Anchored Correlation Explanation: Topic Modeling with Minimal Domain Knowledge

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github.com/gregversteeg/corex_topic

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~~Anchored Correl~~

~~ain Knowledge~~

How to Topic Model with Literally Thousands of Information Bottlenecks 🍾

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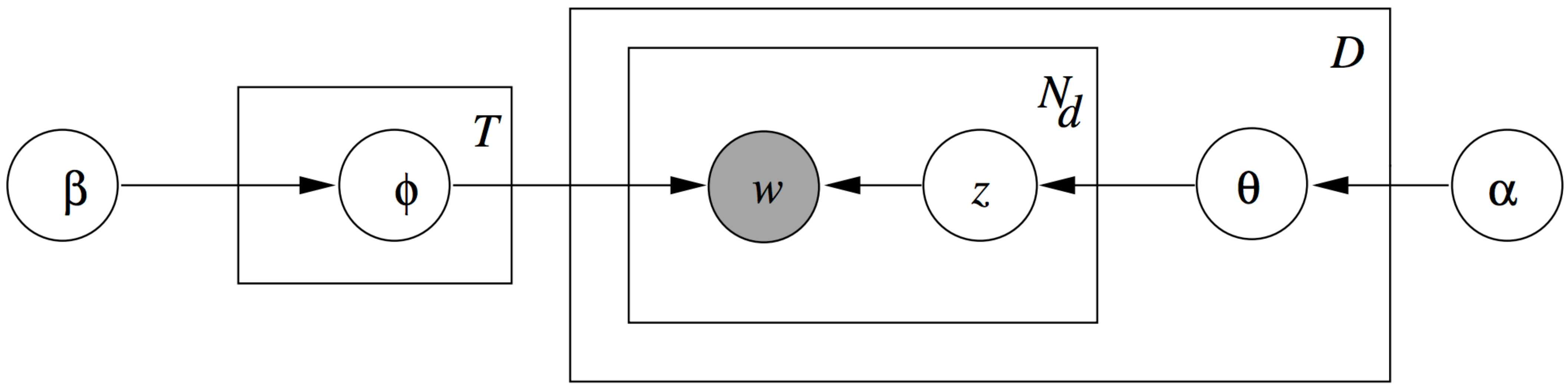
LDA is a *generative* topic model

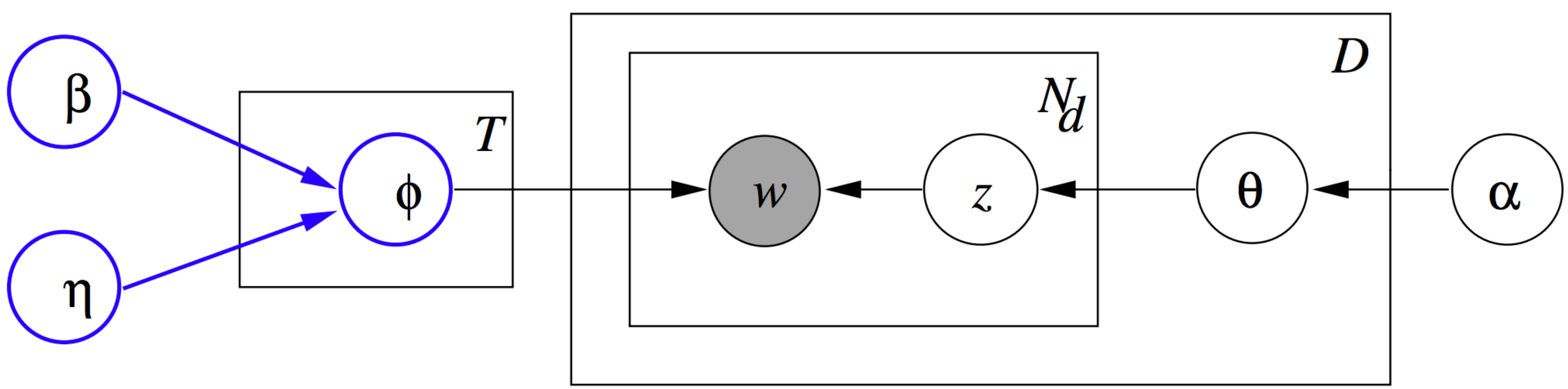


LDA is a *generative* topic model

The Good:

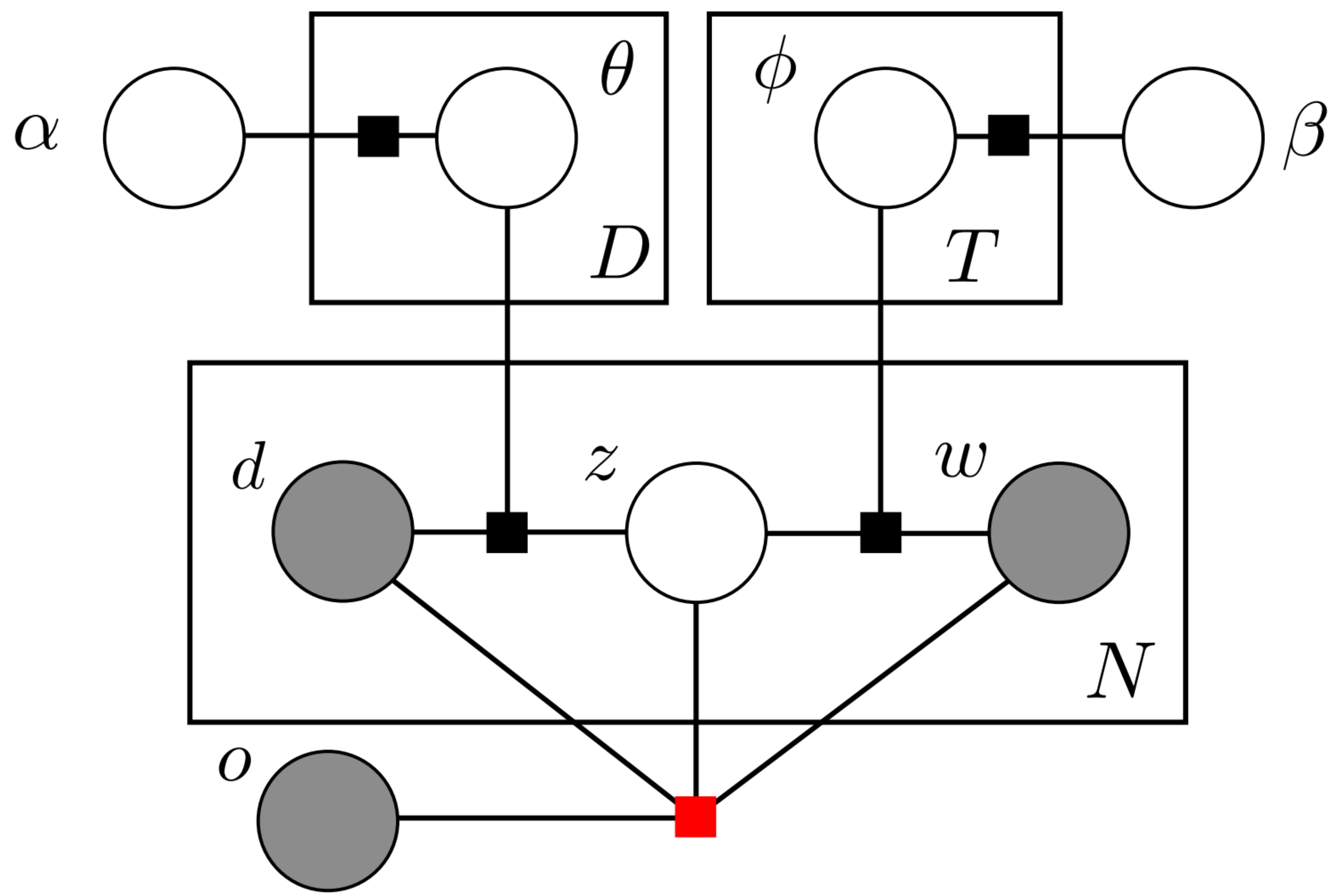
Priors explicitly encode your beliefs about what topics can be, and easily allow for iterative development of new topic models

Domain Knowledge via Dirichlet Forest Priors



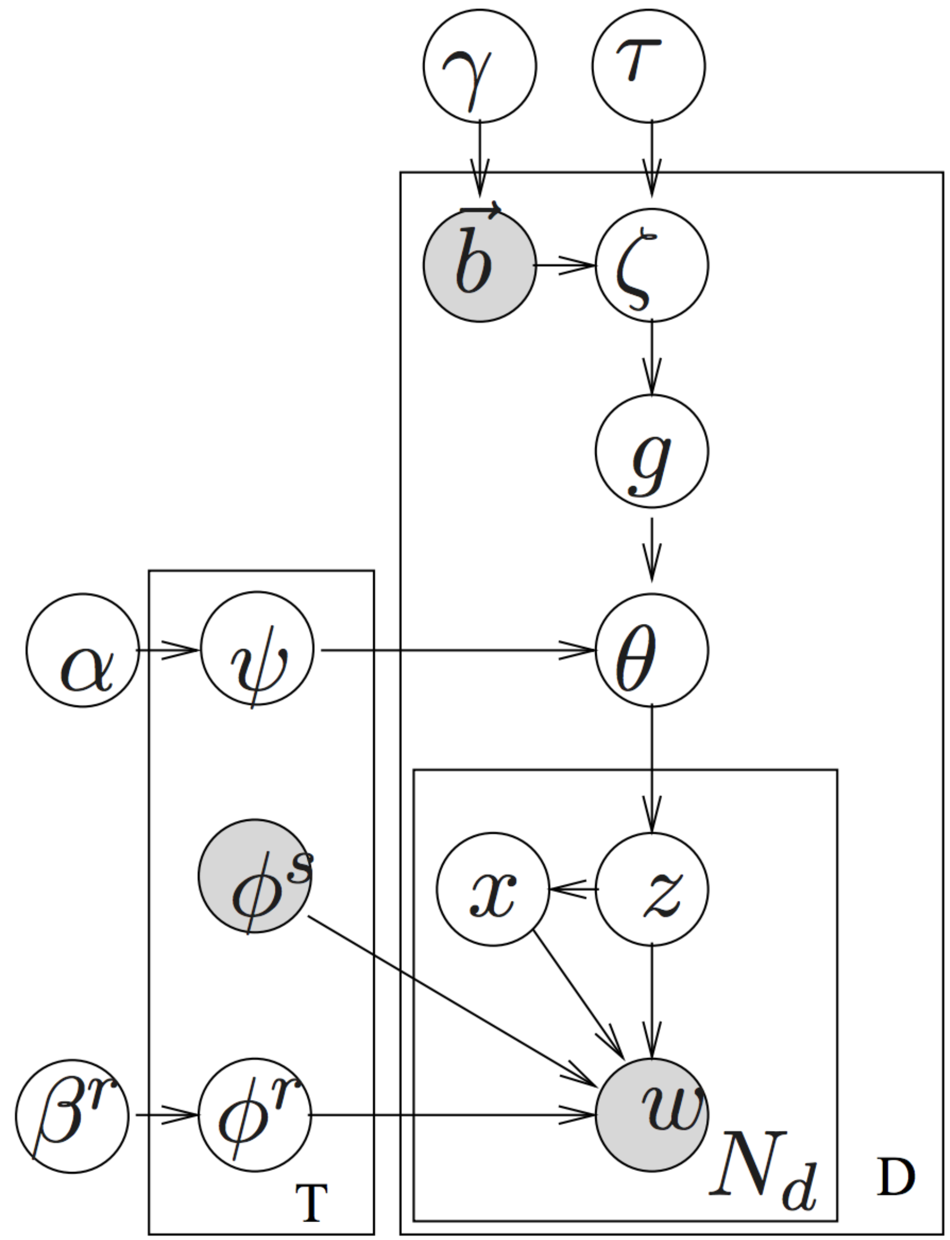
“Incorporating Domain Knowledge into Topic Modeling via Dirichlet Forest Priors.” Andrzejewski et al. *ICML* (2009)

Domain Knowledge via First-Order Logic



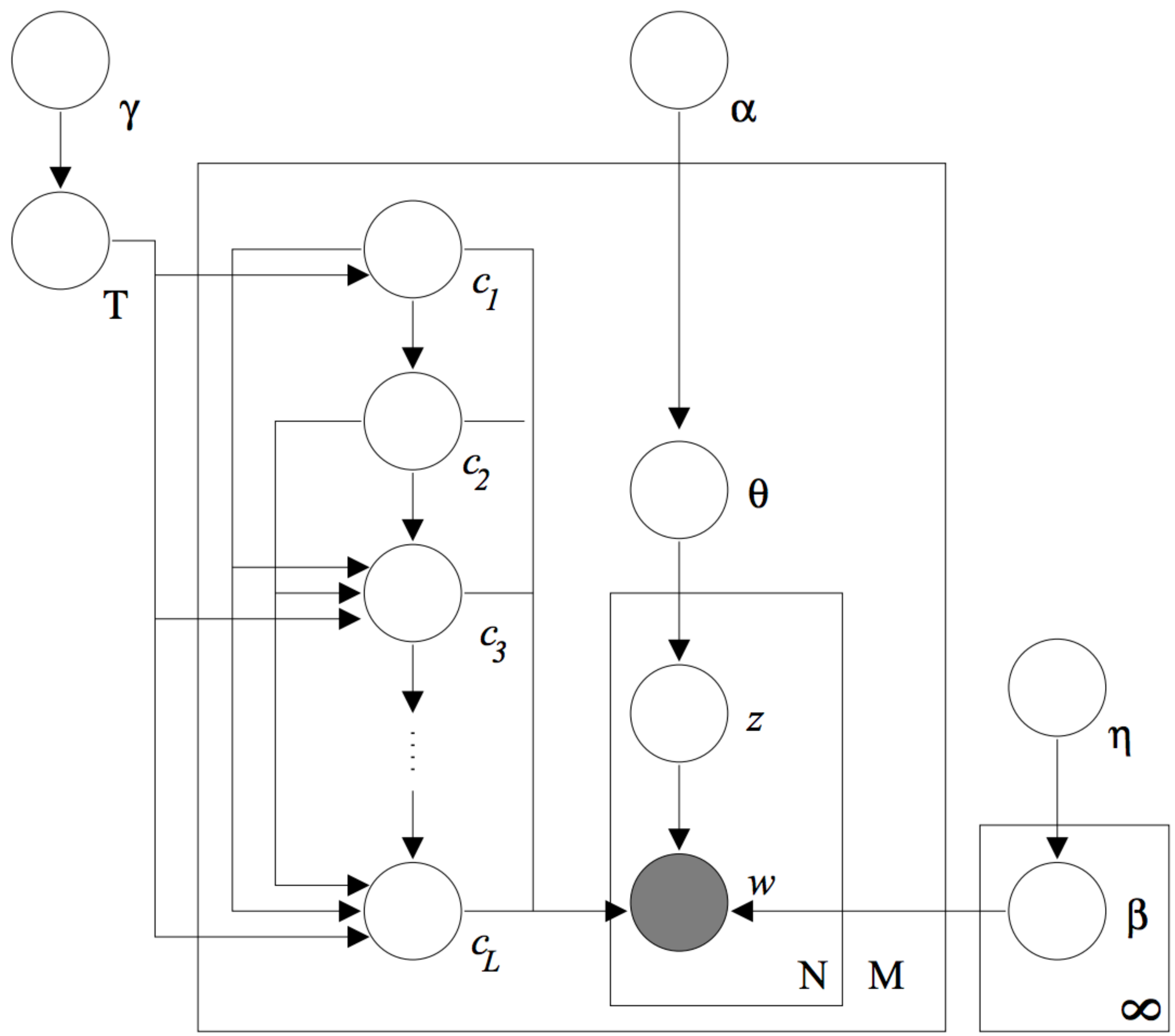
"A Framework for Incorporating General Domain Knowledge into Latent Dirichlet Allocation Using First-Order Logic."
Andrzejewski et al. *IJCAI* (2011).

