



TOPIC MODELING

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09/20/2023

CLASS LOGISTICS

- Hw5 due; Hw6 will be released today

HW5 REVIEW

The Dark Knight

Avengers

Joker

Iron Man

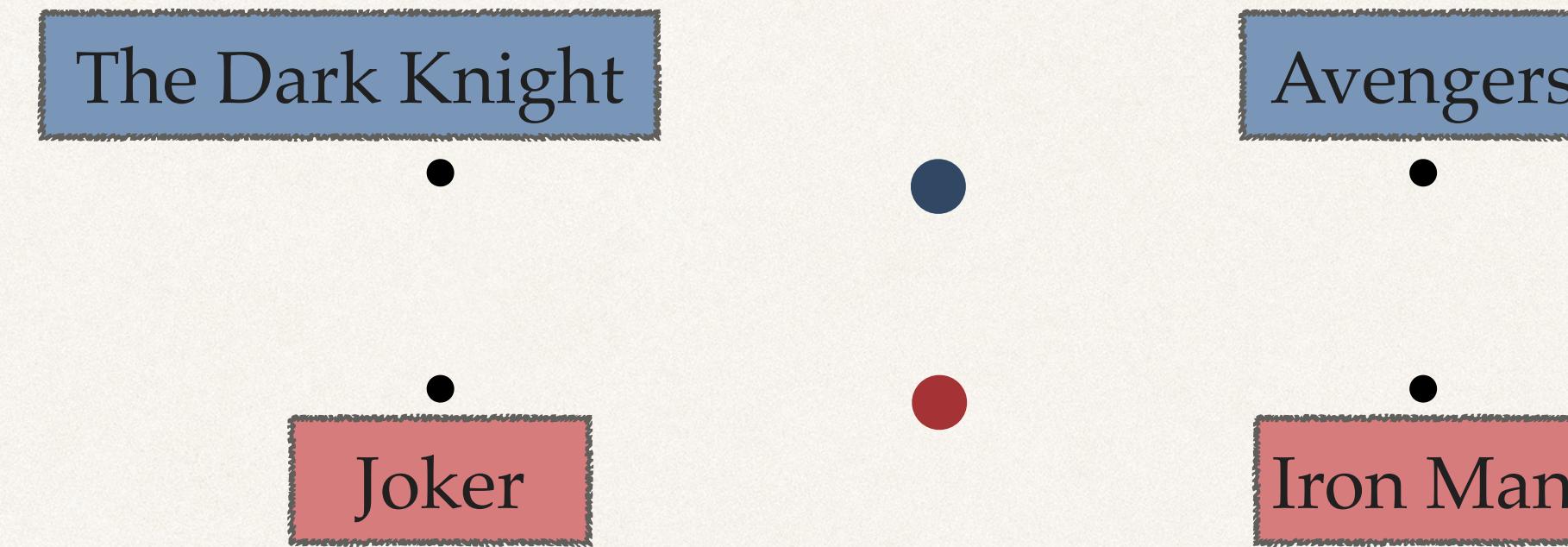
Which movies will be clustered together?

HW5 REVIEW



Q1. Which movies will be clustered together by KMeans?

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HW5 REVIEW

The Dark Knight

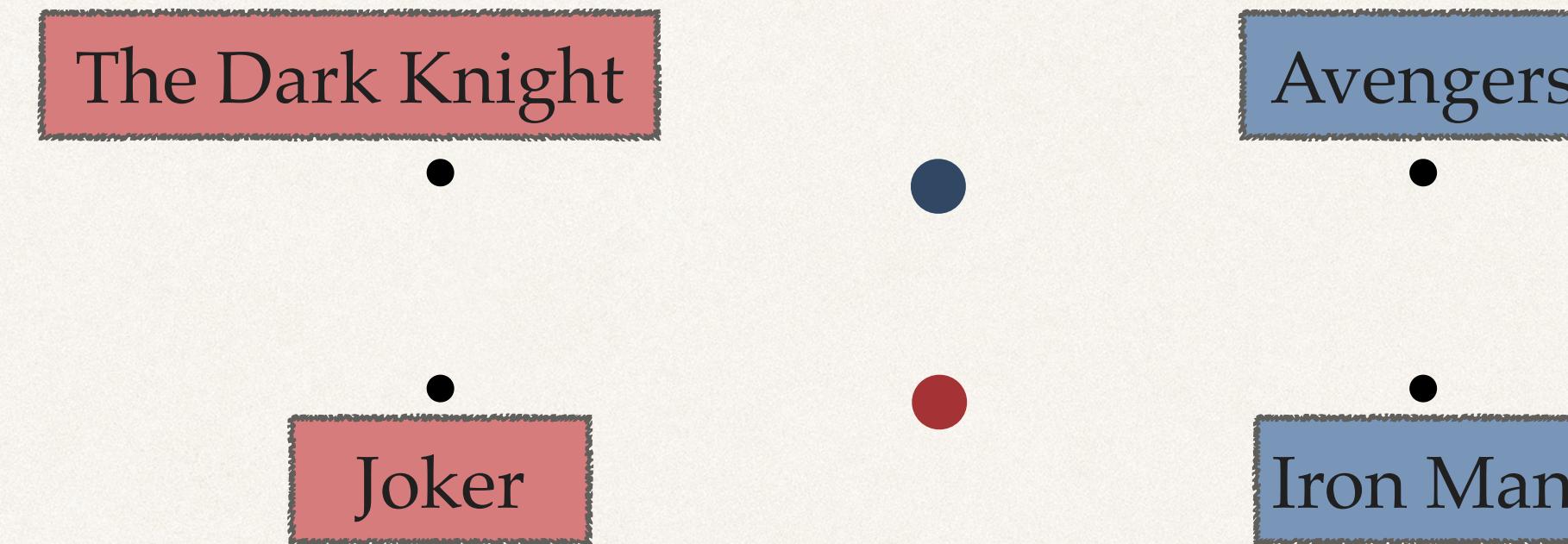
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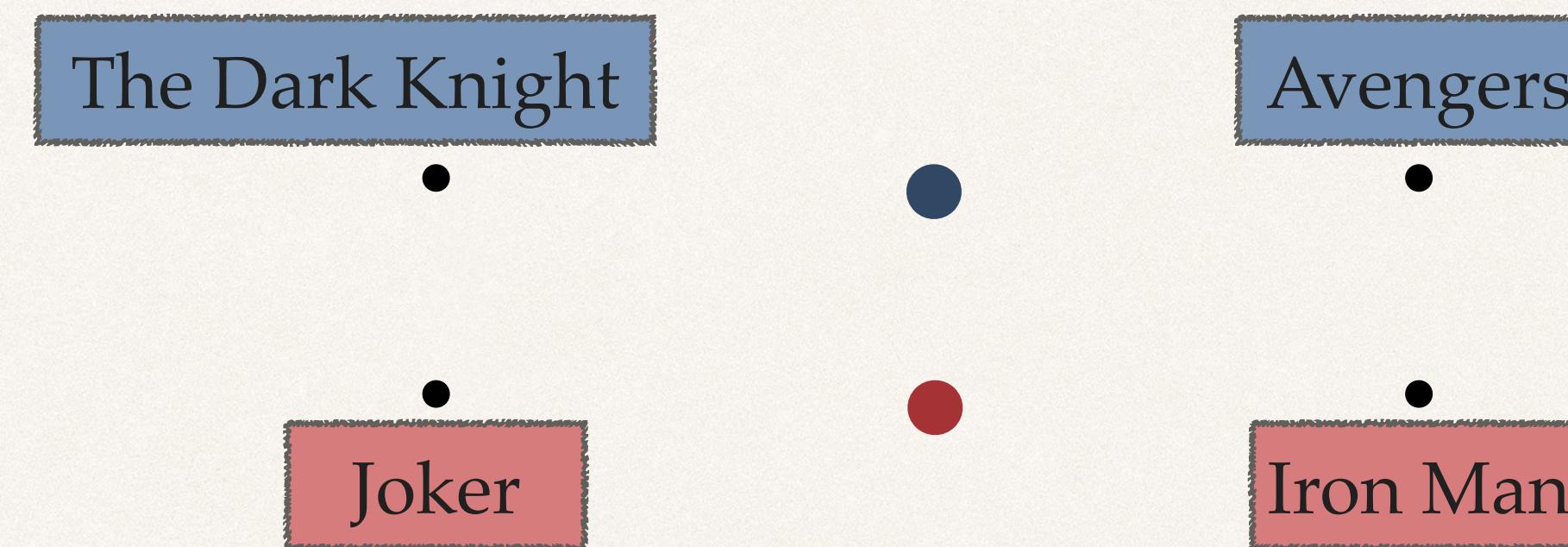
Q2. Which movies should be clustered together ideally?

HW5 REVIEW



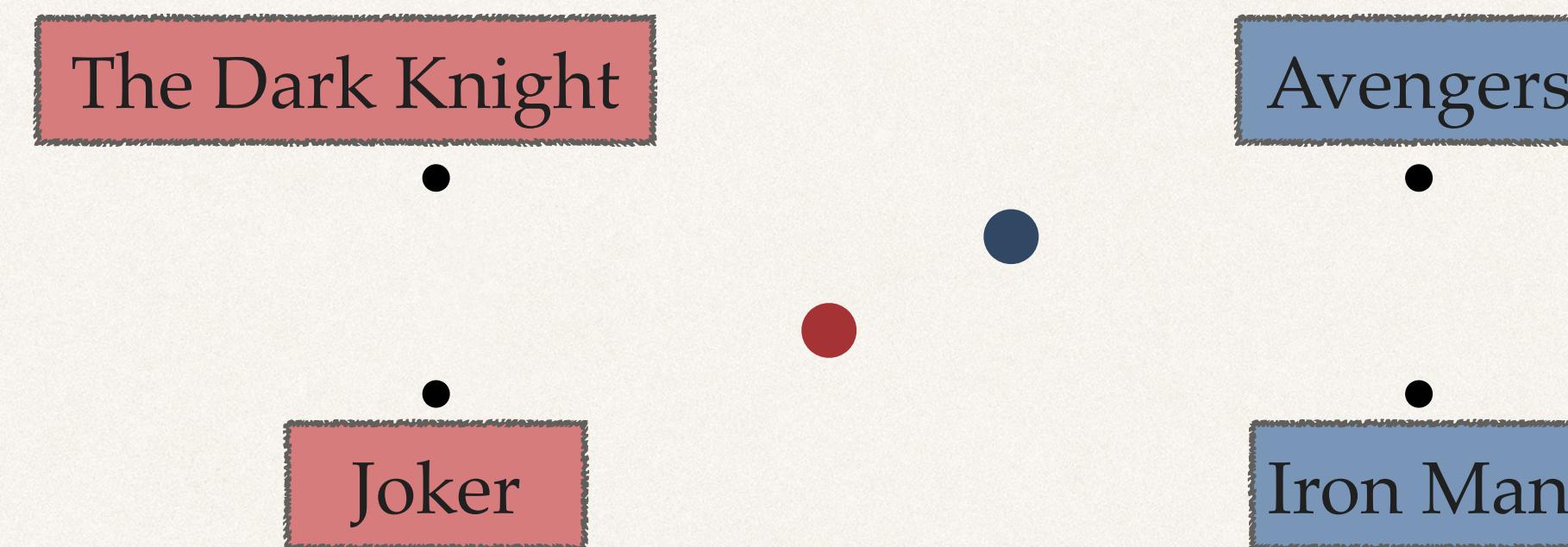
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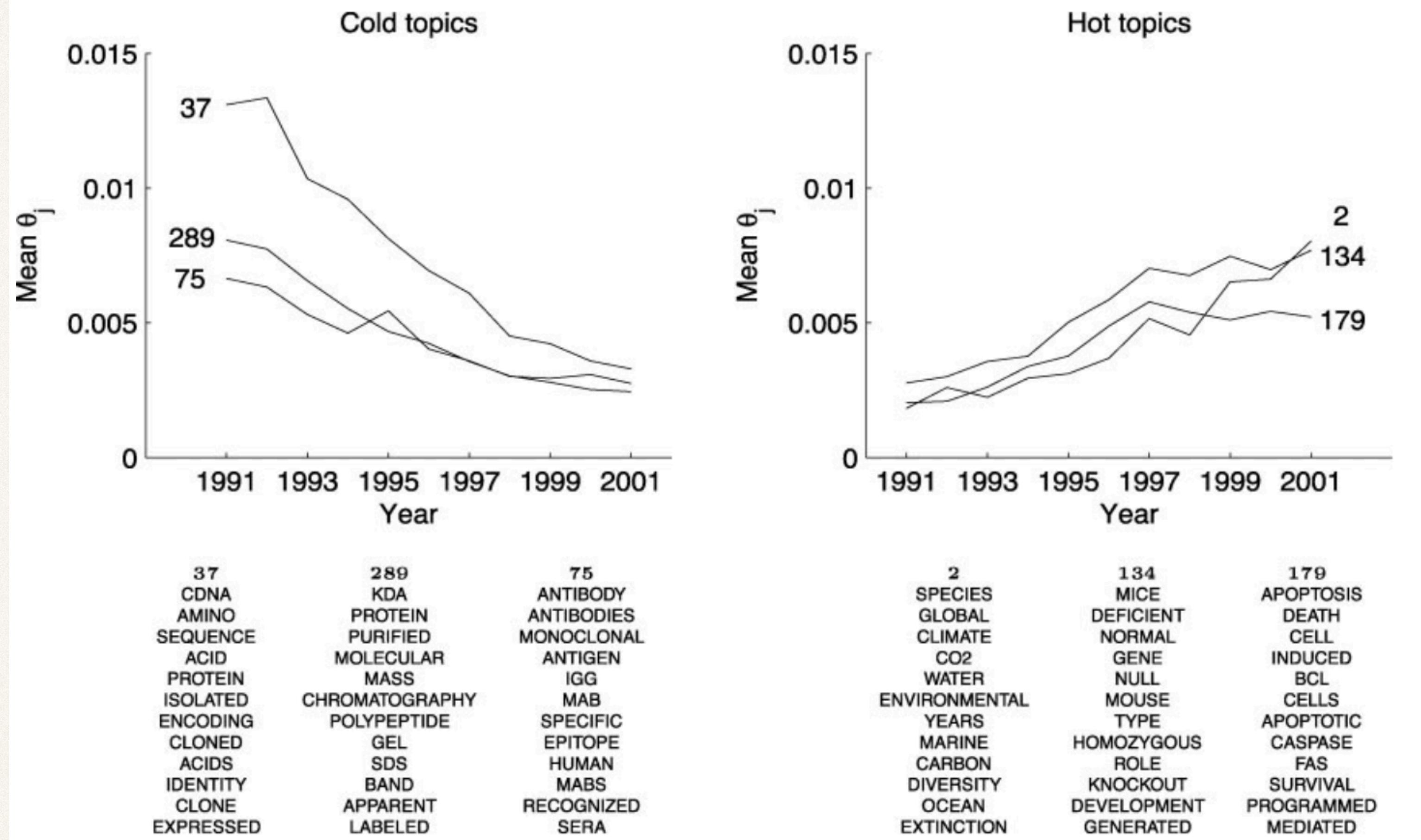
Q3. What can we change to get the above clustering using KMeans?

