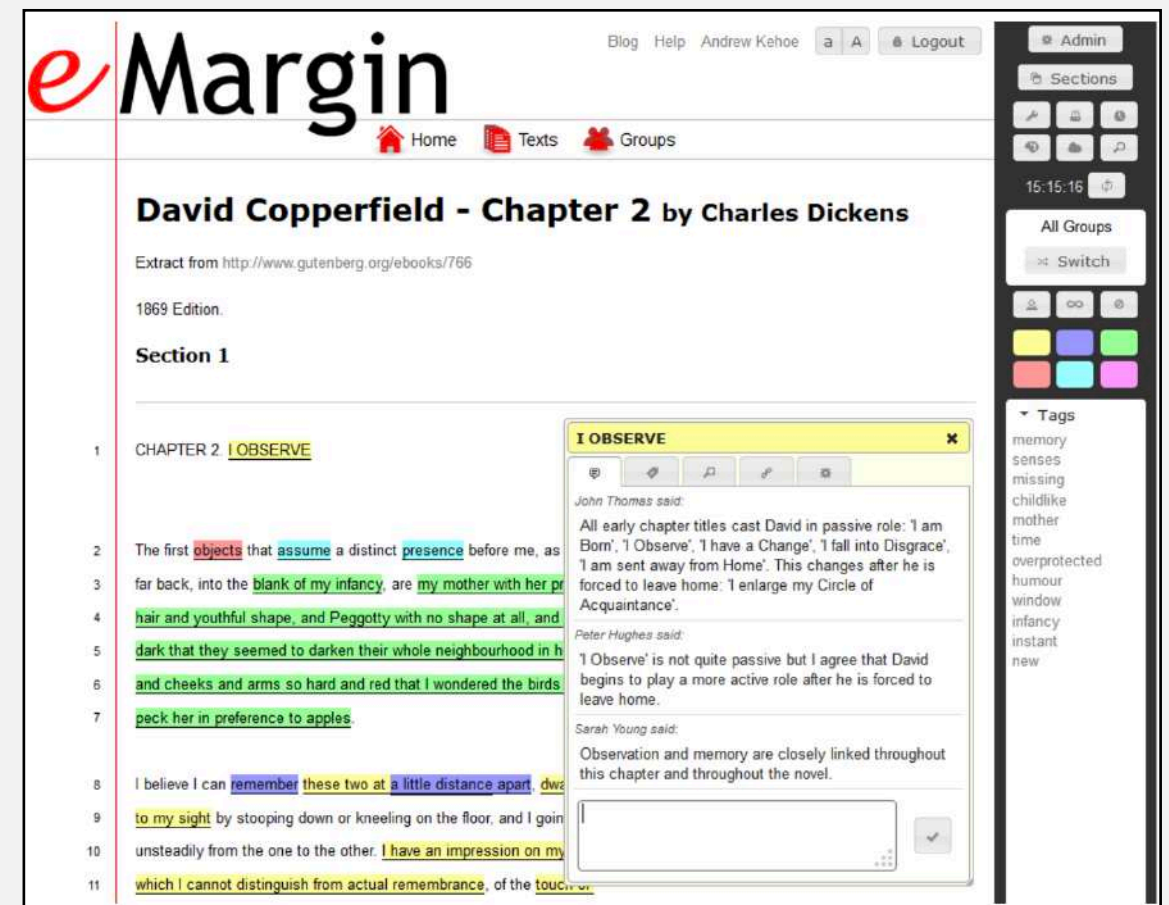


Visually Exploring Documents: Topic Modeling

Working with text

- “Text visualization” can mean many things
 - fonts, sizes, colors, kerning, typography in general
- We should consider text visualization from the more general definition of visualization: *amplify cognition*
 - Help people improve comprehension of a piece of text
 - Understand themes in text corpora
 - Locate/search relevant textual documents

- The way we approach text visualization is highly dependent on tasks.
- Close reading: deeply comprehending text, going beyond the words on the page [Jänicke et al. 2015]



Close Reading Designs

Color

[Alexander et al. 2014]

This elegant shell occurs very rarely on the coasts of this country; we have observed it sparingly distributed on the sands near Tenby, in Pembrokeshire. Da Costa says, he was informed that it is found near Bangor, among the rocks from Bangor Ferry to Anglesea, in Wales, by which he could only mean that the species is an inhabitant of the Menai, the arm of Beaumaris bay, communicating with the St. George's channel which divides Caernarvonshire from the island of Anglesea. The same writer notes it likewise from Cornwall. Dr. Pultney describes it as a scarce shell, which he had found at Weymouth. Having Da Costa's specimens of this shell, and also that of his Pectunculus Vetula before us, we should not refrain from observing, that the opinion of Dr. Pultney respecting these shells is incorrect; they are not merely transitions in growth, or varieties of the same kind, the difference between the two is obvious, and fully authorize us to consider them as distinct species. It should be understood in advancing this remark, that the shell which Da Costa figures and describes, for Pectunculus Vetula is clearly the Linnaean Venus Paphia, a shell well known as a native of the West Indies, and never found to our knowledge in any of the European seas. Da Costa was aware, after his work had been published, that he had erroneously confounded the variety of Fasciatus, Fig. 1, 1, in our Plate, with the West Indian shell; he had conceived the latter to be the same shell in a more perfect condition, and caused it to be engraved accordingly.

This elegant shell occurs very rarely on the coasts of this country; we have observed it sparingly distributed on the sands near Tenby, in Pembrokeshire. Da Costa says, he was informed that it is found near Bangor, among the rocks from Bangor Ferry to Anglesea, in Wales, by which he could only mean that the species is an inhabitant of the Menai, the arm of Beaumaris bay, communicating with the St. George's channel which divides Caernarvonshire from the island of Anglesea. The same writer notes it likewise from Cornwall. Dr. Pultney describes it as a scarce shell, which he had found at Weymouth. Having Da Costa's specimens of this shell, and also that of his Pectunculus Vetula before us, we should not refrain from observing, that the opinion of Dr. Pultney respecting these shells is incorrect; they are not merely transitions in growth, or varieties of the same kind, the difference between the two is obvious, and fully authorize us to consider them as distinct species. It should be understood in advancing this remark, that the shell which Da Costa figures and describes, for Pectunculus Vetula is clearly the Linnaean Venus Paphia, a shell well known as a native of the West Indies, and never found to our knowledge in any of the European seas. Da Costa was aware, after his work had been published, that he had erroneously confounded the variety of Fasciatus, Fig. 1, 1, in our Plate, with the West Indian shell; he had conceived the latter to be the same shell in a more perfect condition, and caused it to be engraved accordingly.

Size [Walsh et al. 2014]

Once upon a midnight dreary, while I pondered weak
and weary,
Over many a quaint and curious volume of forgotten lore,
While I nodded, nearly napping, suddenly there came a
tapping,
As of some one gently rapping, rapping
at my chamber door.
"Tis some visitor," I muttered, "tapping at my
chamber door -
Only this, and nothing more."

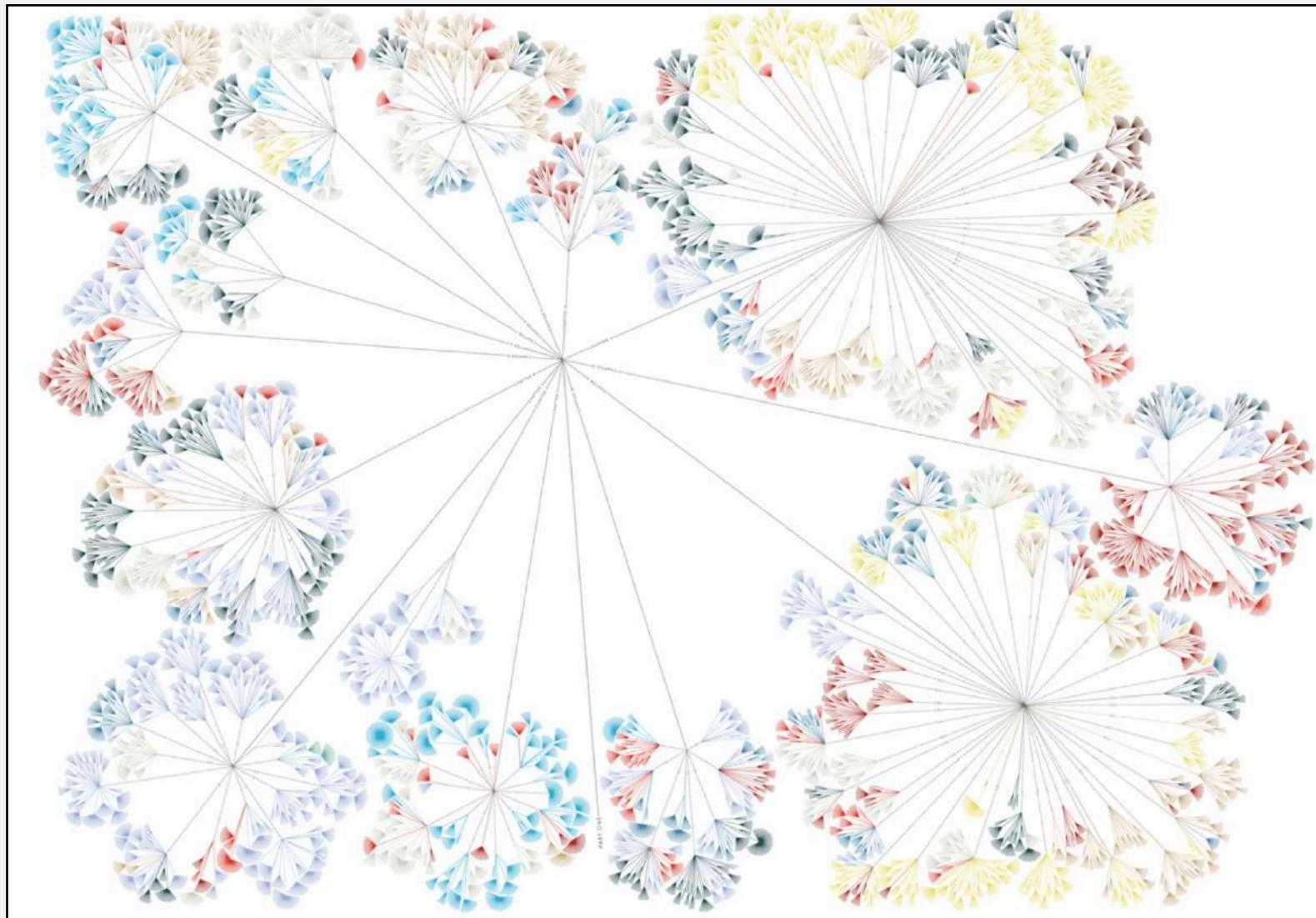
Node-link Diagrams

[Coles et al. 2014]



Distant Reading

- Understand structure, relationships, themes, connections within a document.



[Posavec 2007]

Document Exploration

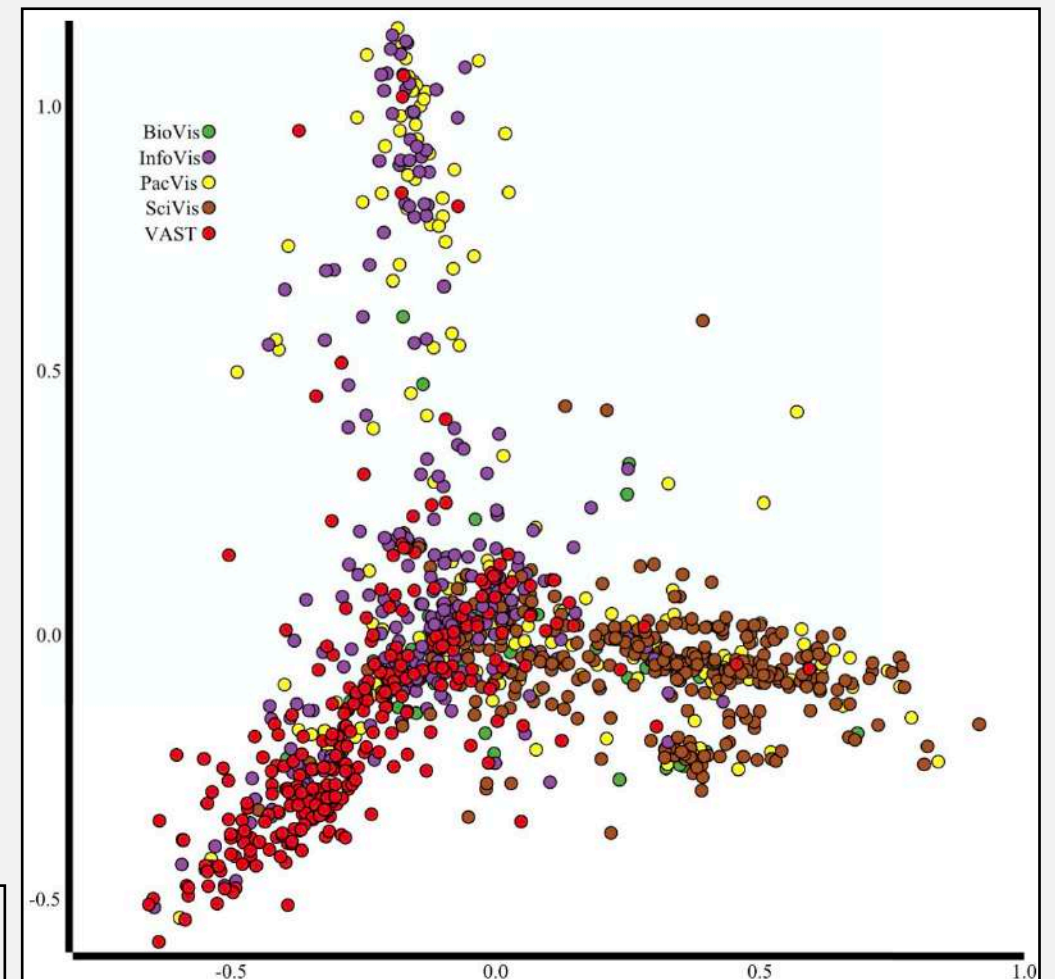
- A “document”: sequence of words.
 - A book, a wikipedia article, a paper abstract, a tweet
- Can view as generic high-dimensional data, apply techniques we’ve discussed so far for visual exploration
- But documents are unique:
 - Really high-dimensional (e.g. dimensionality = size of English vocabulary)
 - Usually sparse
 - Yet, each dimension - word - is interpretable

Document Exploration Tasks

- Suppose you were provided hundreds of articles relevant to your respective research backgrounds.
- What tasks are relevant to you for gaining an understanding - and advancing your research - on the document corpus?

Exploring Documents: Dimensionality Reduction

- We represent each document as a point in a high-dimensional space.
 - Each dimension is a word
 - The value of a dimension is the word count: the number of times the word appeared in the document
- [Anderson et al. 2014]**



Limitations with this approach?

Matrix Factorization

- Dimensionality reduction is ... too reductive. We seek better **representations** of documents.
- Let's consider **matrix factorization**.

$$W \in \mathbb{R}^{n \times d} \longrightarrow \|W - \tilde{U}\tilde{V}^T\| \quad \tilde{U} \in \mathbb{R}^{n \times k} \quad \tilde{V} \in \mathbb{R}^{d \times k}$$

$\mathbf{w}_i \approx \tilde{\mathbf{u}}_i \tilde{V}^T$ a reconstruction of word counts for document i

$\tilde{\mathbf{u}}_i$ assigns importance to each column of \tilde{V}

\tilde{V} each column vector: a set of weights, one for each word \longrightarrow **shared across documents**

k determines approximation quality

$k \ll \min(n, d)$ we share limited information across documents for reconstruction

Ideally: columns represent meaningful, latent factors shared across documents

Optimistic, but unrealistic, example

- We set k to 2

$$\tilde{V} = [\tilde{\mathbf{v}}_1 \ \tilde{\mathbf{v}}_2] \quad \tilde{\mathbf{v}}_1 \in \mathbb{R}^d \quad \tilde{\mathbf{v}}_2 \in \mathbb{R}^d$$

- Then we can represent each document with 2 numbers

$$\tilde{\mathbf{w}}_i = [w_{i1}, w_{i2}]$$

$$\tilde{\mathbf{w}}_i = [1, 0] \quad \text{take on words from } \tilde{\mathbf{v}}_1$$

$$\tilde{\mathbf{w}}_i = [0, 1] \quad \text{take on words from } \tilde{\mathbf{v}}_2$$

- Does this look familiar? What are we doing with documents in this manner?

