

Topic Model Network Visualization

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WHAT IS TOPIC ANALYSIS?

Problems We're Attacking

- Document collections are hard work to explore/manage manually
- Sometimes the contents are completely or mostly “unknown” (e.g., an email archive, or a collection of research papers)
- We'd like at least semi-automated methods to group them, annotate them, explore relationships

The Topic Problem

Text 1

We present a statistical parsing framework for sentence-level **sentiment** classification in this article. Different from previous work employing linguistic parsing results for **sentiment** analysis, we develop a statistical parser to directly analyze the **sentiment** structure of a sentence. We show that the complicated phenomena in **sentiment** analysis (e.g., negation, intensification, and contrast) can be elegantly handled the same as simple and straightforward

Text 2

Sentiment analysis of **Twitter** data is performed. The researcher has made the following contributions via this paper: (1) an innovative method for deriving **sentiment** score dictionaries using an existing **sentiment** dictionary as seed words is explored, and (2) an analysis of **clustered** tweet **sentiment** scores based on tweet length is performed.

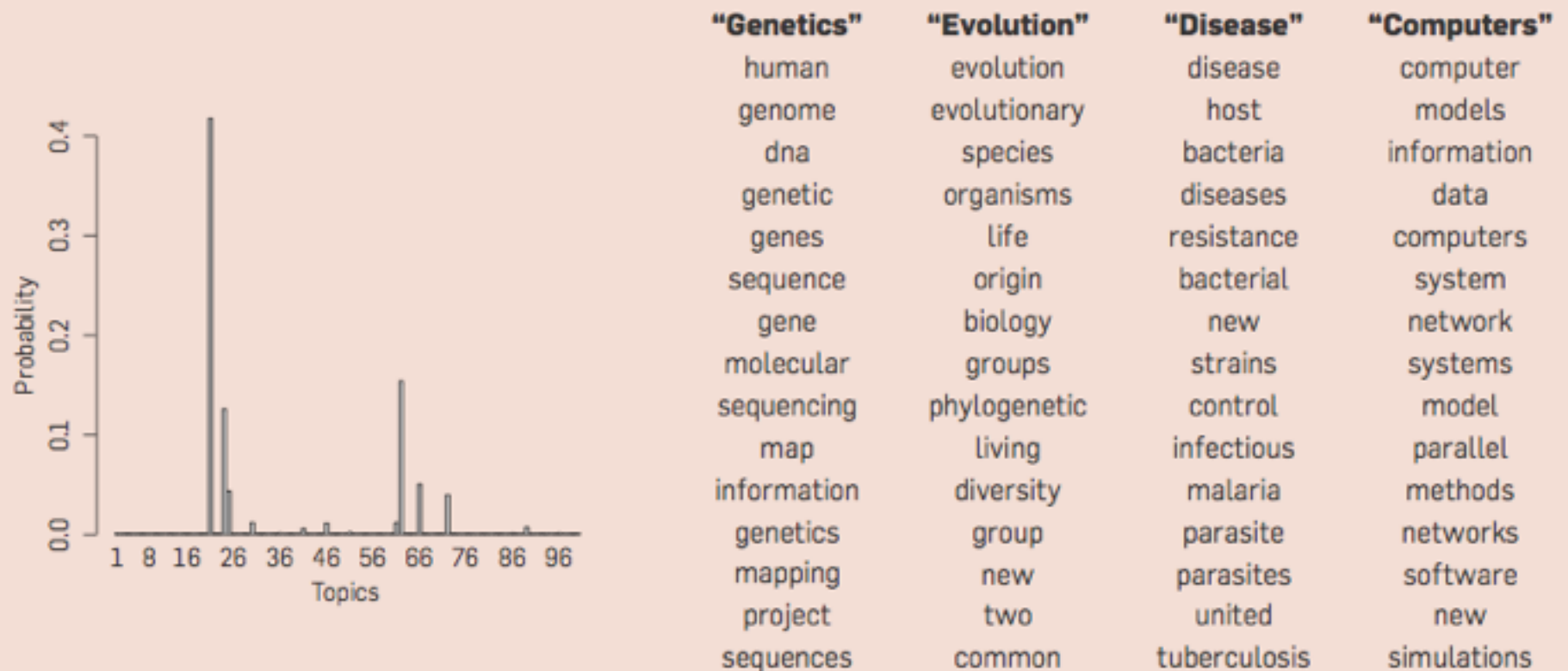
Text 3

We perform a large-scale **linguistic** analysis of language diatopic variation using geotagged microblogging datasets. By collecting all **Twitter** messages written in Spanish over more than two years, we build a corpus from which a carefully selected list of concepts allows us to characterize Spanish varieties on a global scale. A **cluster** analysis proves the existence of well defined macroregions sharing common lexical properties.

Intuitions

- Documents are composed of multiple words (“bag of words”)
- Documents may express multiple topics

Figure 2. Real inference with LDA. We fit a 100-topic LDA model to 17,000 articles from the journal *Science*. At left are the inferred topic proportions for the example article in Figure 1. At right are the top 15 most frequent words from the most frequent topics found in this article.



“LDA”: Latent Dirichlet Allocation

Topics

gene 0.04
dna 0.02
genetic 0.01
...

life 0.02
evolve 0.01
organism 0.01
...

brain 0.04
neuron 0.02
nerve 0.01
...

data 0.02
number 0.02
computer 0.01
...