HW5 REVIEW

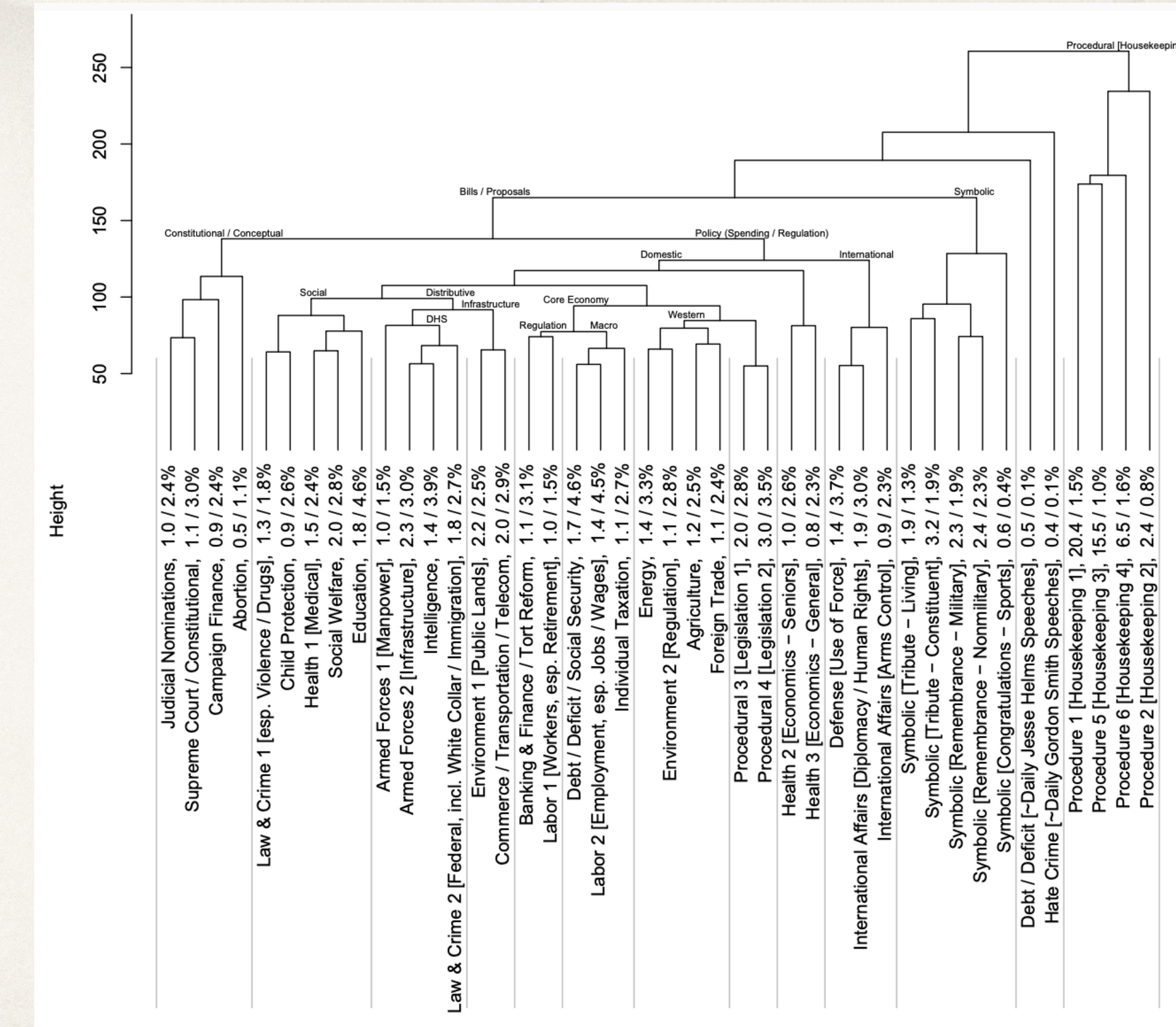


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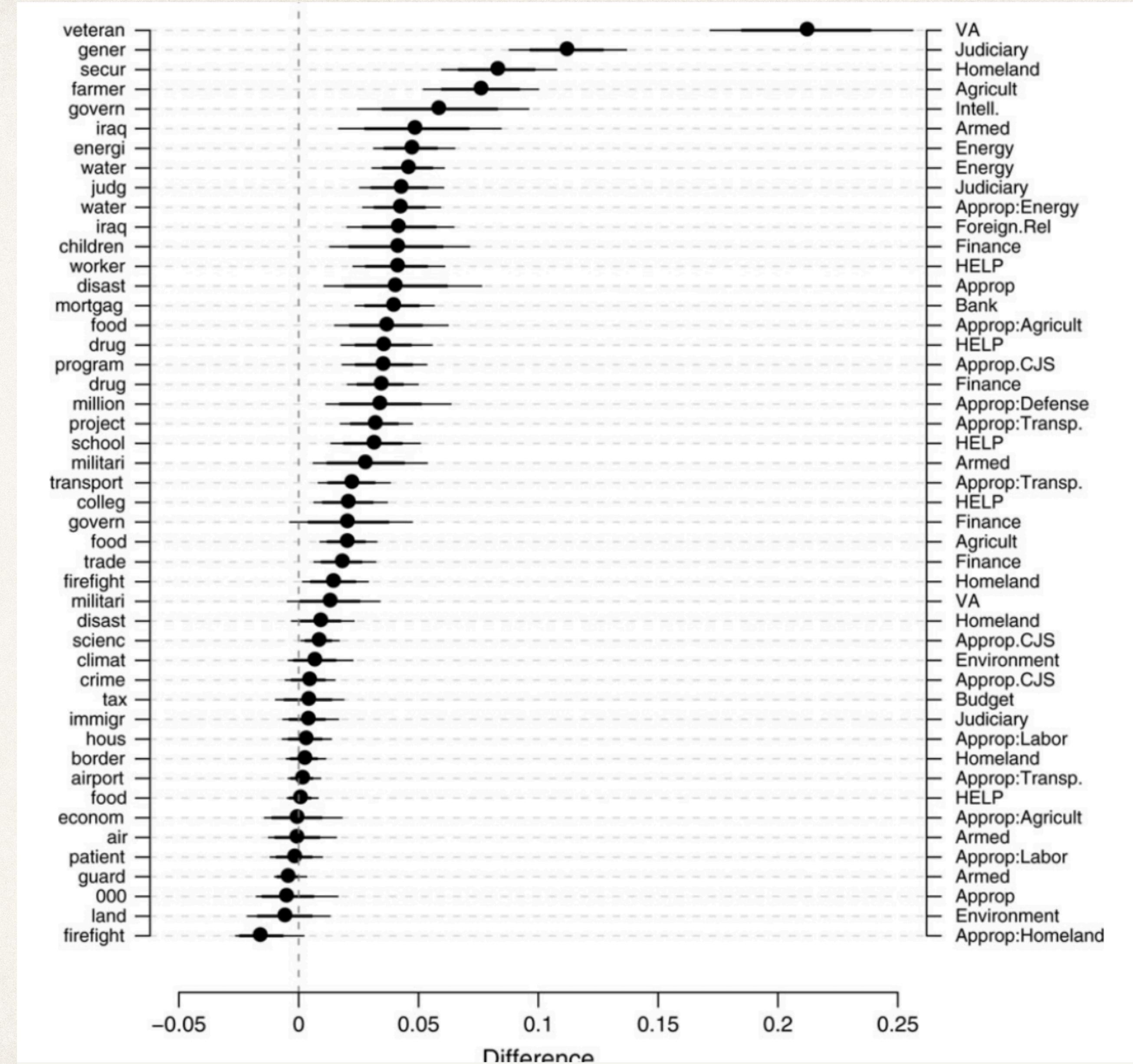
- What are the different scientific topics?
- Which ones are in vogue and which have fell out of fashion?



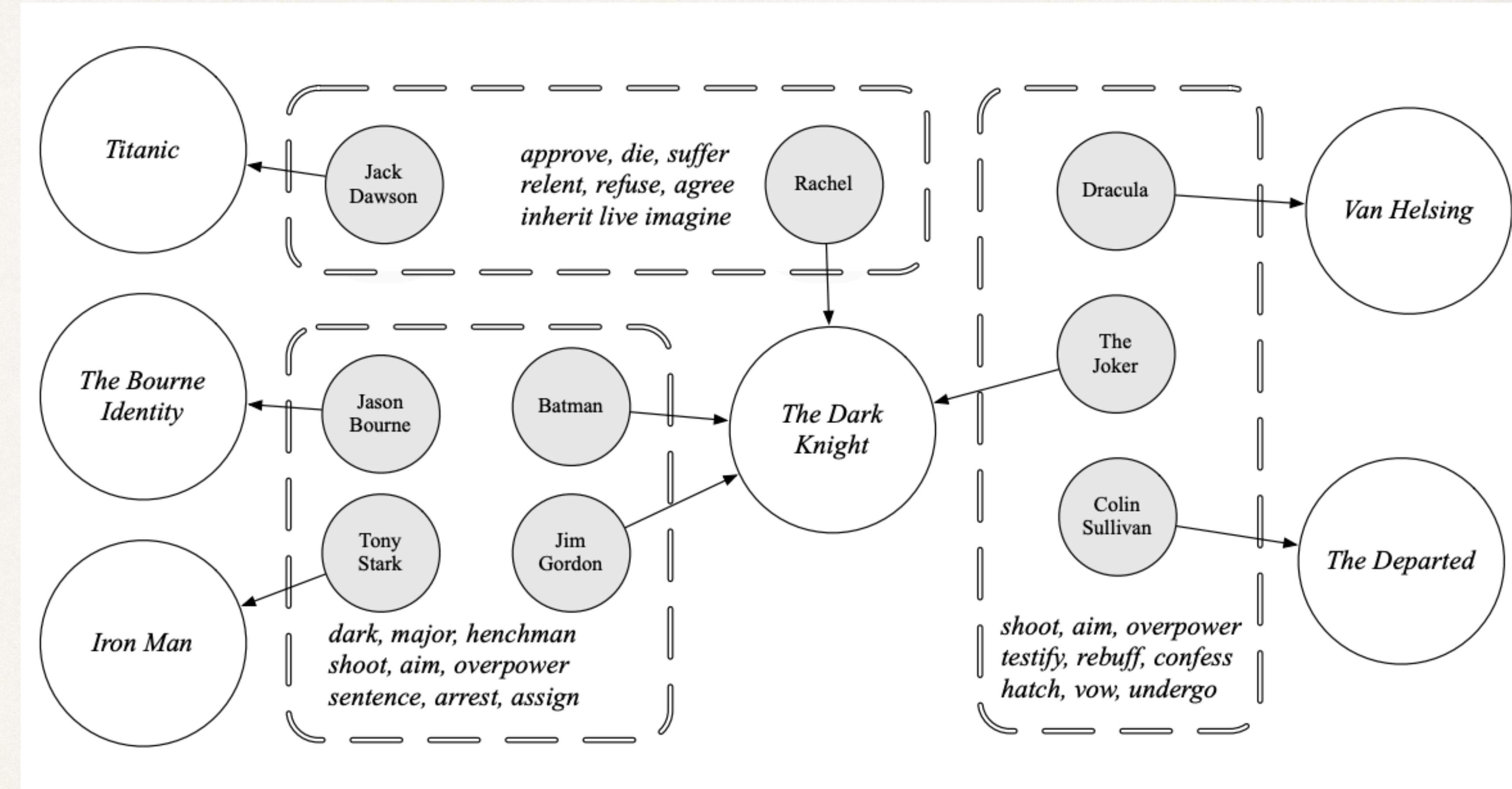
- Which topics are politicians paying attention?