- Clustering! (kind of) $\tilde{\mathbf{v}}_1 \in \mathbb{R}^d$ **set of words that describe one cluster**
 $\tilde{\mathbf{v}}_2 \in \mathbb{R}^d$ **set of words that describe other cluster**

Matrix Factorization: SVD

- Clustering interpretation only meaningful if the reconstruction is good!

$$\|W - \tilde{U}\tilde{V}^T\|_F$$

- We can find the global minimum of this energy via the singular value decomposition (SVD)

$$W = U\Lambda V^T, U \in \mathbb{R}^{n \times n}, \Lambda \in \mathbb{R}^{n \times d}, V \in \mathbb{R}^{d \times d} \quad U^T U = I, V^T V = I$$

- Truncate the SVD to the top k singular values

$$\tilde{U} = U_{1:k} \sqrt{\Lambda_{1:k}} \quad \tilde{V} = V_{1:k} \sqrt{\Lambda_{1:k}}$$

- Can write approximation as the following expansion:

$$W \approx \sum_{i=1}^k \lambda_i \mathbf{u}_i \mathbf{v}_i^T \quad \text{best rank-k approximation}$$

Nonnegative Matrix Factorization

- Limitation: the document and latent factors can be negative - not easily interpretable! Bad for visualization.

- So, then, let's enforce nonnegativity!

$$\|W - UV^T\|_F^2, \quad s.t. \ U, V \geq 0$$

- We can then say “latent factors V contribute u amount to the reconstruction”
- Challenge: fixing U , energy is convex in V . Fixing V , energy is convex in U . But not convex in both! (due to nonnegativity constraint - cannot apply Eckart-Young theorem)

Algorithm: Multiplicative Updates

$$\|W - UV^T\|_F^2, \quad s.t. \ U, V \geq 0$$

- Alternate between the following updates:

$$V_{ab} \leftarrow V_{ab} \frac{(U^T W)_{ab}}{(U^T U V^T)_{ab}} \qquad U_{ab} \leftarrow U_{ab} \frac{(W V)_{ab}}{(U V^T V)_{ab}}$$

- Update can be seen as a particular (per-element) step size chosen for gradient descent:

$$\begin{aligned} E(V) = \|W - UV^T\|_F^2 &= \text{tr}((W - UV^T)^T(W - UV^T)) \\ &= \text{tr}(W^T W - 2VU^T W + VU^T U V^T) \end{aligned}$$

- Take derivative of trace:

$$\frac{dE}{dV^T} = 2(U^T U V^T - U^T W)$$

Algorithm: Multiplicative Updates continued...

$$V_{ab} \leftarrow V_{ab} - \eta_{ab}(U^T U V^T - U^T W)_{ab} \quad , \quad \eta_{ab} = \frac{V_{ab}}{(U^T U V^T)_{ab}}$$

$$V_{ab} \leftarrow V_{ab} - \frac{V_{ab}}{(U^T U V^T)_{ab}}(U^T U V^T - U^T W)_{ab} = \cancel{V_{ab}} - \cancel{V_{ab}} + \underline{V_{ab} \frac{(U^T W)_{ab}}{(U^T U V^T)_{ab}}}$$

- Starting from an initial guess for U and V that are both nonnegative, this scheme ensures:
 - Both will remain nonnegative
 - Energy decreases at each iteration
 - Will arrive at *some* fixed-point solution (local minimum)

[Lee & Seung 2001]

Still, some limitations

- Weights are unbounded:
 - Some latent factors could dominate others.
 - Thus, document weights become hard to interpret.
- At this point, might start introducing regularization terms.
- However, consider the following probabilistic interpretation:

$$w_{ij} \approx \mathbf{u}_i^T \mathbf{v}_j = \sum_{l=1}^k u_{il} v_{jl} \longrightarrow \sum_l \underbrace{p(z_l | \theta)}_{\text{probability of latent factor, given a document}} \underbrace{p(w | z_l, \beta)}_{\text{probability of word, given latent factor}}$$

probability of latent factor, given a document

probability of word, given latent factor

Latent Dirichlet Allocation

- Next, let's consider *all* words in a document:

$$p(\theta, \mathbf{w} \mid \alpha, \beta) = \underbrace{p(\theta \mid \alpha)}_n \prod_n \sum_{z_n} p(z_n \mid \theta) p(w_n \mid z_n, \beta)$$

Probability of latent factors - or **topics**

- We marginalize out θ

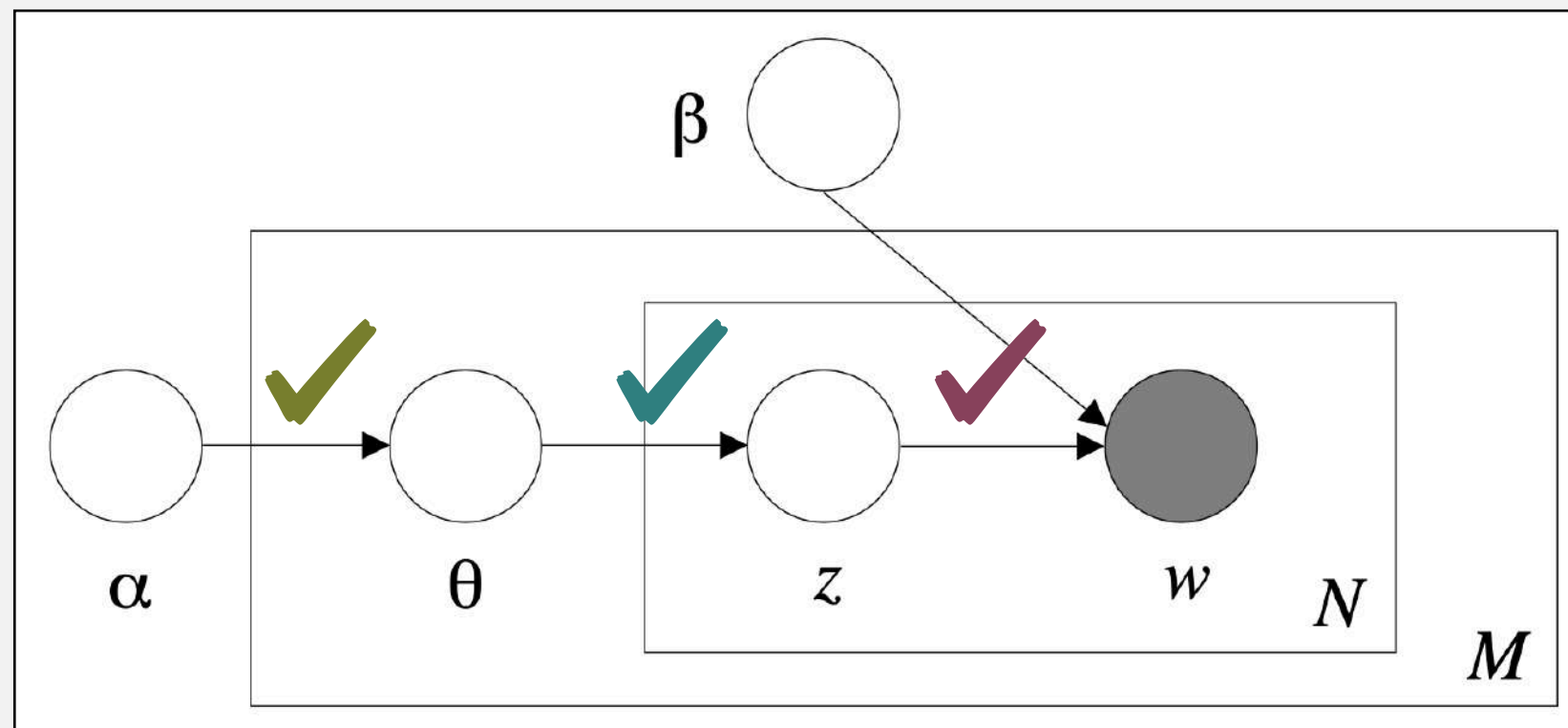
$$p(\mathbf{w} \mid \alpha, \beta) = \int p(\theta \mid \alpha) \left(\prod_n \sum_{z_n} p(z_n \mid \theta) p(w_n \mid z_n, \beta) \right) d\theta$$

- Last, consider *all* documents:

$$p(\mathbf{w} \mid \alpha, \beta) = \prod_{d=1}^M \int p(\theta_d \mid \alpha) \left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn} \mid \theta_d) p(w_{dn} \mid z_{dn}, \beta) \right) d\theta_d$$

Probabilistic Model

$$p(\mathbf{w} \mid \alpha, \beta) = \prod_{d=1}^M \int \underbrace{p(\theta_d \mid \alpha)} \left(\prod_{n=1}^{N_d} \sum_{z_{dn}} \underbrace{p(z_{dn} \mid \theta_d)} \underbrace{p(w_{dn} \mid z_{dn}, \beta)} \right) d\theta_d$$

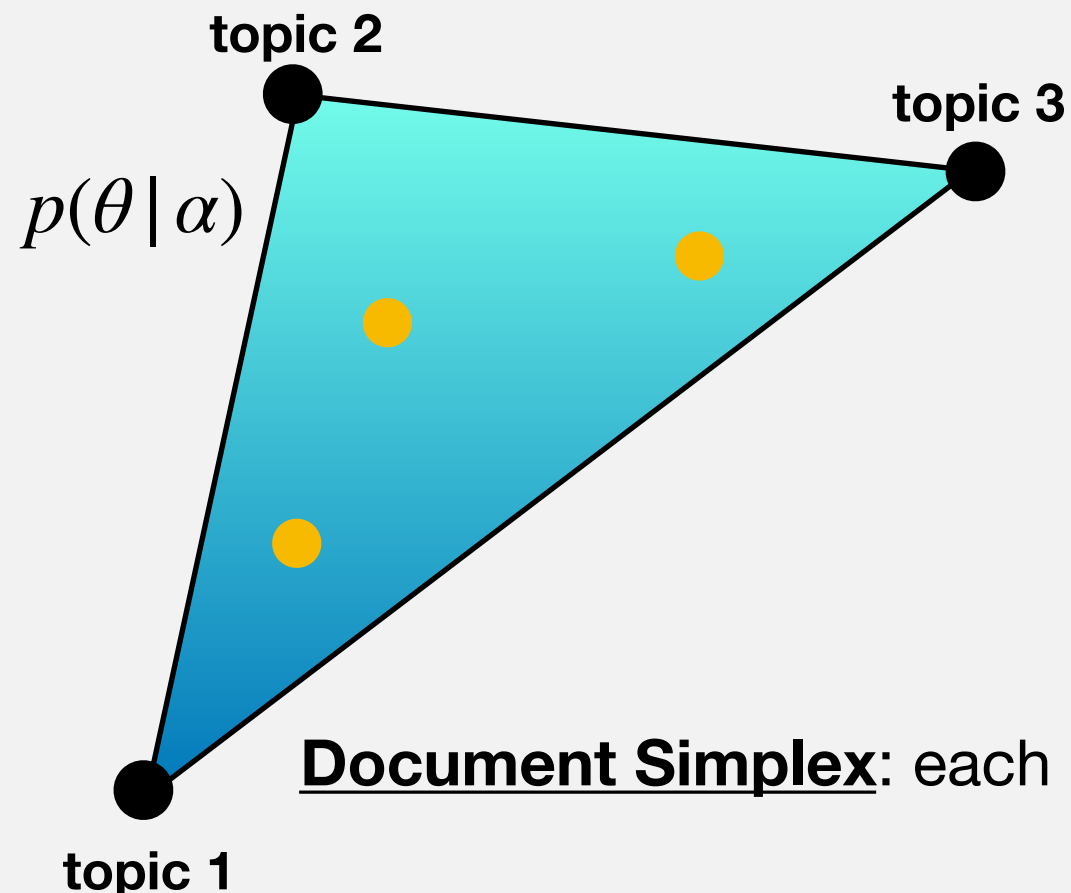
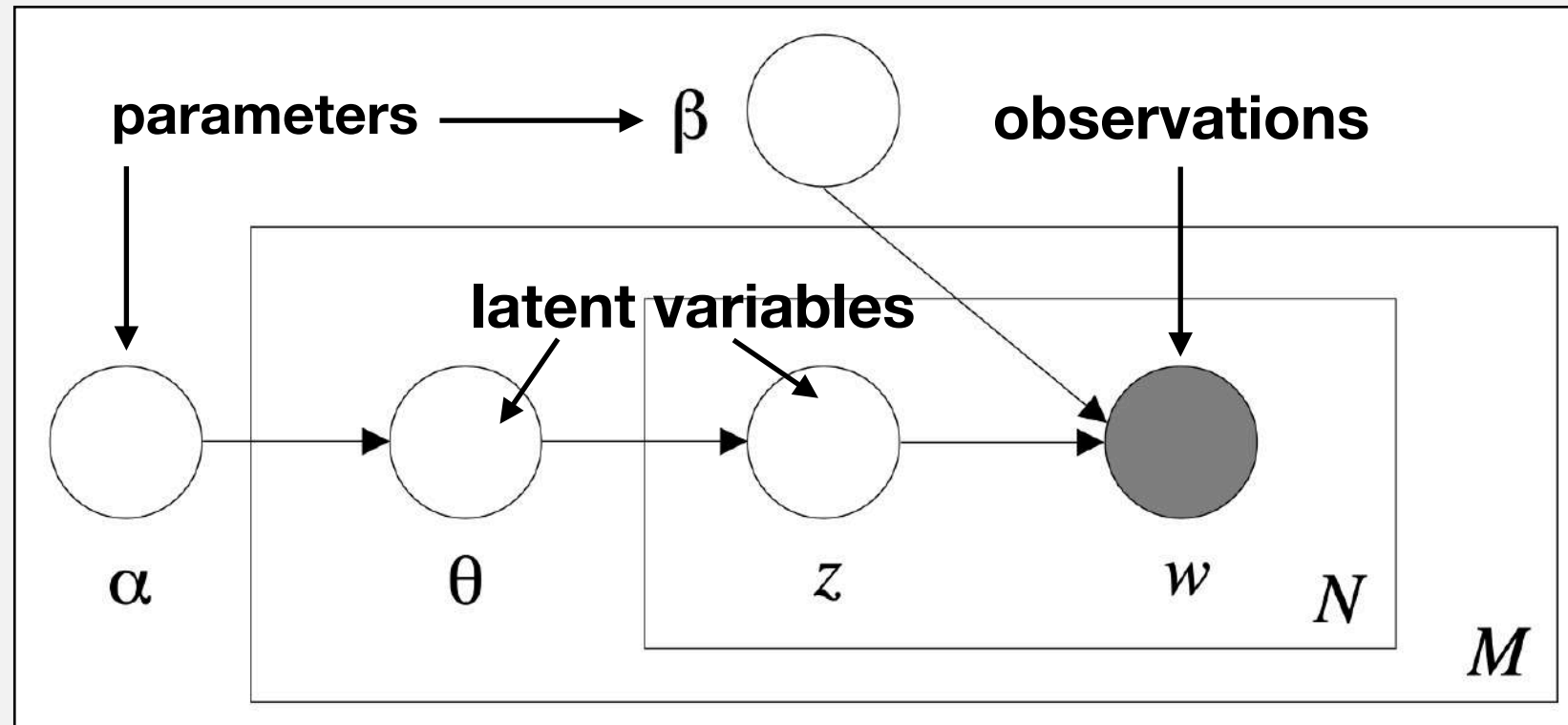