SeededLDA



"Incorporating Lexical Priors into Topic Models." Jagarlamudi et al. *EACL* (2012)

Hierarchical LDA



"Hierarchical Topic Models and the Nested Chinese Restaurant Process." Griffiths et al. *Neural Information Processing Systems* (2003).

A Generative Modeling Tradeoff

The Good:

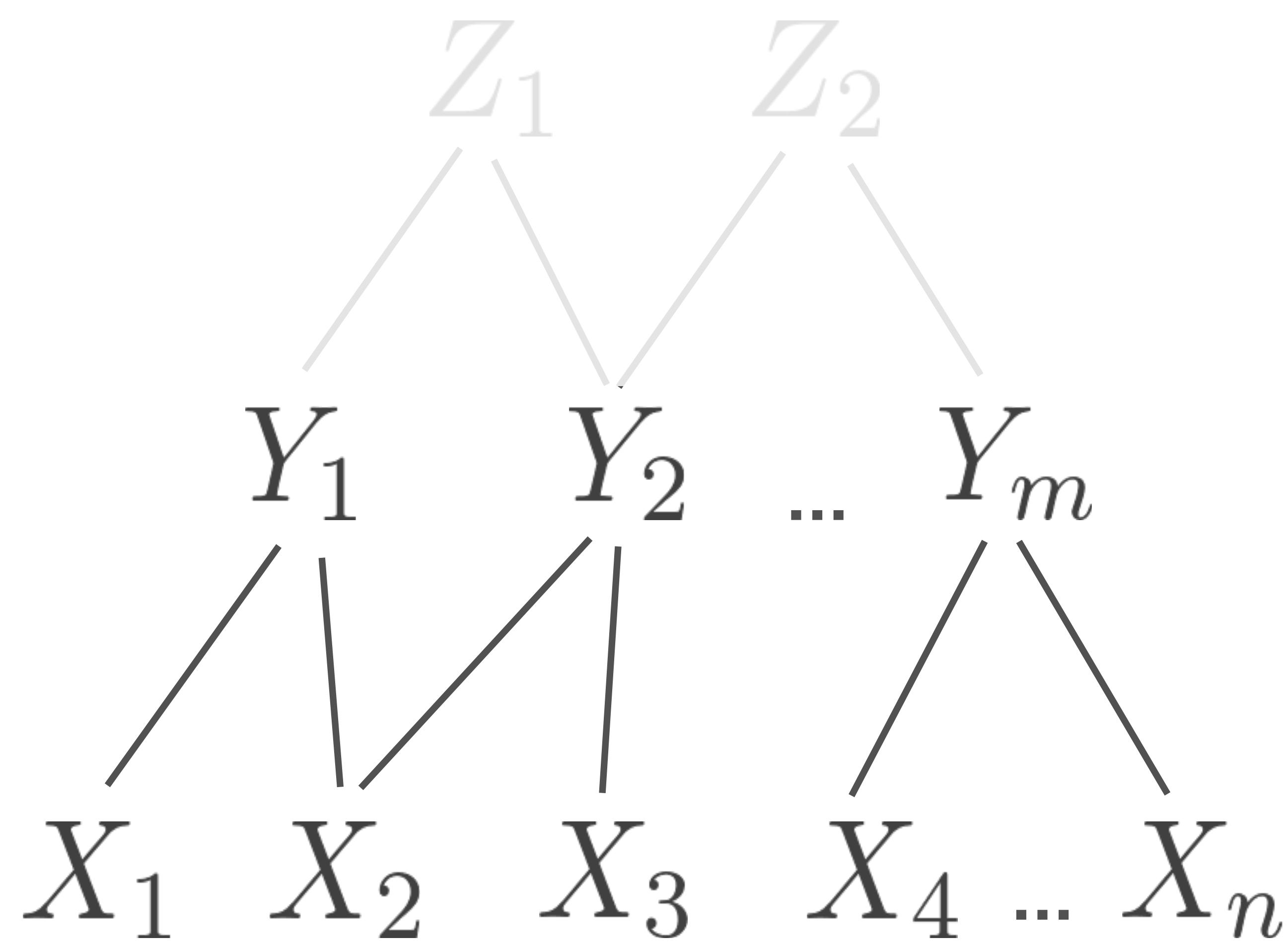
Priors explicitly encode your beliefs about what topics can be, and easily allow for iterative development of new topic models

The Bad:

Each additional prior takes a very specific view of the problem at hand, which both limits what a topic can be and makes it harder to justify in applications and to domain experts

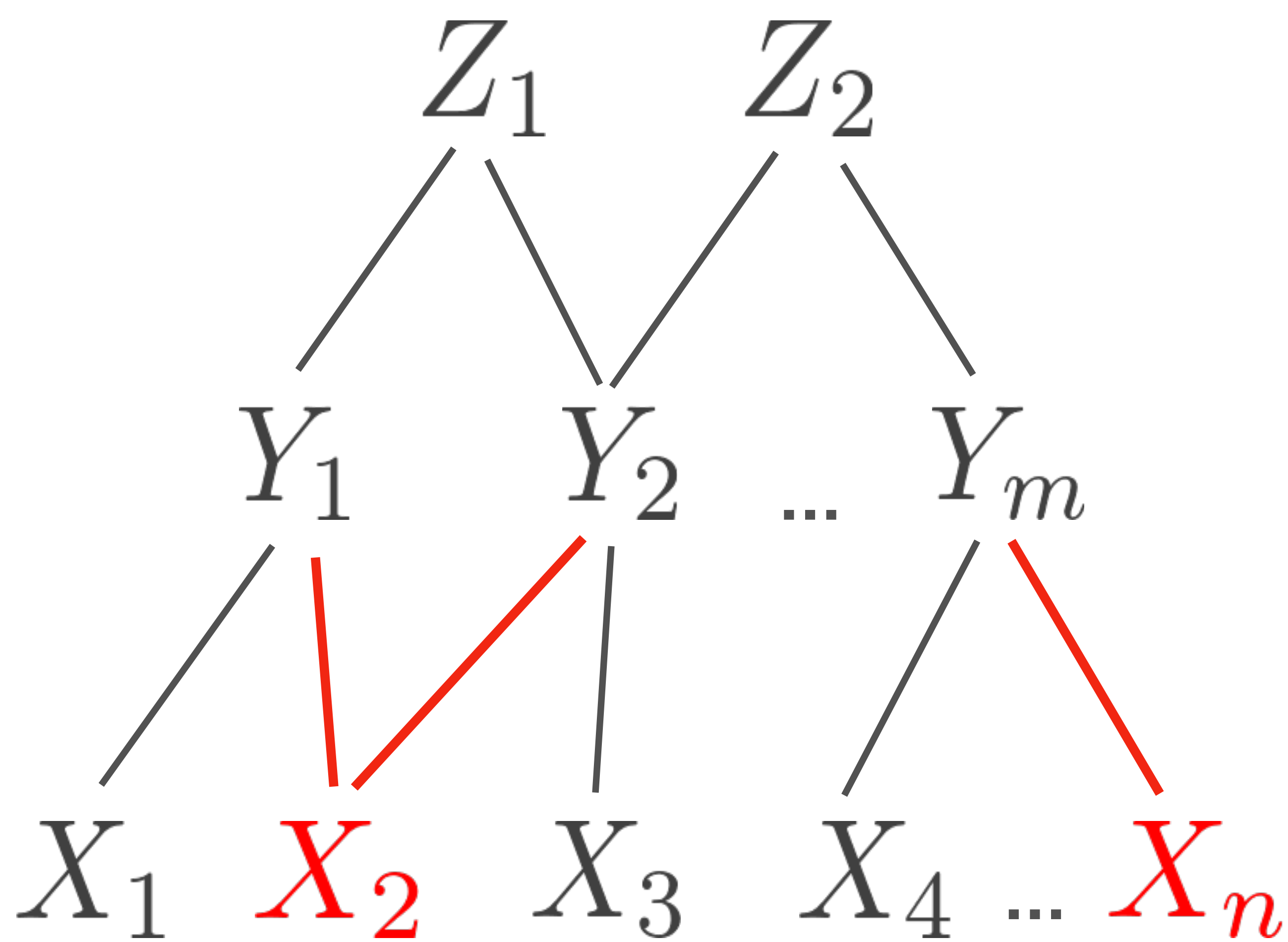
Proposed Work

We propose a topic model that learns topics through information-theoretic criteria, rather than a generative model



Proposed Work

We propose a topic model that learns topics through information-theoretic criteria, rather than a generative model, within a framework that yields **hierarchical** and **semi-supervised** extensions with *no additional assumptions*

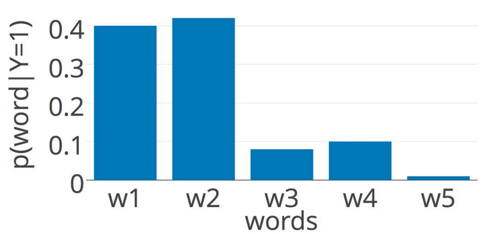


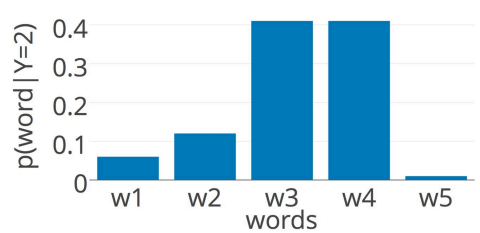
A Different Perspective on "Topics"

Consider three documents:

d_1	d_2	d_3
$x_1 \quad x_2$	$x_3 \quad x_4$	x_5
$(1,1,0,0,0)$	$(0,0,1,1,0)$	$(0,0,0,0,1)$

LDA: a topic is a distribution over words





$$P(Y=1)=1 \xleftarrow{\quad d_1 \quad} \; d_3 \; \xrightarrow{\quad d_2 \quad} P(Y=2)=1$$

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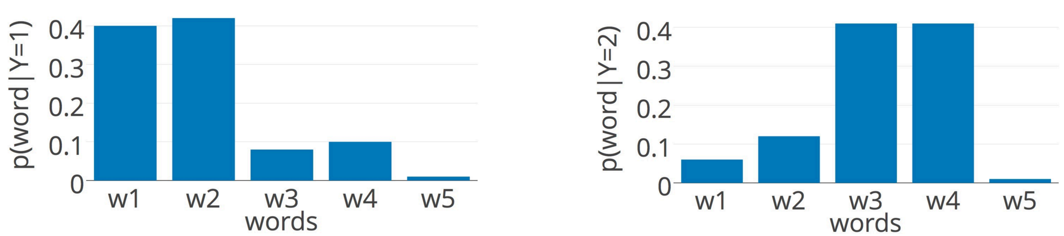
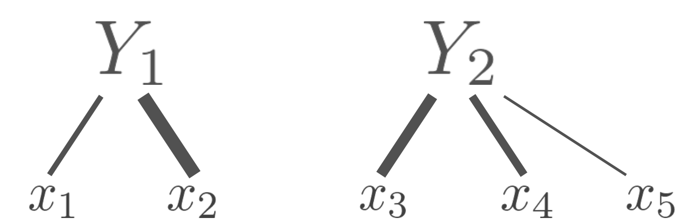


$$P(Y=1)=1 \xleftarrow{\;d_1 \qquad d_3 \qquad d_2\;} \rightarrow P(Y=2)=1$$

CorEx: a topic is a binary latent factor



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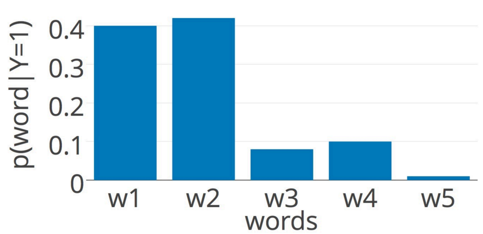

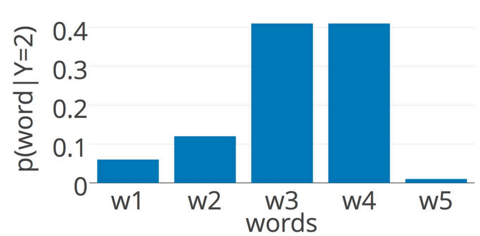

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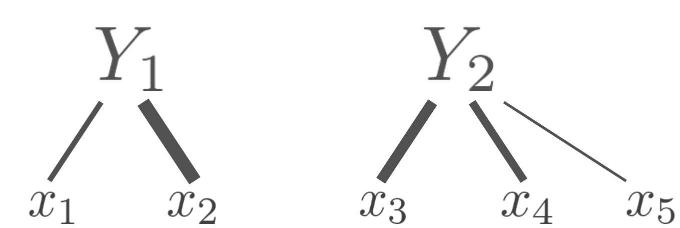

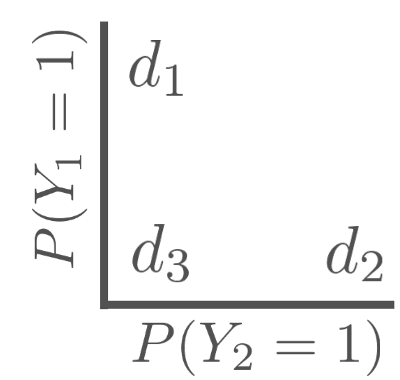

CorEx Objective (example)