Documents

Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions

"are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an

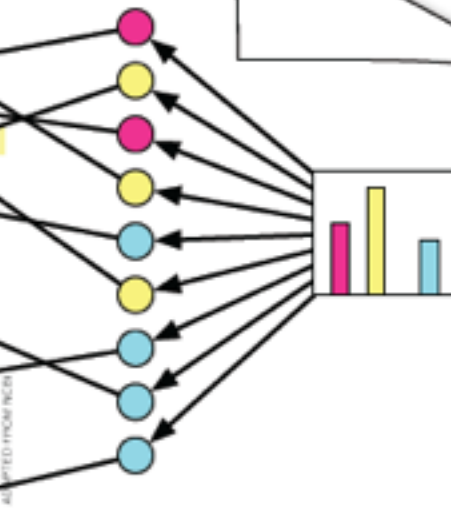


* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

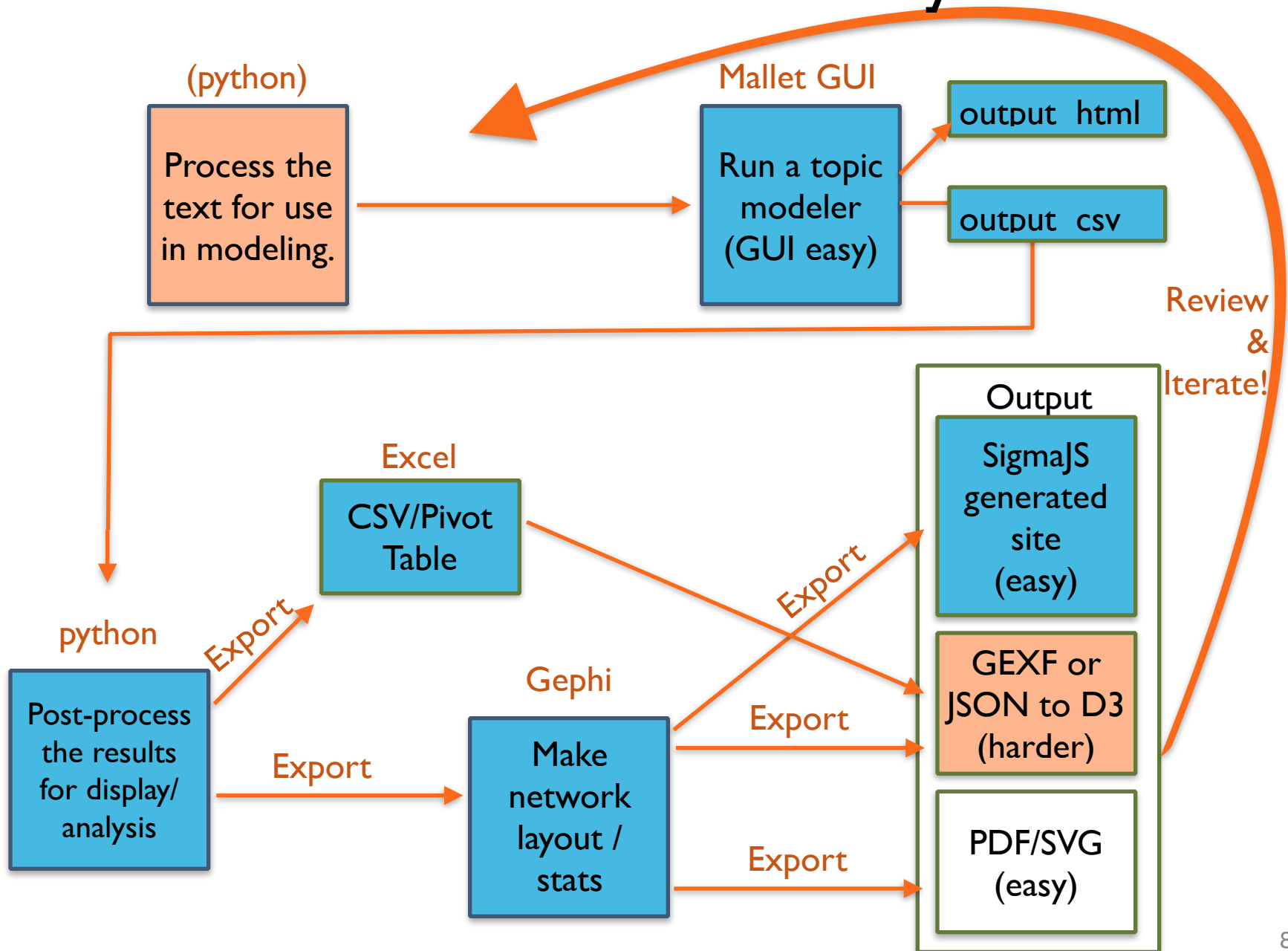
Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

SCIENCE • VOL. 272 • 24 MAY 1996

Topic proportions and assignments



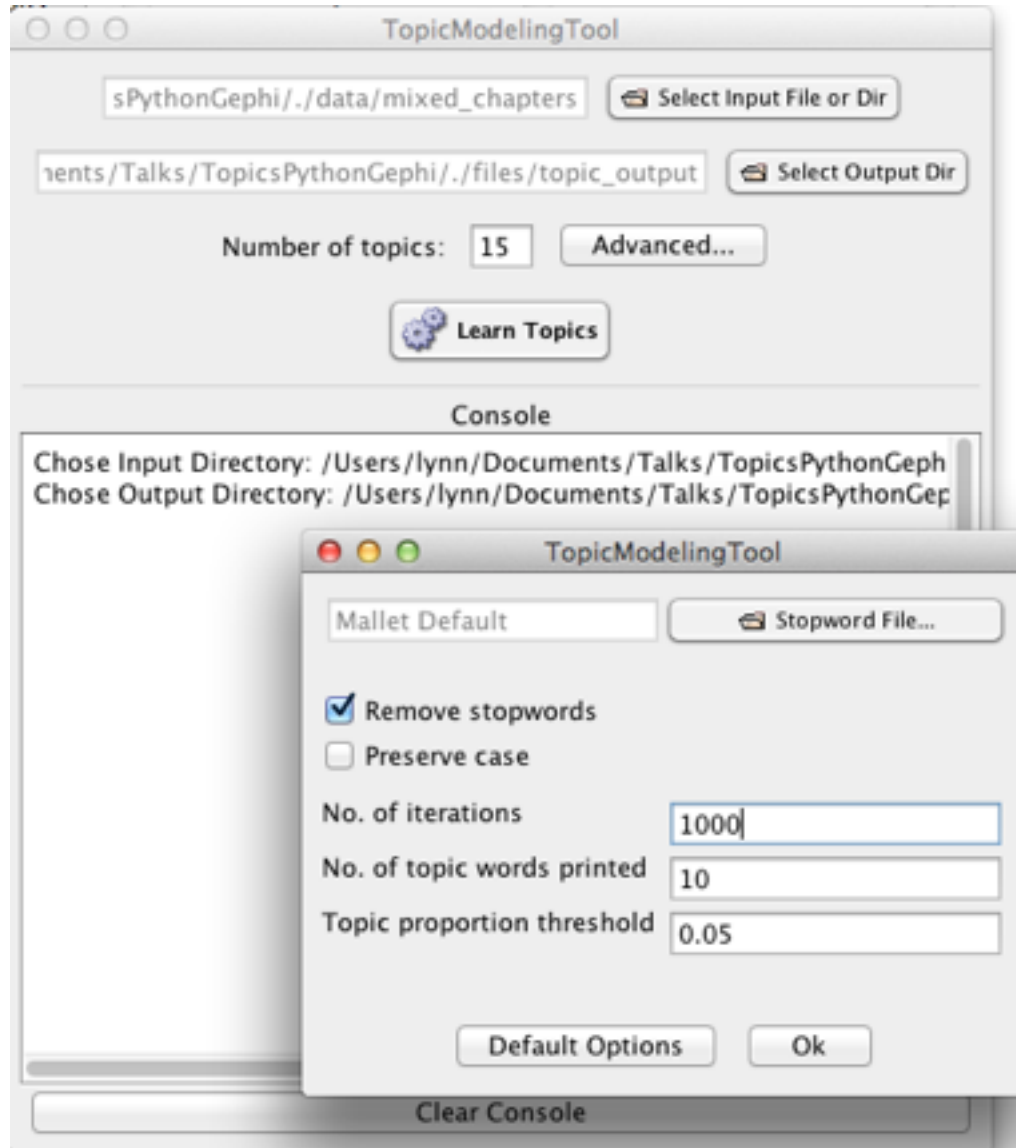
Workflow for Today



Save us some time: David Newman's Topic Modeling GUI

- A tool available for non-technical audiences! A GUI wrapper on the state-of-the-art `mallet` (java-based app by David Mimno).
- <https://code.google.com/p/topic-modeling-tool/>
(Also in the workshop files)
- More of his work: <http://www.ics.uci.edu/~newman/>

Topic Modeling Tool (GUI)