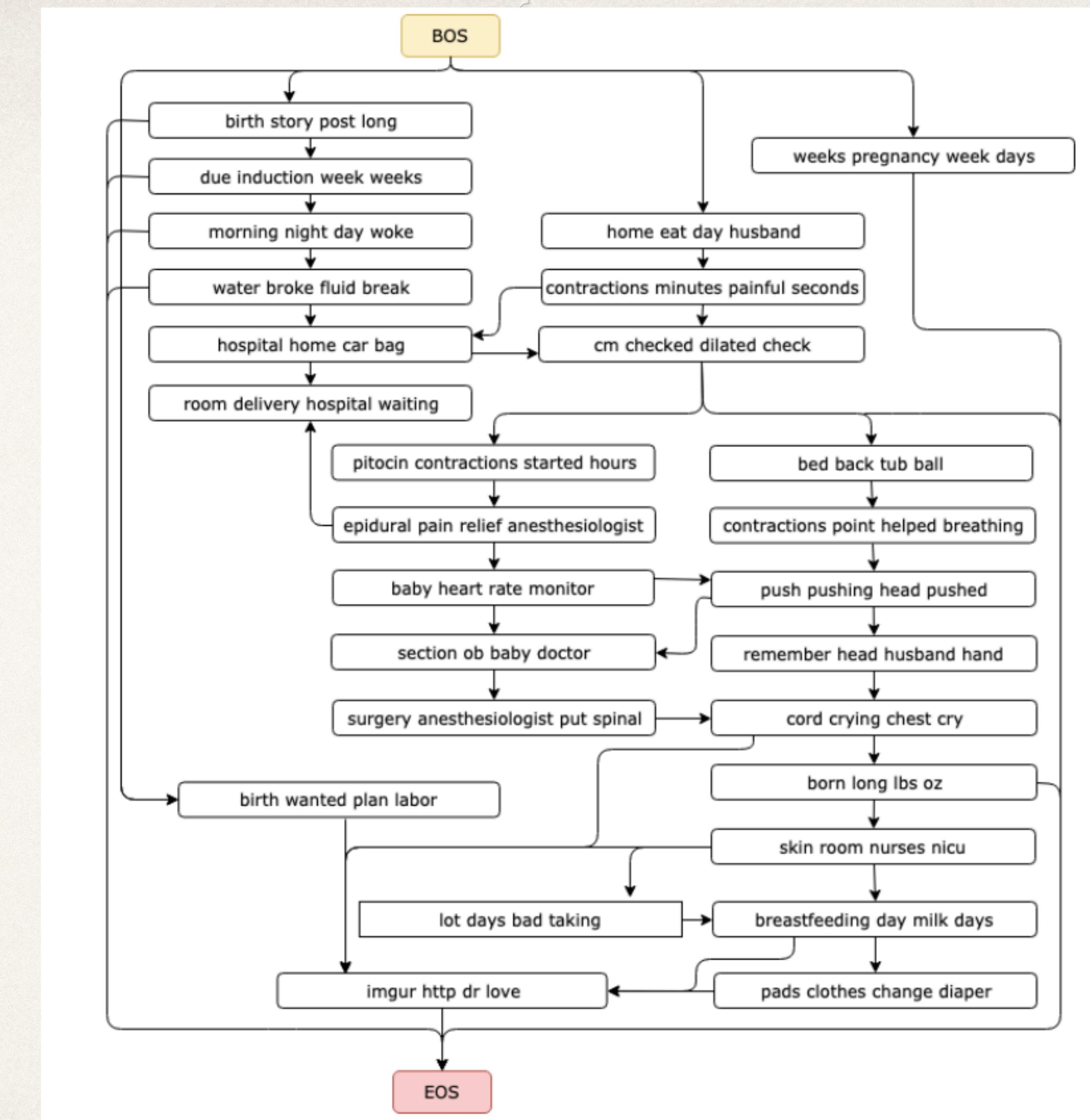
- Which topics are politicians paying attention?



- What are the different types of characters in movies?



- What are narrative sequences in birth stories?
- When do expecting mothers feel most vulnerable?



QUESTION FOR THE DAY

“How to find topics given a document collection?”

CLASS ACTIVITY I

We live in a time of extraordinary change -- change that's reshaping the way we live, the way we work, our planet, our place in the world. It's change that promises amazing medical breakthroughs, but also economic disruptions that strain working families. It promises education for girls in the most remote villages, but also connects terrorists plotting an ocean away. It's change that can broaden opportunity, or widen inequality. And whether we like it or not, the pace of this change will only accelerate.

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AGENDA

- Intro to topic models
- LDA
- Variations of LDA
- Evaluation

DOCUMENT-TERM MATRIX

	w_1	w_2	\dots	w_m
d_1	0	3		1
d_2	2	1		0
\vdots				
d_n	1	0		0

- Every document is a vector of word counts

MATRIX DECOMPOSITION

	w_1	w_2	\dots	w_m
d_1	0	3	\dots	1
d_2	2	1	\dots	0
\vdots				
d_n	1	0	\dots	0

\approx

	k_1	k_2	\dots	$k_{ K }$
d_1	0.3	0.15	\dots	0.1
d_2	0.45	0.05	\dots	0.2
\vdots				
d_n	0.1	0.25	\dots	0

	w_1	w_2	\dots	w_m
k_1	0.1	0.2	\dots	0.25
k_2	0.15	0.2	\dots	0.15
\vdots				
$k_{ K }$	0.05	0.1	\dots	0.1

- Each document can be thought of as a mixture of K “topics”
- Each topic is a distribution over words

LATENT SEMANTIC ANALYSIS

	w_1	w_2	\dots	w_m
d_1	0	3		1
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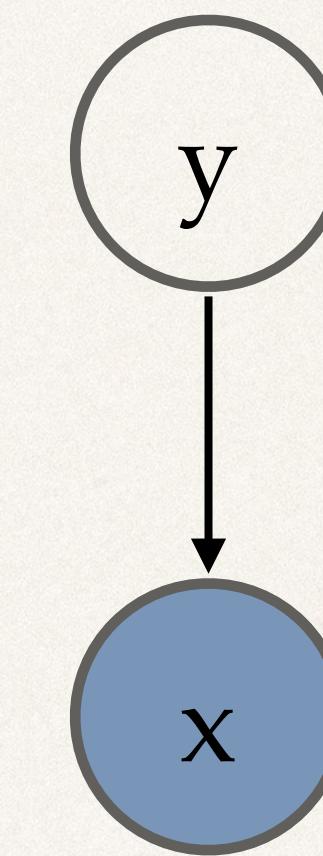
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k_1	0.1	0.2		0.25
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Can we do this probabilistically?

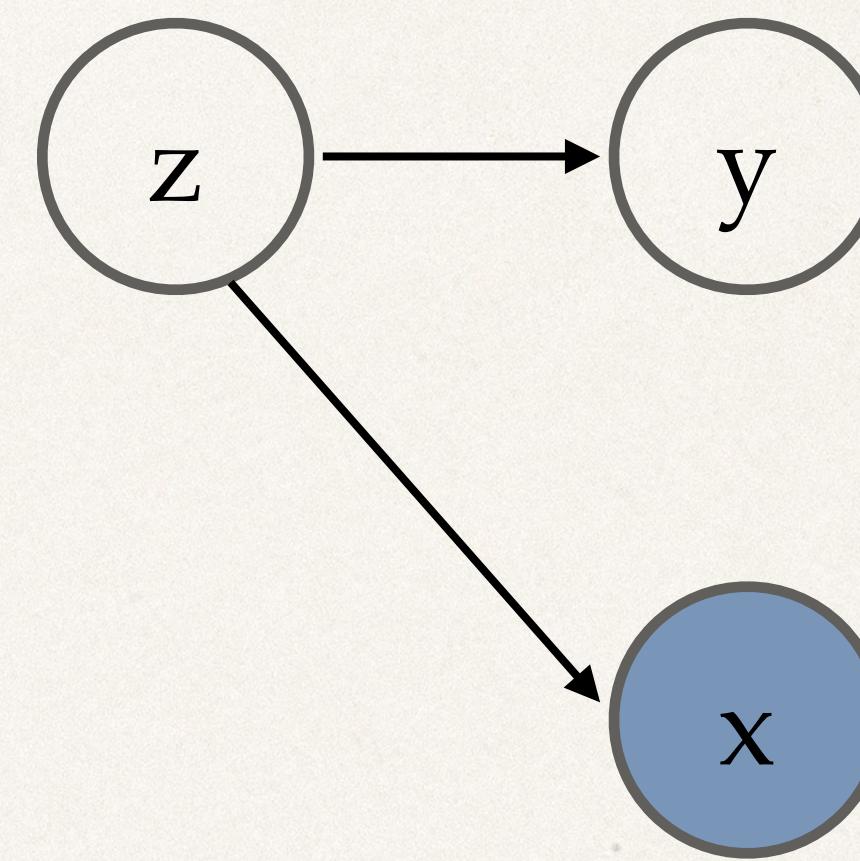
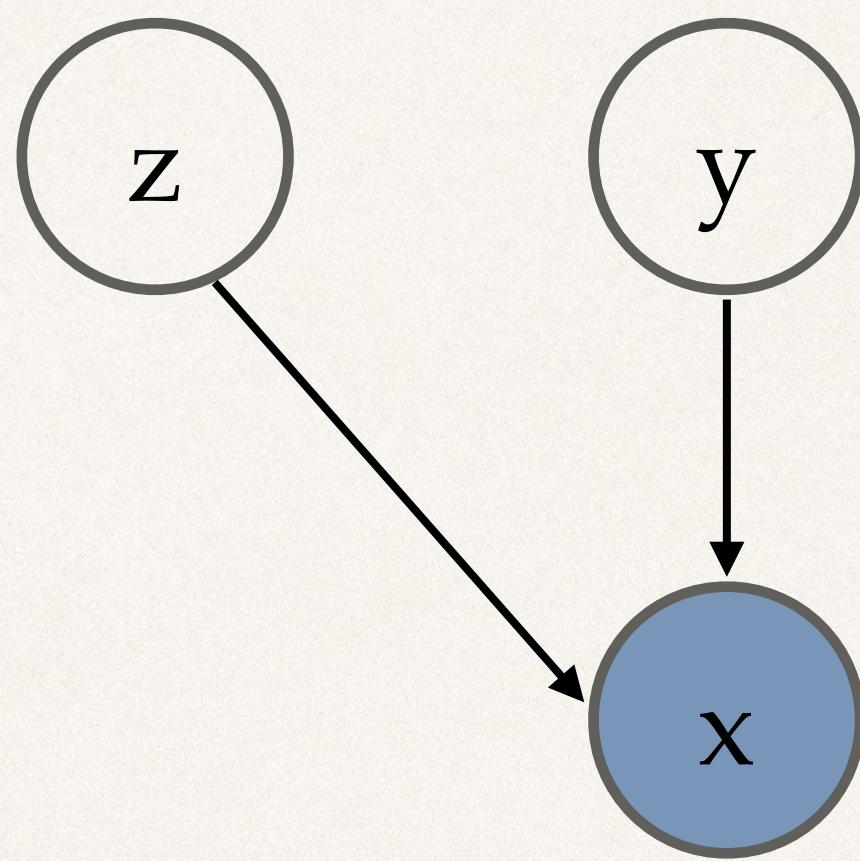
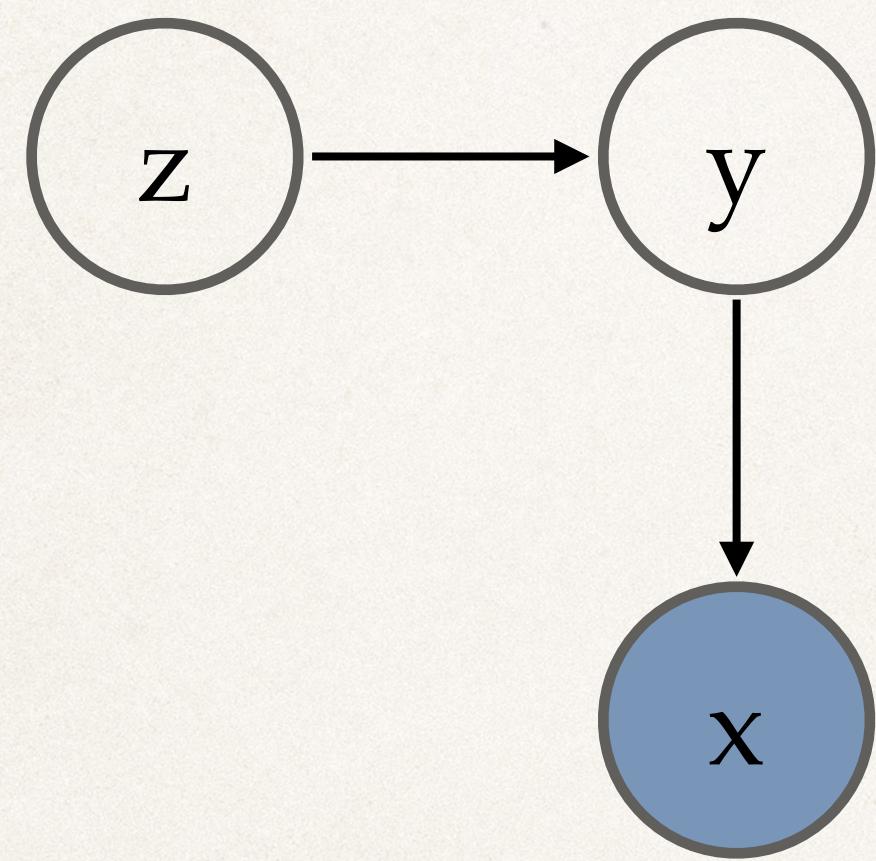
PROBABILISTIC GRAPHICAL MODELS