For a given document, draw a mixture of topics

To generate a word, first draw a random topic, given the mixture

Last, sample a word from the topic

Probabilistic Model

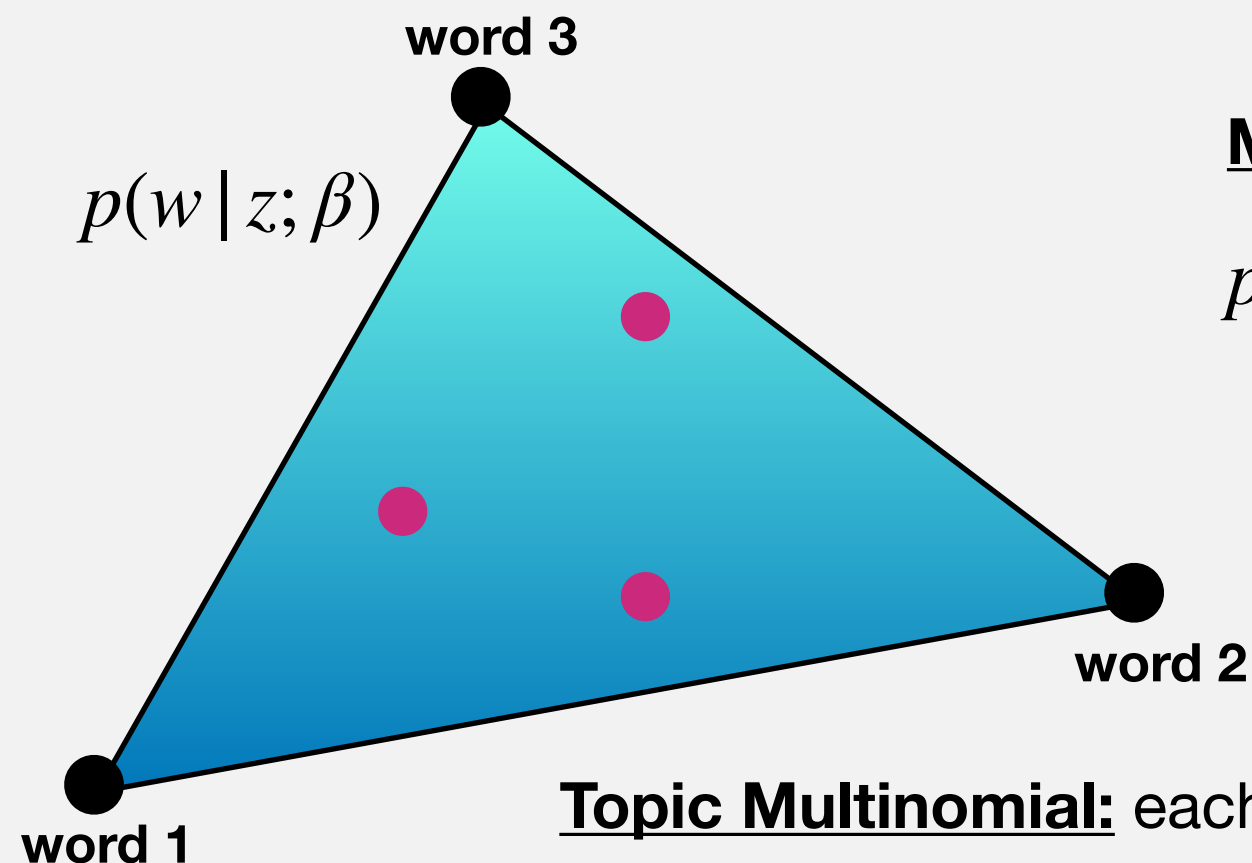
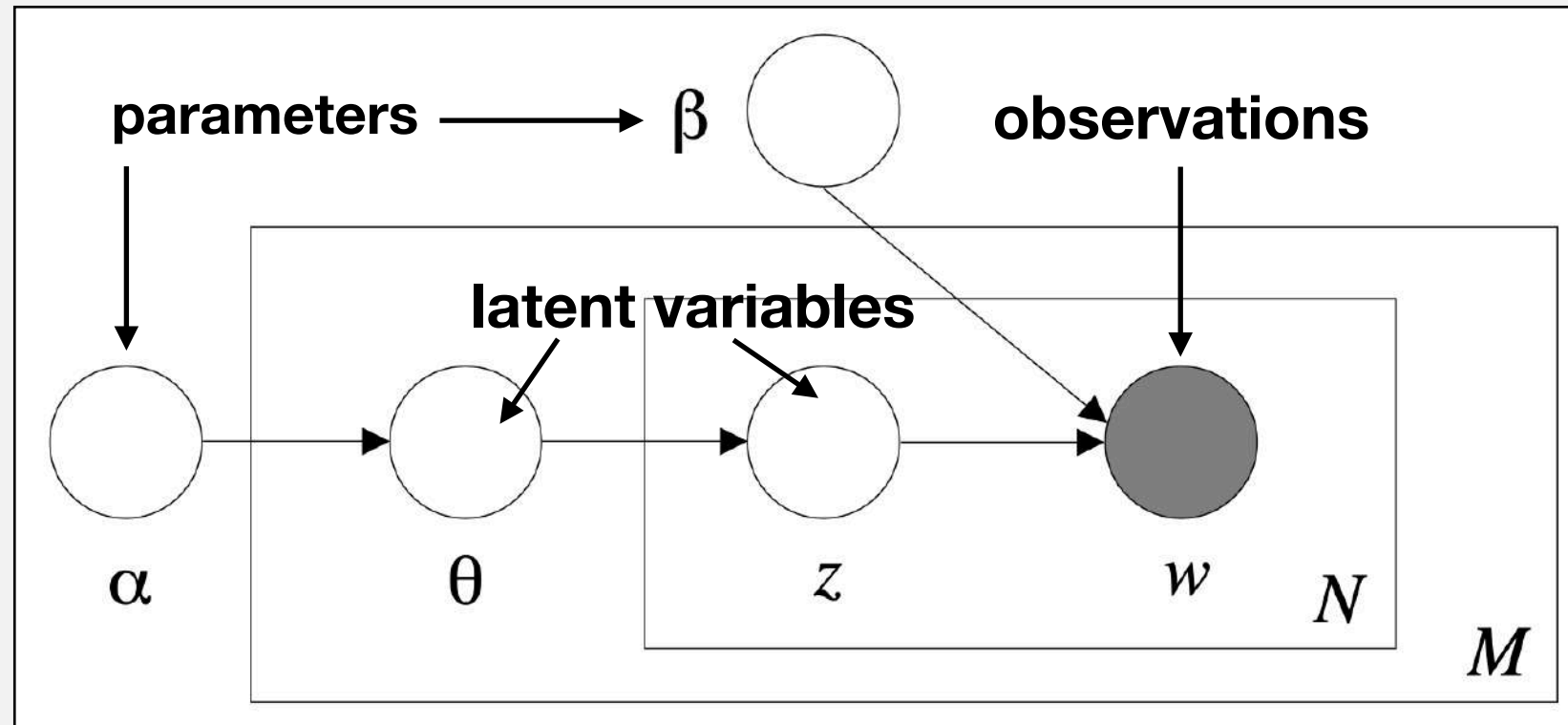


Dirichlet distribution

$$p(\theta | \alpha) = Z(\alpha) \prod_i \theta_i^{\alpha_i - 1}$$

Document Simplex: each point is a mixture over topics

Probabilistic Model



Multinomial distribution

$$p(w | z; \beta) = Z(\beta_{z_i}) \prod_i w_i^{\beta_{z_i}}$$

Topic Multinomial: each point is a distribution over words

Generative Model

TOPIC 1

computer,
technology,
system,
service, site,
phone,
internet,
machine

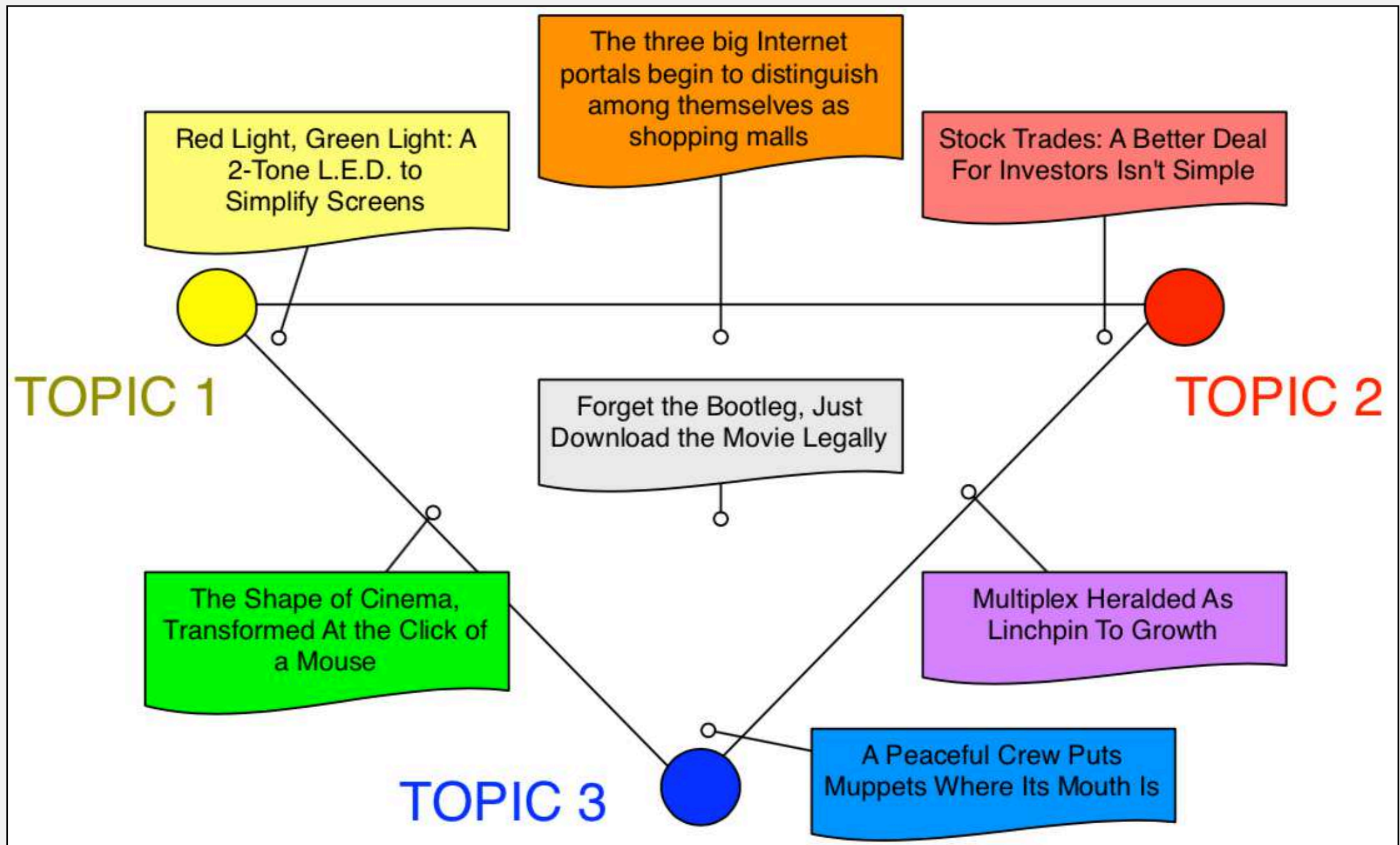
TOPIC 2

sell, sale,
store, product,
business,
advertising,
market,
consumer

TOPIC 3

play, film,
movie, theater,
production,
star, director,
stage

Generative Model



Generative Model

computer,
technology,
system,
service, site,
phone,
internet,
machine

sell, sale,
store, product,
business,
advertising,
market,
consumer

play, film,
movie, theater,
production,
star, director,
stage

Hollywood studios are preparing to let people download and buy electronic copies of movies over the Internet, much as record labels now sell songs for 99 cents through Apple Computer's iTunes music store and other online services ...


(slide from David Mimno)

Generative Model

computer,
technology,
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service, site,
phone,
internet,
machine

sell, sale,
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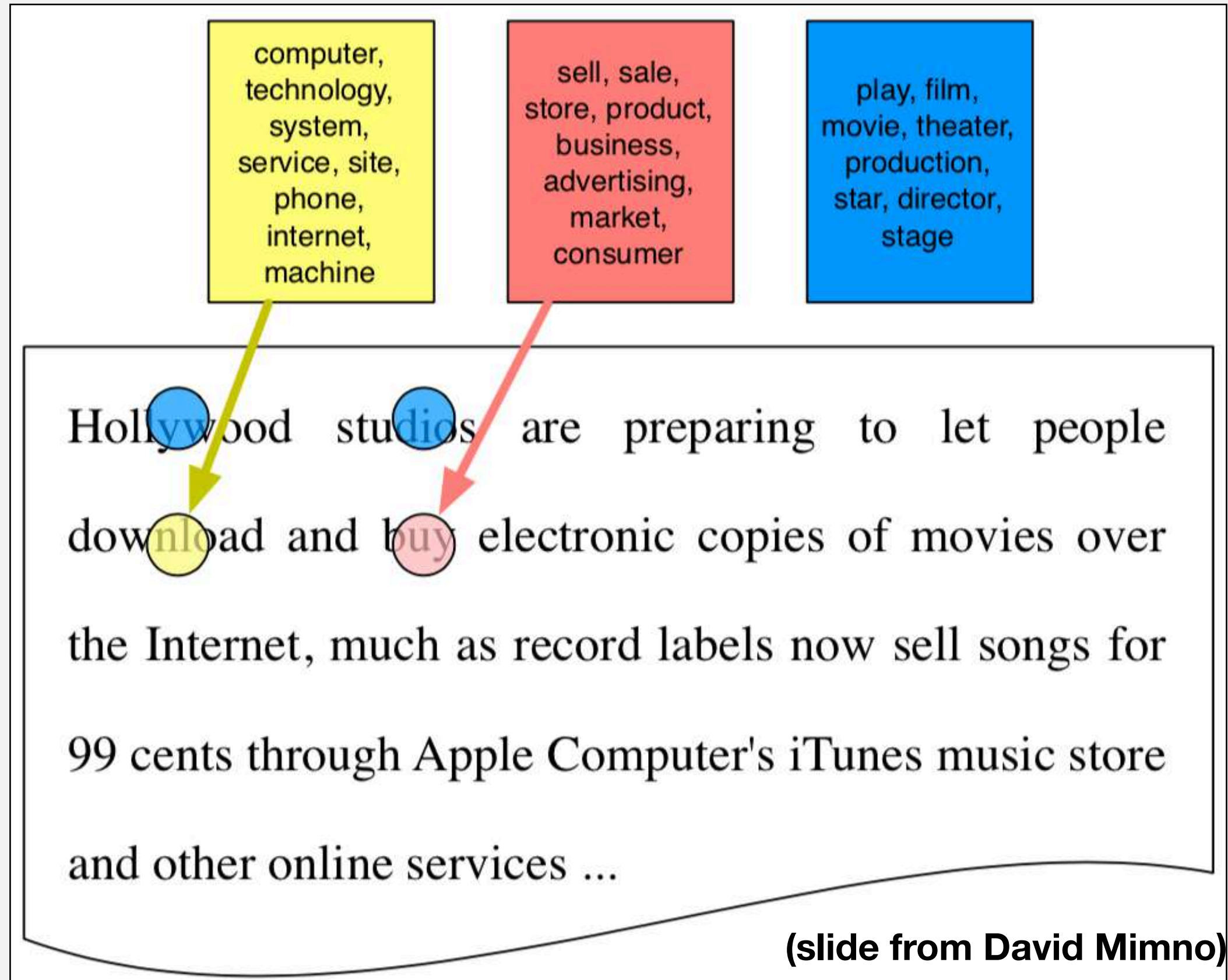
play, film,
movie, theater,
production,
star, director,
stage



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(slide from David Mimno)