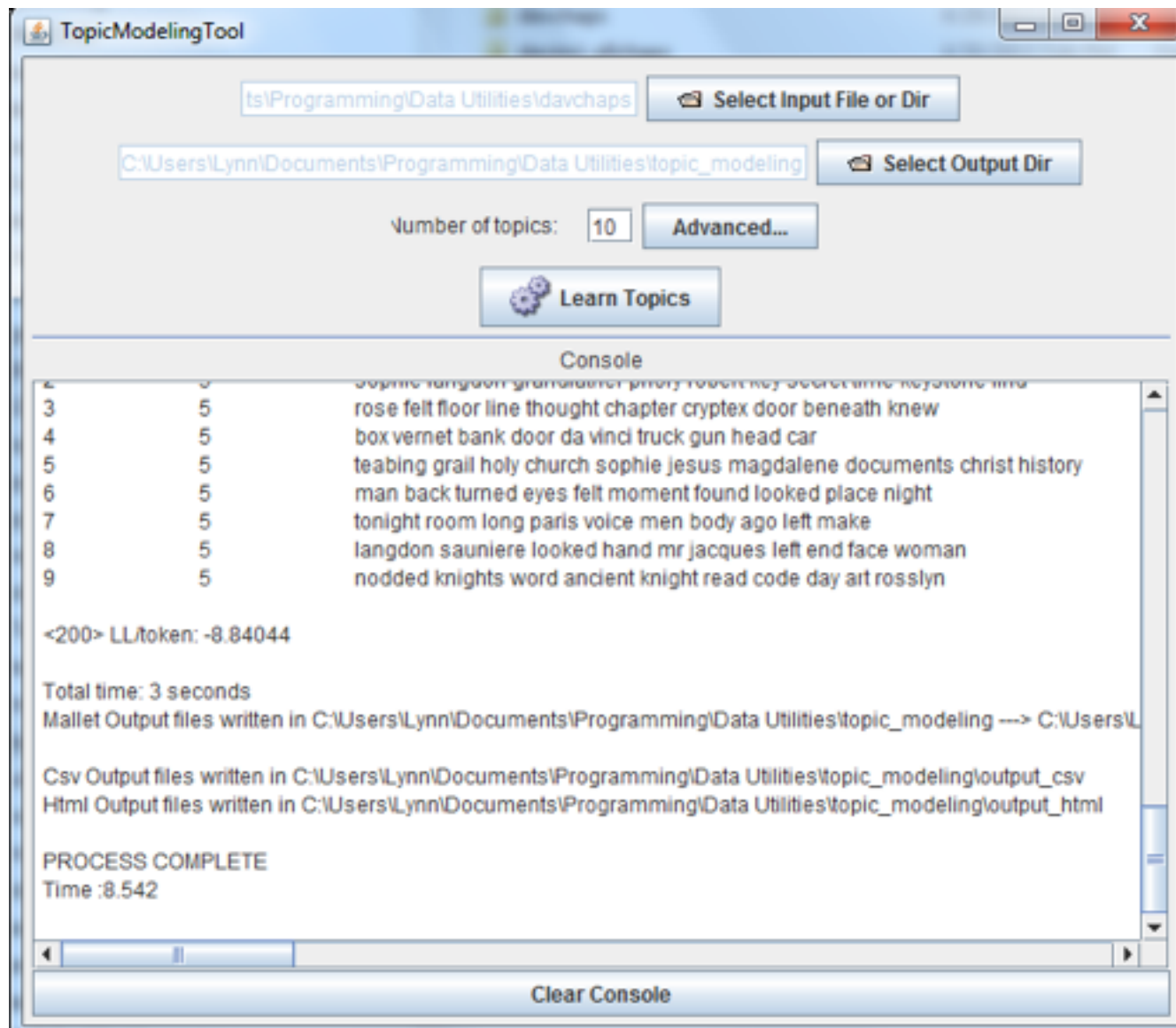


Create an output dir called "topic_output" before you try to select.

Click "Advanced..."



Post run...



Understanding the Output


StackOverflow post: <http://stackoverflow.com/questions/8447393/how-to-understand-the-output-of-topic-model-class-in-mallet>

```
<1450> LL/token: -9.11846  
<1460> LL/token: -9.11803  
<1470> LL/token: -9.10896  
<1480> LL/token: -9.11237  
<1490> LL/token: -9.10845
```

Iteration number



Log Likelihood per word (we want this to increase as the algorithm runs)



Output files: Data (csv), text web site

output_csv

output_html

List of T topics:

Topics_Words.csv

List of topics in each of D
documents:

TopicsInDocs.csv

List of top-ranked documents
in each of T topics

DocsInTopics.csv

all_topics.html

Mallet command line

You could also run mallet from the command line:

[http://programminghistorian.org/lessons/
topic-modeling-and-mallet](http://programminghistorian.org/lessons/topic-modeling-and-mallet)

Or use a Python (or R) wrapper:

[http://radimrehurek.com/2014/03/tutorial-on-
mallet-in-python/](http://radimrehurek.com/2014/03/tutorial-on-mallet-in-python/)

To do the rest of this workshop, you'd need to process the output files yourself similarly to our py code (assume \t seps, not csv)

Pros/Cons vs CMD-Line Mallet

Pros of GUI

- Allows stopword file input
- Takes folder or file of text
- Produces csv and html output in a neat dir structure
- Has a GUI! (simpler to just get going without code and help)
- A nice intro to using mallet on the command line

Cons of GUI

- Runs with defaults, so no optimize-interval or other cmd line options
- No diagnostic output (a command-line option)
- Can get slightly fewer stats for your vis, as a result

2 of the 3 CSV Output files

	A	B	C	D	E	F	G	H
1	topicId	words..						
2		1	silas aringarosa remy teacher church dei opus bishop tomb vatican					
3		2	fache collet police message neveu agent phone captain plane sir					
4		3	sophie langdon grandfather priory robert key secret keystone time find					
5		4	rose floor felt line thought chapter cryptex door knew began					
6		5	box vernet bank vinci door head da louvre truck gun					
7		6	teabing grail holy church sophie jesus magdalene documents history ch					
8		7	man back turned felt eyes moment found looked place night					

DocsInTopics.csv
Topics_Words.csv
TopicsInDocs.csv

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
9	docId	filename	top topics	and contribution to doc ...															
10	2	1 C:\Users\I	9	0.21	4	0.188	8	0.147	7	0.13	5	0.13	6	0.063	1	0.055			
11	3	2 C:\Users\I	8	0.232	9	0.21	7	0.143	4	0.095	2	0.095	3	0.072	10	0.068	5	0.057	
	4	3 C:\Users\I	4	0.274	1	0.212	7	0.137	8	0.127	5	0.062	3	0.053					
	5	4 C:\Users\I	1	0.442	7	0.106	8	0.097	4	0.091	6	0.085							
	6	5 C:\Users\I	6	0.175	3	0.165	4	0.146	9	0.124	7	0.098	5	0.097	1	0.076	8	0.062	
	7	6 C:\Users\I	1	0.333	8	0.235	4	0.216	6	0.069									
	8	7 C:\Users\I	1	0.222	2	0.197	7	0.191	8	0.098	6	0.095	9	0.065					
	9	8 C:\Users\I	4	0.242	10	0.18	3	0.178	7	0.118	9	0.104	6	0.065	5	0.057			
	10	9 C:\Users\I	9	0.252	3	0.187	6	0.134	4	0.097	7	0.087	10	0.08	5	0.055	8	0.054	
	11	10 C:\Users\I	4	0.353	8	0.155	7	0.124	9	0.114	10	0.075	5	0.072					
	12	11 C:\Users\I	2	0.314	9	0.24	3	0.097	7	0.09	8	0.073	10	0.072					
	13	12 C:\Users\I	2	0.261	9	0.229	3	0.15	8	0.132	7	0.083							
	14	13 C:\Users\I	9	0.309	2	0.16	3	0.157	8	0.091	7	0.091	6	0.058					
	15	14 C:\Users\I	2	0.459	8	0.176	3	0.102	7	0.083	9	0.059							
	16	15 C:\Users\I	1	0.25	4	0.182	7	0.12	8	0.104	5	0.089	3	0.089	6	0.057			
	17	16 C:\Users\I	3	0.347	8	0.18	2	0.117	7	0.107	9	0.1	10	0.05	4	0.05			
	18	17 C:\Users\I	2	0.354	8	0.173	3	0.116	9	0.104	10	0.065	7	0.057	5	0.051			
	19	18 C:\Users\I	8	0.292	2	0.223	5	0.185	3	0.085	7	0.071	9	0.064	4	0.06			
	20	19 C:\Users\I	8	0.244	1	0.199	4	0.124	3	0.11	9	0.09	5	0.076	7	0.07	6	0.059	
	21	20 C:\Users\I	1	0.312	8	0.157	3	0.114	6	0.107	4	0.1	7	0.084	5	0.066			
	22	21 C:\Users\I	10	0.368	9	0.284	3	0.066	7	0.06	5	0.06	2	0.053					
	23	22 C:\Users\I	3	0.256	9	0.216	5	0.165	8	0.09	7	0.079	2	0.069	4	0.062			
	24	23 C:\Users\I	4	0.461	1	0.145	8	0.07	7	0.068	9	0.066	10	0.062					
	25	24 C:\Users\I	3	0.368	5	0.131	8	0.111	4	0.107	9	0.099	7	0.087					
	26	25 C:\Users\I	4	0.336	8	0.185	1	0.185	3	0.126	6	0.059							
	27	26 C:\Users\I	2	0.457	8	0.104	9	0.098	7	0.098	10	0.069	3	0.069	4	0.064			
	28	27 C:\Users\I	5	0.34	9	0.261	7	0.084	4	0.07	3	0.07	10	0.059					

The default HTML output is a little lacking...