- All nodes are random variables; dark nodes are observed and the others are latent
- Arrows indicate conditional relationships
- Visual specification of how the joint distribution factors

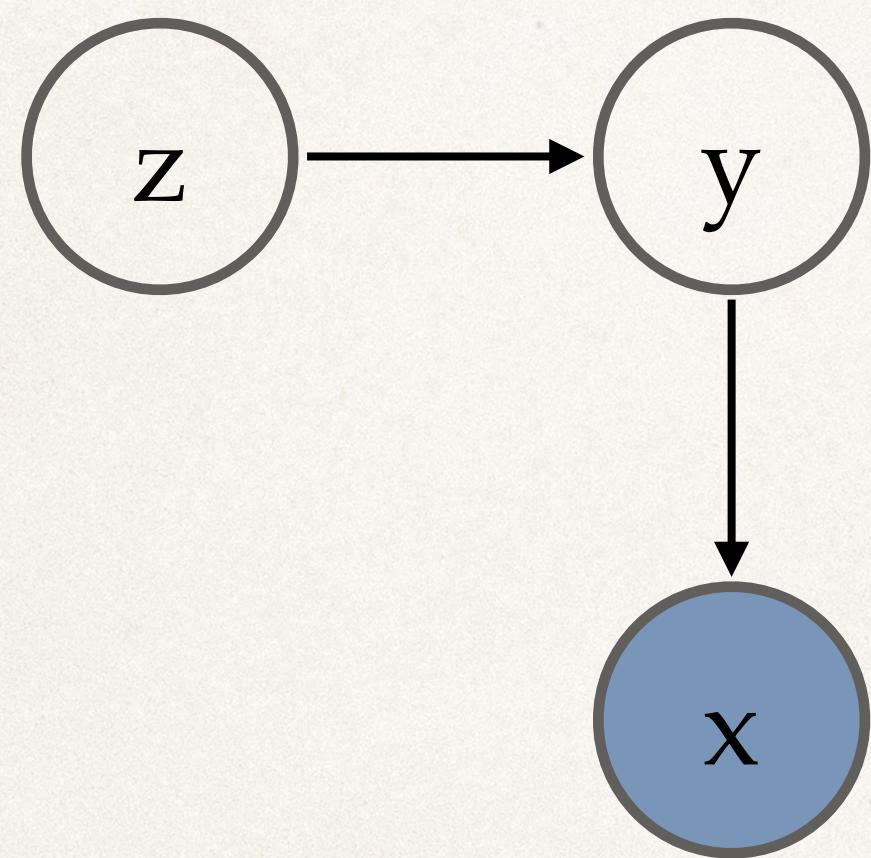


$$P(x, y) = P(y)P(x|y)$$

CLASS ACTIVITY II

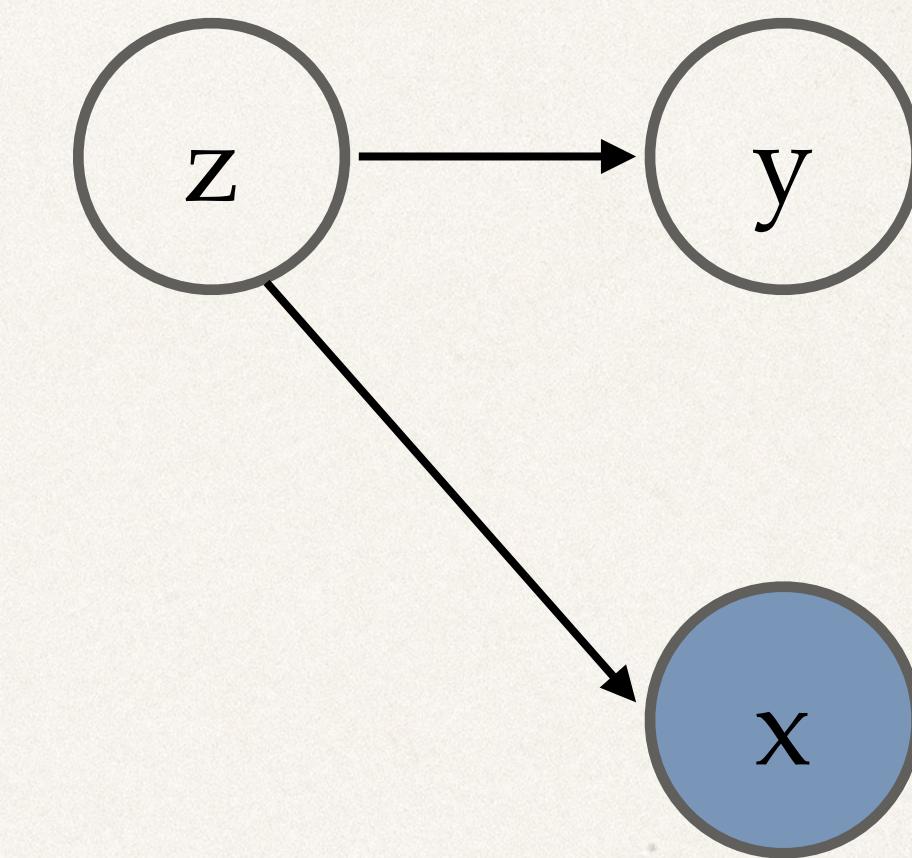


CLASS ACTIVITY II



$$P(x, y, z) = P(z)P(y | z)P(x | y)$$

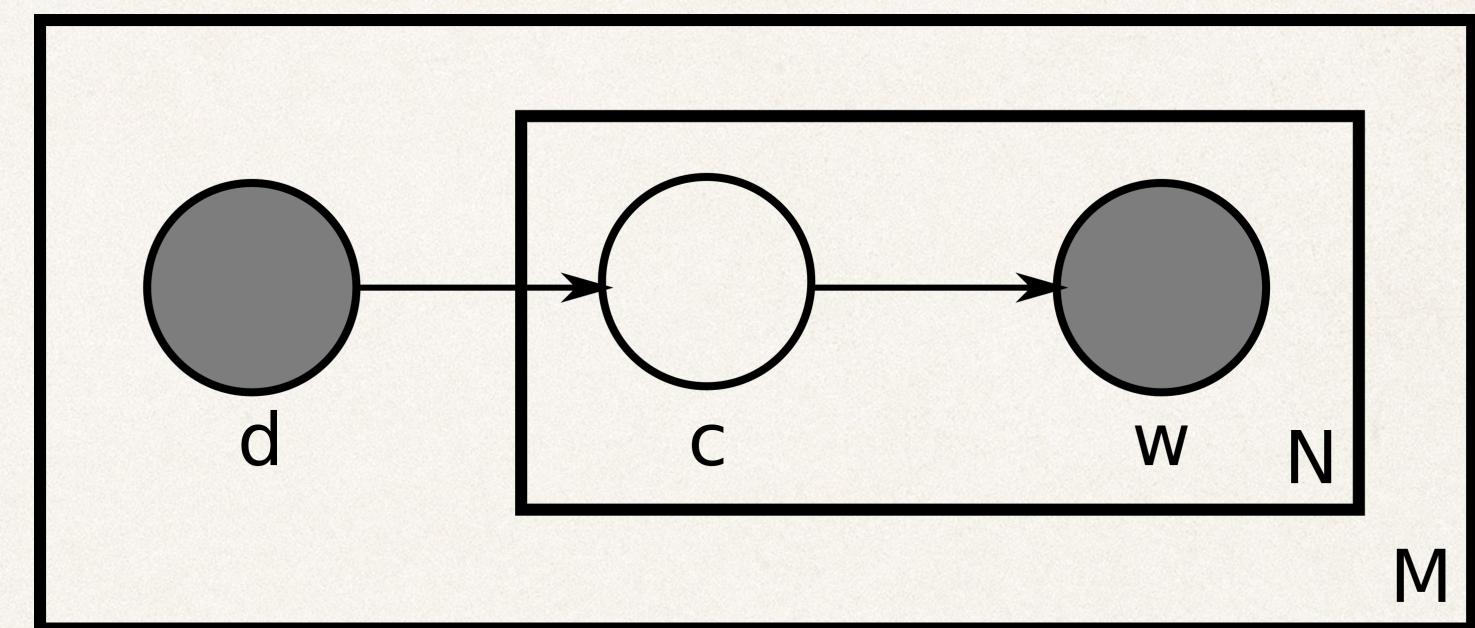
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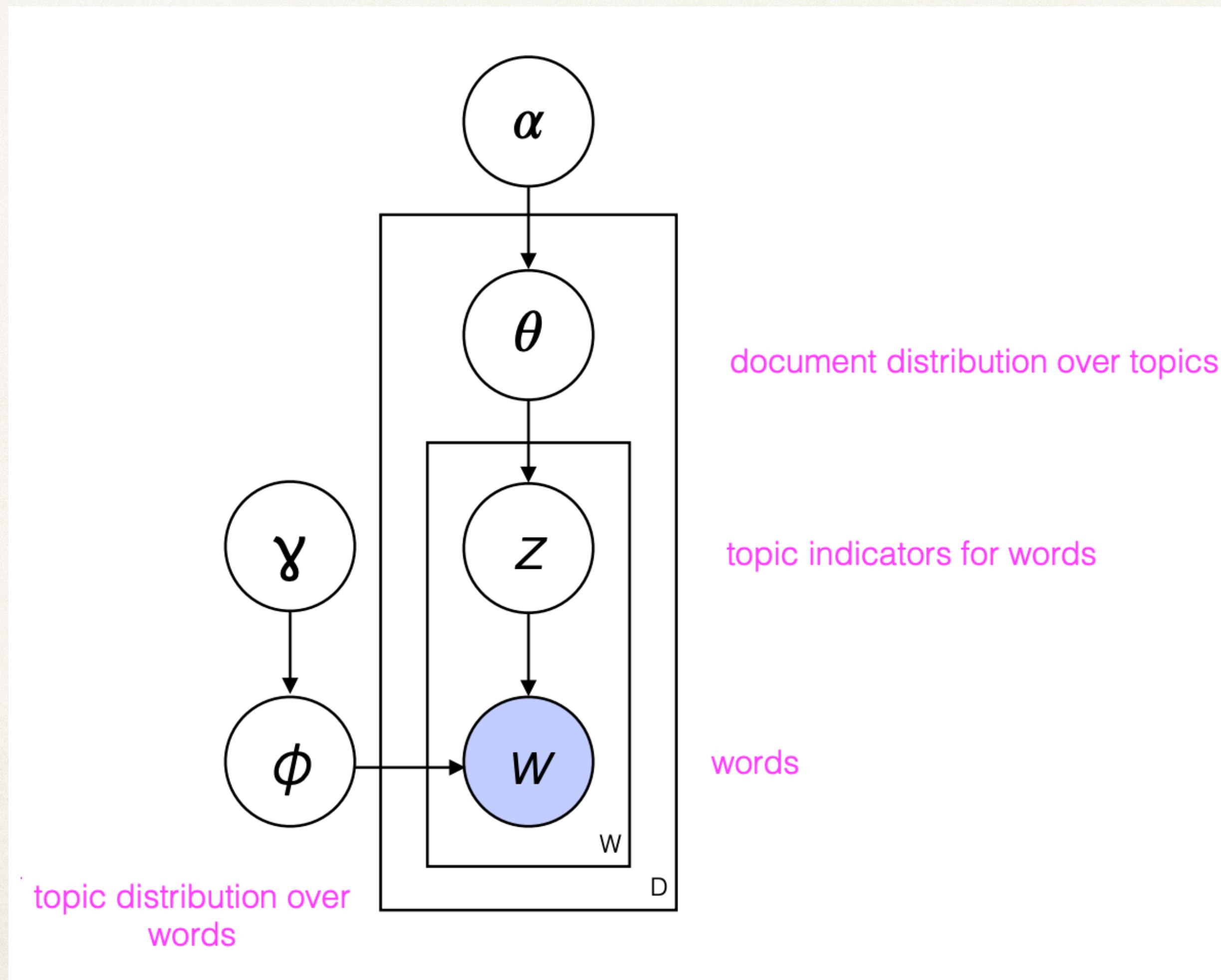
PROBABILISTIC LATENT SEMANTIC ANALYSIS