Generative Model



Generative Model

computer,
technology,
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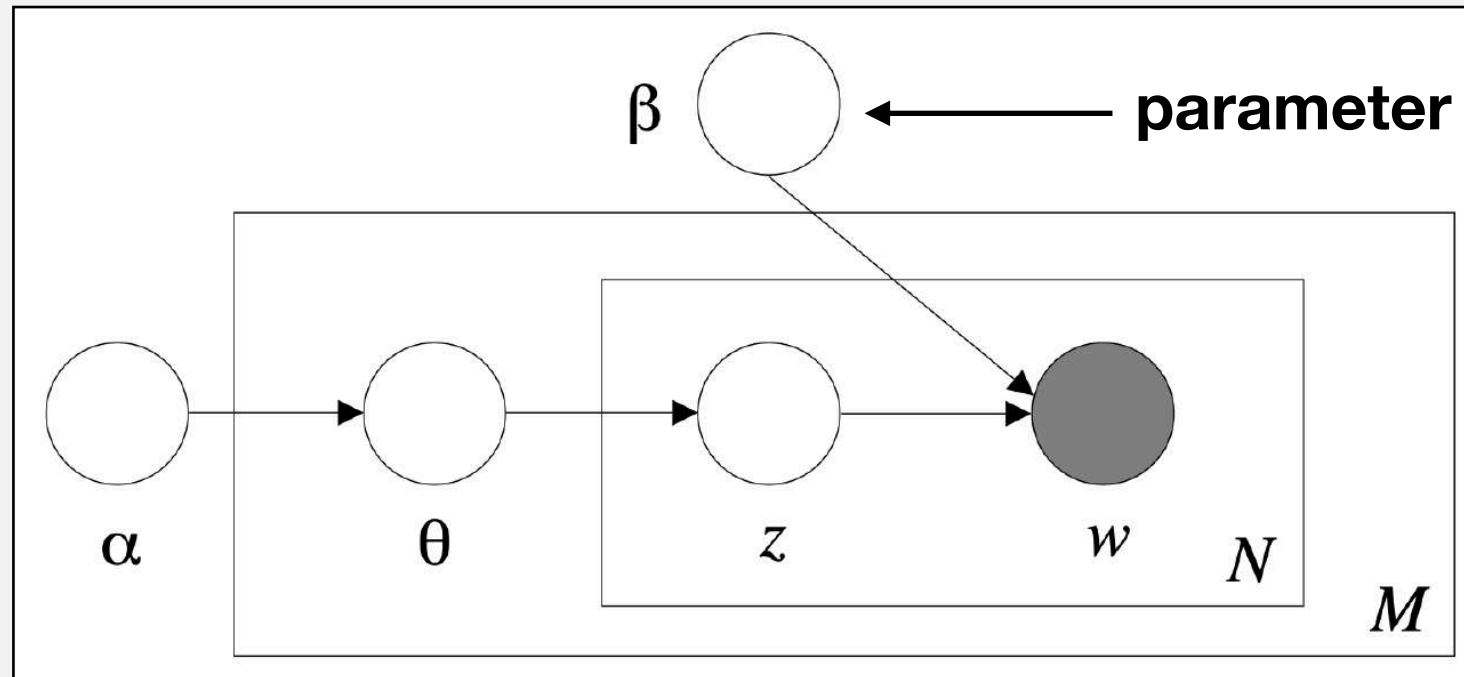
sell, sale,
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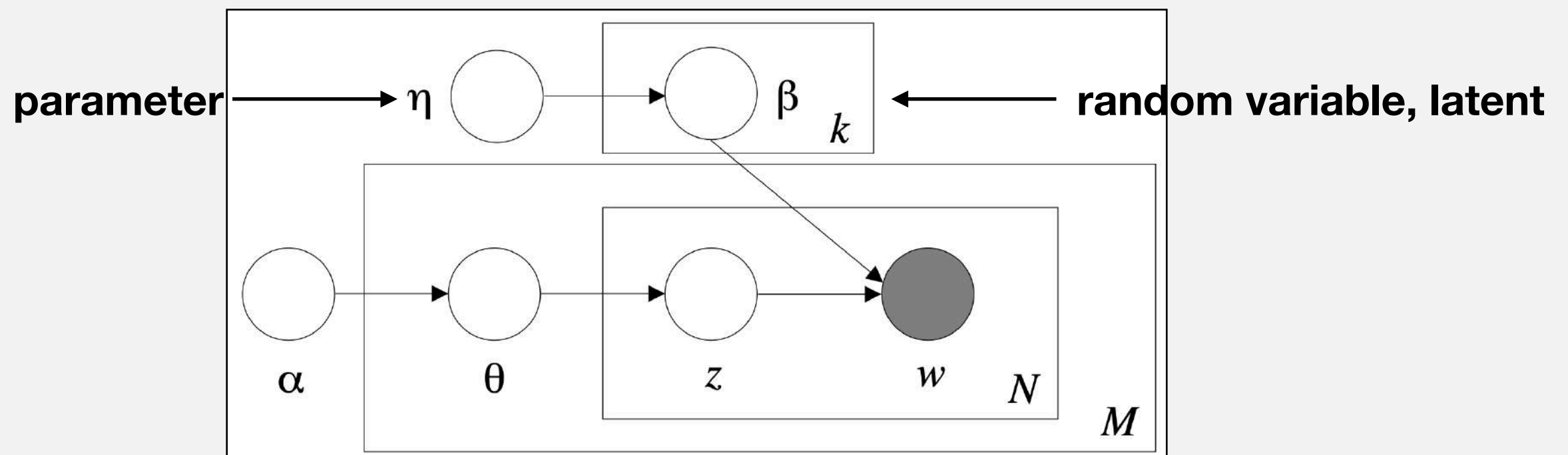
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and other online services ...

(slide from David Mimno)

Problem with Sparsity



- Documents might be similar, but have no words in common!



Inference in LDA

- Need to compute the posterior distribution of hidden variables - intervals, point estimates, etc..
- However, this is intractable: need to evaluate a really complicated integral
- **Variational Inference:** we approximate the distribution we would like, with one that permits tractable optimization

$$q(\beta, \mathbf{z}, \theta | \lambda, \phi, \gamma) = \prod_{i=1}^k \text{Dir}(\beta_i | \lambda_i) \prod_{d=1}^M \text{Dir}(\theta_d | \gamma_d) \prod_{n=1}^N \text{Mult}(z_n | \phi_n)$$

Probability distribution for a topic (over words)

Probability distribution for a document (over topics)


Relating q and p

- We maximize the Evidence Lower BOund (ELBO):

$$\underline{\log p(\mathbf{w} \mid \alpha, \eta)} \geq \mathcal{L}(\mathbf{w}, \lambda, \phi, \gamma) = \mathbb{E}_q[\log p(\mathbf{w}, \underline{\beta}, \underline{\mathbf{z}}, \theta \mid \alpha, \eta)] - \mathbb{E}_q[\log q(\underline{\beta}, \underline{\mathbf{z}}, \theta \mid \lambda, \phi, \gamma)]$$

- Log-likelihood of document
- Latent variables are shared between distributions
- Differences: Dirichlet and Multinomial parameters
- A consequence of Jensen's inequality: a concave (e.g. \log) function of an expectation is lower-bound by the expectation of the concave function

Main Optimization

$$\mathcal{L} = \sum_d \mathbb{E}_q[\log p(\mathbf{w}_d | \beta_d, \mathbf{z}_d, \theta)] + \mathbb{E}_q[\log p(\mathbf{z}_d | \theta_d)] + \mathbb{E}_q[\log p(\theta_d | \alpha)] + \mathbb{E}_q[\log p(\beta | \eta)] \\ - \mathbb{E}_q[\log q(\mathbf{z}_d | \phi_d)] - \mathbb{E}_q[\log q(\theta_d | \gamma_d)] - \mathbb{E}_q[\log q(\beta | \lambda)]$$


- Can solve for variational parameters via coordinate ascent:

$$\phi_{dwk} \propto \exp\{\mathbb{E}_q[\log \theta_{dk}] + \mathbb{E}_q[\log \beta_{kw}]\} \text{ **topic-relevance** } \\ \text{if } k \text{ is related to } d \text{ and } w, \text{ then the topic, document, and word are all related}$$
$$\gamma_{dk} = \alpha + \sum_w n_{dw} \phi_{dwk}$$

a topic is relevant to a document, if document-conditioned words are topic-relevant

$$\lambda_{kw} = \eta + \sum_d n_{dw} \phi_{dwk}$$

a topic is relevant to a word, if documents that contain the word are topic-relevant

What does inference give us?

- We have now estimated our variational parameters.
 - One describes a probability distribution for each topic
 - The other describes a probability distribution for each document

$$\begin{array}{c} \textbf{Topics} \\ \textbf{Dir}(\beta_i | \lambda_i) \end{array}$$

$$\begin{array}{c} \textbf{Documents} \\ \textbf{Dir}(\theta_d | \gamma_d) \end{array}$$

- We can draw random samples from each distribution ... or, if we just want a single realization, we take expectations:

$$\mathbb{E}[\textbf{Dir}(\beta_i | \lambda_i)] = \frac{\lambda_i}{\sum_{j=1}^n \lambda_{ij}}$$

$$\mathbb{E}[\textbf{Dir}(\theta_d | \gamma_d)] = \frac{\gamma_d}{\sum_{j=1}^k \gamma_{dj}}$$

Tasks in Visualizing Topic Models

- Comparing documents
- Comparing topics
- Understanding a topic
- Understanding a document, *in terms of* topics
- Other data:
 - Time? Document Categories?

Tasks determine how we prioritize visual encodings and interactions!

Visualizing a topic?

- Easy? choose its highest-probability words.
- **Visualizing multiple topics:** some decisions need to be made...

Topic 02 graphics virtual simulation **interaction** pis visualization surface **visual** human-machine physical haptic touch imagine realistic interactive force tracking

Topic 07 recognition speech sign musical music signed signing sound speaker computer-based automatic auditory emotional **processing** channel synthesis communication

Topic 22 language text tagging linguistic **natural** categorization **machine** relation **processing** message meaning nlp corpora extraction sentence translation word training

Topic 23 mining discovery dataset massive **machine** **network** **scientific** detection **statistical** pattern **novel** **knowledge** **complex** **field** developing time source

Topic 28 **network** security privacy response service communication distributed emergency policy collaborative justice **wireless** criminal released internet private fire sharing

Topic 01 parallel database query relational management **processing** **http** **performance** estimate optimizer spatio-temporal implementation answer operation hardware

Topic 04 model reduction **performance** dimensionality existing space **statistical** measure optimization selection approach based **novel** popular method **machine**

Topic 13 reasoning planning **complex** decision theory causal intelligence uncertainty **computational** domain real-world probabilistic **knowledge** graphical

Topic 19 undergraduate graduate course education program educational **computing** engineering university curriculum interdisciplinary project school women underrepresented

Topic 00 creative creativity **computational** media scratch children interactive reading designer **content** artist study technology animation **collaboration**

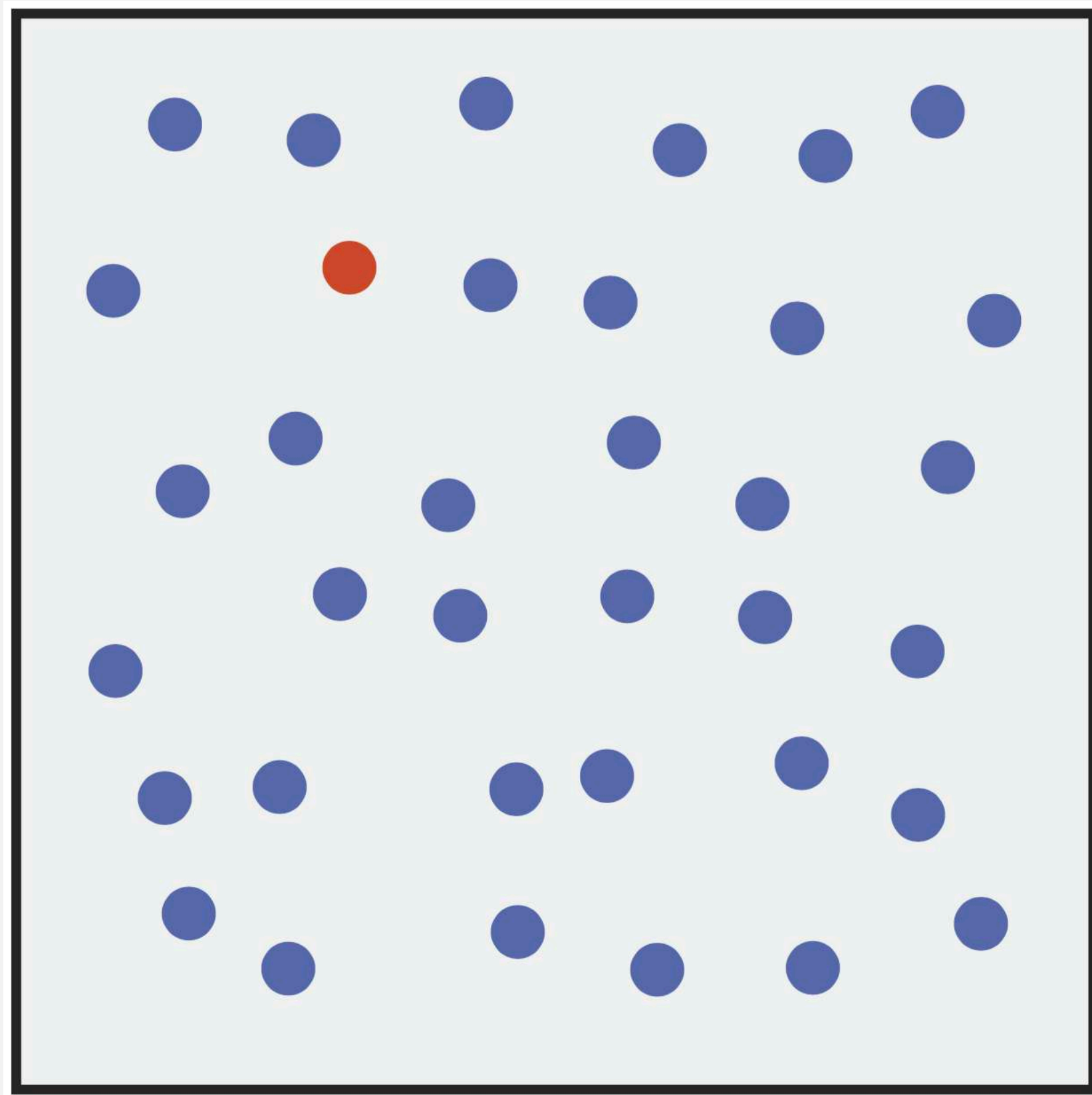
Topic 05 user create **help** potential available goal process **people** generate ability current solution **set** building example enable cost **knowledge** difficult **complex**

Topic 11 intelligence cognitive agent **people** human behavior intelligent strategy **interaction** individual learn environment ability **understanding** **machine**

Topic 12 **visual** **computational** neuroscience brain cortex stimuli memory response activity **understanding** mechanism neuronal natural neural movement

Topic 09 biology **computational** biological **network** sequencing high-throughput sequence **interaction** protein gene **proposed** bioinformatics evolutionary

Preattentive Processing

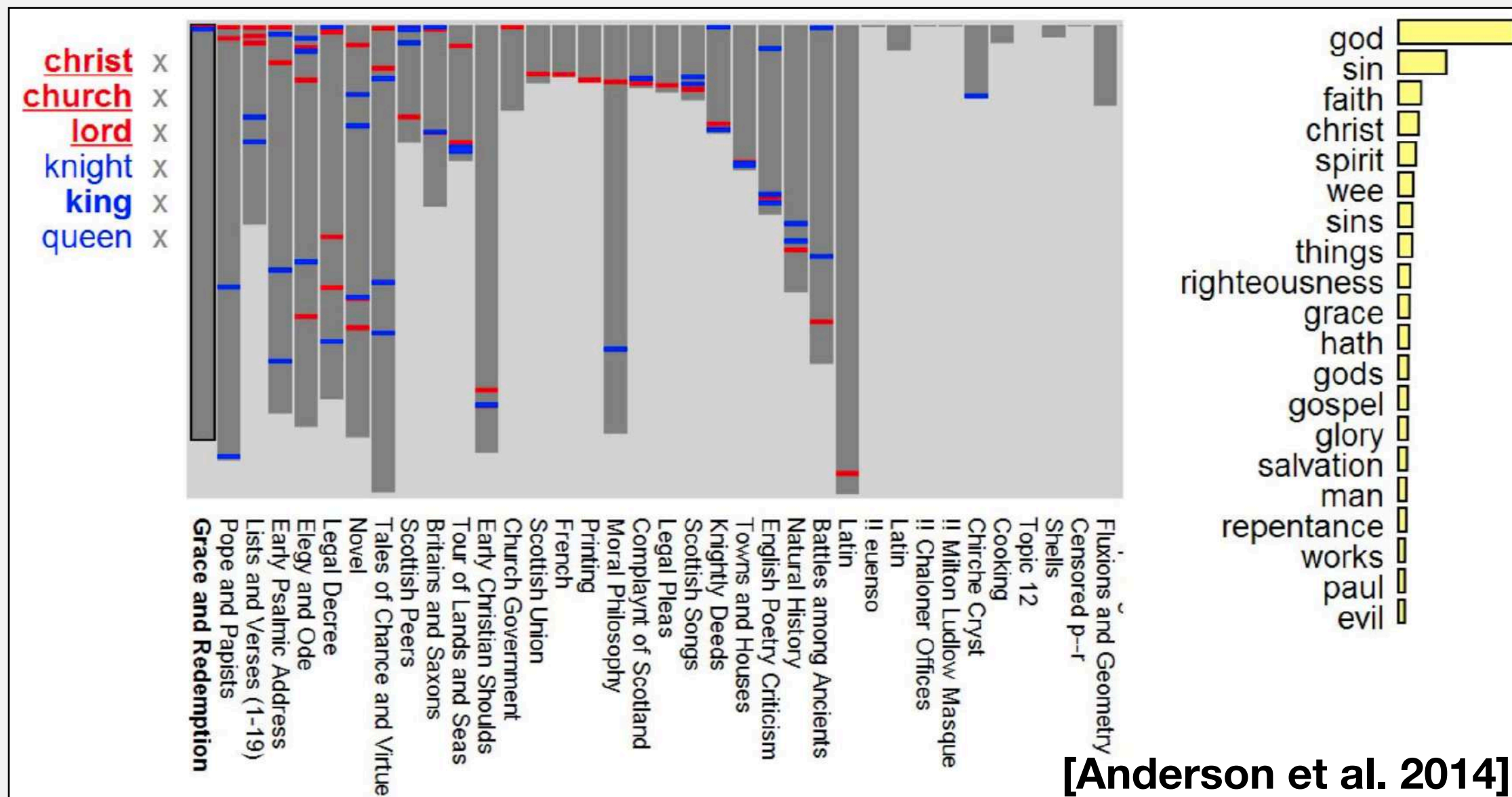


Implications for Text Visualization

- Showing a list/scatterplot of text, without consideration of visual channels, can result in serial processing - *slow!*
- If possible, use other visual channels to style text.
- Topic modeling gives us additional information which we may use to visually style text data - **so we should use it.**