TOPIC : man back turned felt eyes moment found looked place night ...

top-ranked docs in this topic (#words in doc assigned to this topic)

2. (219) chap_67.txt
3. (193) chap_104.txt
4. (180) chap_84.txt
5. (179) chap_99.txt
6. (160) chap_51.txt
7. (153) chap_32.txt
8. (145) chap_81.txt

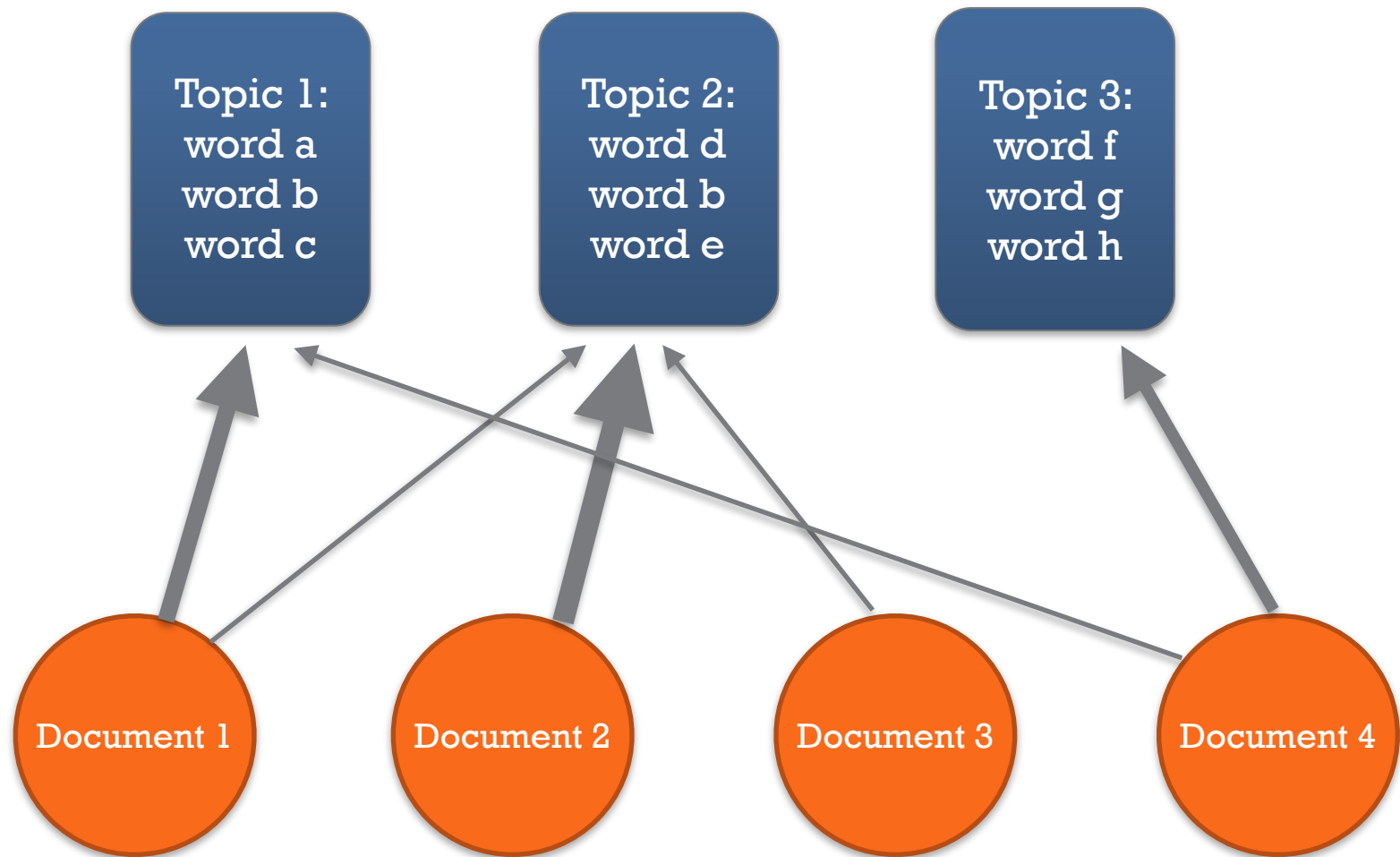
A bipartite graph of chapters and topics is an obvious vis method....

This workshop has lots of code to process these files...
see the .ipynb files and make_gephi_file.py

