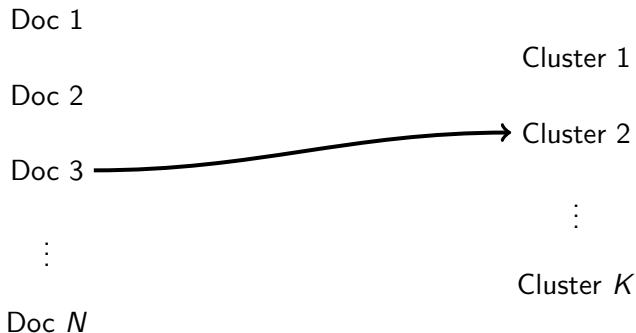
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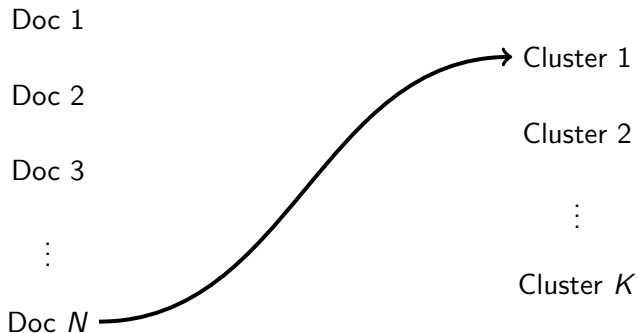
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Topic Models (Mixed Membership)

Document \rightsquigarrow Many clusters

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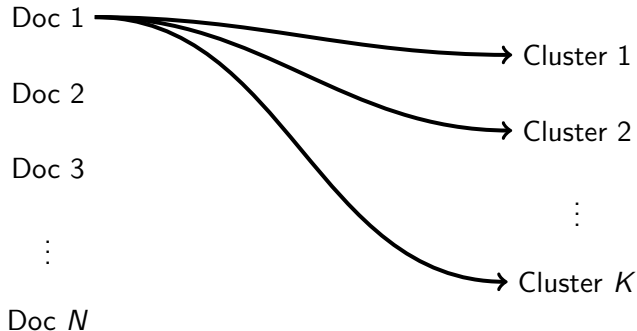
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What is Topic Modeling?

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It is **mixed membership** because it considers each document to be a **mixture** of different topics.

How does topic modeling work?

Goal: Topic model the following documents:

- I like to eat broccoli and bananas.
- I ate a banana and spinach smoothie for breakfast.
- Hamsters and kittens are cute.
- My sister adopted a kitten yesterday.
- Look at this cute hamster munching on a piece of broccoli.

We suspect that this corpus contains 2 topics. We want to reverse engineer those topics from the co-occurrence of words in each document.

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Topic A (interpreted to be about Food)

Topic B (interpreted to be about Pets)

Latent Dirichlet Allocation

LDA: Popular topic modeling method.

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Inputs

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- 2 K : the desired number of topics.

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Outputs

- 1 π_k : Topic distribution over words.
- 2 θ_i : Document distribution over topics.

LDA: Outputs

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1) Topic distribution over words (π_k).

Topic	broccoli	banana	breakfast	kitten	cute	hamster	like	yesterday	Total
<i>A</i>	.30	.25	.20	.01	.01	.01	.12	.10	1
<i>B</i>	.01	.01	.01	.35	.24	.25	.08	.05	1

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2) Document distribution over topics (θ_i).

Document	Topic A Weight	Topic B Weight	Total
1	.99	.01	1
2	.99	.01	1
3	.01	.99	1
4	.01	.99	1
4	.60	.40	1

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How do we decide?

What makes a good topic model?

A good topic model is one for which topics are **substantially / semantically interpretable**.

How do we interpret the topics?

- 1 Look at top / distinctive words for each topic.
- 2 Read most representative documents for each topic.

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Structural Topic Model

The **structural topic model** is an extension of LDA.

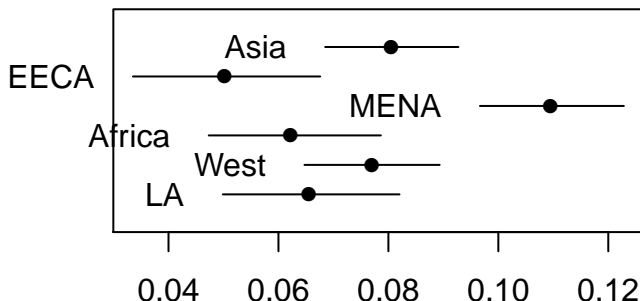
How does the **prevalence** of topics vary across groups of documents (by region, author, etc)?

Label	Probability Keywords	FREX Keywords
Business	said, work, compani, year, percent, job, busi, worker, million, market	compani, bank, industri, factori, employ, market, employe, busi, corpor, manag
Sports	team, women, game, play, world, said, olymp, sport, player, first	game, olymp, sport, player, soccer, athlet, coach, team, medal, championship
Fashion	black, dress, one, cloth, wear, design, street, fashion, citi, white	restaur, jacket, shirt, color, skirt, blue, worn, cloth, fashion, pant
Arts	film, book, show, art, work, stori, life, one, play, write	film, artist, novel, art, museum, theater, movi, charact, fiction, reader
Women's Rights & Gender Equality	women, men, femal, law, right, chang, male, equal, mani, issu	equal, male, gender, femal, discrimin, men, women, law, status, chang
Politics	polit, minist, govern, elect, parti, presid, said, vote, leader, prime	elect, vote, minist, prime, parti, candid, voter, cabinet, politician, polit
Religion	said, islam, religi, right, church, ban, law, countri, women, practic	islam, religi, religion, secular, veil, circumcis, fundamentalist, church, genit, koran

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Business	said, work, compani, year, percent, job, busi, worker, million, market	compani, bank, industri, factori, employ, market, employe, busi, corpor, manag
Sports	team, women, game, play, world, said, olymp, sport, player, first	game, olymp, sport, player, soccer, athlet, coach, team, medal, championship
Fashion	black, dress, one, cloth, wear, design, street, fashion, citi, white	restaur, jacket, shirt, color, skirt, blue, worn, cloth, fashion, pant
Arts	film, book, show, art, work, stori, life, one, play, write	film, artist, novel, art, museum, theater, movi, charact, fiction, reader
Women's Rights & Gender Equality	women, men, femal, law, right, chang, male, equal, mani, issu	equal, male, gender, femal, discrimin, men, women, law, status, chang
Politics	polit, minist, govern, elect, parti, presid, said, vote, leader, prime	elect, vote, minist, prime, parti, candid, voter, cabinet, politician, polit
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Expected Topic Proportion Across Region

Women's Rights and Gender Equality



R Code!