Documents

d_1	d_2
$x_1 \quad x_2$	$x_3 \quad x_4$
$(1,1,0,0,0)$	$(0,0,1,1,0)$

Probability table

	$X_2 = 0$	$X_2 = 1$
$X_1 = 0$	1/2	0
$X_1 = 1$	0	1/2

CorEx Objective (example)

Documents

d_1: $x_1 \quad x_2$ — $(1, 1, 0, 0, 0)$

d_2: $x_3 \quad x_4$ — $(0, 0, 1, 1, 0)$

Probability table

	$X_2 = 0$	$X_2 = 1$
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Words 1 and 2 are related:

$$I(X_1 : X_2) = D_{KL}\big(p(x_1, x_2) \,||\, p(x_1)p(x_2)\big) = 1 \text{ bit}$$

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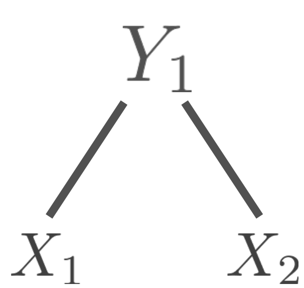

Hypothesize a latent factor: $Y_1 = X_1 = X_2$

CorEx Objective (example)

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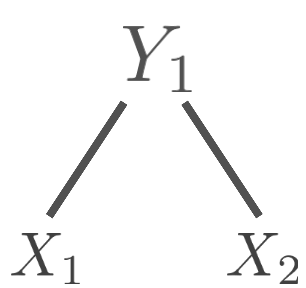

Hypothesize a latent factor: $Y_1 = X_1 = X_2$

Then conditioned on Y_1, words 1 and 2 are independent

$$D_{KL}\big(p(x_1, x_2 \mid y_1) \,||\, p(x_1 \mid y_1)p(x_2 \mid y_1)\big) = 0 \text{ bits}$$

CorEx Objective (example)

Documents

d_1: $\boxed{x_1 \quad x_2}$ $(1, 1, 0, 0, 0)$

d_2: $\boxed{x_3 \quad x_4}$ $(0, 0, 1, 1, 0)$

Probability table

	$X_2 = 0$	$X_2 = 1$
$X_1 = 0$	1/2	0
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Words 1 and 2 are related:

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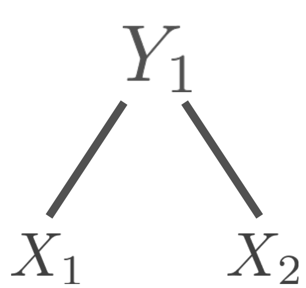

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Goal: find latent factors that make words conditionally independent

CorEx Objective

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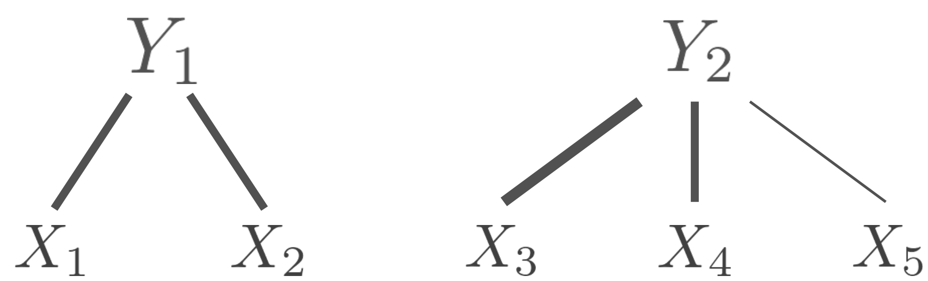
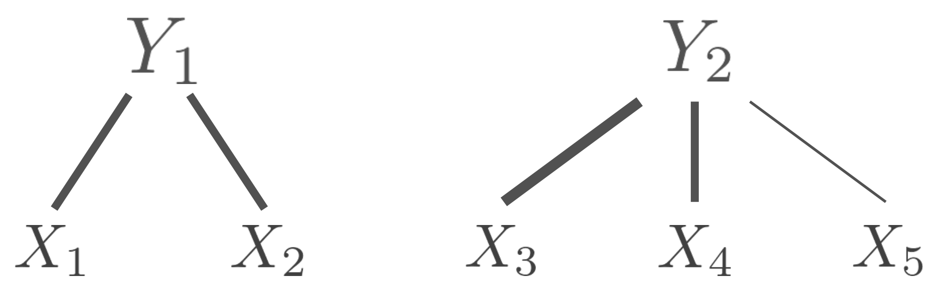


$$\min_{Y} D_{KL}\left(p(x_1, x_2, \ldots x_n \mid y) \,||\, \prod_i p(x_i \mid y)\right)$$

CorEx Objective

Goal: find latent factors that make words conditionally independent

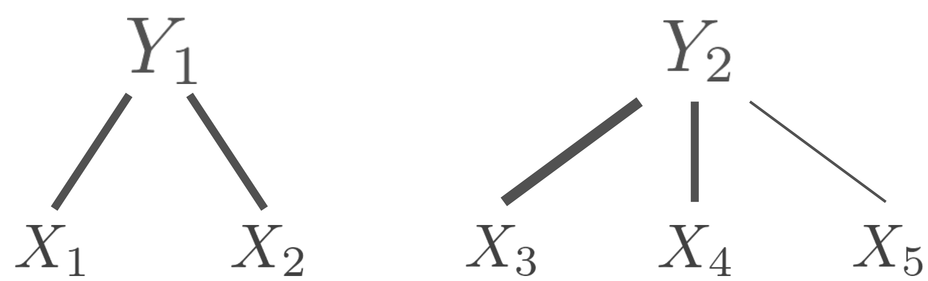


$$\min_Y D_{KL}\left(p(x_1, x_2, \ldots x_n \mid y) \,||\, \prod_i p(x_i \mid y)\right) = \min_Y \underline{TC(X_1, X_2, \ldots, X_N \mid Y)}$$

Total correlation conditioned on *Y*

CorEx Objective

Goal: find latent factors that make words conditionally independent



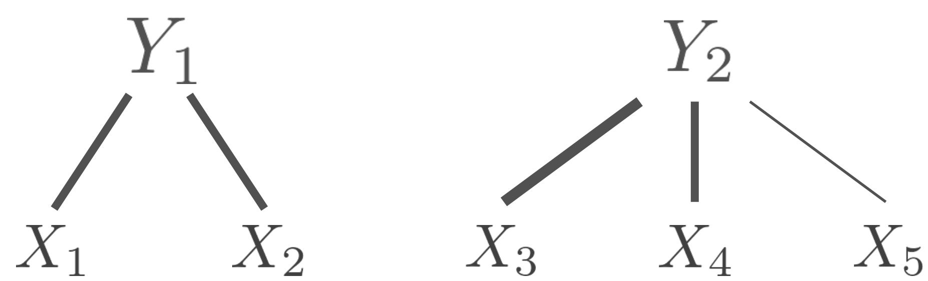
$$\min_Y D_{KL}\left(p(x_1, x_2, \ldots x_n \mid y) \,||\, \prod_i p(x_i \mid y)\right) = \min_Y TC(X_1, X_2, \ldots, X_N \mid Y)$$

$TC(X \mid Y) = 0$ if and only if the topic “explains” all the dependencies (total correlation)

Hence, “Total **Cor**relation **Ex**planation” (CorEx)

CorEx Objective

Goal: find latent factors that make words conditionally independent



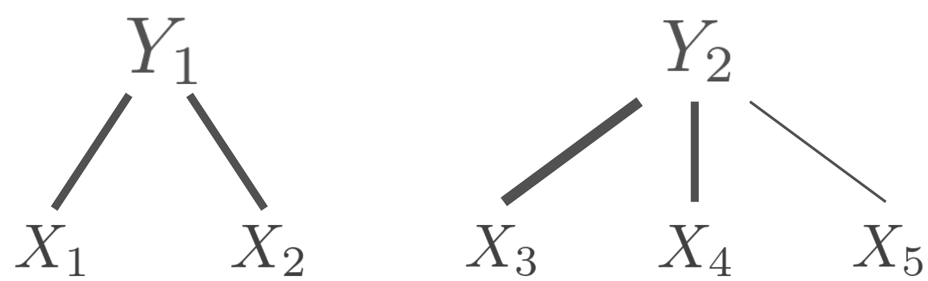
$$\min_Y D_{KL}\left(p(x_1, x_2, \dots x_n \mid y) \,||\, \prod_i p(x_i \mid y)\right) = \min_Y TC(X_1, X_2, \dots, X_N \mid Y)$$

In order to maximize the information $TC(X_{G_j})$ between a group of words G_j in topic j we consider a tractable lower bound:

$$TC(X_{G_j}) - TC(X_{G_j} \mid Y_j) \leq TC(X_{G_j})$$

CorEx Objective

Goal: find latent factors that make words conditionally independent



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$$TC(X_{G_j}) - TC(X_{G_j} \mid Y_j) \leq TC(X_{G_j})$$

We maximize this lower bound over m topics

$$\max_{G_j, p(y_j | x_{G_j})} \sum_{j=1}^{m} TC(X_{G_j}) - TC(X_{G_j} \mid Y_j)$$

CorEx Objective

We can now rewrite the objective:

$$\max_{G_j, p(y_j | x_{G_j})} \sum_{j=1}^{m} TC(X_{G_j}) - TC(X_{G_j} \mid Y_j) = \max_{G_j, p(y_j | x_{G_j})} \sum_{j=1}^{m} \sum_{i \in G_j} I(X_i : Y_j) - I(X_{G_j} : Y_j)$$

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We transform this from a combinatorial to a continuous optimization by introducing variables $\alpha_{i,j} \in [0,1]$ and “relaxing” words into informative topics

$$\max_{G_j, p(y_j|x_{G_j})} \sum_{j=1}^{m} \sum_{i \in G_j} \alpha_{i,j} I(X_i : Y_j) - I(X_{G_j} : Y_j)$$

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This relaxation yields a set of update equations which we can iterate through until convergence

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Under the hood:

1. We introduce a sparsity optimization for the update equations,

$$O(N_{\text{docs}} n_{\text{types}}) \to O(N_{\text{docs}}) + O(n_{\text{types}}) + O(\rho_{\text{tokens}})$$

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These are issues of speed, not theory

CorEx Topic Examples

Data: news articles about Hillary Clinton's presidential campaign, up to August 2016

Work by Abigail Ross and the Computational Story Lab, University of Vermont

CorEx Topic Examples

Data: news articles about Hillary Clinton's presidential campaign, up to August 2016

Clinton Article Topics

1: server, department, classified, information, private, investigation, fbi, email, emails, secretary

3: sanders, bernie, primary, vermont, win, voters, race, nomination, vote, polls

6: crowd, woman, speech, night, women, stage, man, mother, audience, life

8: percent, poll, points, percentage, margin, survey, according, 10, polling, university

9: federal, its, officials, law, including, committee, staff, statement, director, group

13: islamic, foreign, military, terrorism, war, syria, iraq, isis, u, terrorist

14: trump, donald, trump's, republican, nominee, party, convention, top, election, him

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Clinton Article Topics

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Words ranked by mutual information with topic

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Topics ranked by total correlation

Clinton Article Topics

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Clinton Article Topics

Most informative topic

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Clinton Article Topics

1: server, department, classified, information, private, investigation, fbi, email, emails, secretary

3: sanders, bernie, primary, vermont, win, voters, race, nomination, vote, polls

6: crowd, woman, speech, night, women, stage, man, mother, audience, life

8: percent, poll, points, percentage, margin, survey, according, 10, polling, university

9: federal, its, officials, law, including, committee, staff, statement, director, group

13: islamic, foreign, military, terrorism, war, syria, iraq, isis, u, terrorist

14: trump, donald, trump's, republican, nominee, party, convention, top, election, him

Work by Abigail Ross and the Computational Story Lab, University of Vermont

CorEx Topic Examples

Data: news articles about Hillary Clinton's presidential campaign, up to August 2016

Clinton Article Topics

1: server, department, classified, information, private, investigation, fbi, email, emails, secretary

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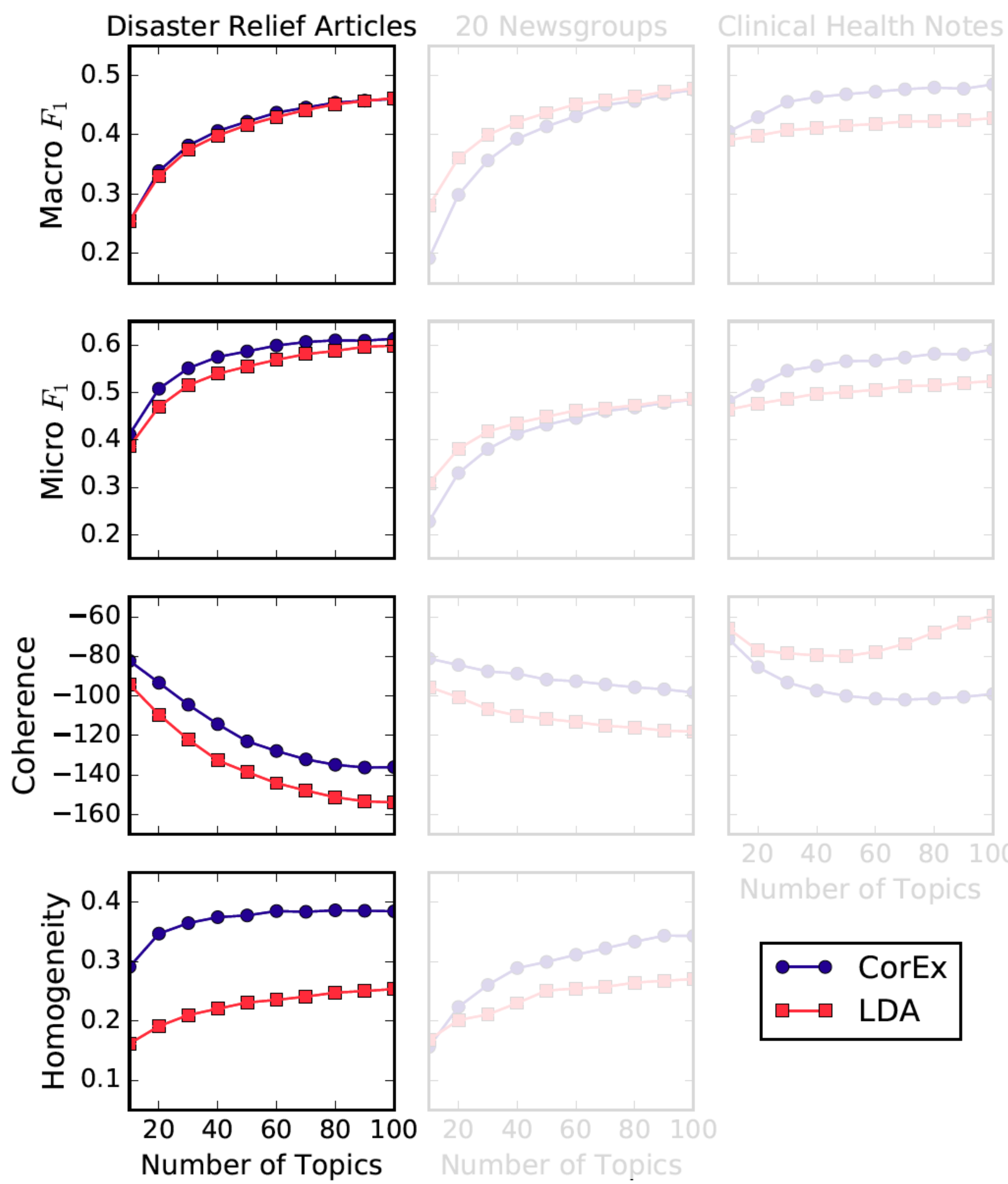
CorEx Performs Favorably Against LDA