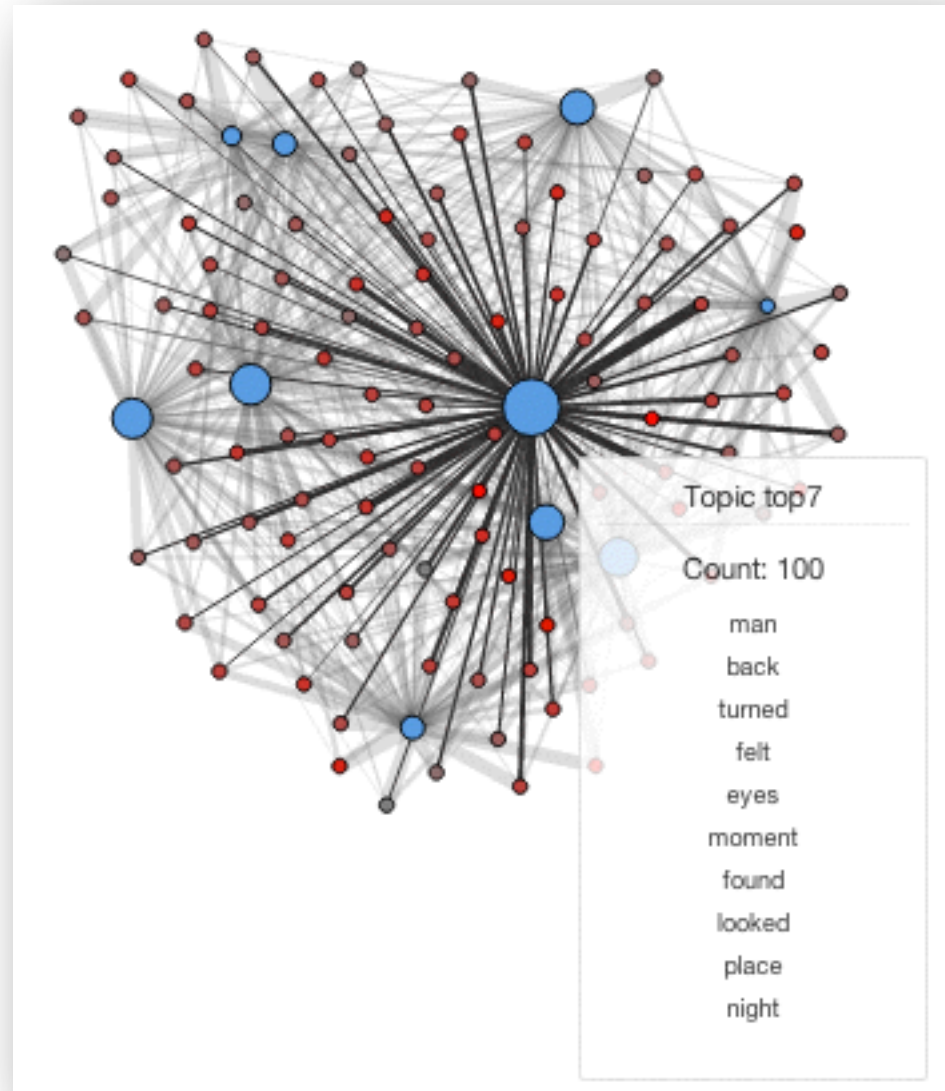
```
In [36]: topics_per_doc = read_doctopics(topic_docs) # keep in mind the input GUI said to cut off classification a

chap_0 {'1': '0.055', '5': '0.130', '4': '0.188', '7': '0.130', '6': '0.063', '9': '0.210', '8': '0.147'}
chap_1 {'10': '0.068', '3': '0.072', '2': '0.095', '5': '0.057', '4': '0.095', '7': '0.143', '9': '0.210'}
chap_10 {'1': '0.212', '3': '0.053', '5': '0.062', '4': '0.274', '7': '0.137', '8': '0.127'}
chap_100 {'1': '0.442', '8': '0.097', '4': '0.091', '7': '0.106', '6': '0.085'}
chap_101 {'1': '0.076', '3': '0.165', '5': '0.097', '4': '0.146', '7': '0.098', '6': '0.175', '9': '0.124'}
chap_102 {'1': '0.333', '8': '0.235', '4': '0.216', '6': '0.069'}
chap_103 {'1': '0.222', '2': '0.197', '7': '0.191', '6': '0.095', '9': '0.065', '8': '0.098'}
chap_104 {'10': '0.180', '3': '0.178', '5': '0.057', '4': '0.242', '7': '0.118', '6': '0.065', '9': '0.10'}
chap_105 {'10': '0.080', '3': '0.187', '5': '0.055', '4': '0.097', '7': '0.087', '6': '0.134', '9': '0.25'}
chap_106 {'10': '0.075', '5': '0.072', '4': '0.353', '7': '0.124', '9': '0.114', '8': '0.155'}
chap_11 {'10': '0.072', '3': '0.097', '2': '0.314', '7': '0.090', '9': '0.240', '8': '0.073'}
chap_12 {'9': '0.229', '8': '0.132', '3': '0.150', '2': '0.261', '7': '0.083'}
chap_13 {'3': '0.157', '2': '0.160', '7': '0.091', '6': '0.058', '9': '0.309', '8': '0.091'}
chap_14 {'9': '0.059', '8': '0.176', '3': '0.102', '2': '0.459', '7': '0.083'}
```

The results of topic modeling



The basic idea... without coding so much.



chap_41

Excitement: 0.5

Demo:
http://www.ghostweather.com/essays/talks/openvisconf/topic_docs_network/index_better.html

Our next step: Process GUI CSV Output

After running the Topic Modeling gui, we start with the IPython notebook “Topic Analysis of Mixed Fiction.ipynb.”

If you want to run the notebooks, make sure you are in an active virtual env:

```
> source activate topic_workshop  
(topic_workshop)> ipython notebook
```

If you don't want to run it, you can achieve the same outputs with the path to the gui output csv file:

```
(topic_workshop)> cd files  
(topic_workshop)> python make_gephi_file.py topic_output/output_csv all
```

Our next steps:

1. Excel pivot table analysis with the for_excel.csv file
2. Gephi for the gdf file output!

Tips on Gephi layout and UI are in the PDF:

GephiToSigmaJS_Mixed.pdf

Item of Score	Topic0	Topic1	Topic2	Topic3	Topic4	Topic5	Topic6	Topic7	Topic8	Topic9	Topic10	Topic11	Topic12	Topic13	Topic14	Topic15	Topic16	Topic17	Grand Total
Author	0.237	0.144		0.06															0.36
Battle																			1.764
Brown	0.147																		1.294
Conrad		0.485	0.115																1.275
World	0.102		0.119	1.1															1.908
Walt	0.482		0.11																1.908
Germany																			1.908
James	0.113		0.09																1.908
World																			1.908
Major	0.122																		1.908
Discussion																			1.908
Grand Total	1.303	0.485	1.505	1.1	1.161	1.876	1.348	2.705	0.318	1.31	0.368	0.881	0.892	0.313	1.004				27.428



How can you improve on the results?

Iterate on number of topics you output. Try 10, instead of 15!

Rerun the GUI with 10, then use command line:

```
> cd files
```

```
> python make_gephi_file.py topic_output/output_csv 10
```

How else can you improve?

Pre-process the documents — change what's modeled! Maybe only verbs?

- Use stop words tuned for your data set (don't want proper nouns? or only proper nouns?)
- Read in a document, parse it, save out a new “document” of the POS you want, then use those in the topic modeler

Our next step... Preprocess docs.

Use the notebook POS_Text_Conversion.ipynb

In this notebook, we'll look at how to handle text: tokenize it, clean it, strip out words/punctuation, find parts of speech...

For faster, command-line use (requires pattern and nltk installed!)

```
>cd files
```

```
>python preprocess_files.py ../data/mixed_chapters ../data/verbs_only VB
```

Now look at those results...