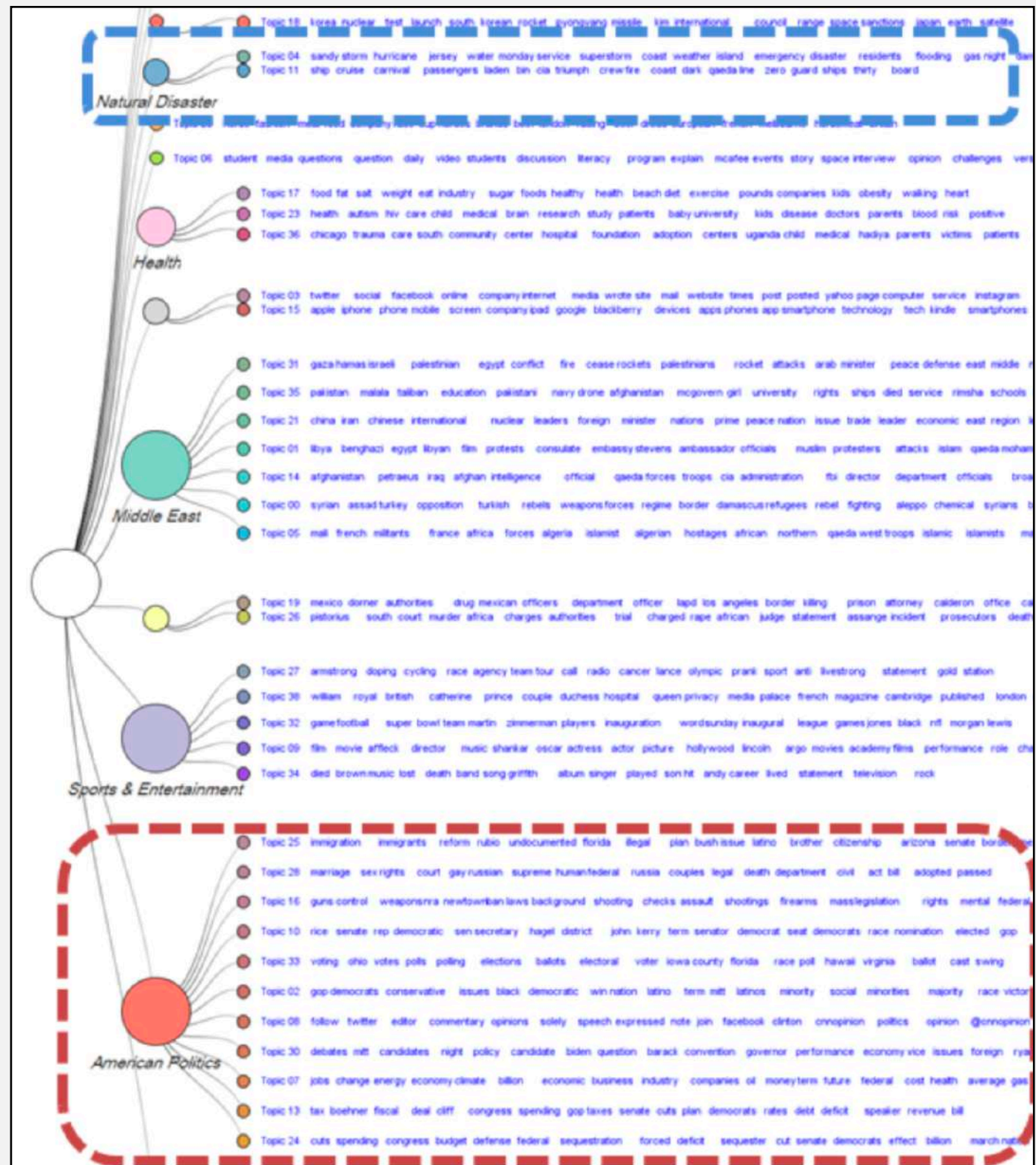
Topic Vis, Pt. 2

- An alternative:



Topic Vis, Pt. 3

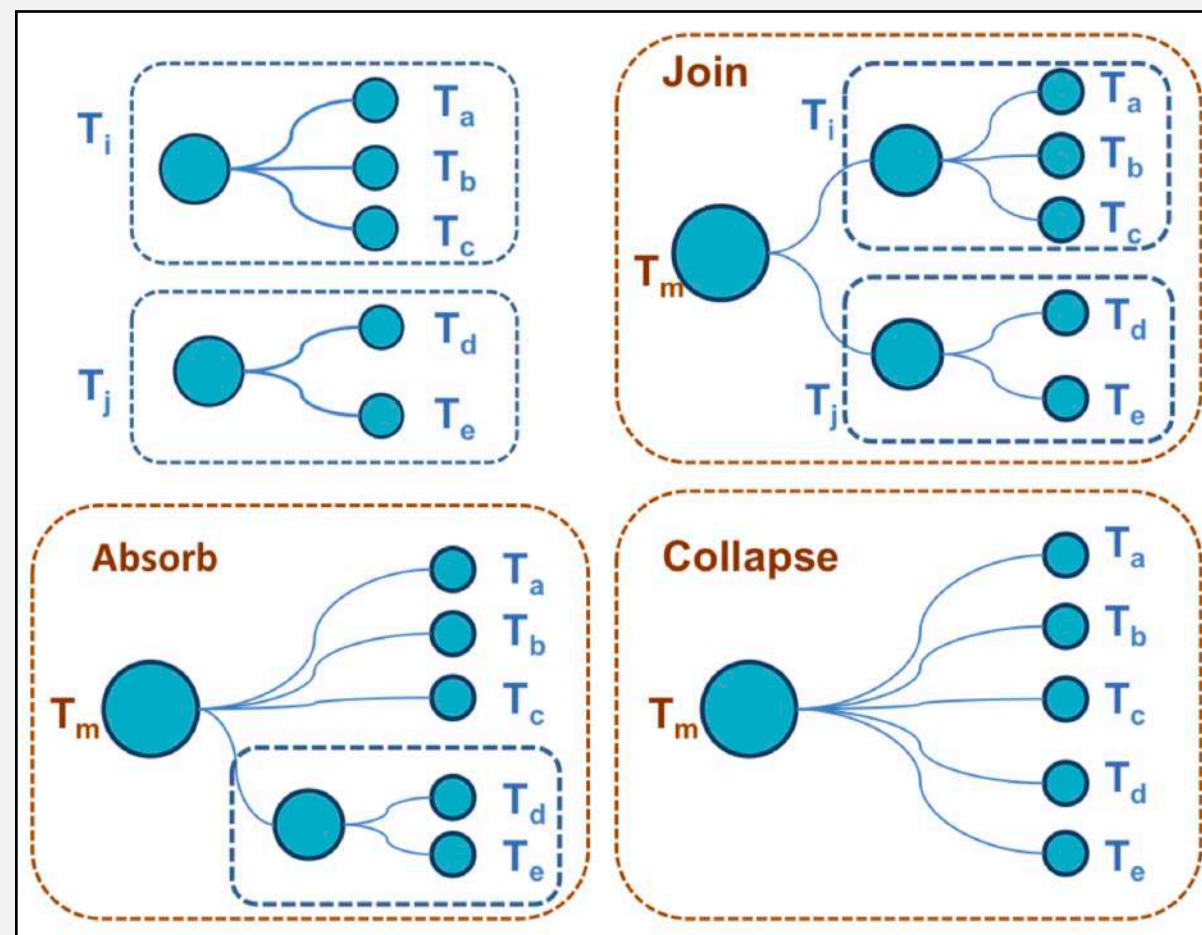
- Lots of topics?
- Hierarchies!



[Dou et al. 2013]

Building the Hierarchy

- Start from a set of topics, treat each as leaf nodes in a tree, repeat:
- Consider the following types of operations for a pair of subtrees:



Building the Hierarchy

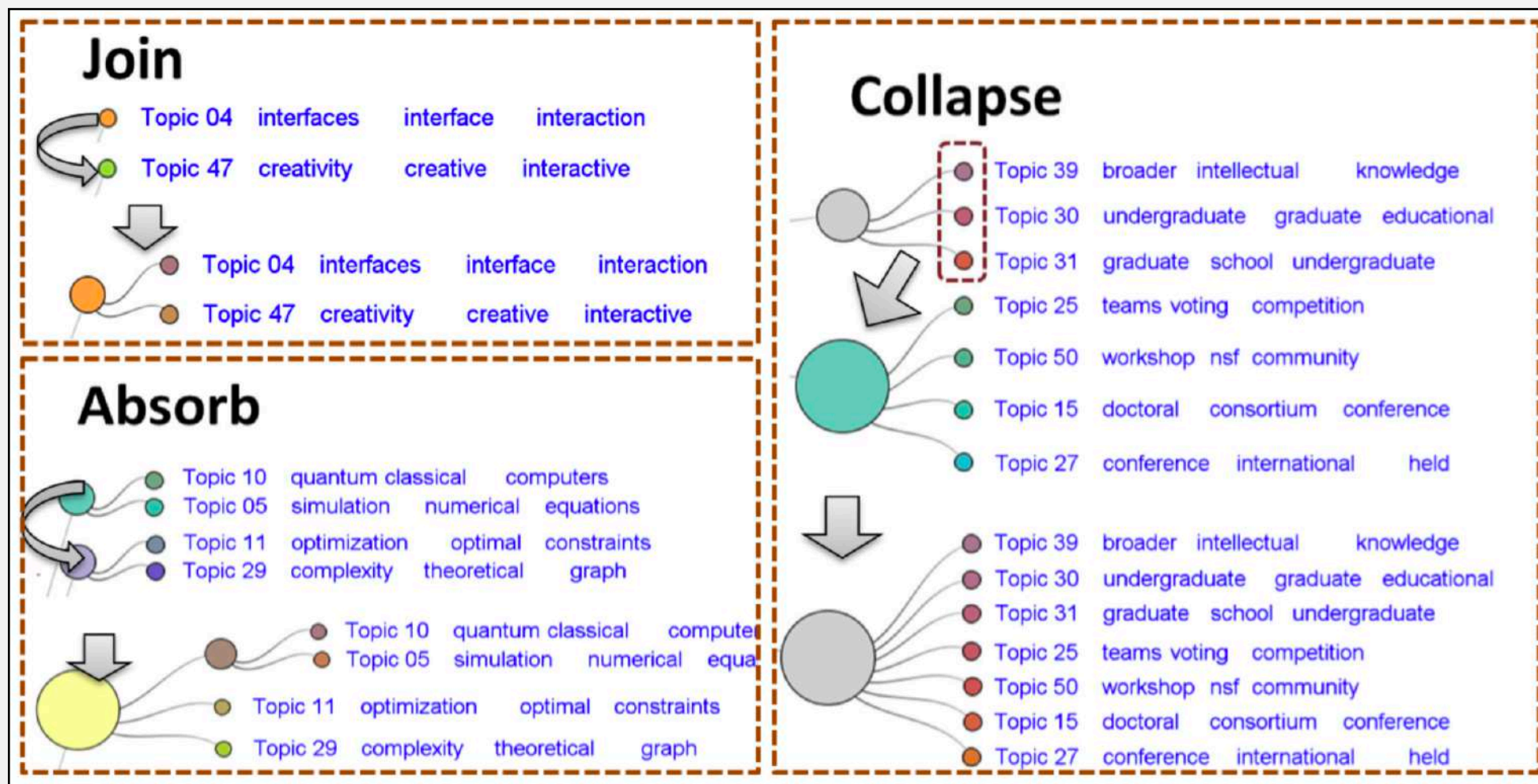
- Find the operation that gives a pair of subtrees the “lowest cost”. Cost? Distance between topics?

$$d_H(t_i, t_j) = \sum_{v=1}^N (\sqrt{t_{i,v}} - \sqrt{t_{j,v}})^2$$

- Non-leaf nodes? Average their distributions...
- Sidebar: any potential issues with this distance?
- Algorithm continued: merge the two nodes with lowest cost, repeat until we reach the root!

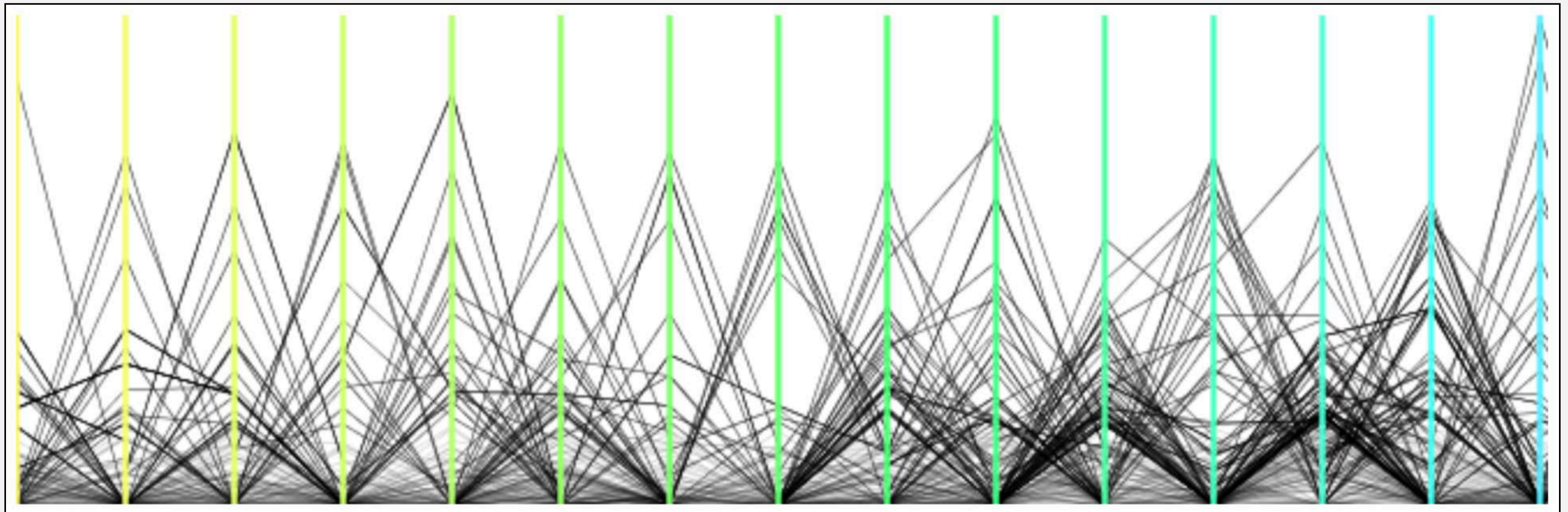
Hierarchy: Good?

- Might be imperfect, so allow the user to adjust by exposing these operations:



Visualizing a document?

- Easy? Show topic assignments.
- Visualizing multiple topics? Parallel coordinates!