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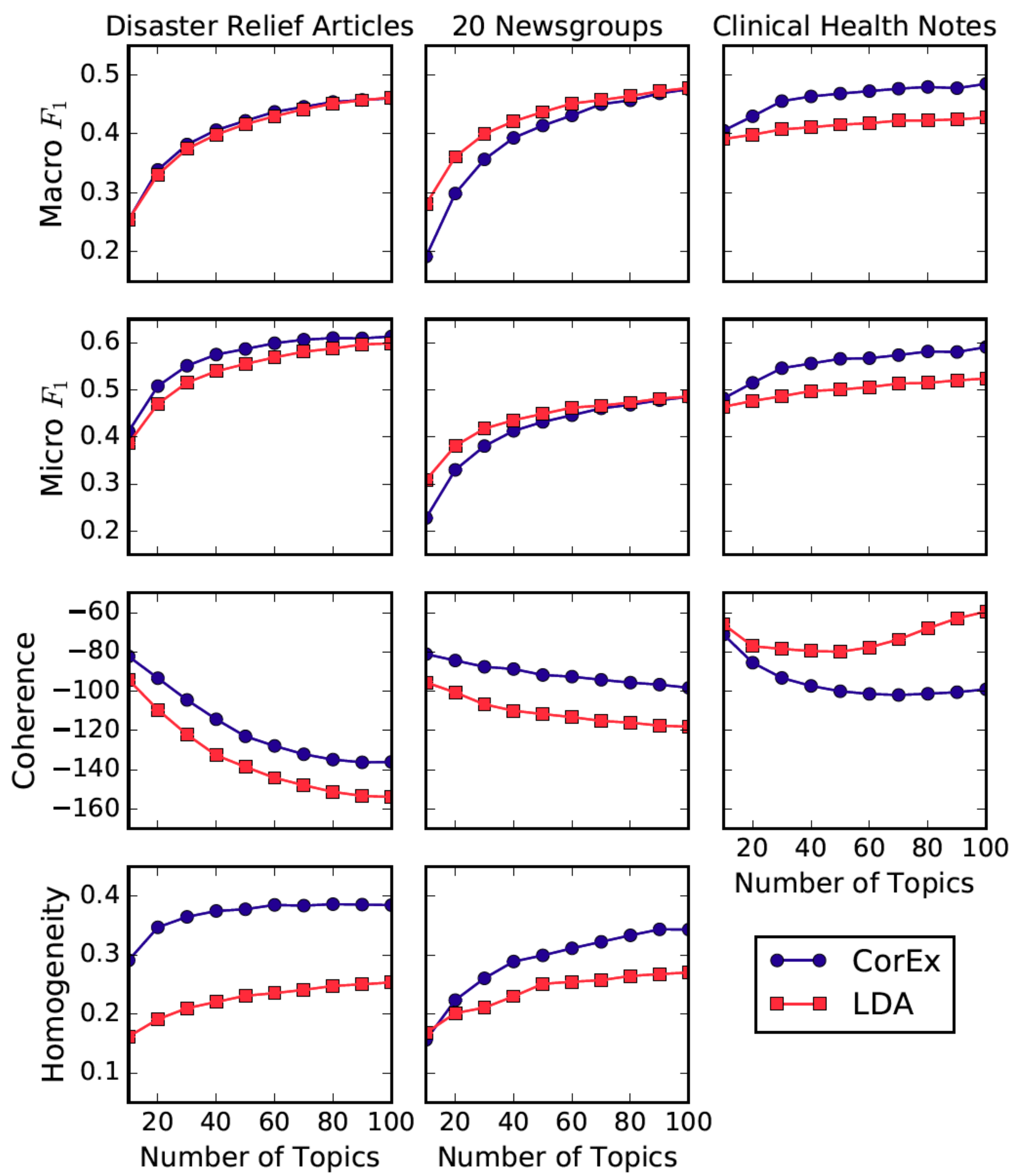


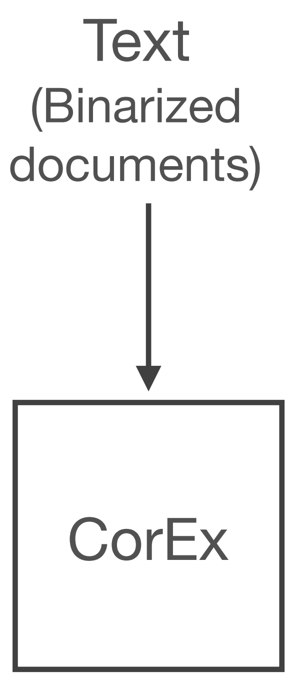
CorEx Extensions

With no additional assumptions, the CorEx topic model yields two extensions:

1. A hierarchical topic model

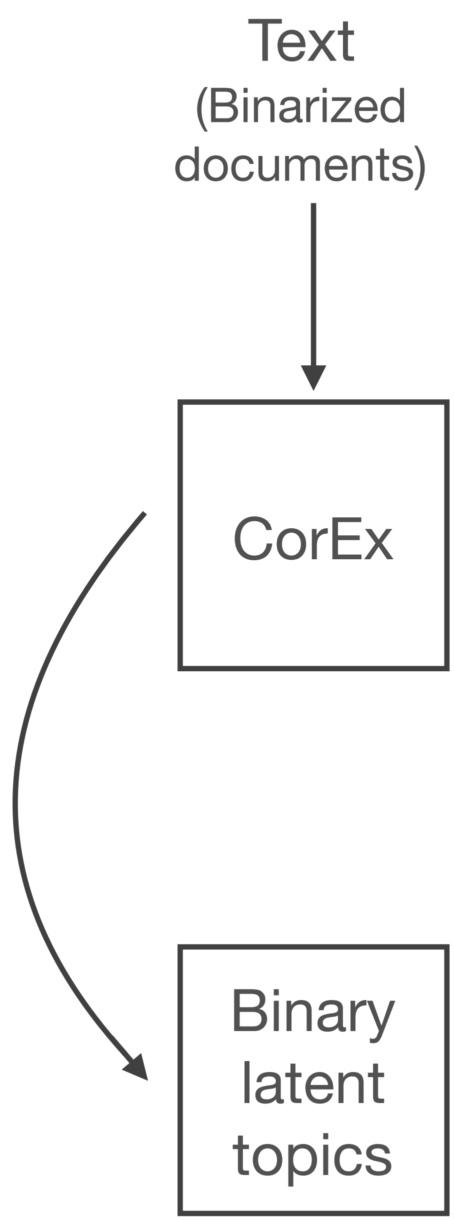
2. A semi-supervised topic model at the word level