1. Make a directory for the new topic modeled files under files:

```
>mkdir verb_output
```

2. Rerun the GUI with this as output directory, and the verb files as your input files!

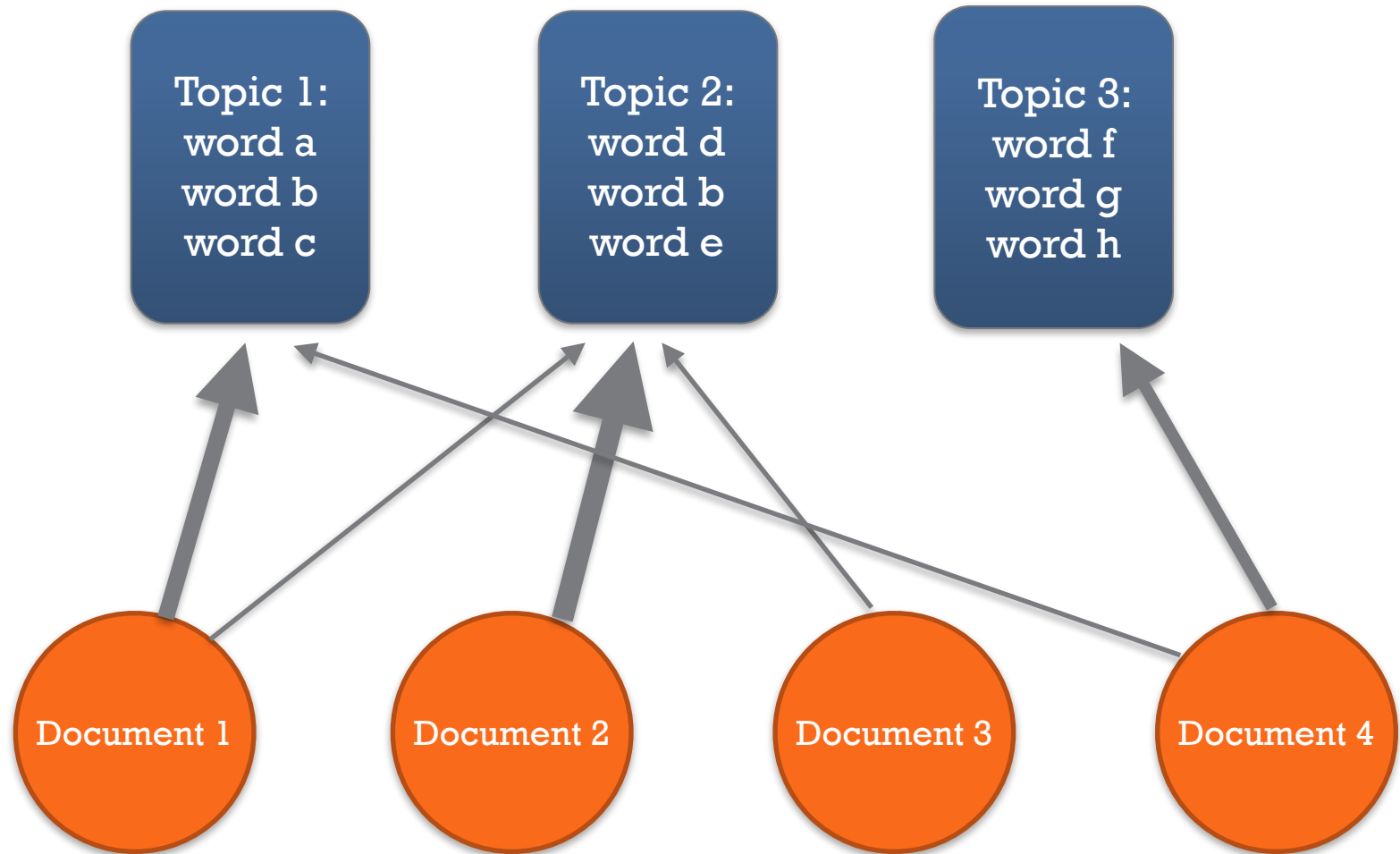
3. Then use command line:

```
> cd files
```

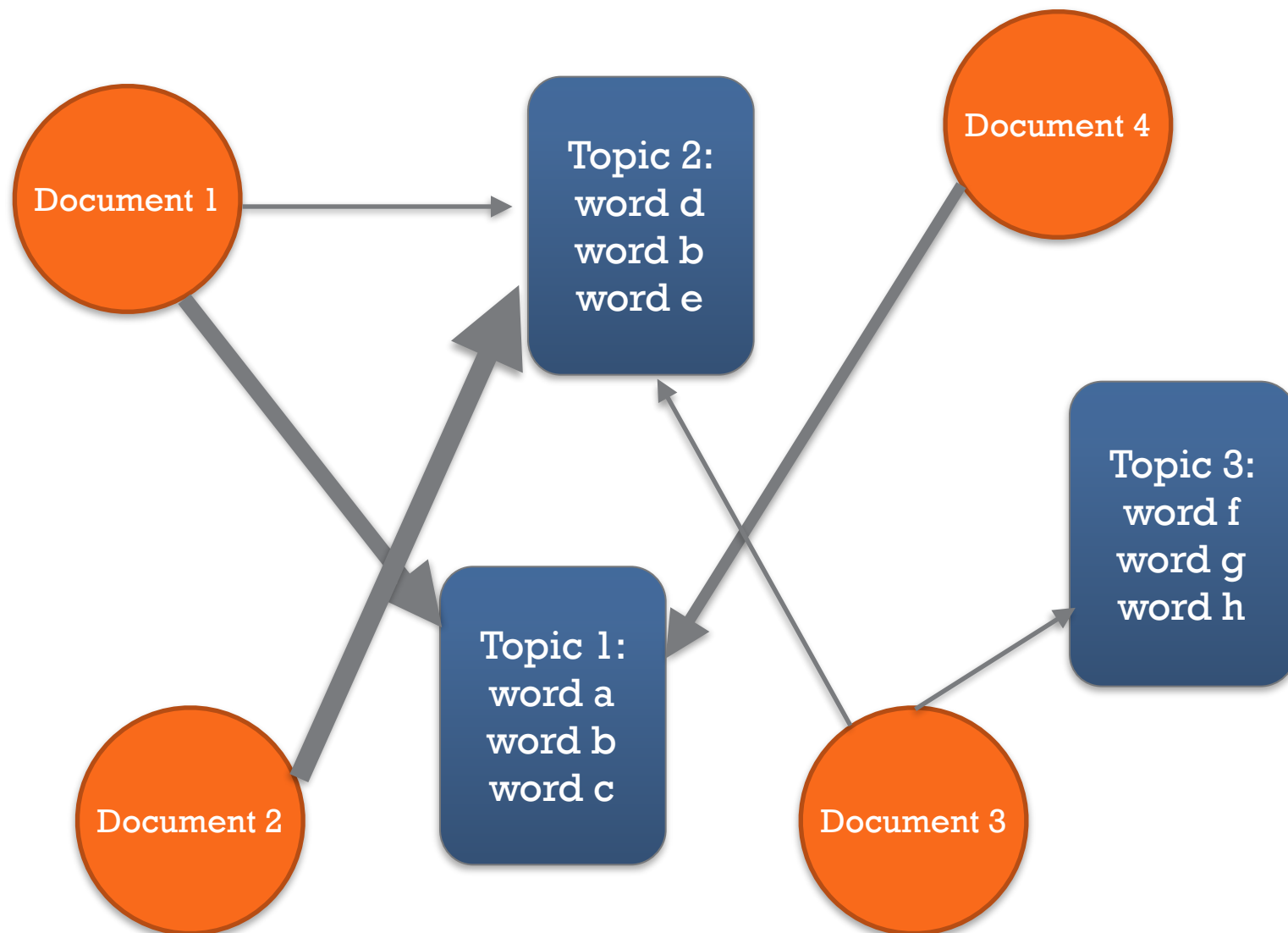
```
> python make_gephi_file.py verb_output/output_csv verbs
```