- There are M documents and N words in the vocabulary.
- Blocks surrounding the circle means repeating structure
- We observe document indices and the words within each document
- c is the topic assigned to every word

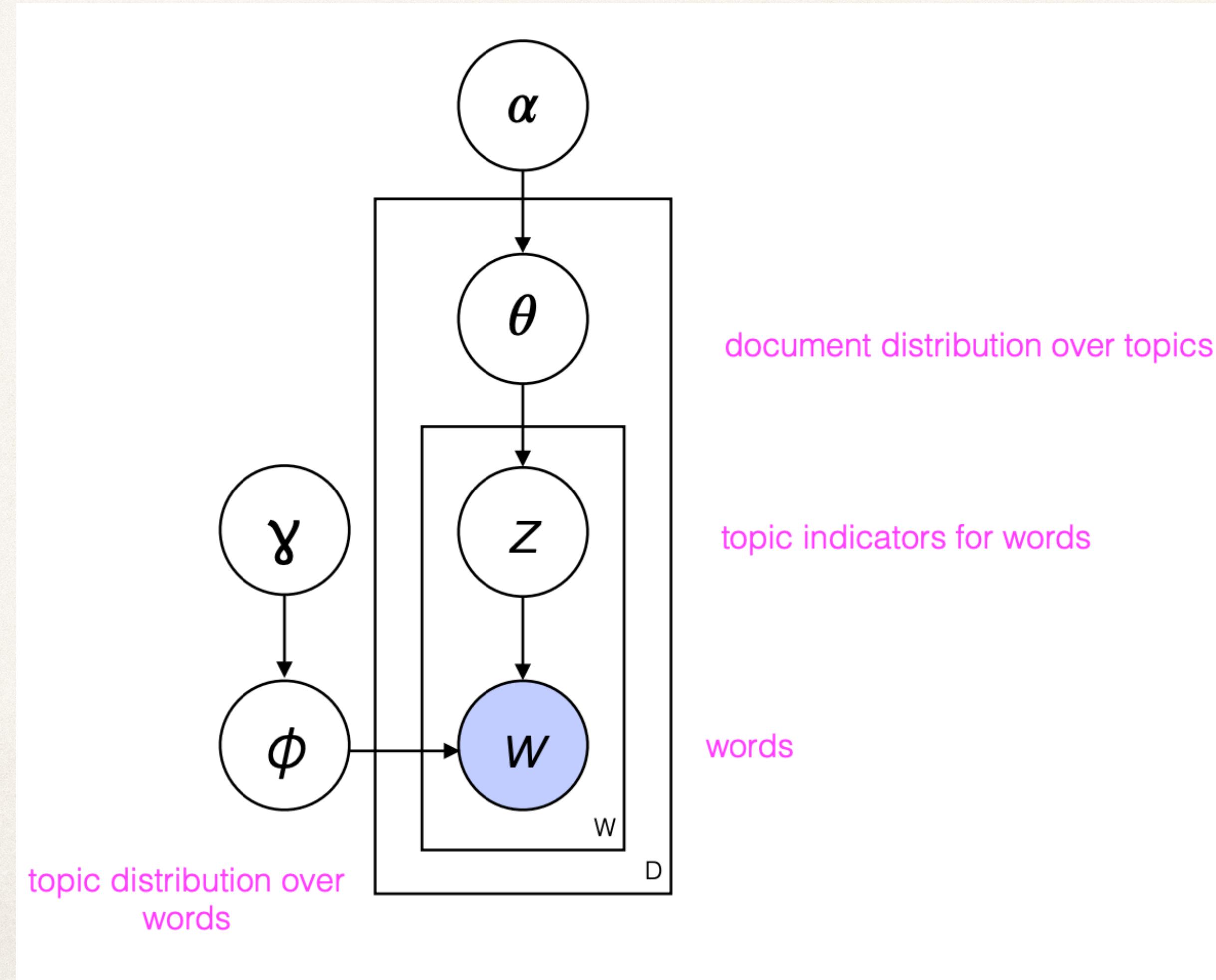


- Generative story:
 - Generate doc indices
 - For every doc index
 - generate the topic
 - Generate word for the topic

LATENT DIRICHLET ALLOCATION



TOPIC MODELS

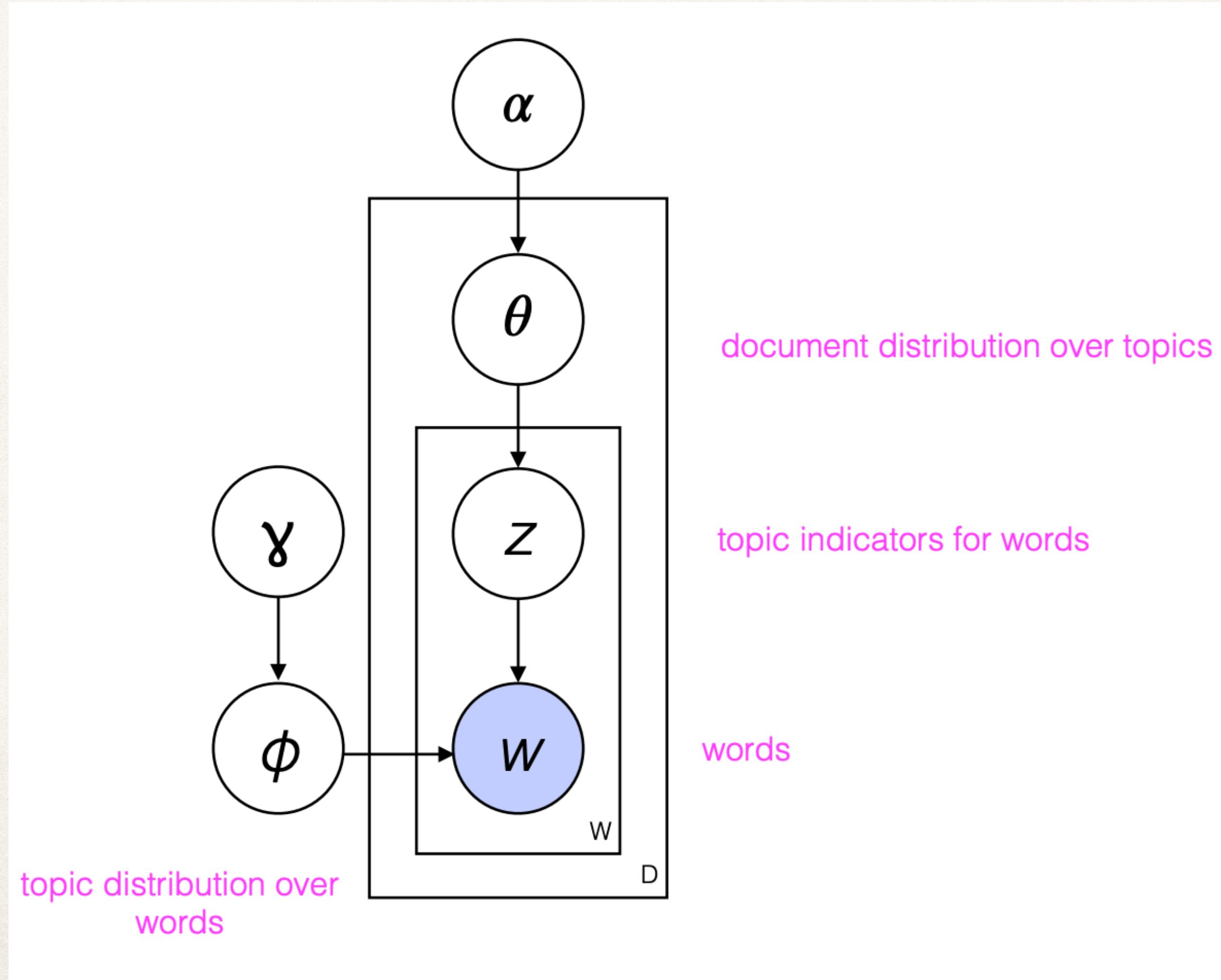


TOPIC MODELS

- A document is conceptualized as a distribution over topics
- θ gives this distribution

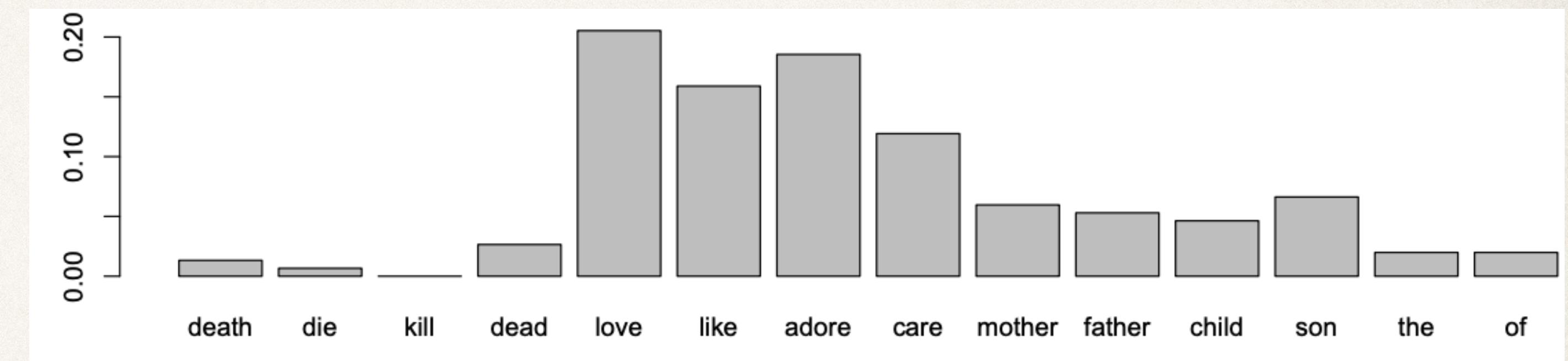


TOPIC MODELS



TOPIC MODELS

- A topic is a distribution over words
- ϕ gives this distribution
- $P(\text{"like"} | \text{topic}=\text{love})=0.15$