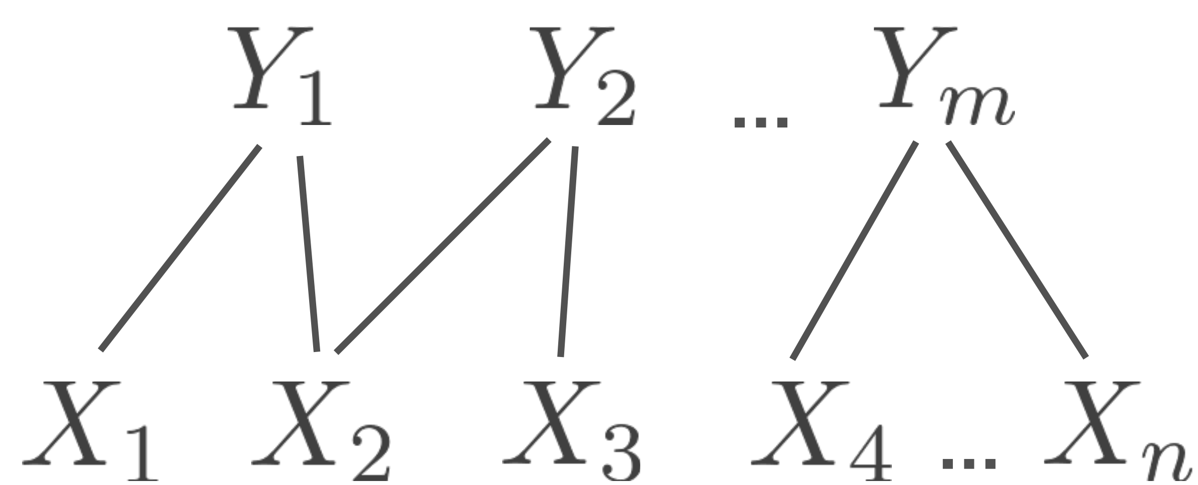
Hierarchical CorEx



$X_1 \quad X_2 \quad X_3 \quad X_4 \ldots X_n$

Hierarchical CorEx





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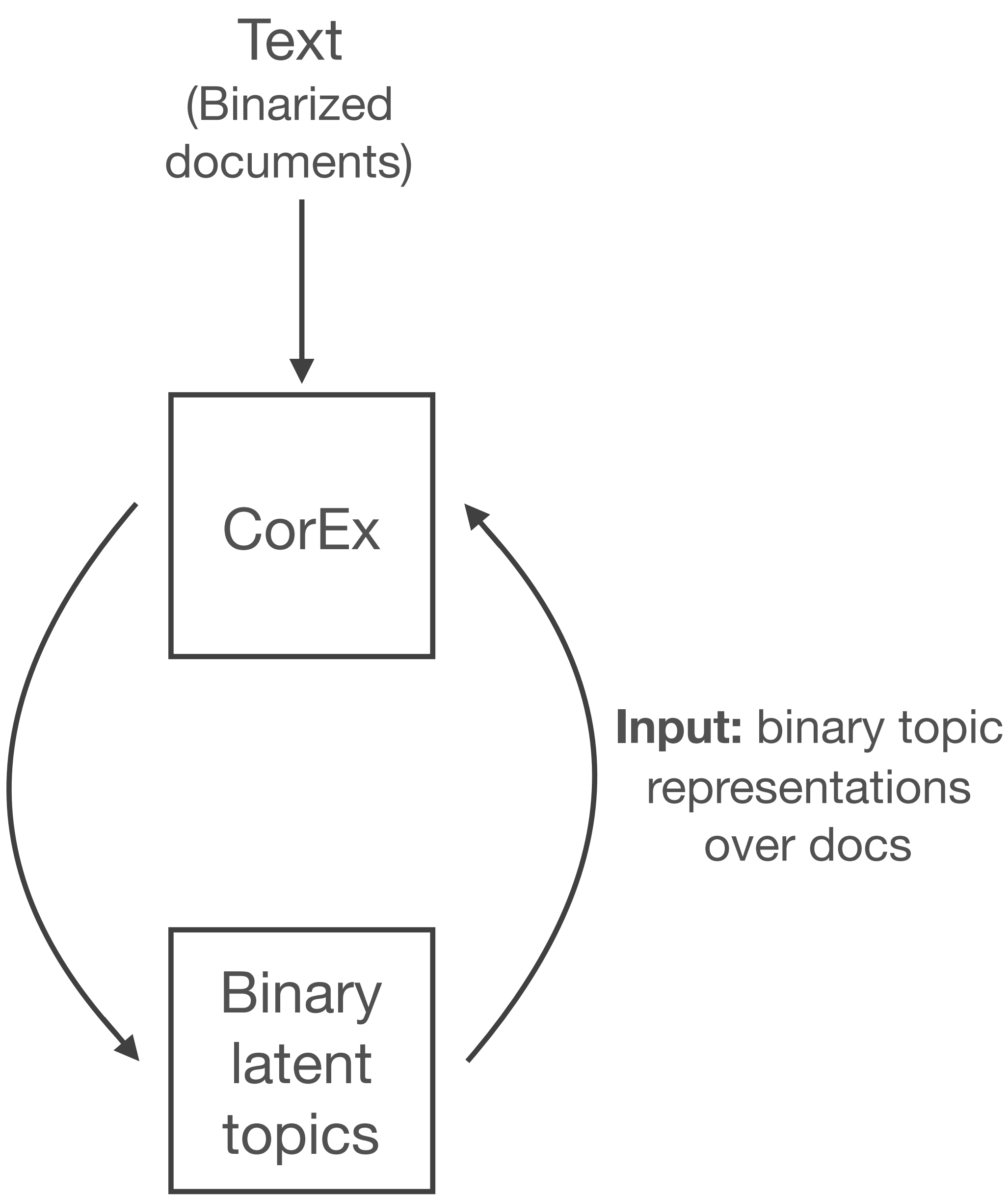
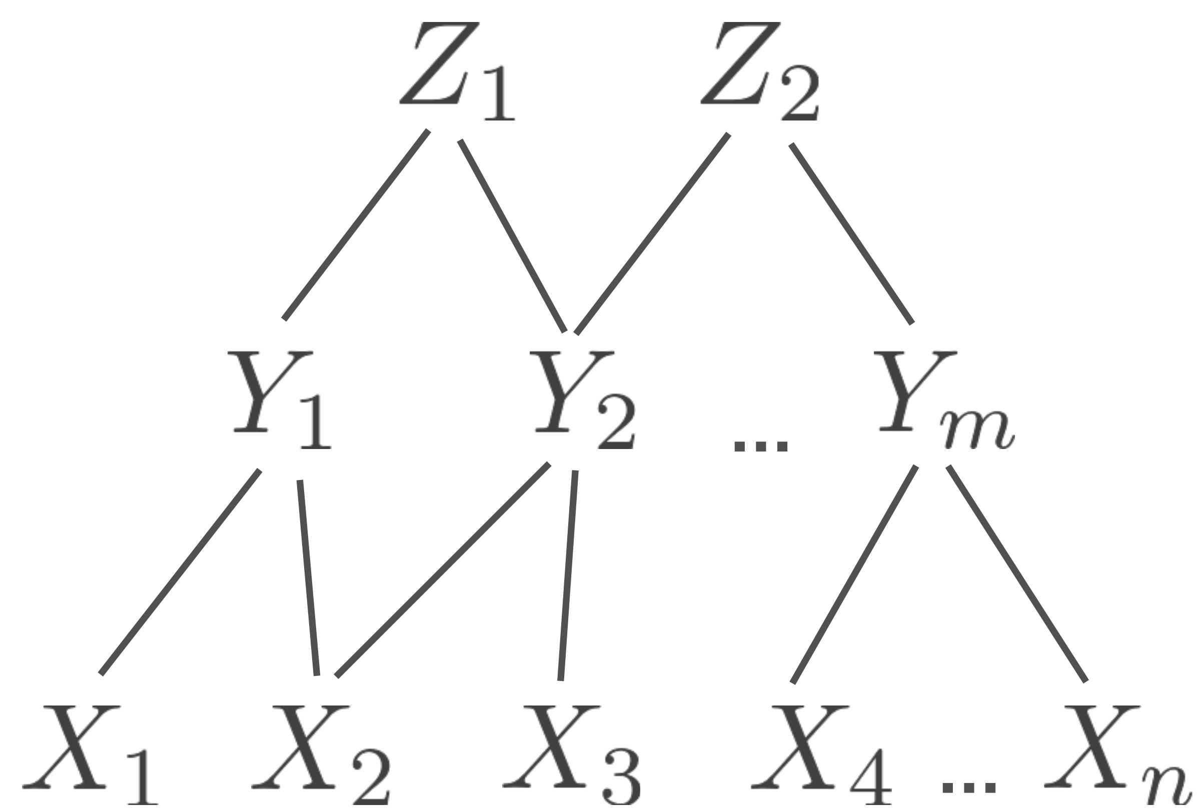
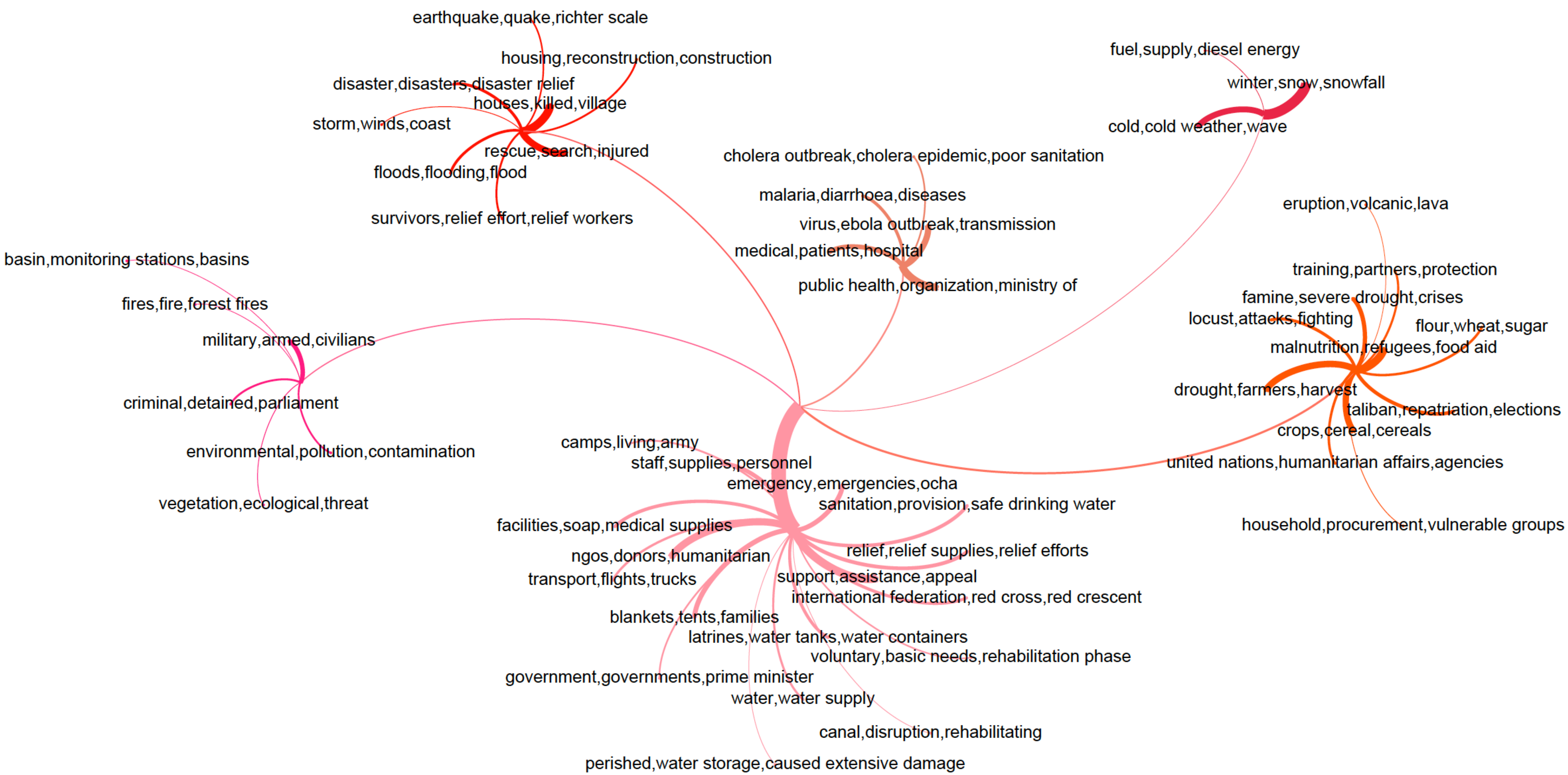


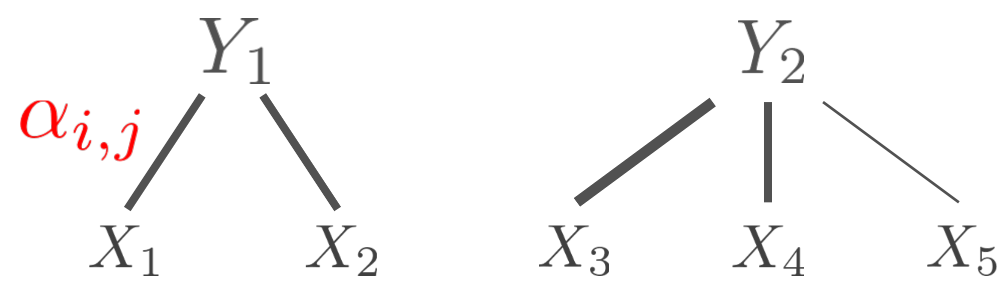


Hierarchical CorEx

Data: ~20,000 humanitarian assistance and disaster relief news articles

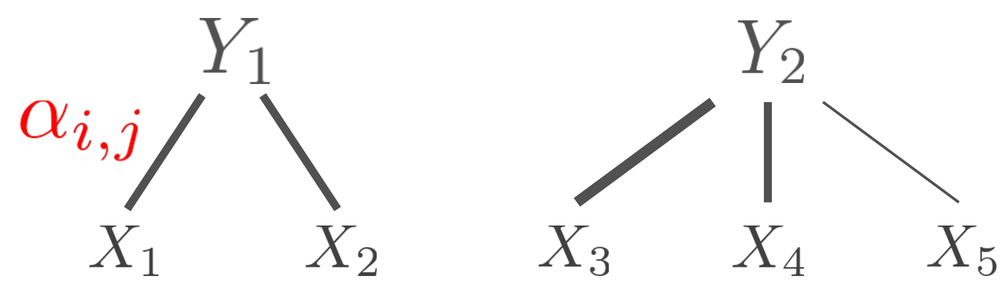


Anchored CorEx and the Information Bottleneck



Objective: $$\max_{G_j, p(y_j|x_{G_j})} \sum_{j=1}^{m} \sum_{i \in G_j} \alpha_{i,j} I(X_i : Y_j) - I(X_{G_j} : Y_j)$$

Anchored CorEx and the Information Bottleneck



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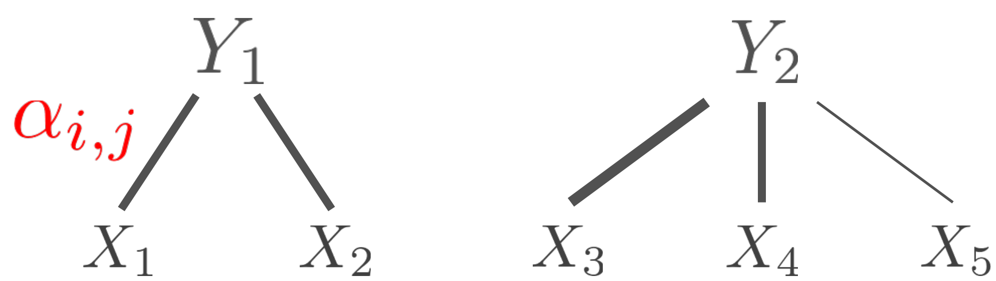
Maintain information about individual words

Anchored CorEx and the Information Bottleneck



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Maintain information about individual words

Compress documents into topics

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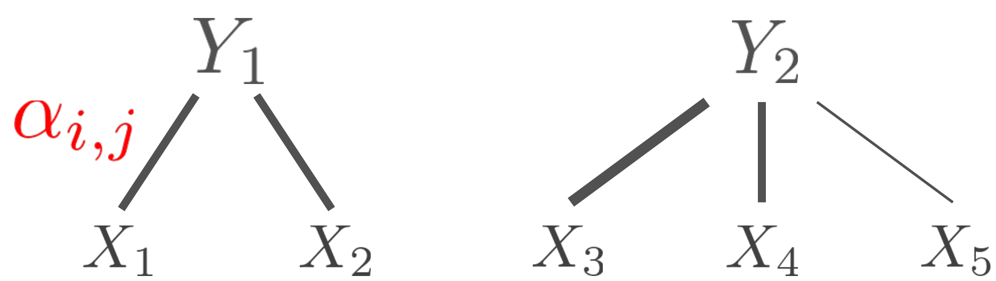

Objective:

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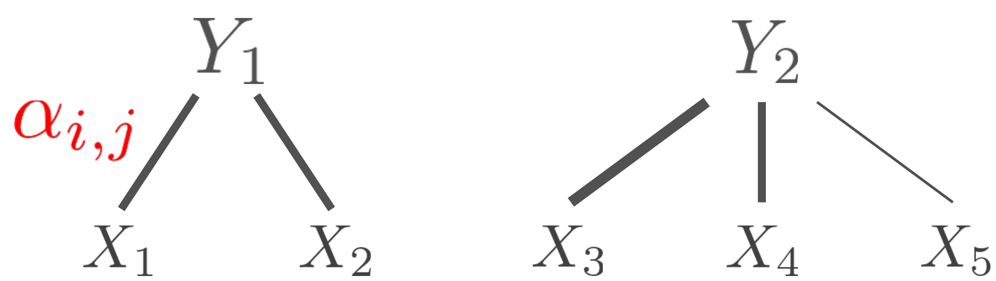
Maintain information about individual words

Compress documents into topics

Information bottleneck

"The Information Bottleneck Method." Tishby et al. (2000).

Anchored CorEx and the Information Bottleneck



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Maintain information about individual words

Compress documents into topics

Information bottleneck

A user can **anchor** words to the latent topics by modifying the **weight** of the relationship between a word and a topic

"The Information Bottleneck Method." Tishby et al. (2000).

Anchoring Strategies

Topic Representation

Anchoring to unveil topics that do not naturally emerge

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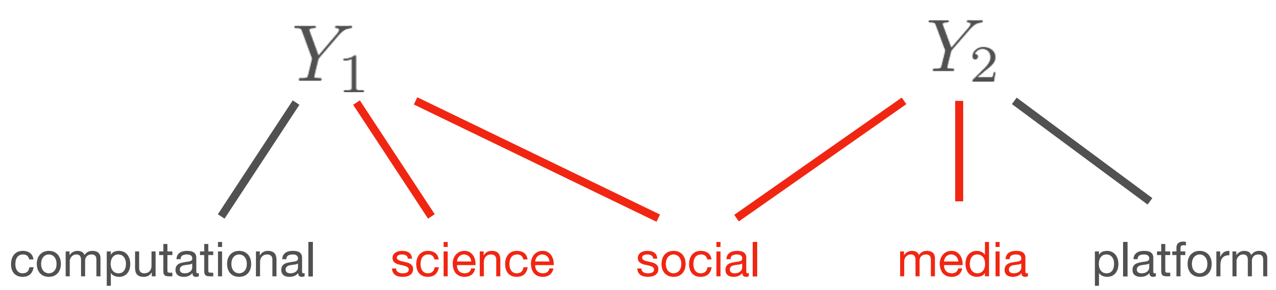
Anchoring to unveil topics that do not naturally emerge