4. Then find the output
for_gephi_topics_verbs.gdf & visualize in Gephi.

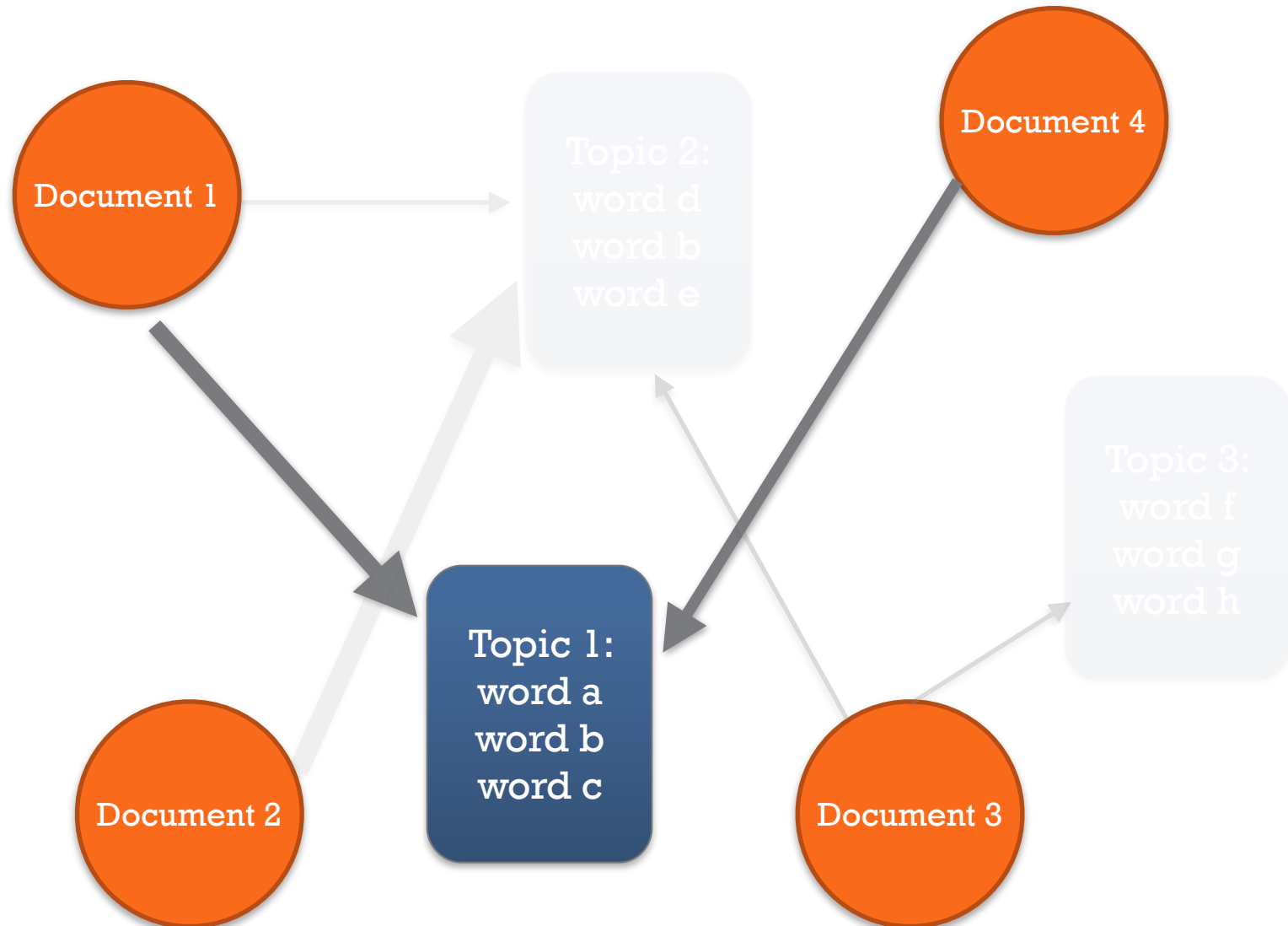
How we started...



Another view: More Like Ours



Another view: Related Document to Document



Going to D3

- Raw nodes-edges json:
 - export json from gephi (using JSON plugin)
 - or post-process and create the json: see next step
 - Example of d3 network use: <http://bl.ocks.org/mbostock/4062045>
- Export gexf and use Elijah Meeks' code to process and display it from gexf format:
 - <http://bl.ocks.org/emeeks/9357371>

But we need to account for link weights

- Doc A — Topic 1, 40% words
- Doc B — Topic 1, 20% words
- How do you compute the weight of the relation between the Doc A and Doc B?
 - Options: difference ($1 / \text{diff}$) (normalized)
 - Average, Median, Count of edges

Our next step... Advanced: Doc to Doc in D3.

We want to combine some of the output we created as JSON files.

Use code in Advanced-D3 and GEXF Network of Docs Only.ipynb or files/d3_gexf.py.

From the command line:

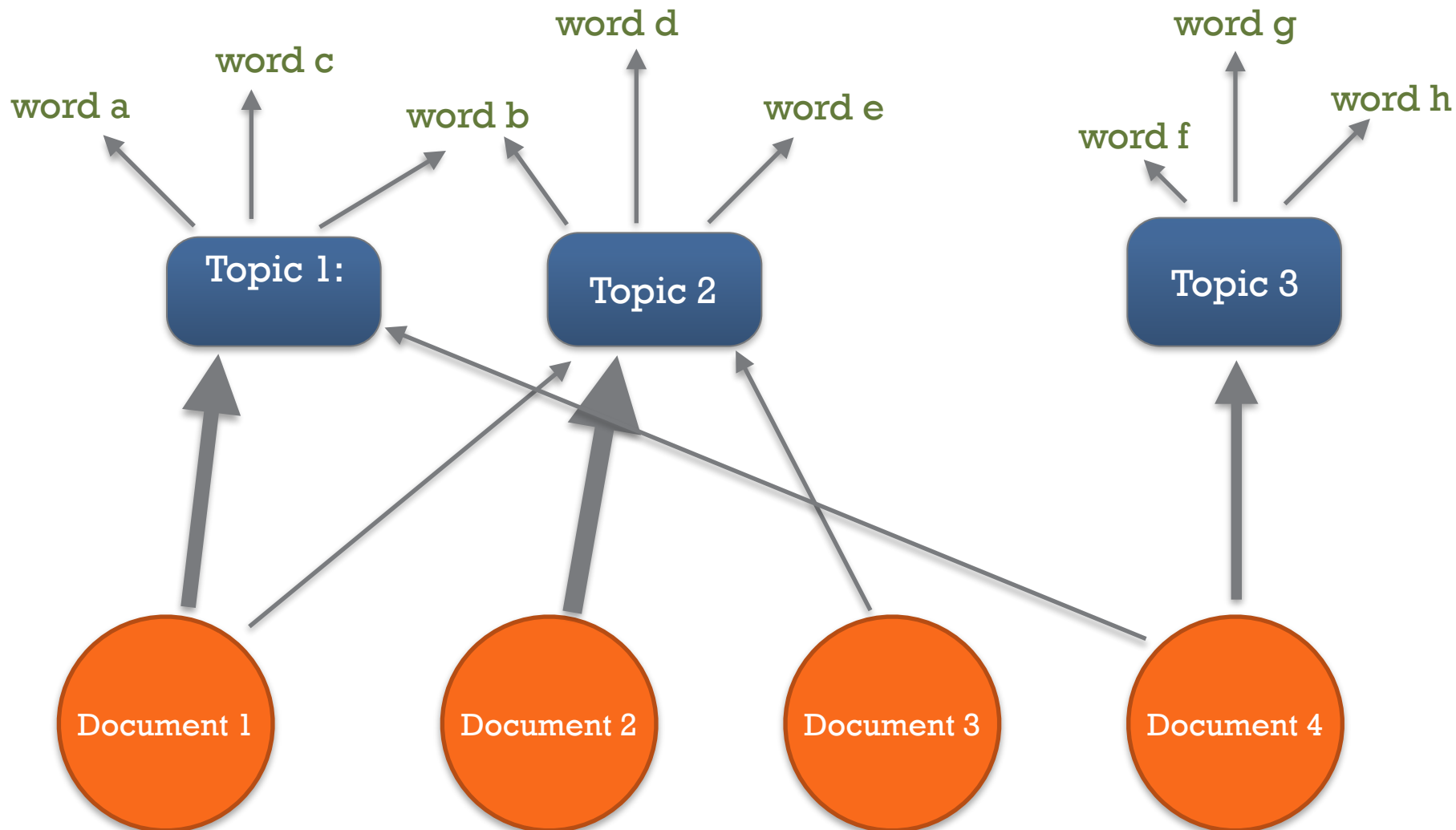
```
>cd files
```

```
>python d3_gexf.py for_excel.csv all for_excel_verbs.csv verbs
```