[Dou et al. 2011]

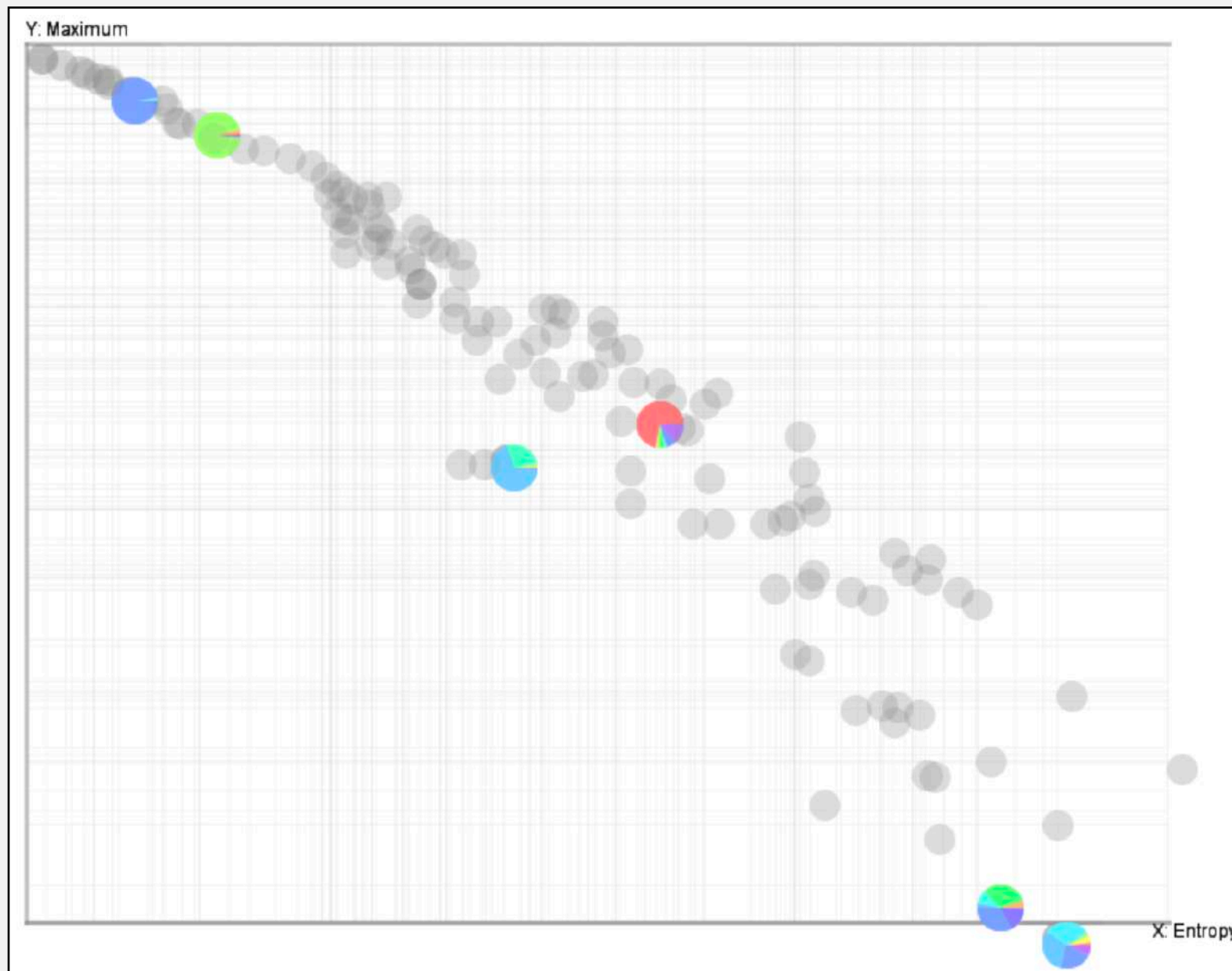
Document Vis, Pt. 2

- Poly-lines can quickly become a source of clutter!
- An alternative:



Document Vis, Pt. 3

- Order matters!
- An alternative:



[Dou et al. 2011]

Text Vis?

- Show the document directly:

The screenshot shows a 'Document Viewer' window. The top part contains a table with columns: Award N..., Program ..., Program, Amo..., Principle Investigator, Dire..., Org..., Year, Title, and Abstr... The table lists various research entries, with the entry for 'Tedrake, Russell' highlighted. Below the table, a text document is displayed, showing a paragraph about machine learning control of underactuated mechanical systems. The word 'robot' is highlighted in blue in the text. At the bottom, there is a search bar with the text '7 Highlighted' and 'robot' entered, and a 'Search' button.

Award N...	Program ...	Program	Amo...	Principle Investigator	Dire...	Org...	Year	Title	Abstr...
0738091	Paul Yu ...	ROBUST INTELLIGEN...	500...	Dixon, Warren	CSE	IIS	20...	SGE...	Motiv...
0545934	Paul Yu ...	ROBUST INTELLIGEN...	438...	Brock, Oliver	CSE	IIS	20...	CAR...	CAR...
0545931	Paul Yu ...	EXP PROG TO STIM C...	423...	Deng, Xinyan	CSE	IIS	20...	CAR...	Abstr...
0746194	Paul Yu ...	ROBUST INTELLIGEN...	296...	Tedrake, Russell	CSE	IIS	20...	CAR...	The n...
0412541	Paul Yu ...	ROBUST INTELLIGEN...	370...	Fearing, Ronald	CSE	IIS	20...	Robo...	Robo...
0094604	Vladimir ...	ROBOTICS COMPUTA...	807...	Reif, John	CSE	IIS	20...	SGE...	This ...
0746655	Paul Yu ...	ROBUST INTELLIGEN...	445...	Langelaan, Jacob	CSE	IIS	20...	CAR...	Smal...
0412912	Paul Yu ...	ROBUST INTELLIGEN...	154...	Keskinocak, Pinar	CSE	IIS	20...	Colla...	Colla...
0412884	C.S. Ge...	ROBOTICS	450...	Rock, Stephen	CSE	IIS	20...	Robo...	Robo...
0413078	Paul Yu ...	ROBUST INTELLIGEN...	200...	Burdick, Joel	CSE	IIS	20...	Colla...	A nov...
0413138	Paul Yu ...	ROBUST INTELLIGEN...	293...	Kumar, R. Vijay	CSE	IIS	20...	Gras...	This ...
0413196	Paul Yu ...	ROBUST INTELLIGEN...	316...	Koenig, Sven	CSE	IIS	20...	Colla...	Colla...
0413251	Paul Yu ...	ROBOTICS	340...	Rizzi, Alfred	CSE	IIS	20...	Auto...	This ...
0413300	Paul Yu ...	ROBUST INTELLIGEN...	342...	Mohseni, Kamran	CSE	IIS	20...	Colla...	A nov...

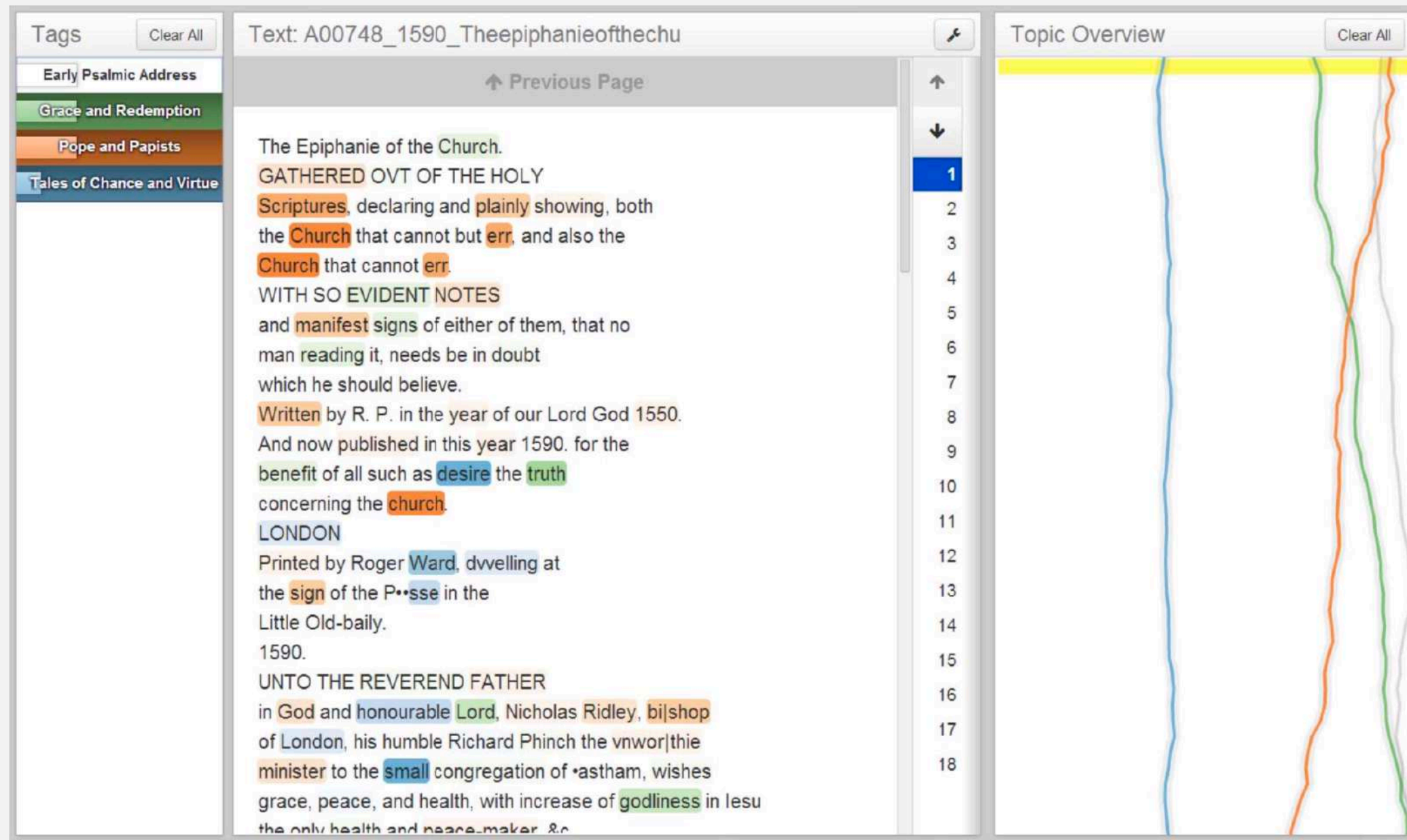
CAREER: Machine Learning Control of Underactuated Mechanical Systems

The nonlinear underactuated systems represent an important and general class of problems in robotics which have proven mostly intractable for analytical and numerical control design paradigms. Machine learning approaches to underactuated control, which employ approximations to make numerical optimal control techniques tractable, will have broad applications from walking robots to the control of aerial vehicles and fluid systems. Here we pursue a careful analysis of the algorithms applied to linear time-invariant (LTI) systems. This will contribute fundamental results on the convergence rate of different learning algorithms, and the design of robot mechanisms and input-output "features" which maximize the rate of convergence. Theoretical results are coupled with experiments on a strongly nonlinear control problem - a two-link bipedal robot walking over rough terrain. Acquiring a near optimal feedback policy for this robot would produce a result that is surprising and compelling (because a simple robot will be traversing more complicated terrain than has been demonstrated by any humanoid), but also clear and revealing (because the simplicity of the robot expos

7 Highlighted robot Search

Text Vis, Pt. 2

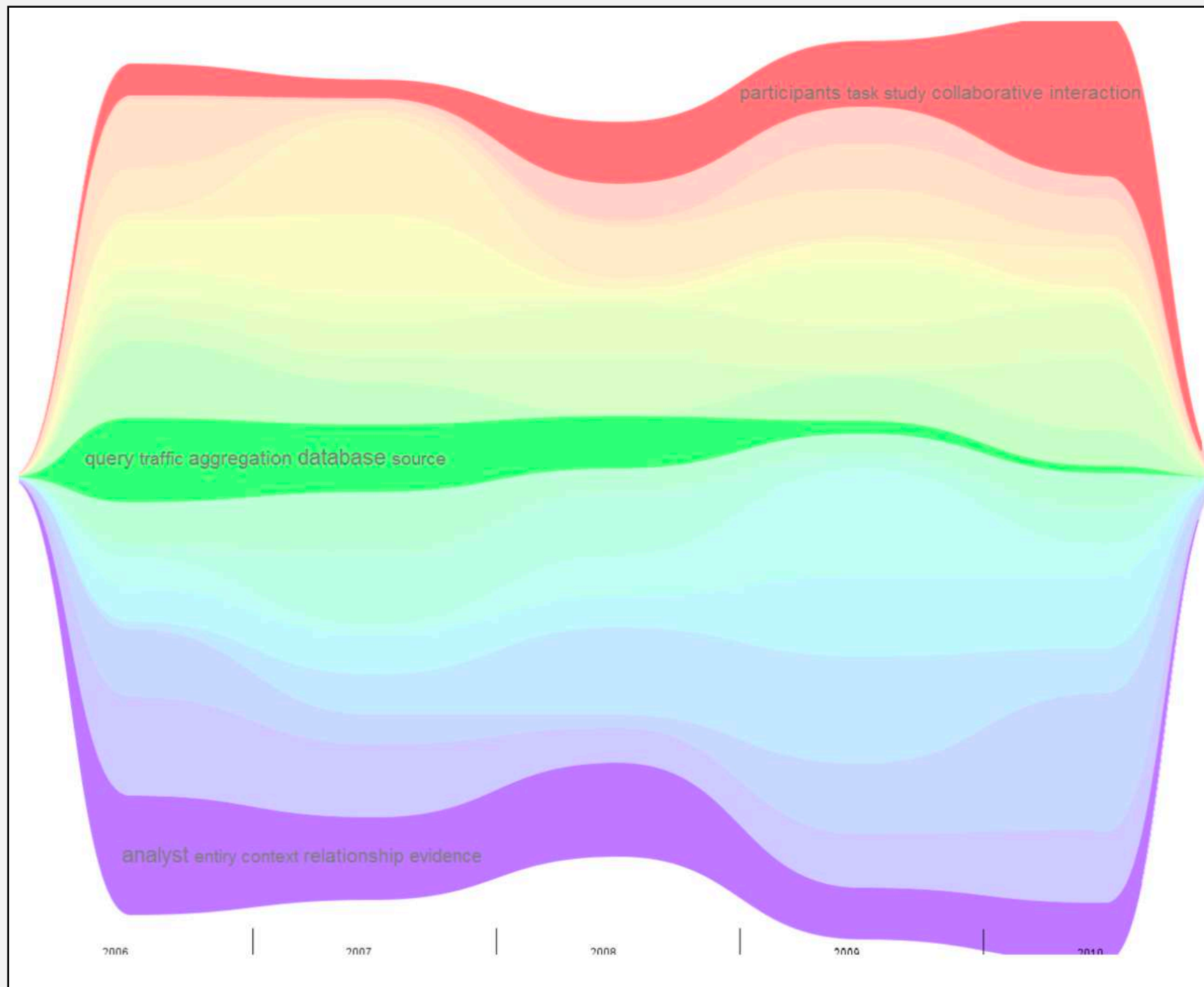
- Use topic model to aid in showing text!



[Anderson et al. 2014]

Handling Time

- How do topics vary over time?



[Dou et al. 2011]

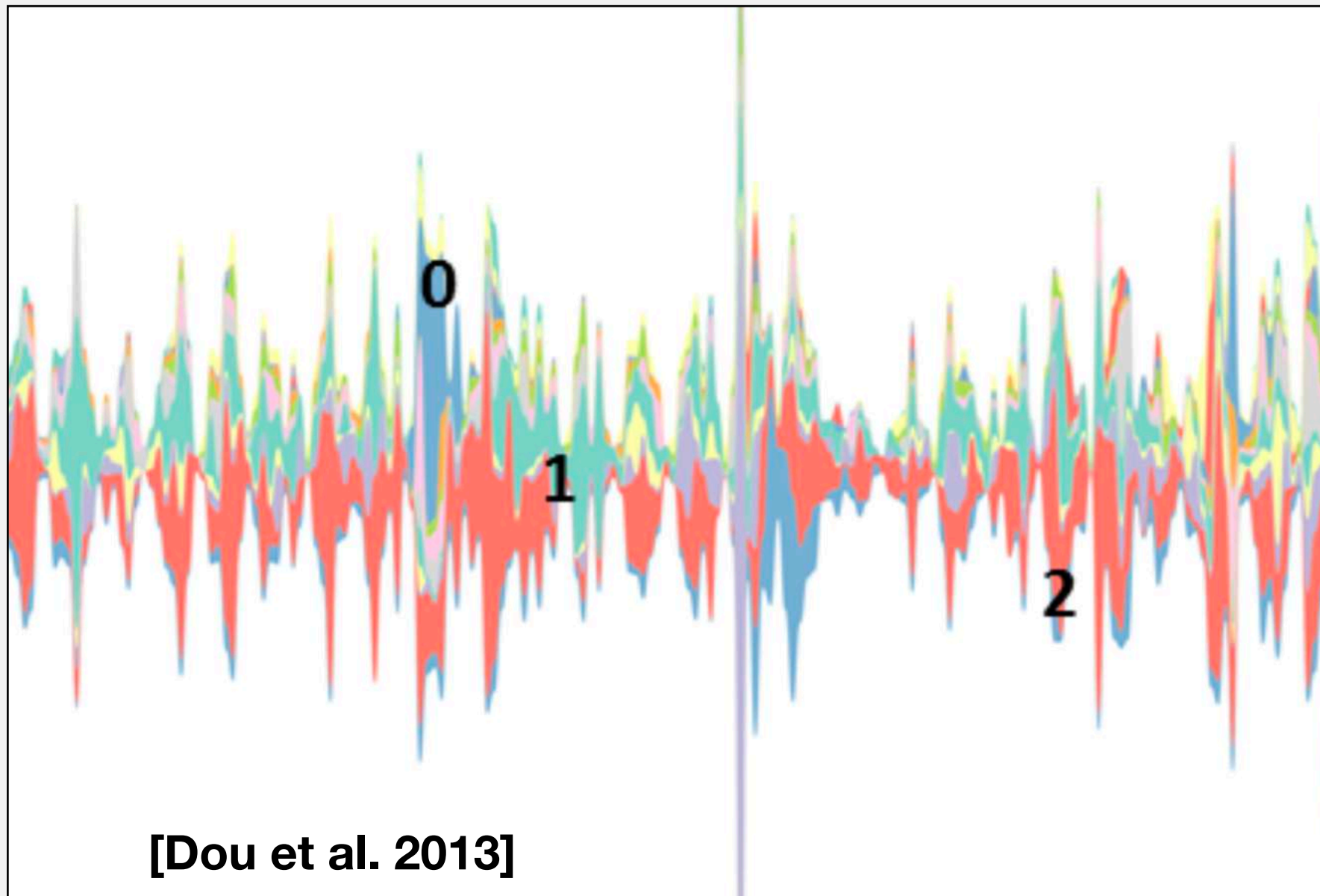
What is this time series?