Topic Separability
Anchoring to help enforce separation between topics



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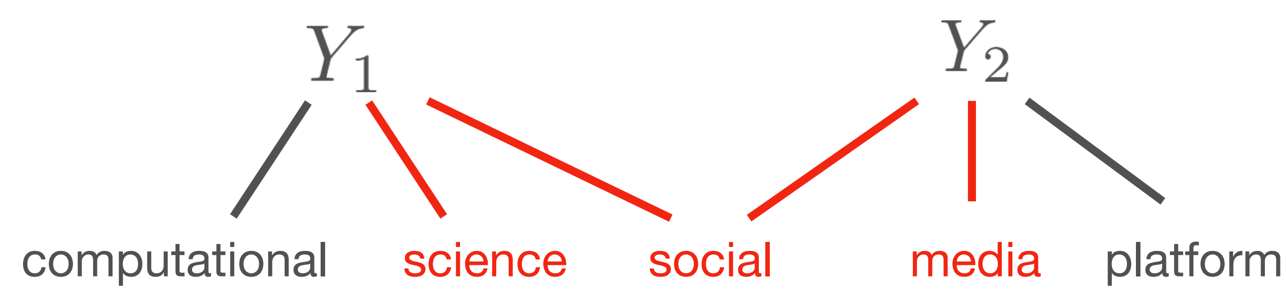
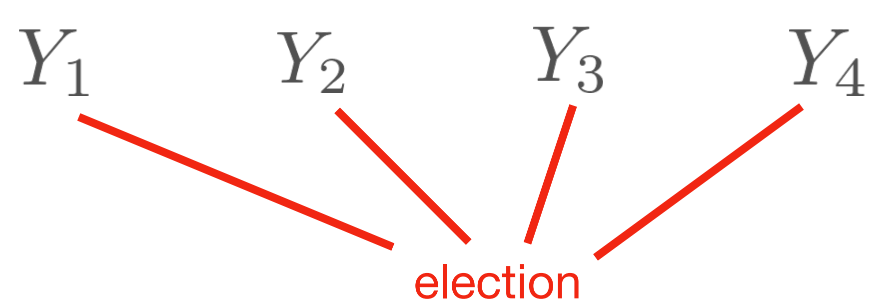


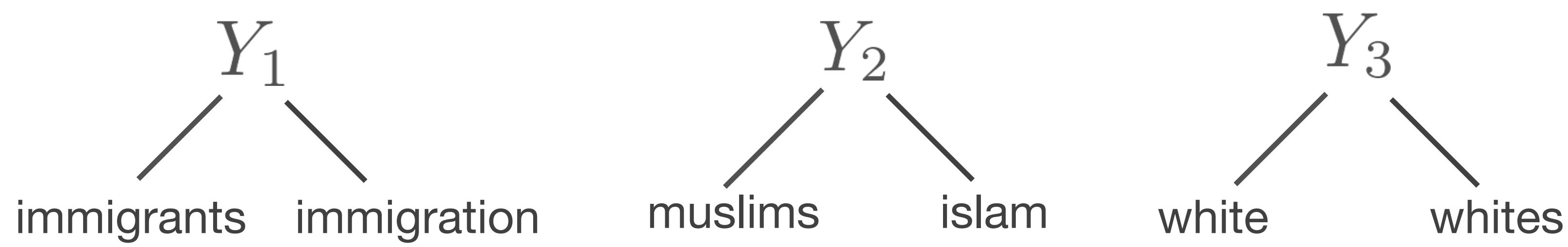
Topic Aspects

Anchoring to disambiguate different frames around a word



Anchoring for Topic Representation

Data: news articles about the campaigns of Clinton and Trump, up to August 2016
Method: train one CorEx topic model for each corpus, anchor words for comparison



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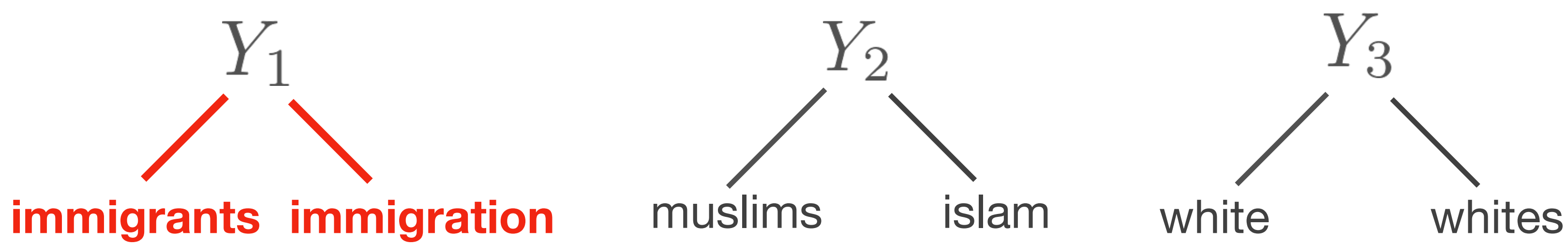

Clinton Topic

1: **immigration**, **immigrants**, jobs, economic, trade, health, tax, wall, care, economy

Trump Topic

1: **immigration**, **immigrants**, illegal, border, mexican, undocumented, rapists, mexico, wall, illegally

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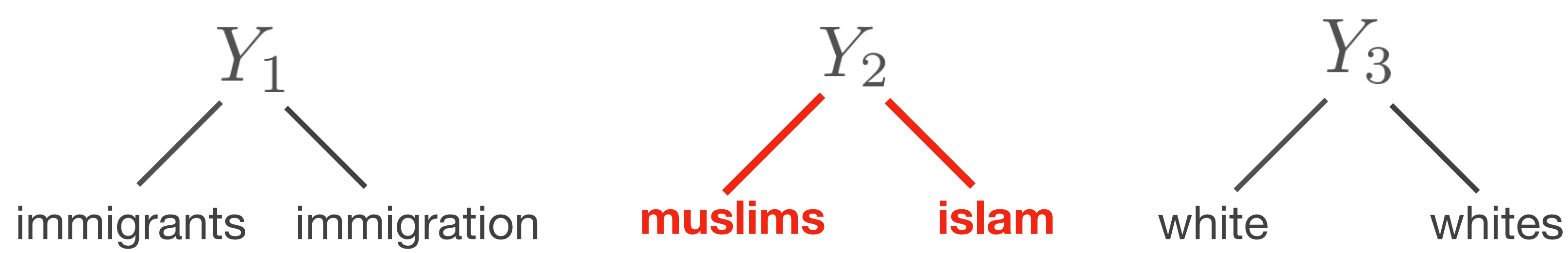

Clinton Topic

2: **muslims**, **islam**, islamic, gun, terrorism, war, military, iraq, terrorist, syria

Trump Topic

2: **muslims**, **islam**, united, ban, entering, islamic, muslim, terrorism, terrorist, terrorists

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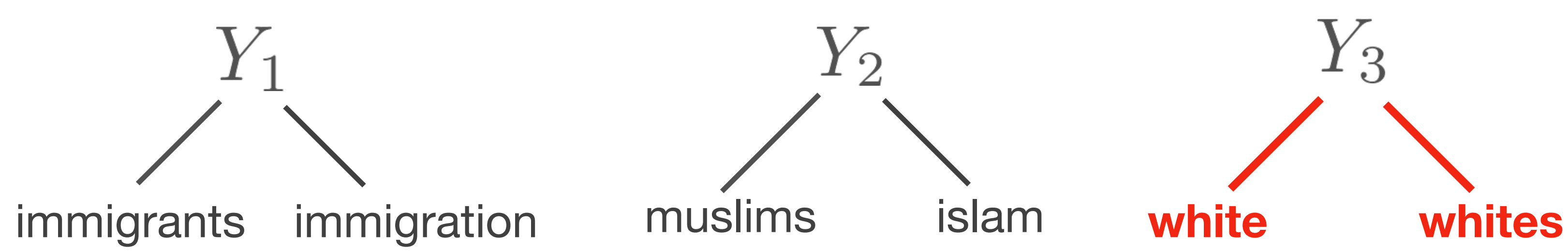


Clinton Topic

3: **white**, i, you, what, do, if, we, it's, like, people

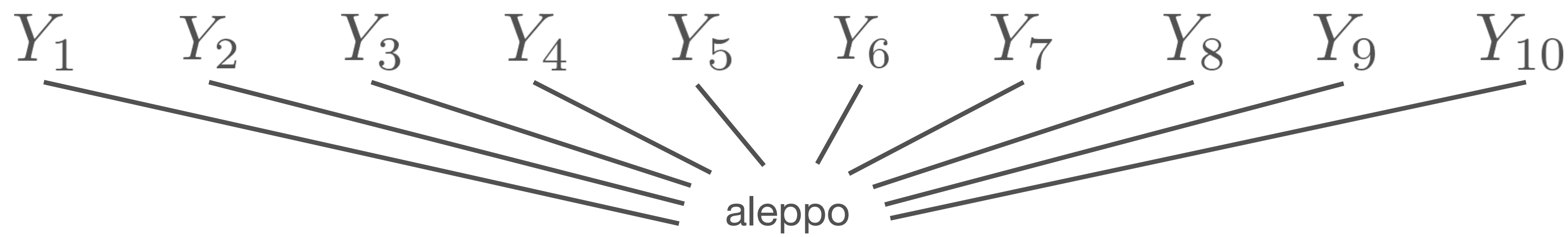
Trump Topic

3: **white**, house, **whites**, supremacists, supremacist, duke, klan, klux, ku, supremacy

Work by Abigail Ross and the Computational Story Lab, University of Vermont

Anchoring for Topic Aspects

Data: ~1 million English newswire articles since June 2015 from countries in the Middle East



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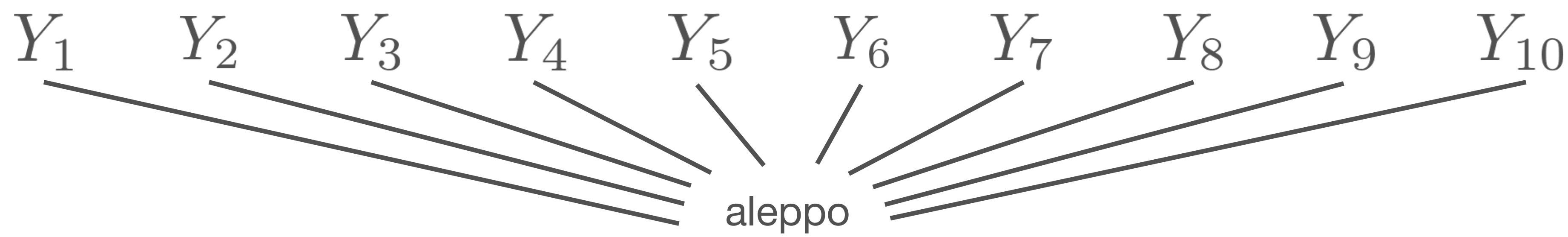

Note: this data broadly covers the Middle East and a priori we do not expect 10 topics to emerge about Aleppo

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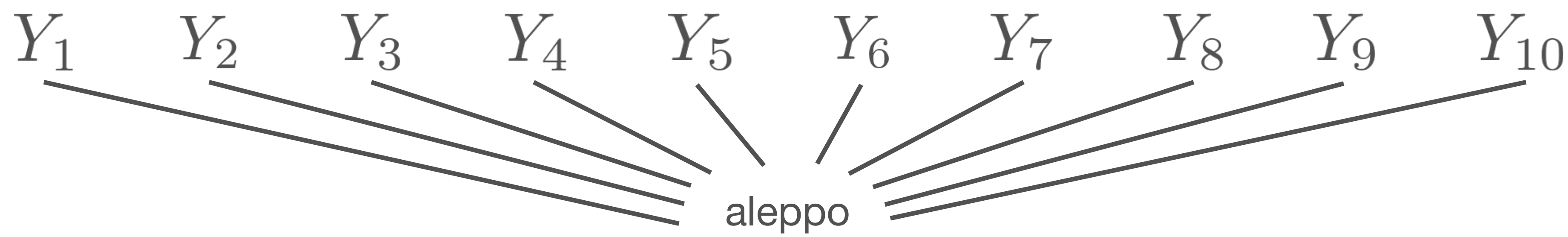

1: **aleppo**, killed, police, security, attack, state, arrested, authorities

2: **aleppo**, forces, syria, military, war, army, civilians, iraq, militants

3: **aleppo**, health, medical, food, care, water, small, conditions, treatment, patients

4: country, **aleppo**, east, across, group, region, middle

5: two, **aleppo**, took, another, place, taking, leaders

6: **aleppo**, russia, iran, barack, obama, moscow, washington, putin

7: **aleppo**, political, court, part, accused, opposition, called, saying, parliament, democratic

8: government, **aleppo**, minister, foreign, states, united, prime, UN, law, nations

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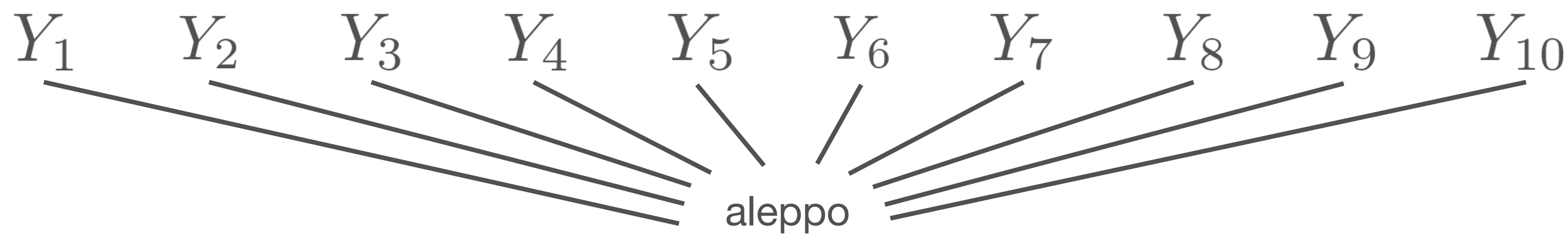

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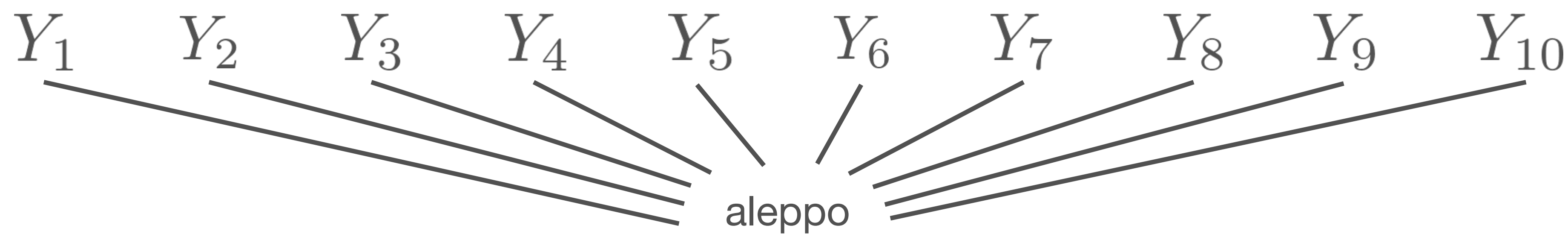