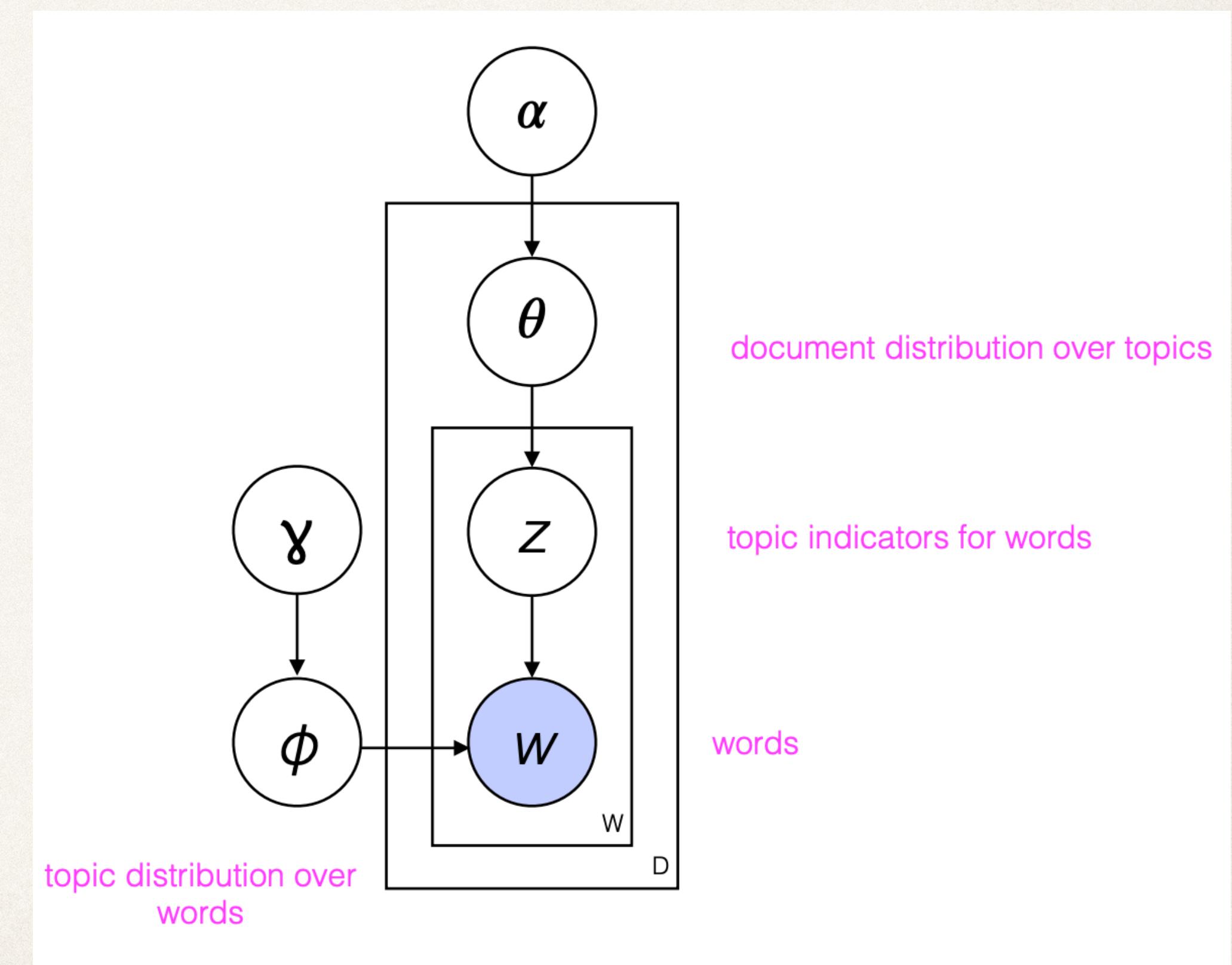


TOPIC MODELS

- For every document, you will have a different topic distribution
- For every topic, you will have a different word distribution

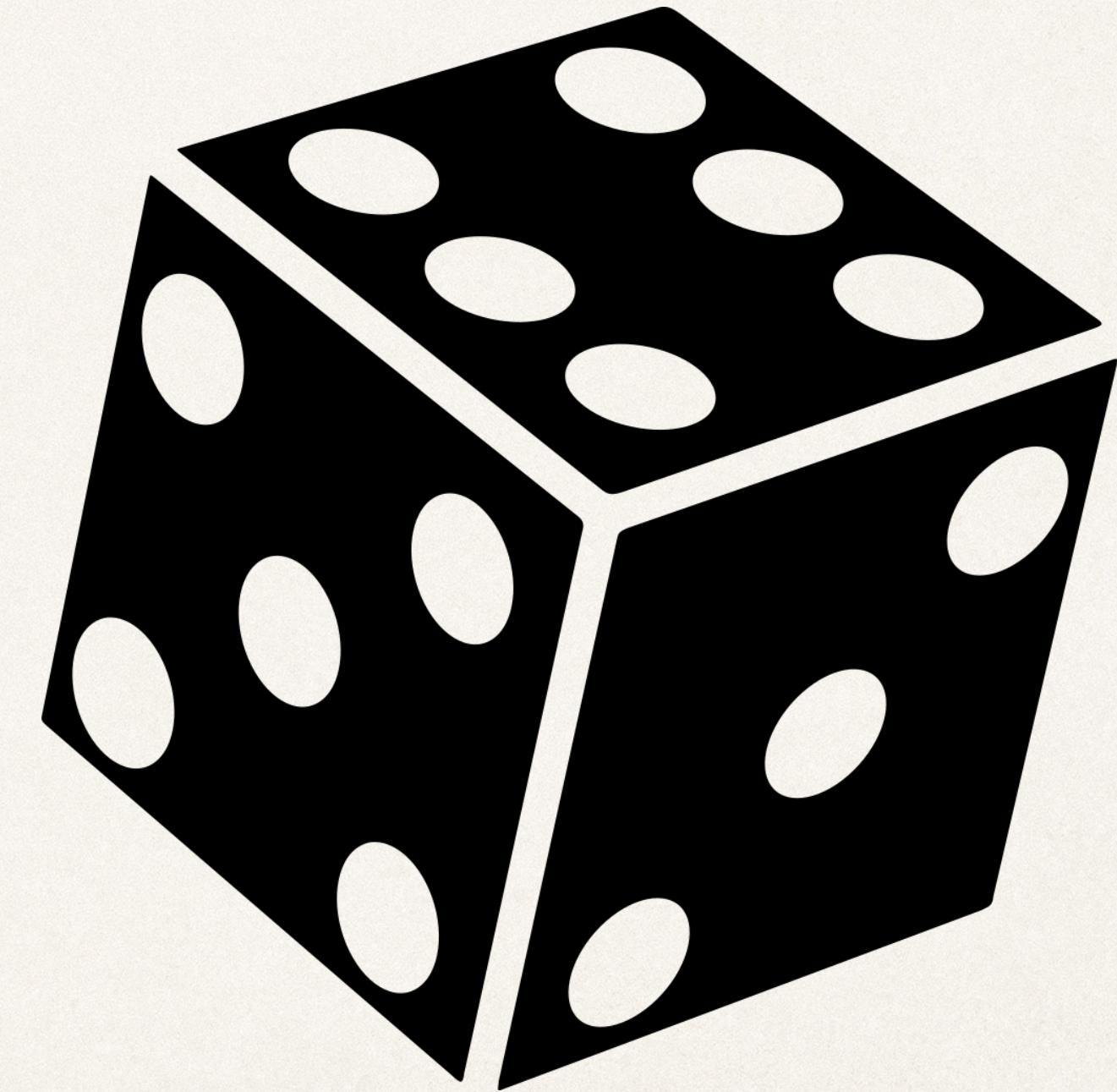
GENERATIVE STORY

- For every document d :
 - Generate topic distribution θ_d
 - For every word position in d :
 - Draw topic $z_{w,d}$
 - Draw word w from $\phi_{z_{w,d}}$



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GENERATE FIRST WORD

$\theta_d = \{“love”=0.5,$
 $“war”=0.2,$
 $“aliens” = 0.3\}$

- $z_{w,d} = “love”$
- $w = \text{like}$

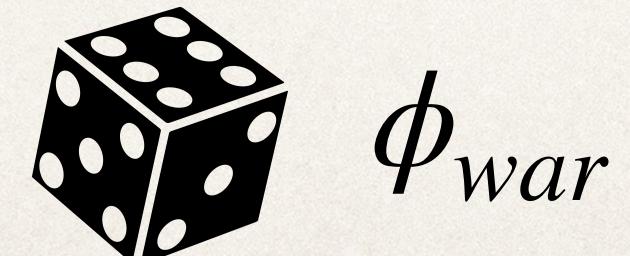


like

GENERATE NEXT WORD

$\theta_d = \{“love”=0.5,$
 $“war”=0.2,$
 $“aliens” = 0.3\}$

- $z_{w,d} = “war”$
- $w = \text{peace}$

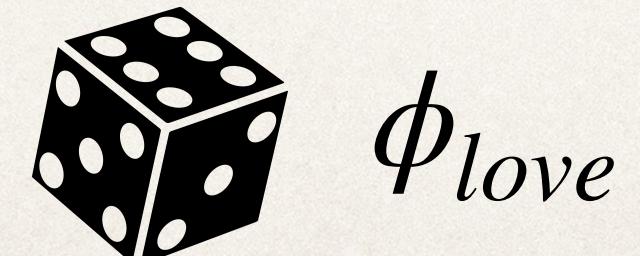


like peace

GENERATE NEXT WORD

$\theta_d = \{$ “love”=0.5,
“war”=0.2,
“aliens” = 0.3 $\}$

- $z_{w,d} = \text{“love”}$
- $w = \text{love}$



like peace love

GENERATE NEXT WORD

$\theta_d = \{$ “love”=0.5,
“war”=0.2,
“aliens” = 0.3 $\}$

- $z_{w,d} = \text{“aliens”}$
- $w = \text{people}$



like peace love people

AND SO ON

like peace love people ...

SOFTWARE

SOFTWARE

- Mallet (<https://mimno.github.io/Mallet/>)

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- Gensim (<https://radimrehurek.com/gensim/>)

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- Gensim (<https://radimrehurek.com/gensim/>)
- BertTopic (<https://maartengr.github.io/BERTopic/index.html>)

INFERENCE

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- How do we estimate the distributions?

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 - Markov chain Monte Carlo (Metropolis Hastings, Gibbs sampling)

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 - Variational methods

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- How do we estimate the distributions?
 - Markov chain Monte Carlo (Metropolis Hastings, Gibbs sampling)
 - Variational methods
 - Hybrid methods

THINGS TO REMEMBER

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- Priors matter [Wallach et. al. 2009]

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- Preprocessing matters [Schofield et. al. 2016, 2017]

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- Priors matter [Wallach et. al. 2009]
- Preprocessing matters [Schofield et. al. 2016, 2017]
- Inference techniques matter

LDA ASSUMPTIONS

- A word gets a single topic assigned
- A document gets a single distribution of topics
- No sequential info. used
- No other structure assumed except word and document identities

SOME POPULAR TOPIC MODELS

- Probabilistic graphical models offer much flexibility in modeling the generation of documents