- Need to derive a time-dependent measure of **topic relevance**.
- Method:
 - Fix a time interval unit
 - Take a temporal sliding window over all time steps, where the window length is this interval.
 - For a given temporal window, gather all documents:

$$\tau_D(i) = \sum_{d \in D} d_i$$

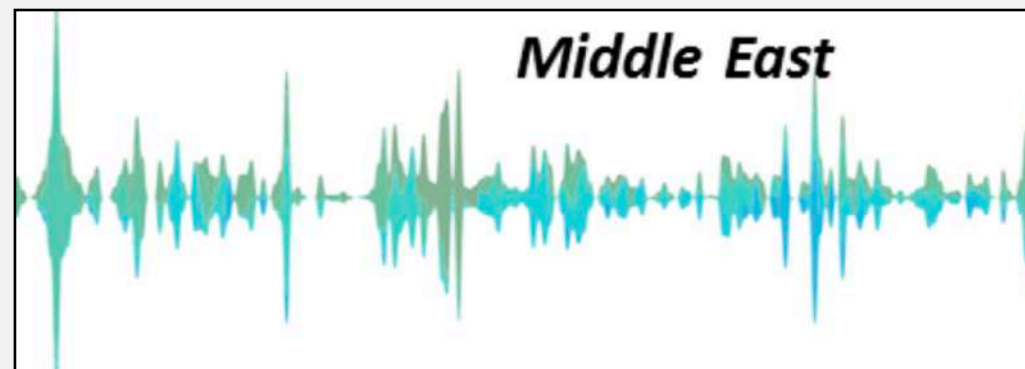
Hierarchical Temporal Evolution

- Top-level nodes:



Hierarchical Temporal Evolution

- Interactive! Click on a node, expand to its children:



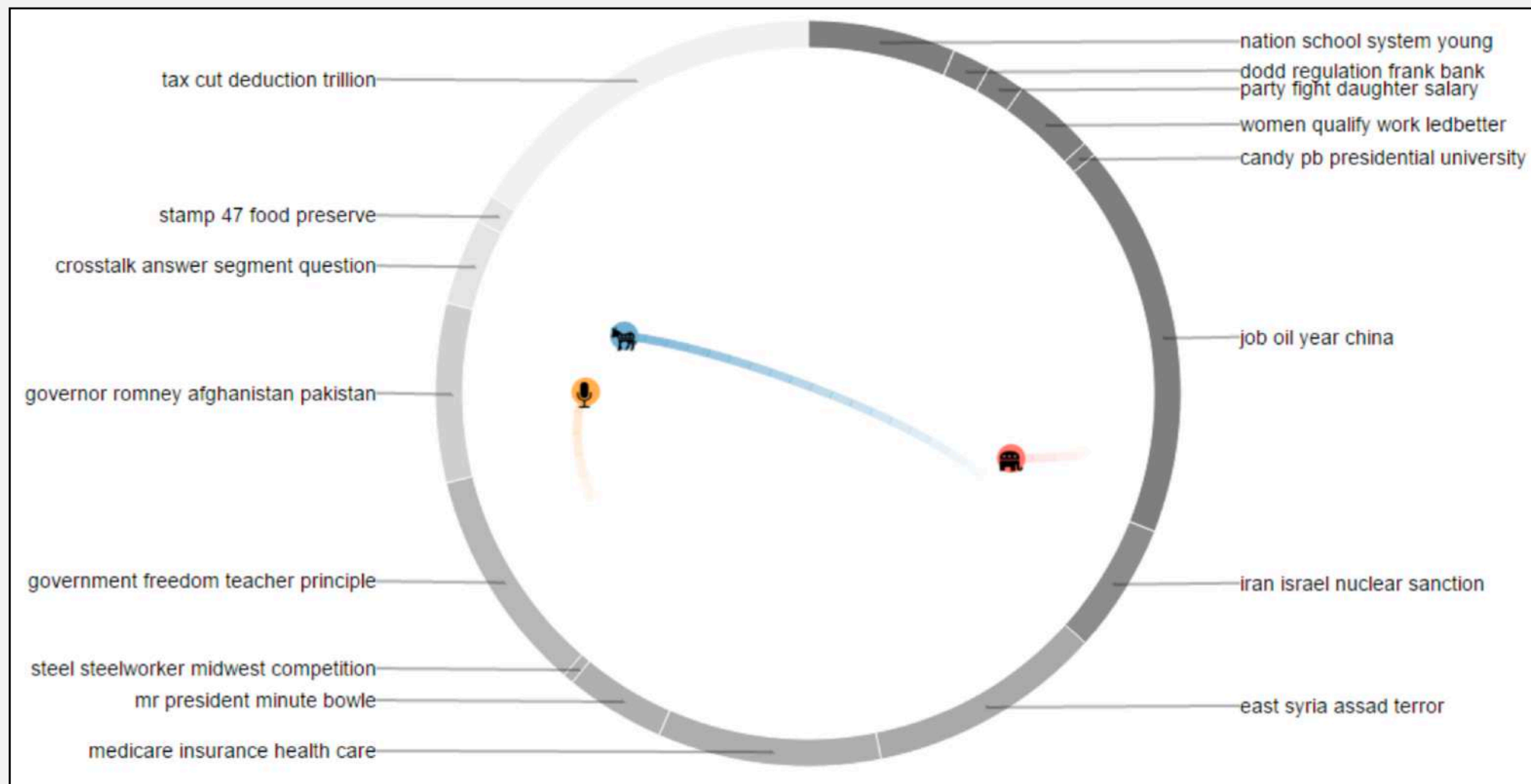
Topic Modeling for Exploring Conversations

- Conversation data
 - Set of speakers
 - Each speaker delivers an utterance: a set of statements, at a particular time.
- Treat each utterance as a document: topic modeling!

ConToVi: Multi-Party Conversation Exploration

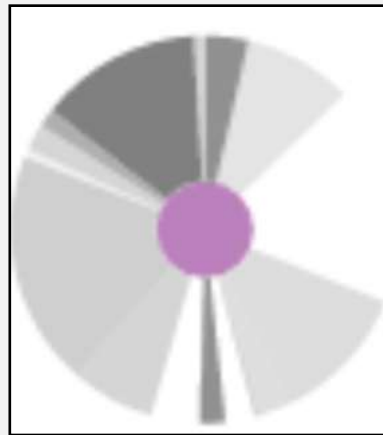
- Objective: show the progression of a conversation, in the context of topic membership
- Necessitates different views:

[El-Assady et al. 2016]



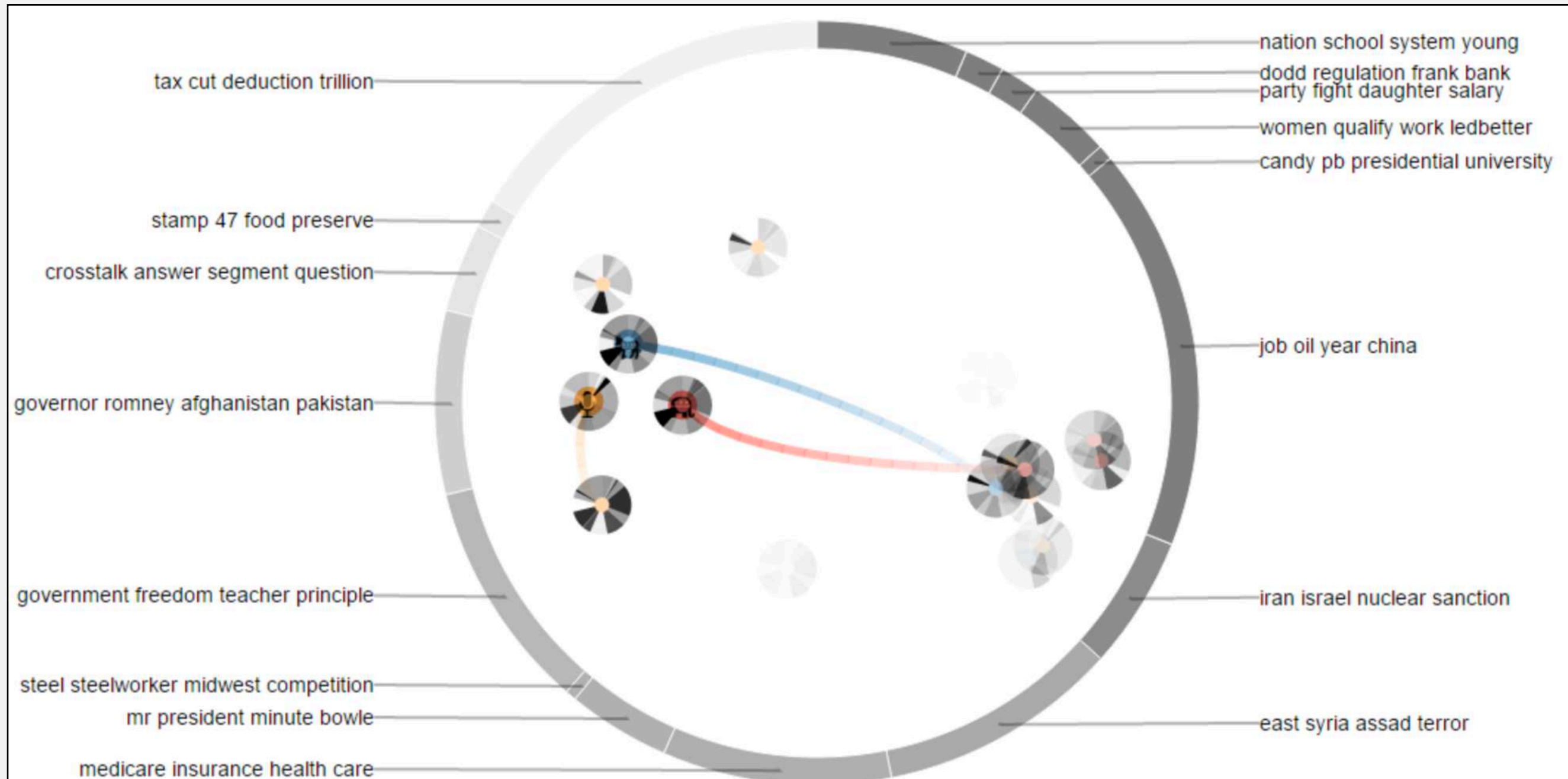
Topic Glyph

- Explicitly visually encode topic membership:



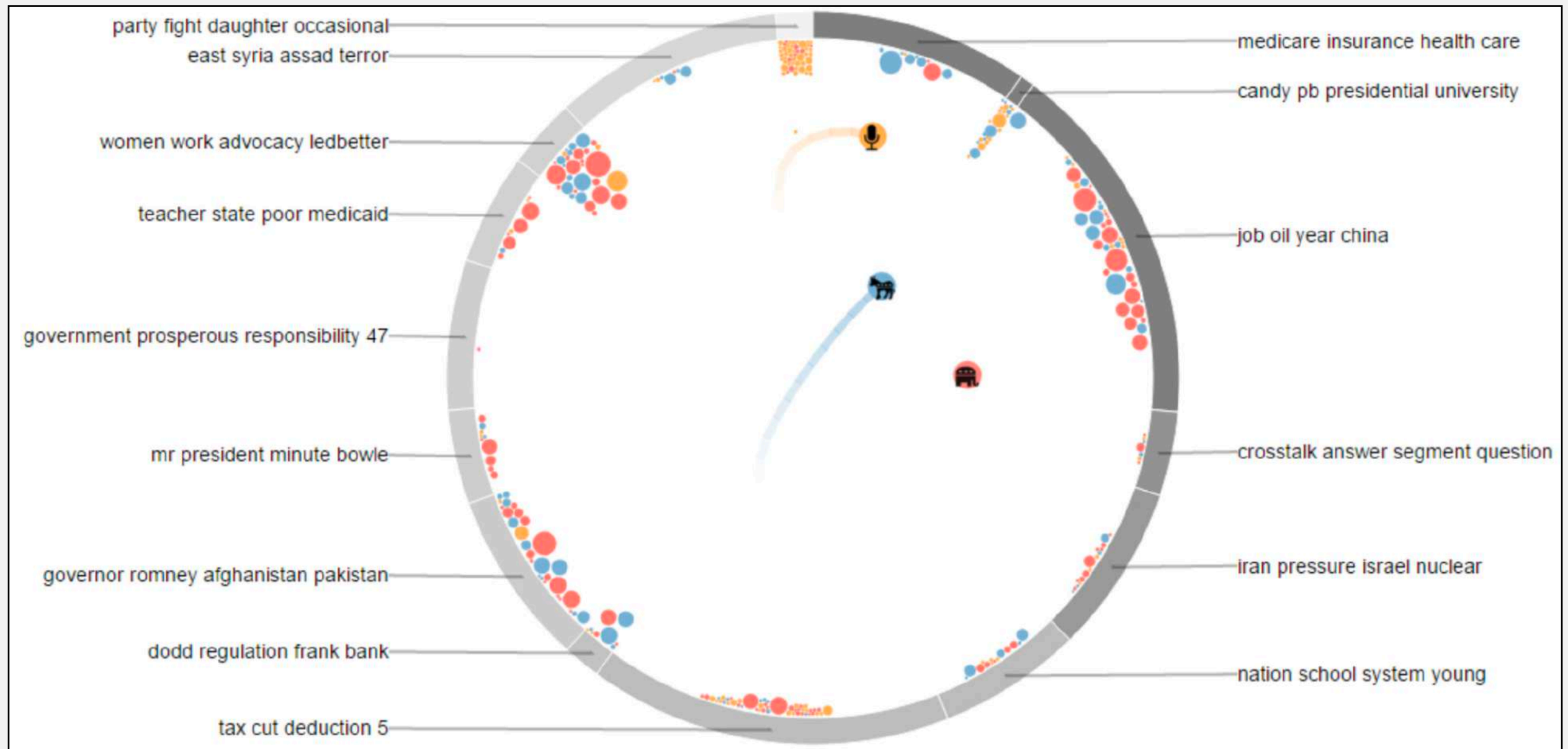
- Arc angles: map to the global view (previous slide)
- Brightness: document-topic weight
- Other visual encodings?

View 2: Glyphs



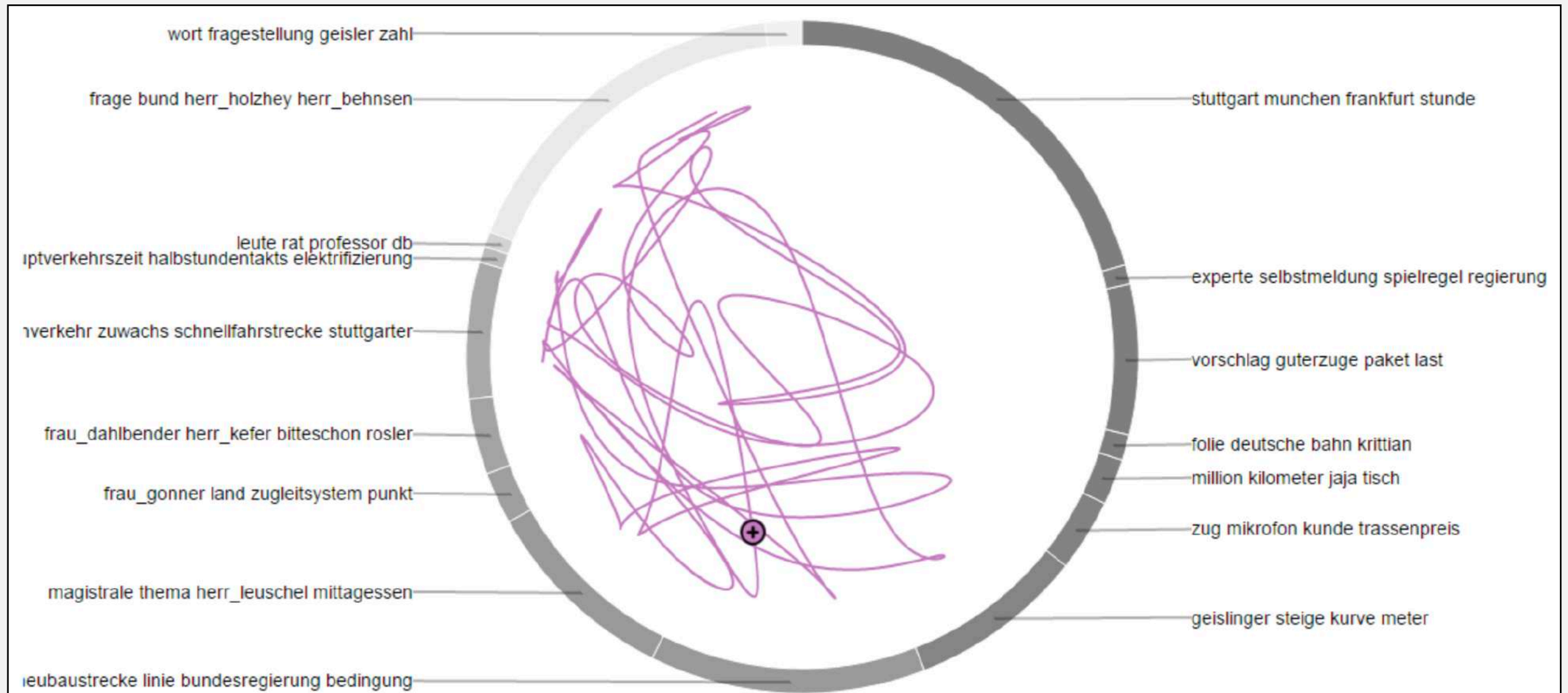
Animation with Context!