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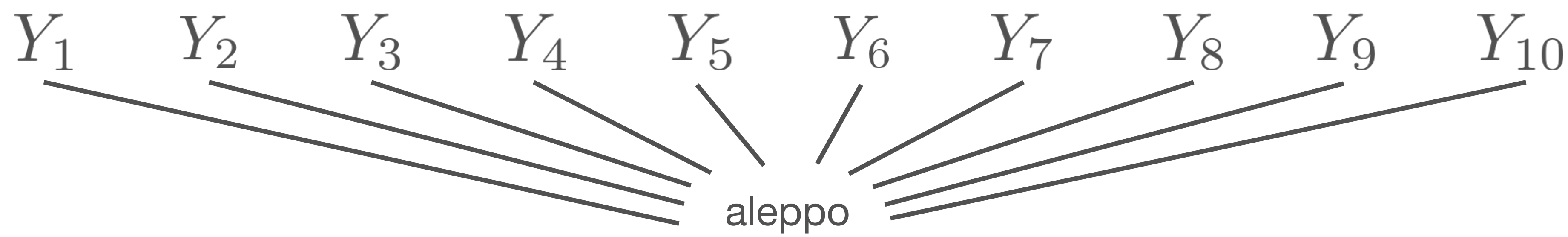

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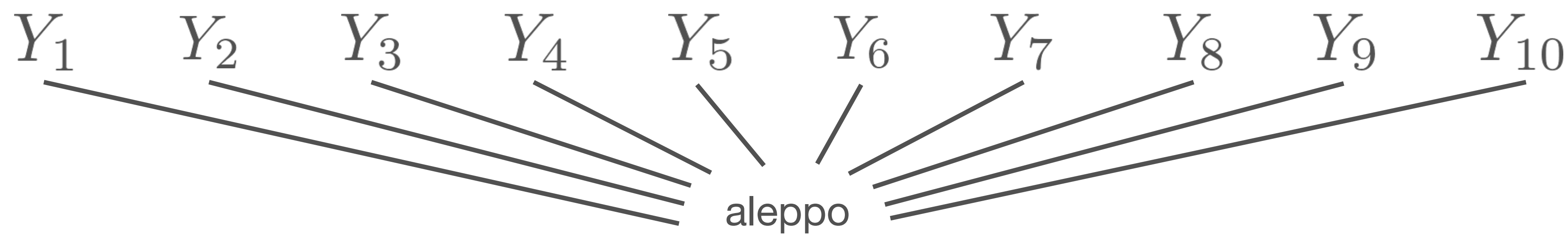

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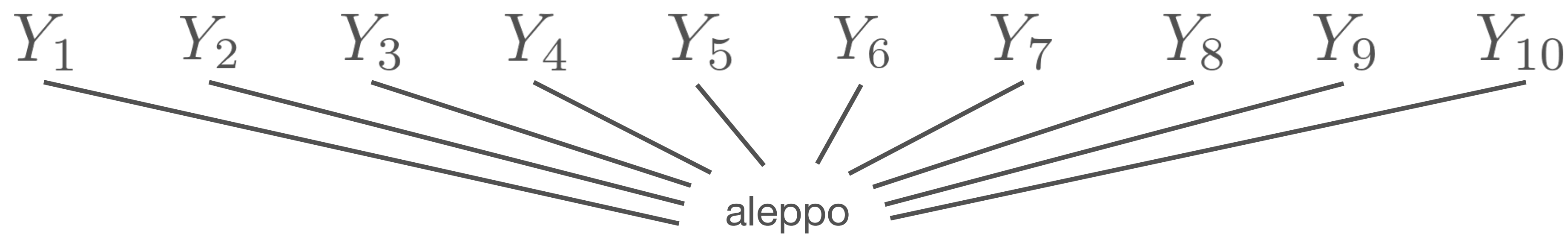

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Shape of the CorEx Topic Model to Come

CorEx Topic Model

By defining topics in terms of information content, the CorEx topic model takes a new perspective on topic modeling

CorEx is competitive with unsupervised and semi-supervised variants of LDA while making far fewer assumptions

Anchoring through the information bottleneck provides a flexible mechanism to retrieve topics of interest and inject expert domain knowledge

Future Work

Extend CorEx to efficiently learn multi-membership topics (*in progress*)

Incorporate count data into the CorEx topic model while preserving the benefits of the sparsity optimization

Code: github.com/gregversteeg/corex_topic

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Collaborators

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Information Sciences Institute

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Information Sciences Institute

USC University of Southern California
Information Sciences Institute
netsi
Northeastern University
Network Science Institute
VACC
VERMONT ADVANCED COMPUTING CORE
UNIVERSITY OF VERMONT
VERMONT COMPLEX SYSTEMS CENTER

The anchored Clinton and Trump election article topics come from work by **Abigail Ross** and the **Computational Story Lab** at the University of Vermont's Complex Systems Center

Thank you for your time!

@ryanjgallag
ryanjgallag@gmail.com

github.com/gregversteeg/corex_topic

CorEx Implementation

Update Equations

$$p_t(y_j) = \sum_{\bar{x}} p_t(y_j \mid \bar{x}) p(\bar{x})$$

$$p_t(x_i \mid y_j) = \sum_{\bar{x}} \frac{p_t(y_j \mid \bar{x}) p(\bar{x}) \mathbb{I}[\bar{x}_i = x_i]}{p_t(y_j)}$$

Marginals in terms of the optimization parameter $p_t(y_j \mid x)$

$$\log p_{t+1}(y_j \mid x^\ell) = \log p_t(y_j) + \sum_{i=1}^{n} \alpha_{i,j}^t \log \frac{p_t(x_i^\ell \mid y_j)}{p(x_i^\ell)} - \log \mathcal{Z}_j(x^\ell)$$

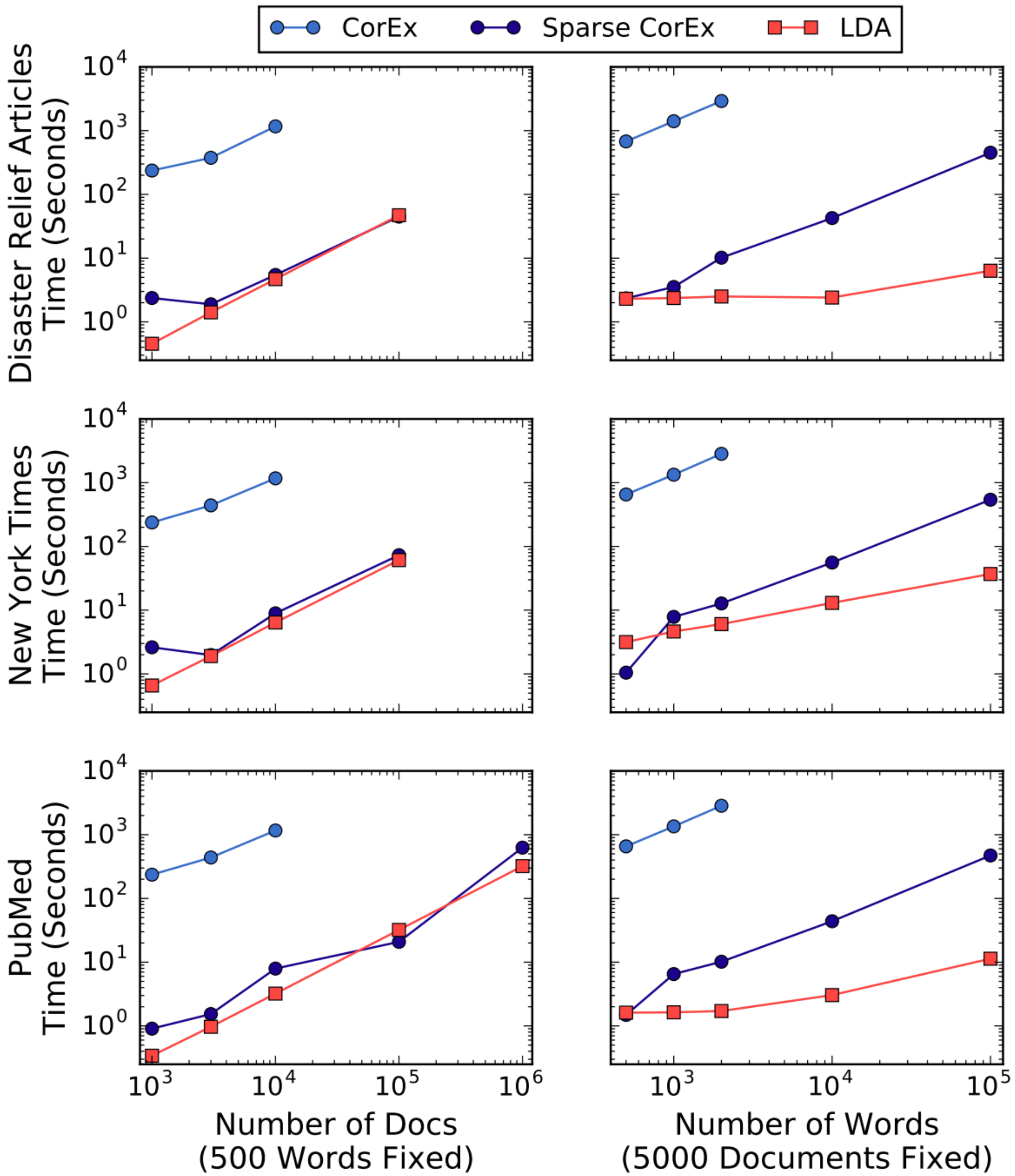
Probabilistic labels for each latent factor given sample

Sparsity Optimization

$$\log \frac{p_t(x^\ell \mid y_j)}{p(x_i^\ell)} = \log \frac{p_t(X_i = 0 \mid y_j)}{p(X_i = 0)} + x_i^\ell \log \frac{p_t(X_i^\ell = 1 \mid y_j) p(X_i = 0)}{p_t(X_i = 0 \mid y_j) p(x_i^\ell = 1)}$$

Substituting above turns the sum into a matrix multiplication between a matrix of size (# docs) x (# types) and a matrix of size (# types) x (# topics)

Sparsity Optimization Speed Comparison



CorEx Example Topics

Data: news articles about Clinton and Trump, train one CorEx topic model for each corpus

Clinton Article Topics

1: server, department, classified, information, private, investigation, fib, email, emails, secretary

3: sanders, bernie, primary, vermont, win, voters, race, nomination, vote, polls

8: percent, poll, points, percentage, margin, survey, according, 10, polling, university

9: federal, its, officials, law, including, committee, staff, statement, director, group

13: islamic, foreign, military, terrorism, war, syria, iraq, isis, u, terrorist

14: trump, donald, trump's, republican, nominee, party, convention, top, election, him

Trump Article Topics

1: primary, party, win, cruz, delegates, voters, ted, nomination, republicans, vote

4: $, tax, money, million, jobs, economic, companies, billion, pay, taxes

7: percent, poll, percentage, points, polls, survey, 10, polling, margin, according

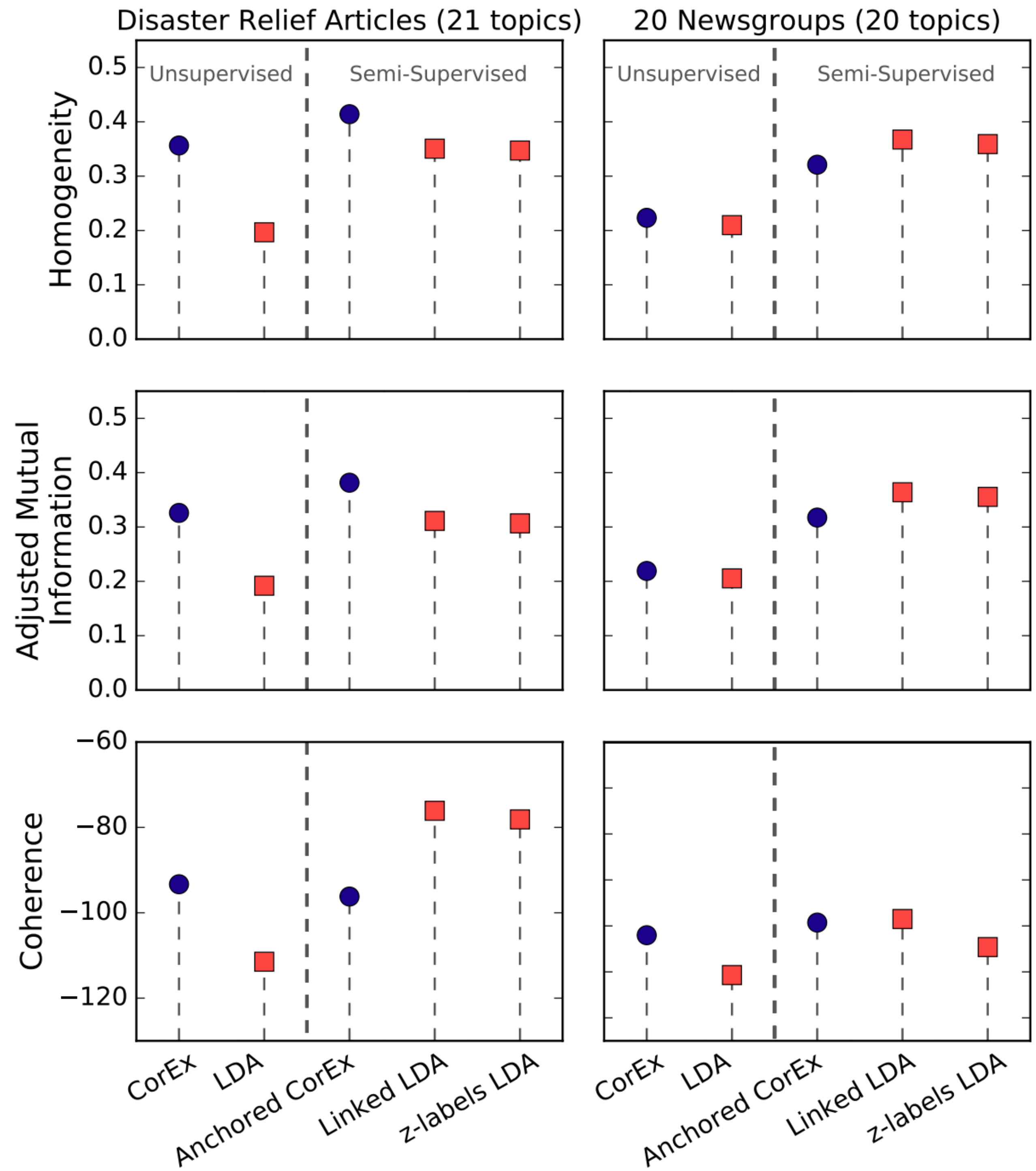
12: crowd, rally, night, event, speech, stage, audience, spoke, wife, took