HIERARCHICAL TOPIC MODELING

- Model the data generating process as a nested Chinese restaurant process

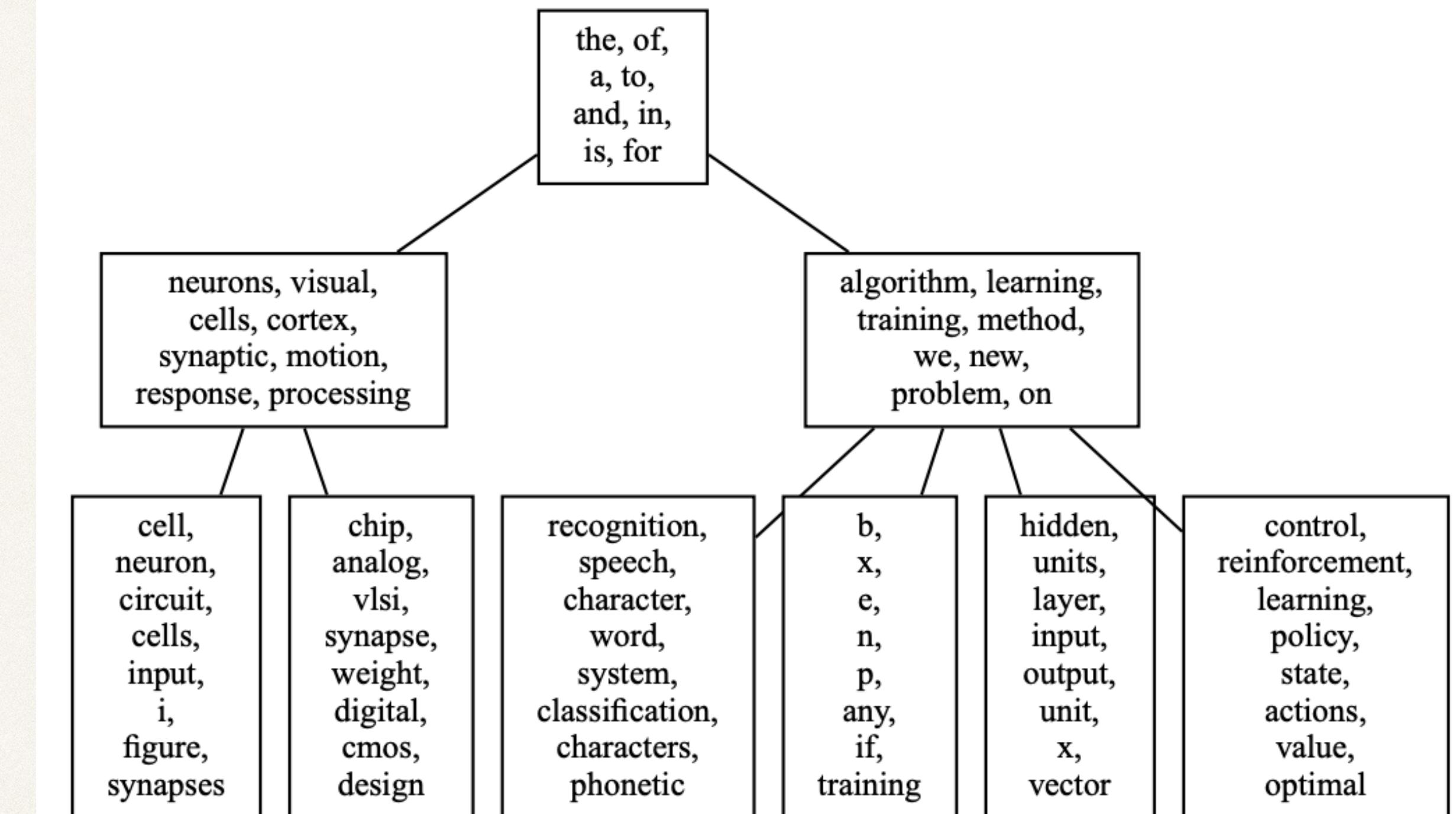


Figure 5: A topic hierarchy estimated from 1717 abstracts from NIPS01 through NIPS12. Each node contains the top eight words from its corresponding topic distribution.

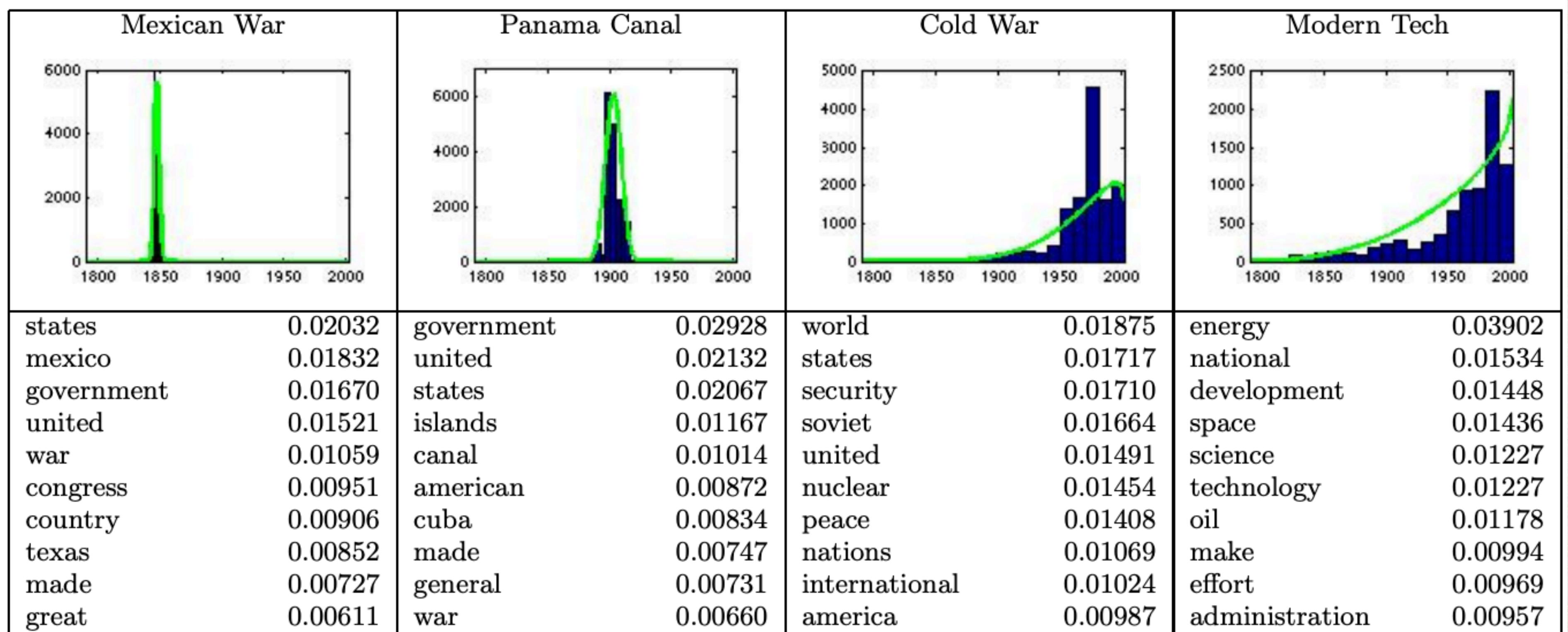
GEOGRAPHICAL TOPIC MODEL

- Model text and author geolocation

	“basketball”	“popular music”	“daily life”	“emoticons”	“chit chat”
	PISTONS KOBE LAKERS game DUKE NBA CAVS STUCKEY JETS KNICKS	album music beats artist video #LAKERS ITUNES tour produced vol	tonight shop weekend getting going chilling ready discount waiting iam	:) haha :d :(;) :p xd :/ hahaha hahah	lol smh jk yea wyd coo ima wassup somethin jp
Boston		CELTICS victory BOSTON CHARLOTTE	playing daughter PEARL alive war comp	BOSTON	;p gna loveee <i>ese</i> exam suttin sippin
N. California		THUNDER KINGS GIANTS pimp trees clap	SIMON dl mountain seee	6am OAKLAND	<i>pues</i> hella koo SAN fckn hella flirt hut iono OAKLAND
New York		NETS KNICKS	BRONX	iam cab	oww wasssup nm
Los Angeles		#KOBE #LAKERS AUSTIN	#LAKERS load HOLLYWOOD imm MICKEY TUPAC	omw tacos hr HOLLYWOOD	af <i>papi</i> raining th bomb coo HOLLYWOOD wyd coo af <i>nada</i> tacos messin fasho bomb
Lake Erie		CAVS CLEVELAND OHIO BUCKS od COLUMBUS	premiere prod joint TORONTO onto designer CANADA village burr	stink CHIPOTLE tipsy	foul <i>WIZ</i> salty excuses lames officer lastnight ;d blvd BIEBER hve OHIO

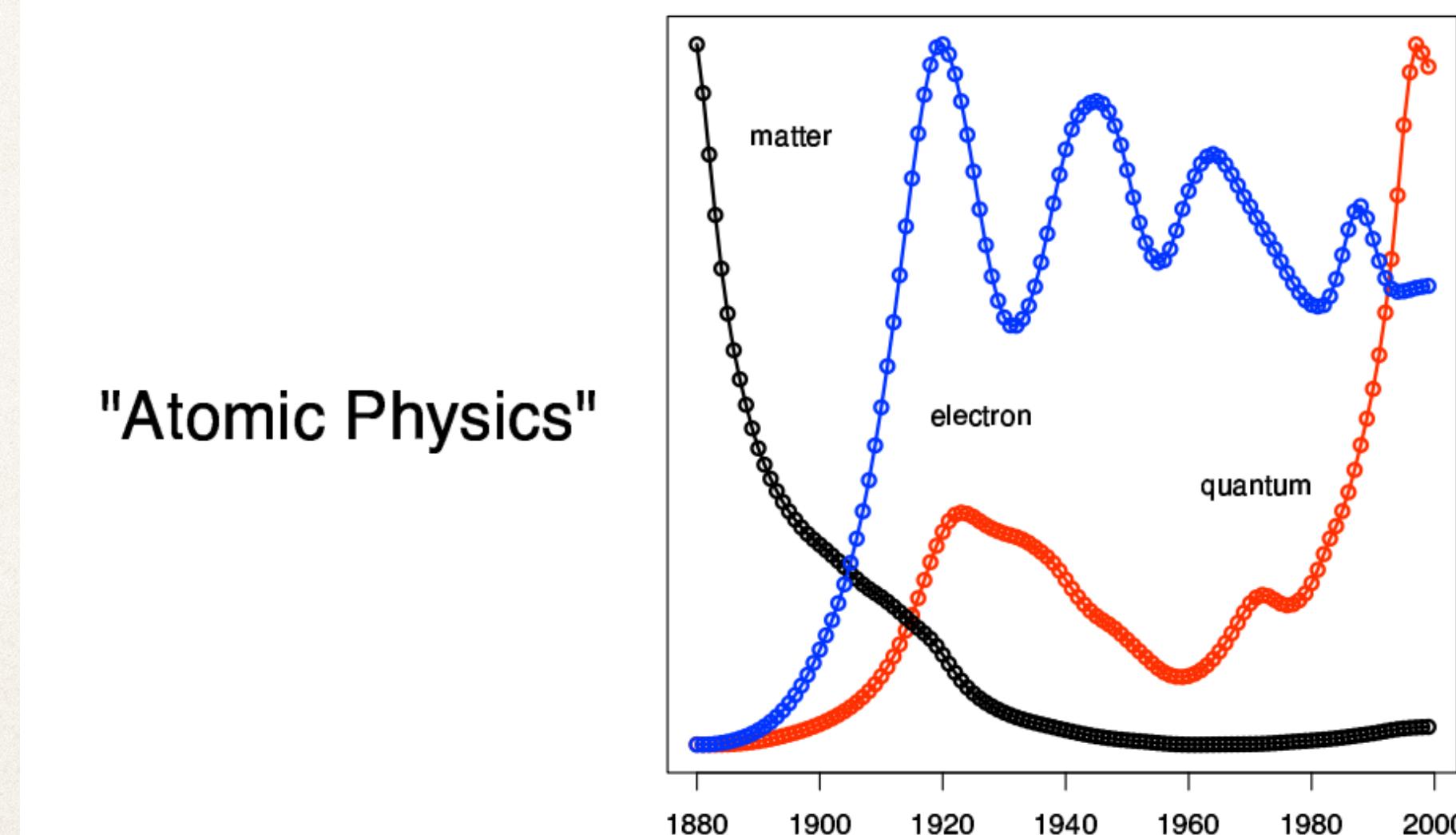
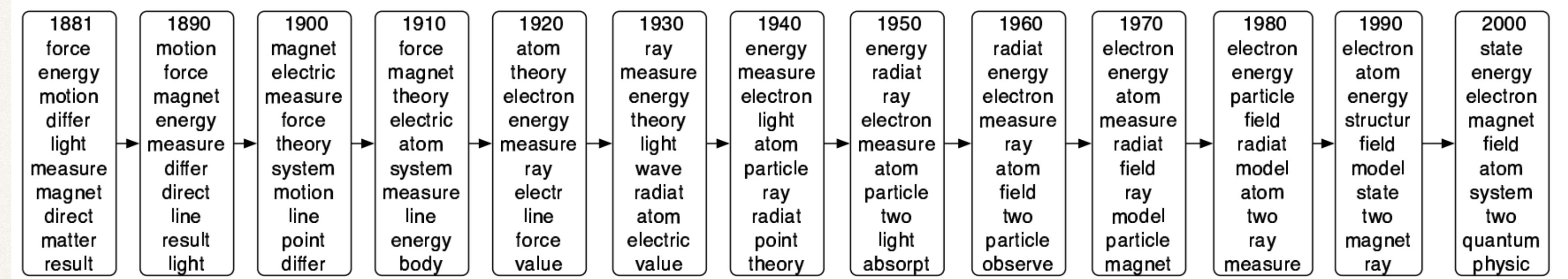
TOPICS OVER TIME