View 3: “Sedimentation”



Animation with Context!

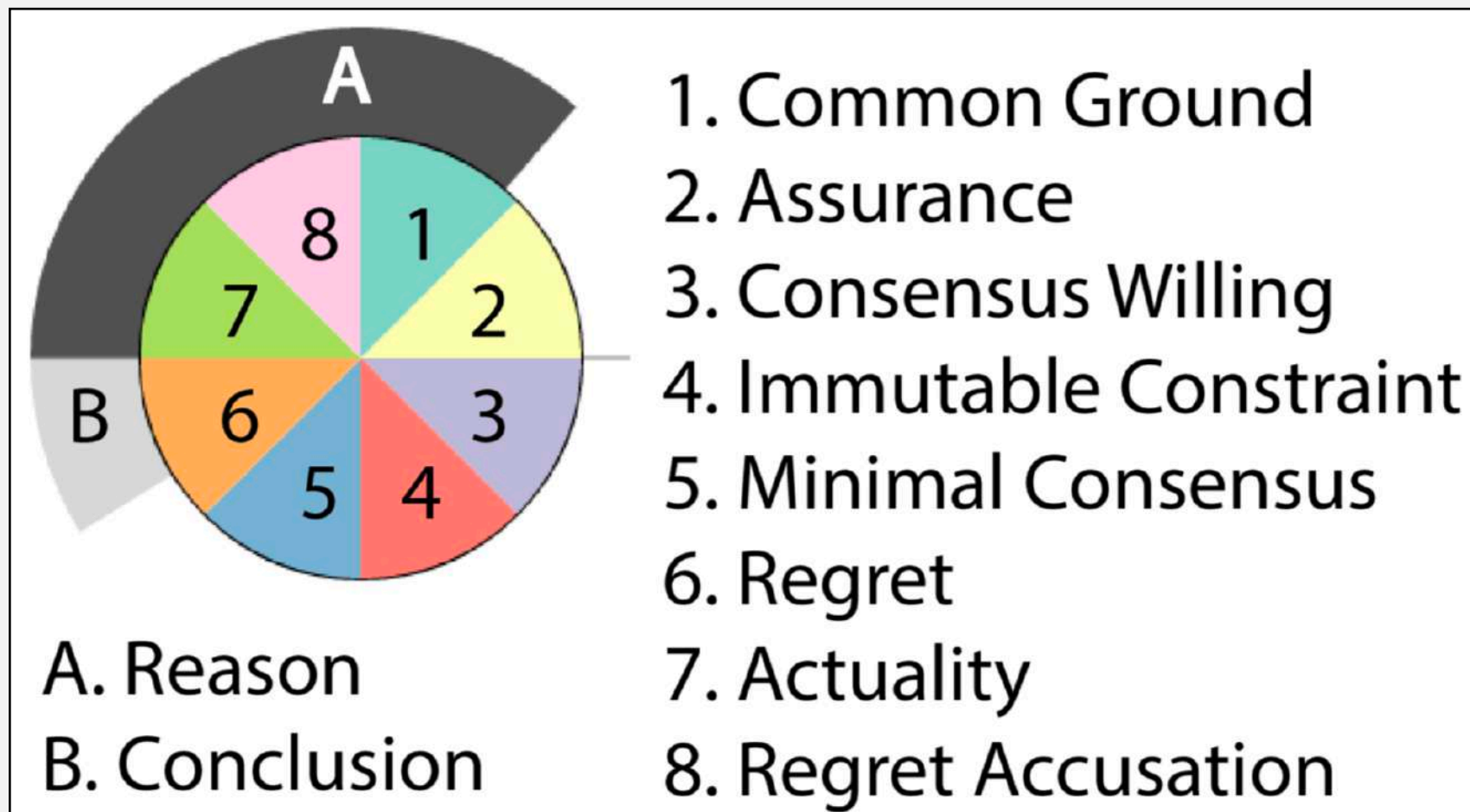
View 4: Speaker Paths



Potential Issues? Improvements?

Argumentation Patterns

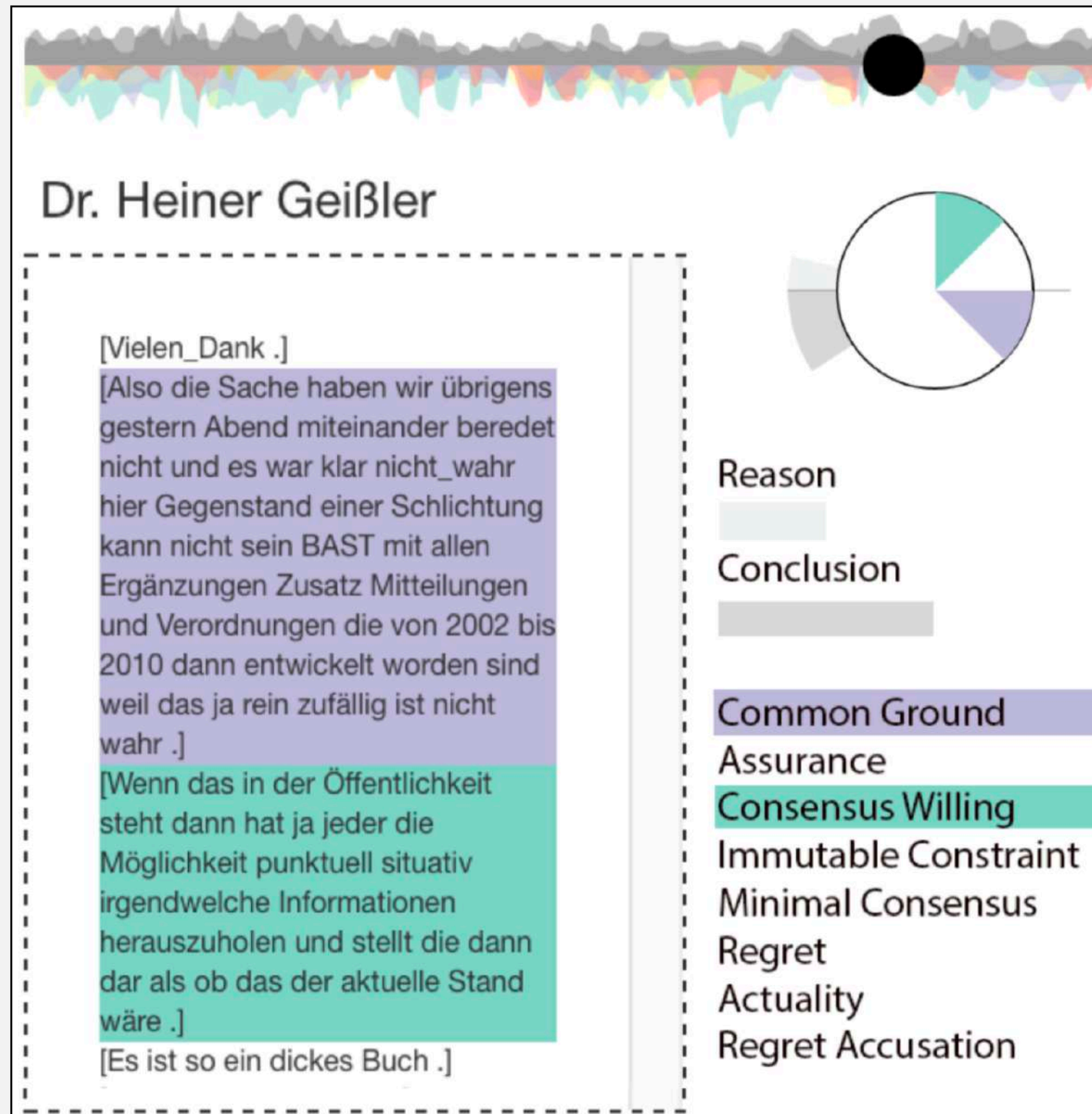
- Speaker patterns are extracted, used as additional semantics to understand utterances:



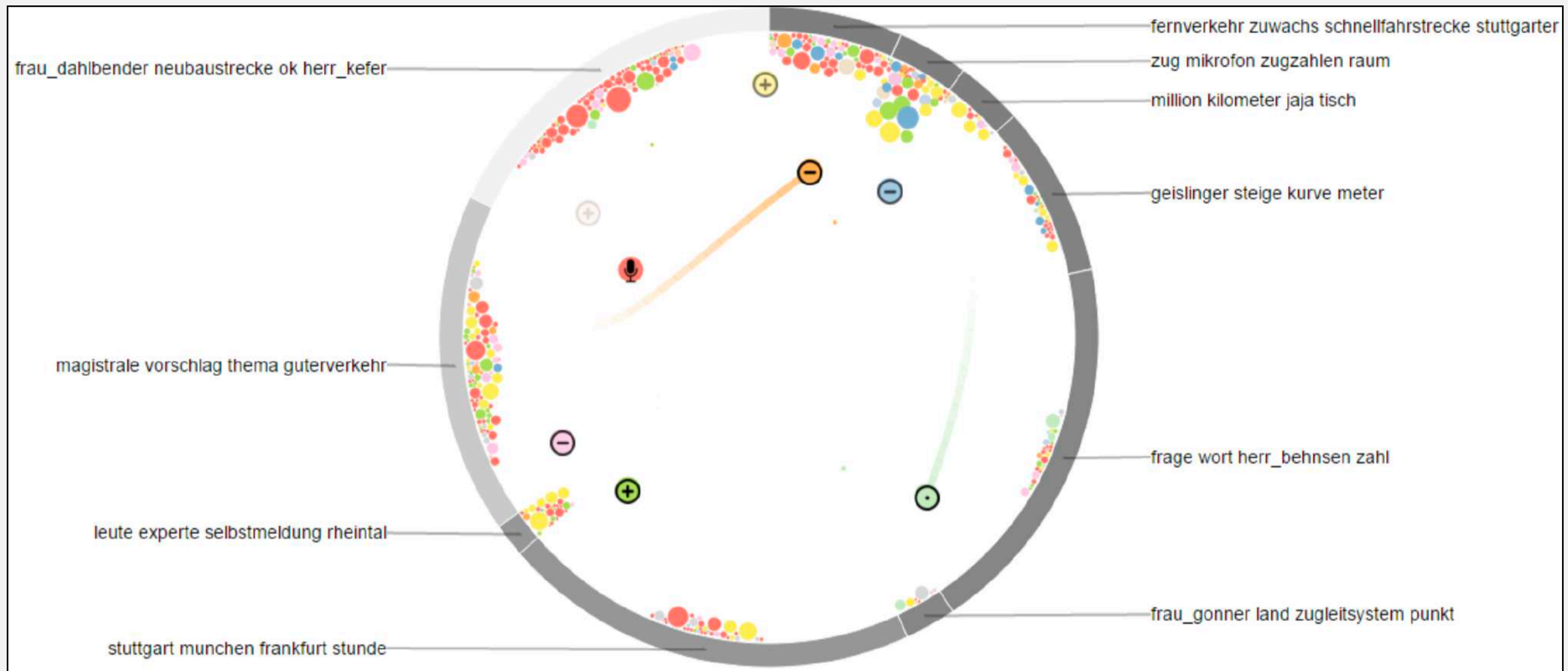
Comparing Stances



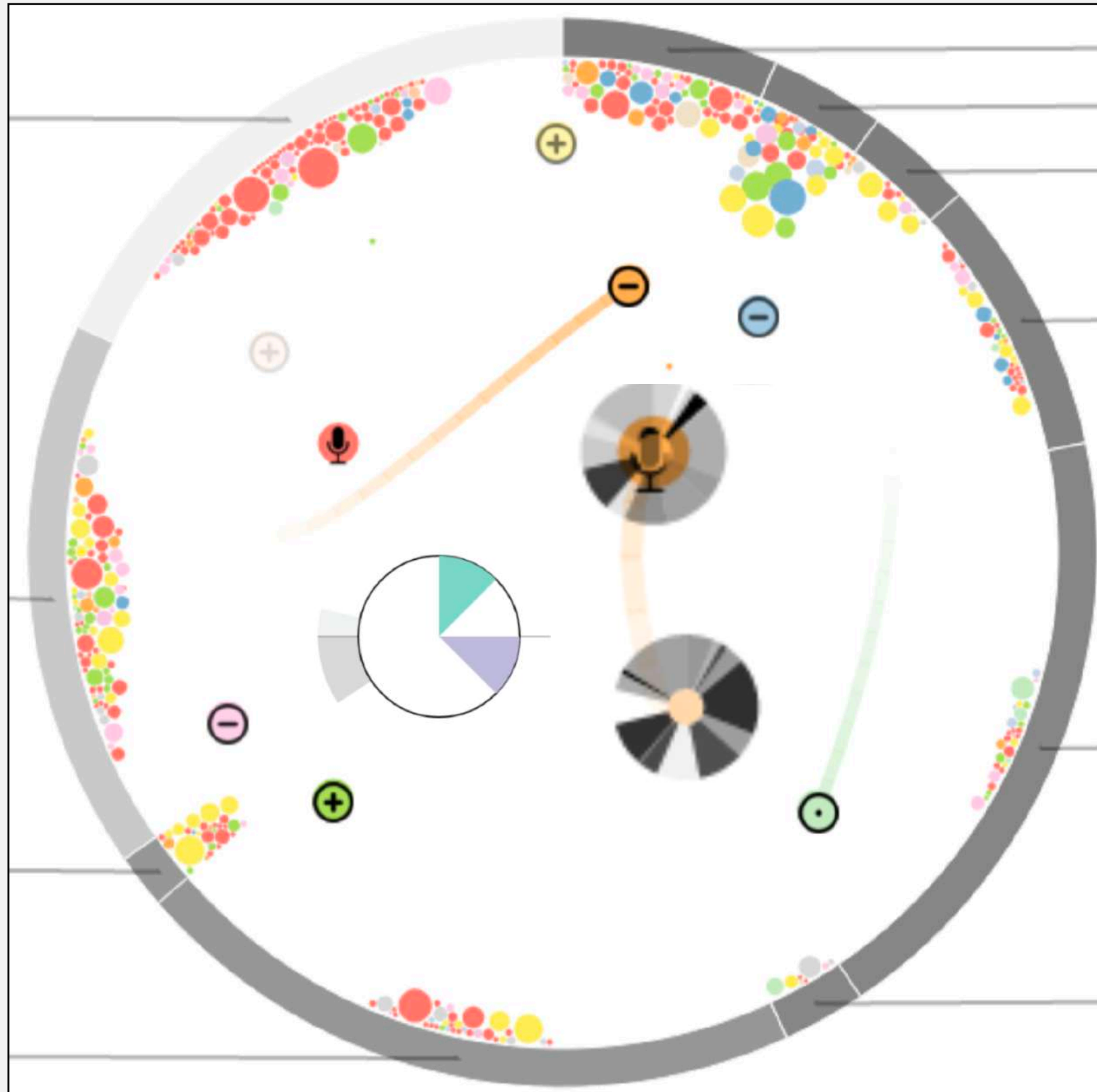
Detail-on-Demand



Putting it together



Sidebar: Encoding Overload?



Sidebar: Encoding Overload?

- Equally important to designing visual encodings is the ability for us (humans) to *decode* the visualization.
- **Decode:** going from visual channel back to data
- Be careful about *prioritizing* visual encodings:
 - Most important aspects of data should get mapped to channels, or combination of channels, that a human can easily decode (e.g. *channel effectiveness*)