14: rubio, marco, jeb, bush, carson, florida, ben, candidates, iowa, gov

25: clinton, hillary, bernie, sanders, democratic, clinton's, her, she, vermont, secretary

Work by Abigail Ross and the Computational Story Lab, University of Vermont

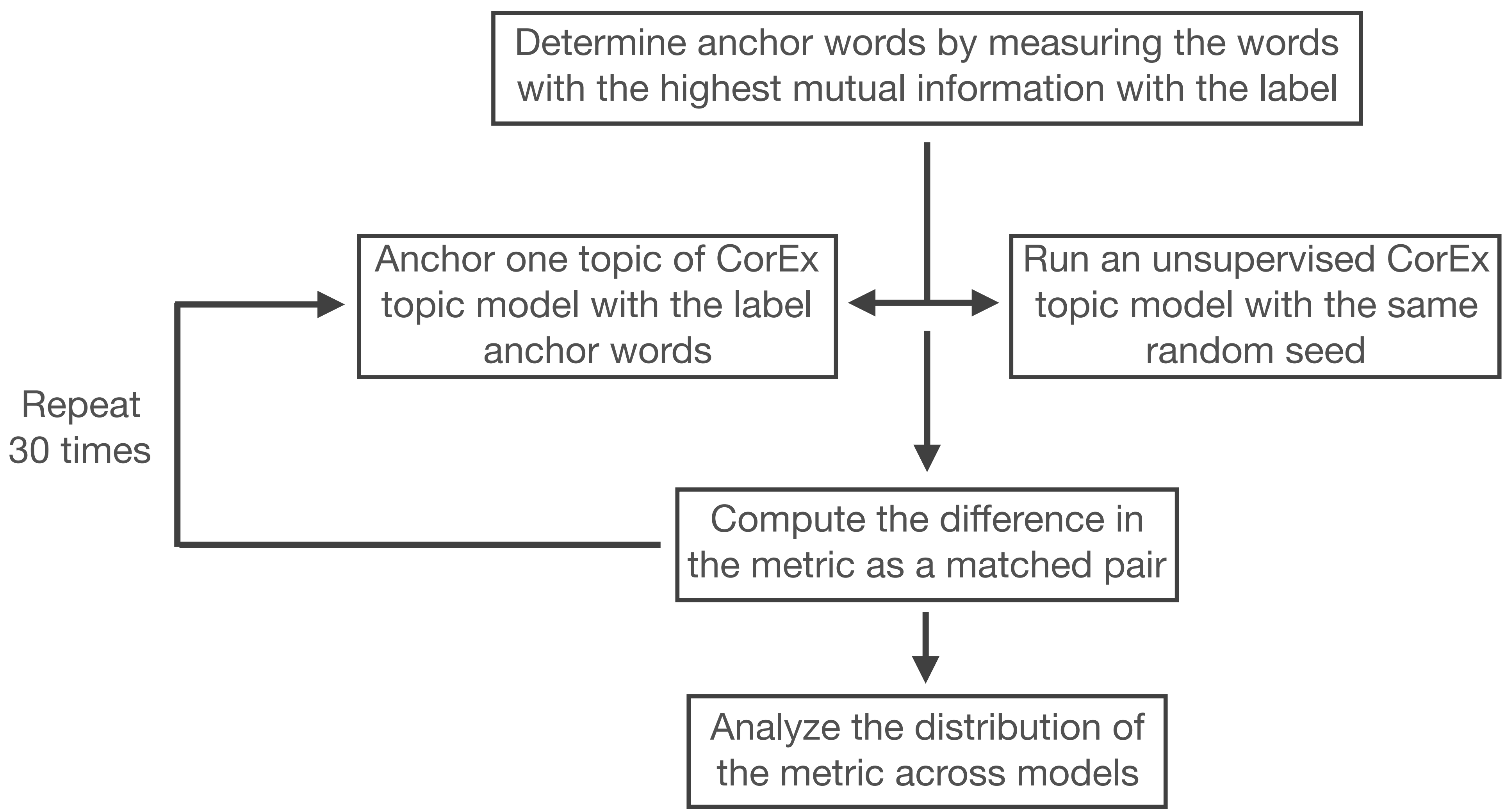
Comparisons to Semi-Supervised LDA



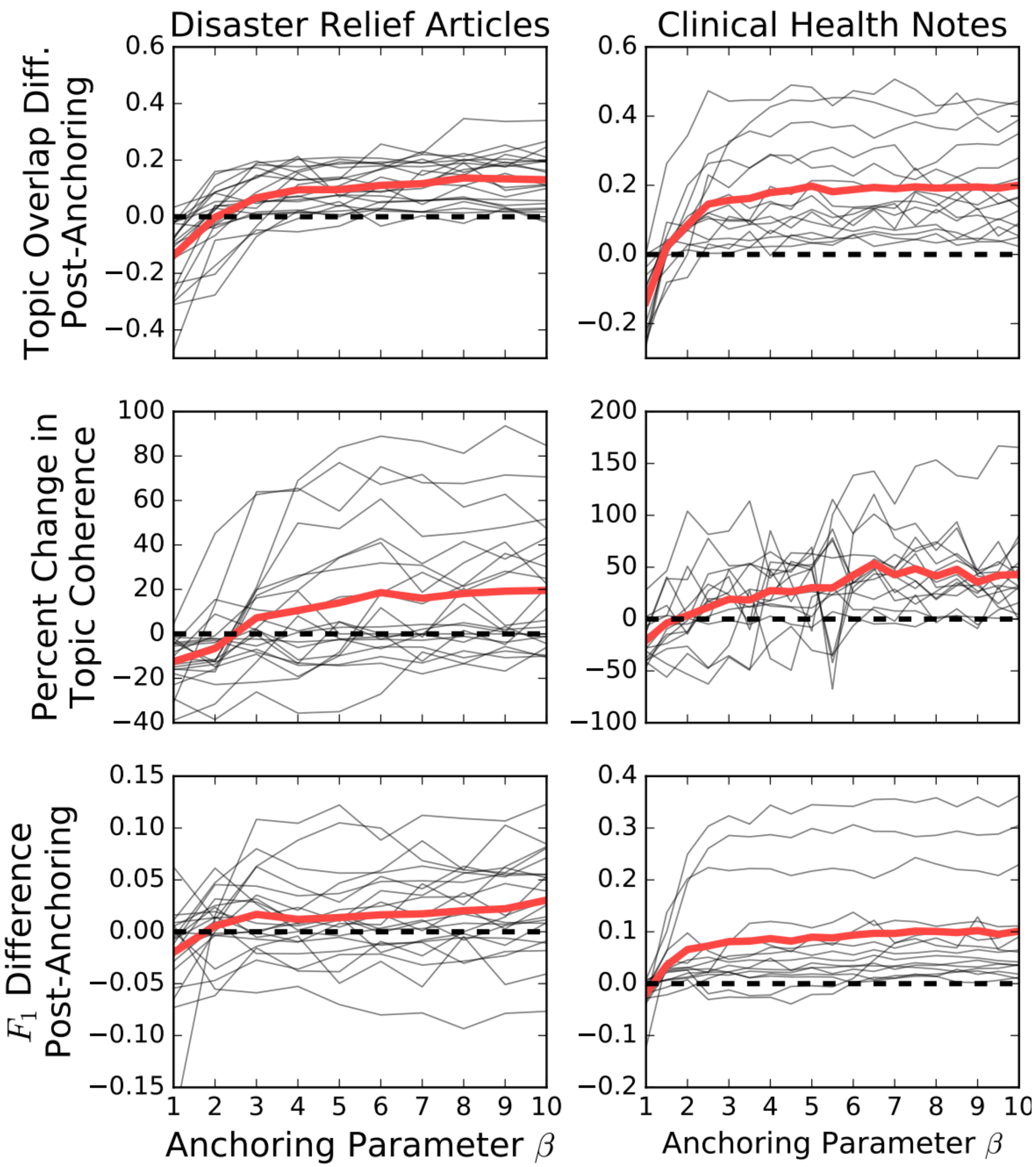
Anchoring Experiment

Data: HA/DR news articles and clinical health notes

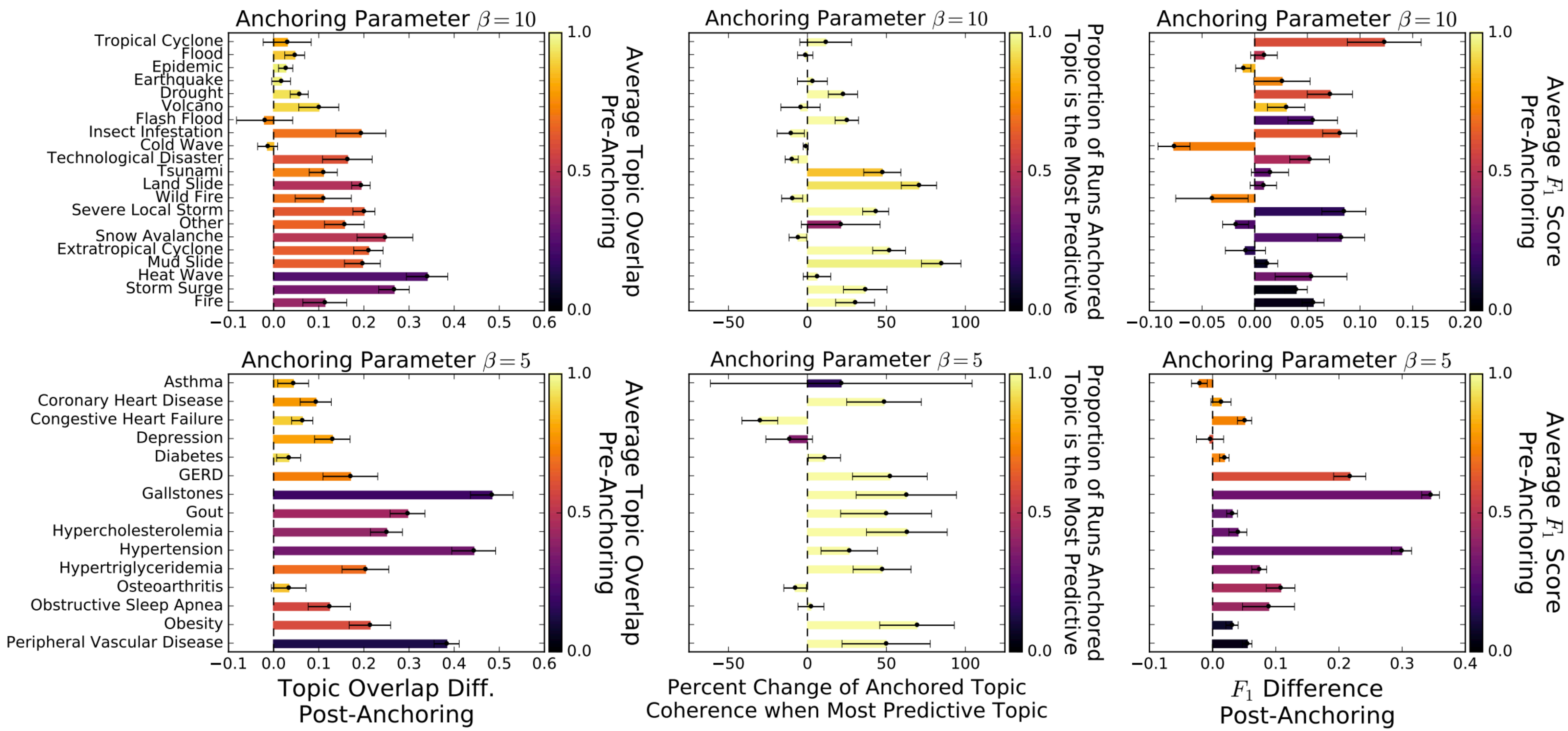
For each document label:



Anchoring Experiment: Effect of Parameter

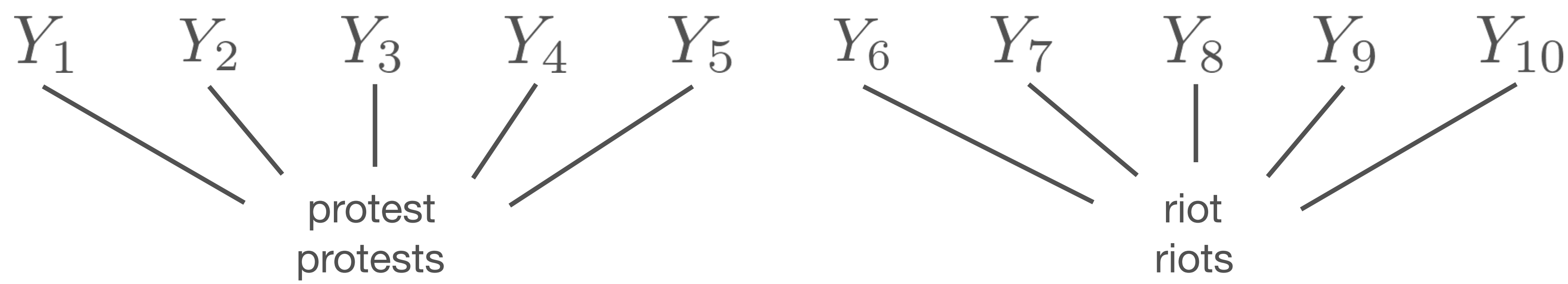


Anchoring Experiment: Heterogeneity of Effects



Anchoring for Topic Aspects

Data: ~870,000 unique tweets containing #Ferguson from Aug. 9th-Nov. 30th, 2014



"protest" Topics

1: **protest**, **protests**, peaceful, violent, continue, night, island, photos, staten, nights

2: **protest**, **protests**, #hiphopmoves, #cole, hiphop, nationwide, moves, fo, anheuser, boeing

3: **protest**, **protests**, st, louis, guard, national, county, patrol, highway, city

4: **protest**, **protests**, paddy, covering, beverly, walmart, wagon, hills, passionately, including

5: **protest**, **protests**, solidarity, march, square, rally, #oakland, downtown, nyc, #nyc

"riot" Topics

6: **riot**, **riots**, unheard, language, inciting, accidentally, jokingly, watts, waving, dies

7: **riot**, black, **riots**, white, #tcot, blacks, men, whites, race, #pjnet

8: **riot**, **riots**, looks, like, sounds, acting, act, animals, looked, treated

9: **riot**, **riots**, store, looting, businesses, burning, fire, looted, stores, business

10: gas, **riot**, tear, **riots**, gear, rubber, bullets, military, molotov, armored