- Text and time
- Time is discrete



DYNAMIC TOPIC MODELS

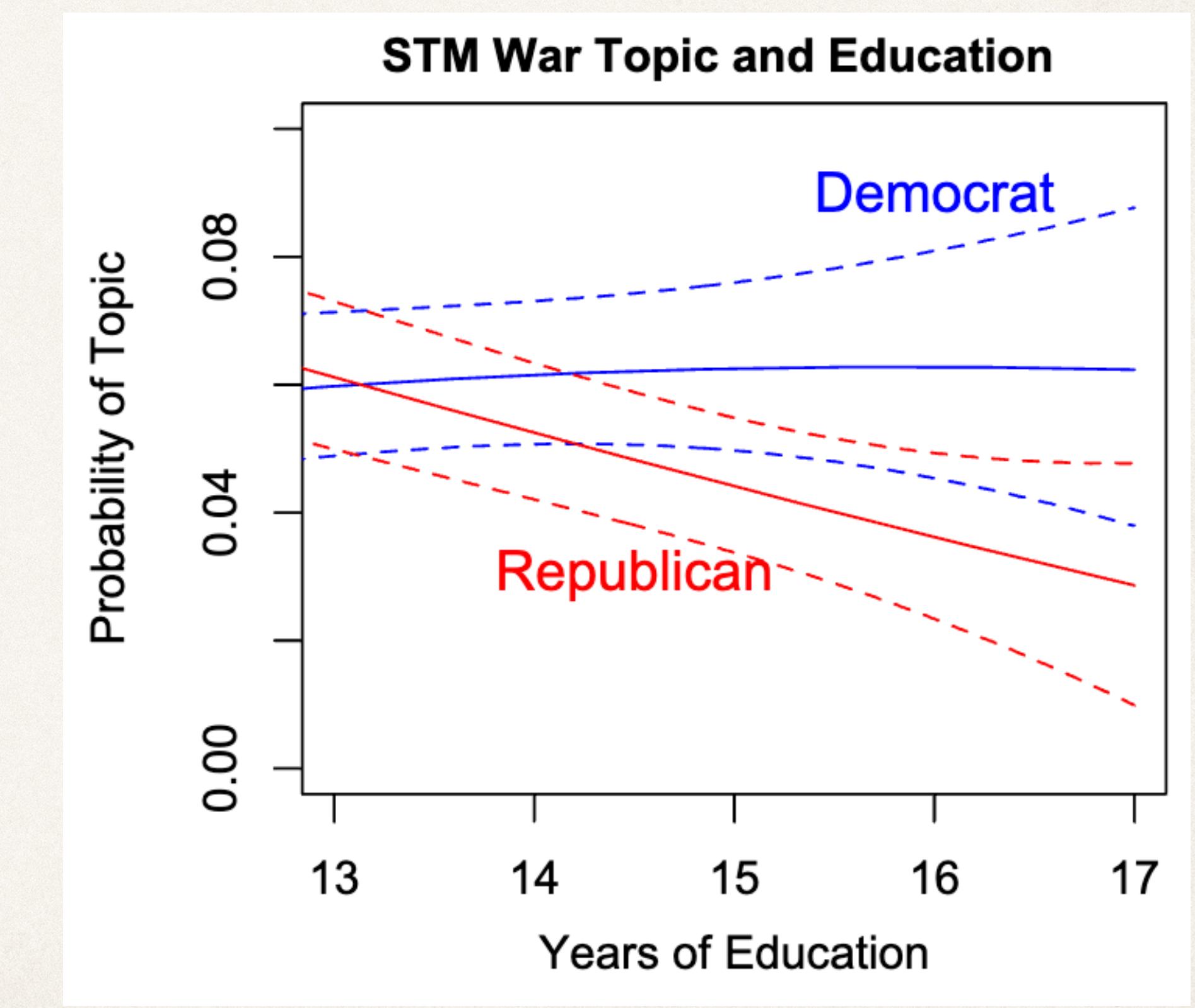
- Text and time
- Time is continuous



- 1881 On Matter as a form of Energy
- 1892 Non-Euclidean Geometry
- 1900 On Kathode Rays and Some Related Phenomena
- 1917 ``Keep Your Eye on the Ball''
- 1920 The Arrangement of Atoms in Some Common Metals
- 1933 Studies in Nuclear Physics
- 1943 Aristotle, Newton, Einstein. II
- 1950 Instrumentation for Radioactivity
- 1965 Lasers
- 1975 Particle Physics: Evidence for Magnetic Monopole Obtained
- 1985 Fermilab Tests its Antiproton Factory
- 1999 Quantum Computing with Electrons Floating on Liquid Helium

STRUCTURAL TOPIC MODELS

- Model the text and all the associated metadata together
- Useful to do causal analysis



EVALUATION

EVALUATION

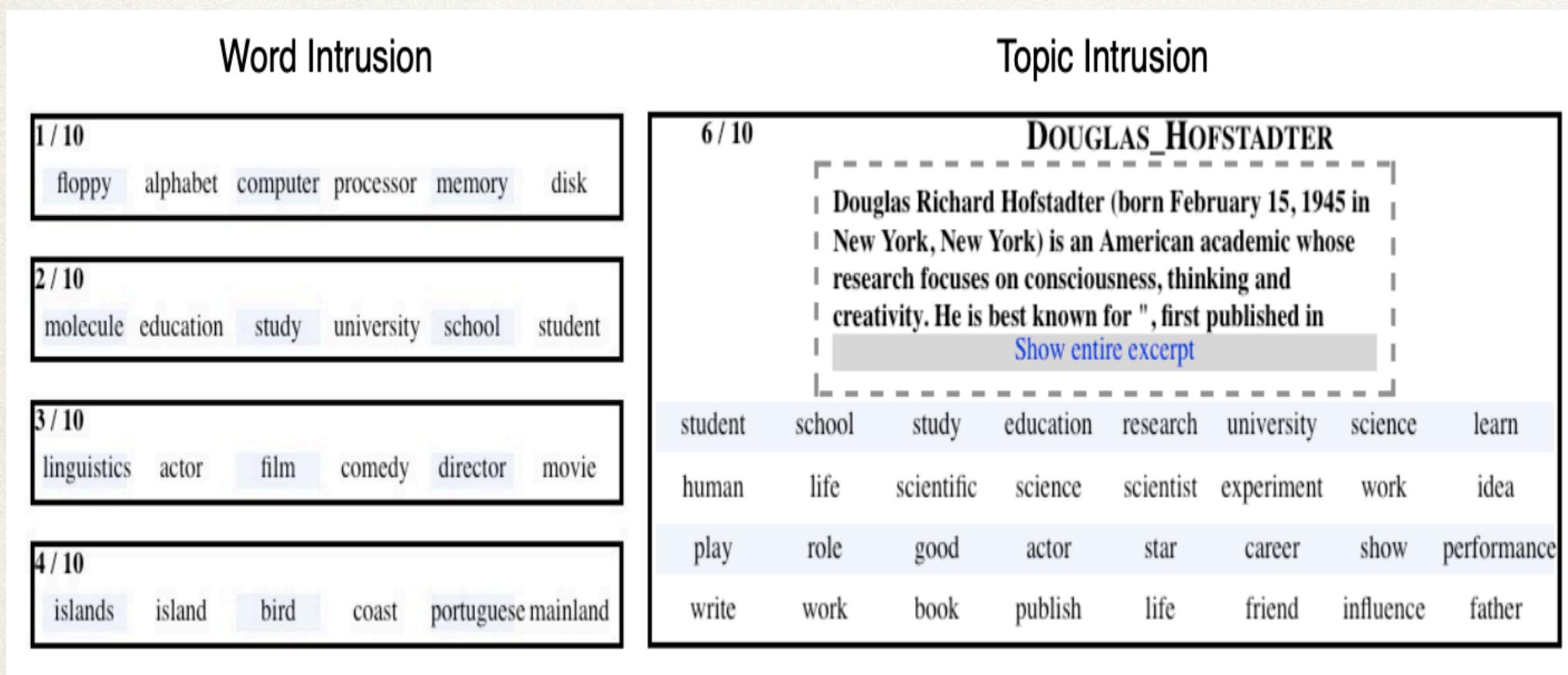
Human evaluation

Word Intrusion		Topic Intrusion	
1 / 10	floppy alphabet computer processor memory disk	6 / 10	DOUGLAS_HOFSTADTER
2 / 10	molecule education study university school student	Douglas Richard Hofstadter (born February 15, 1945 in New York, New York) is an American academic whose research focuses on consciousness, thinking and creativity. He is best known for ", first published in	
3 / 10	linguistics actor film comedy director movie	student school study education research university science learn	
4 / 10	islands island bird coast portuguese mainland	human life scientific science scientist experiment work idea	
		play role good actor star career show performance	
		write work book publish life friend influence father	

Chang et. al. 2009

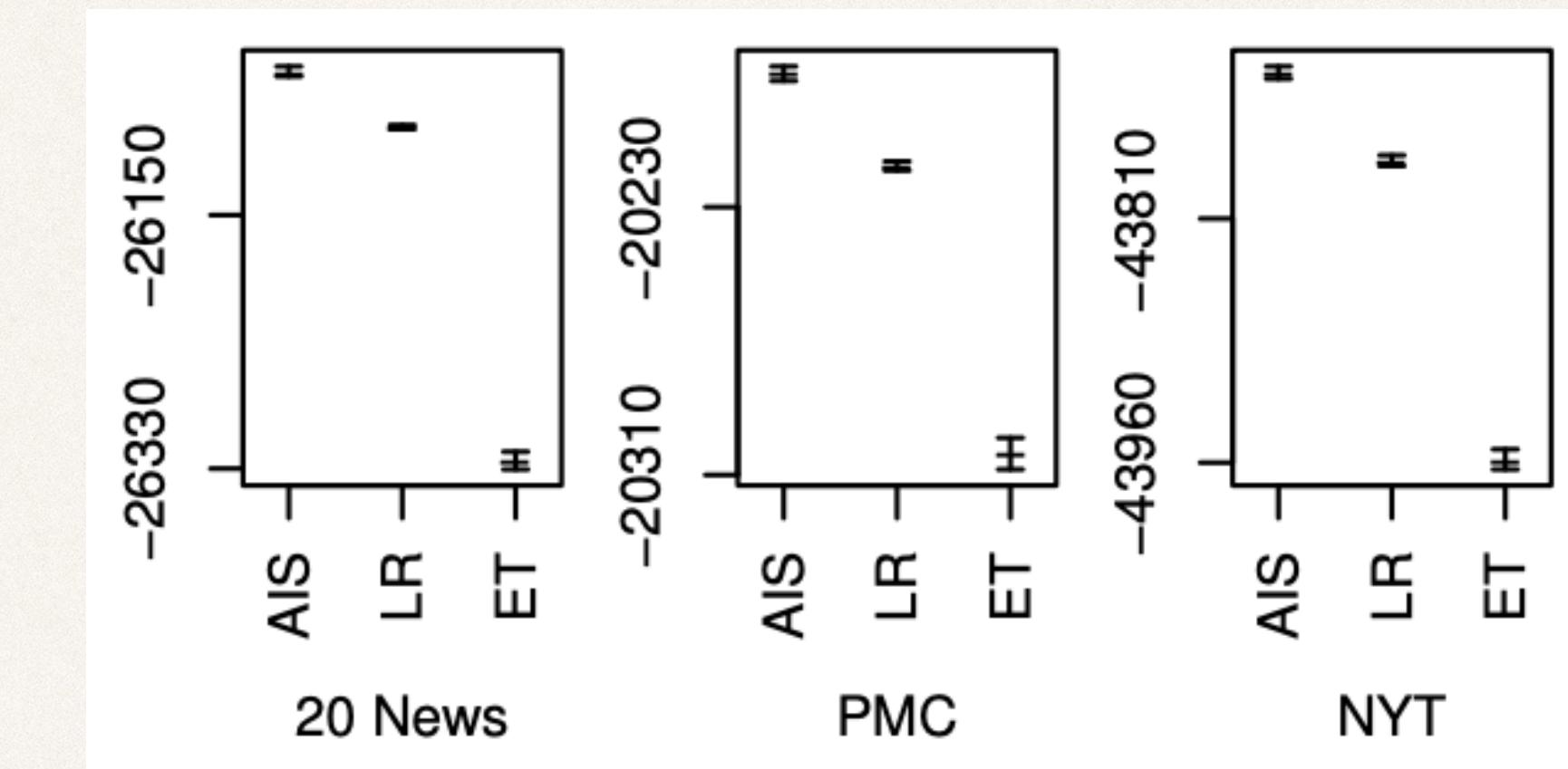
EVALUATION

Human evaluation



Chang et. al. 2009

Evaluating generation ability



Wallach et. al. 2009

IN CLASS

- Topic modeling demo