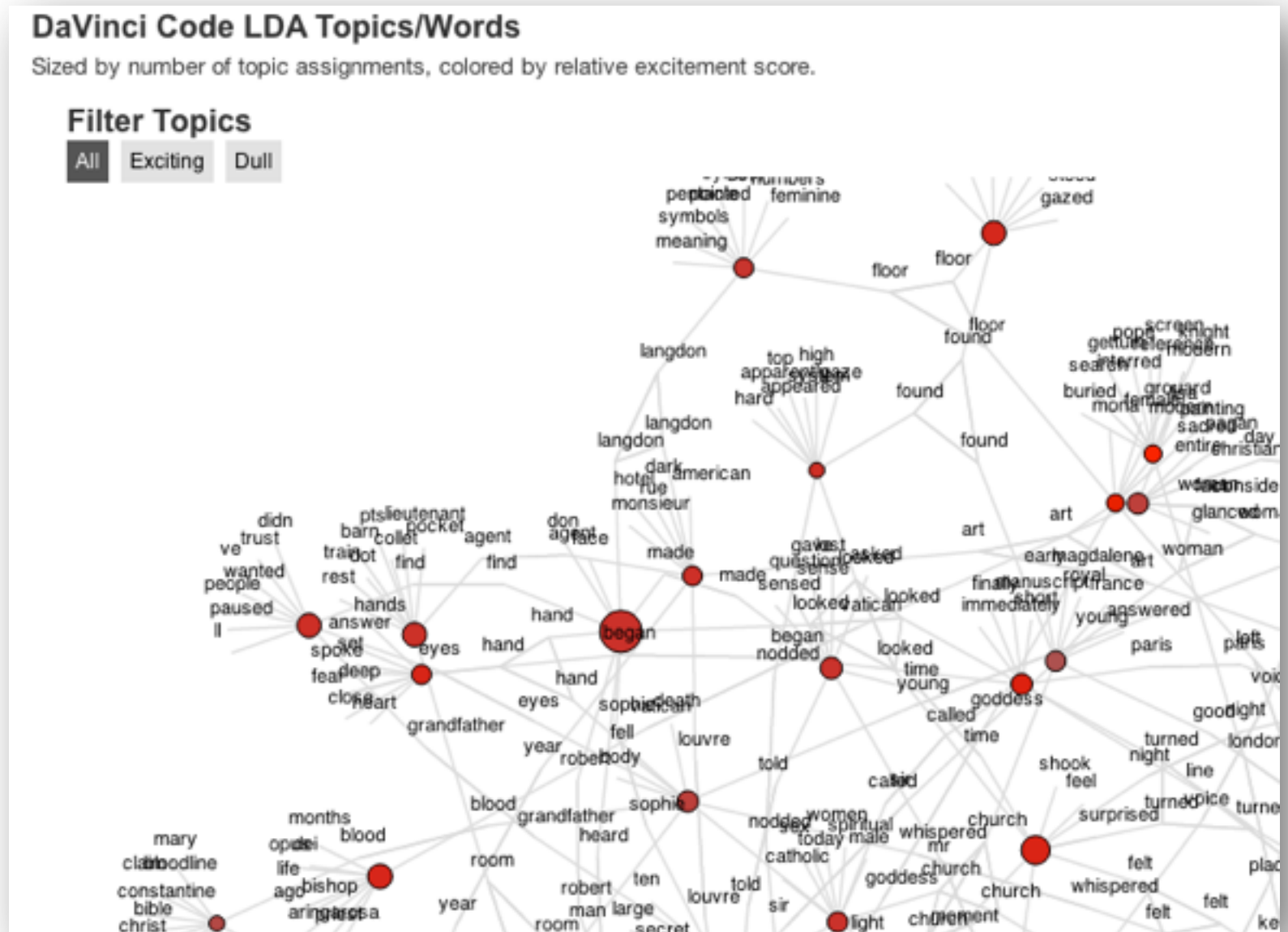

Output

- gexf file — for use in gephi if you want
- json files for use in d3
- combined json, if you input 2 csv files. Don't forget you need to include labels after each csv filename!

A further level of network you could draw....



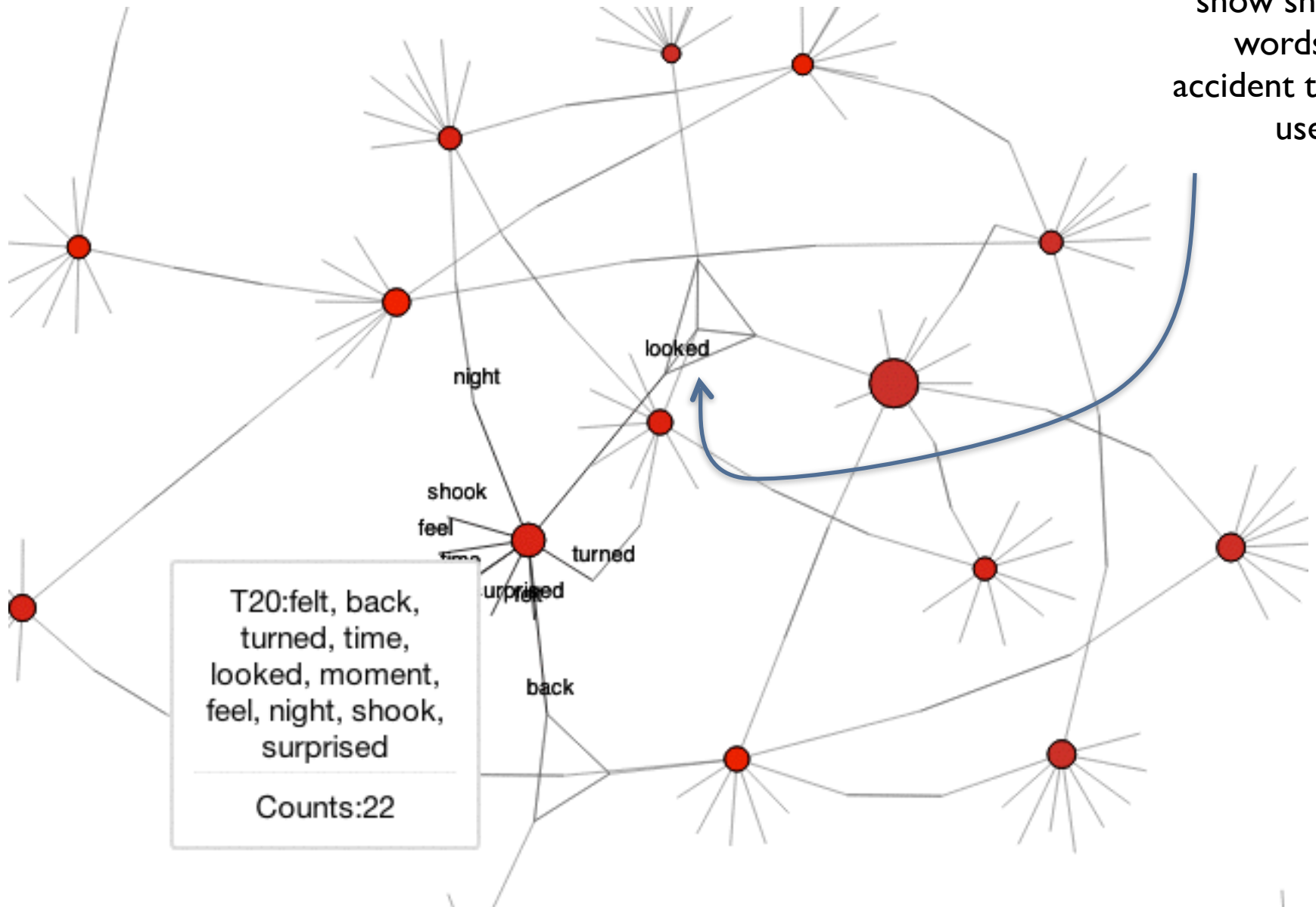
Maybe I need One More Tool. Any word relations of interest?
Let's try another hairball...



Demo: http://www.ghostweather.com/essays/talks/openvisconf/topic_words_network/index.html

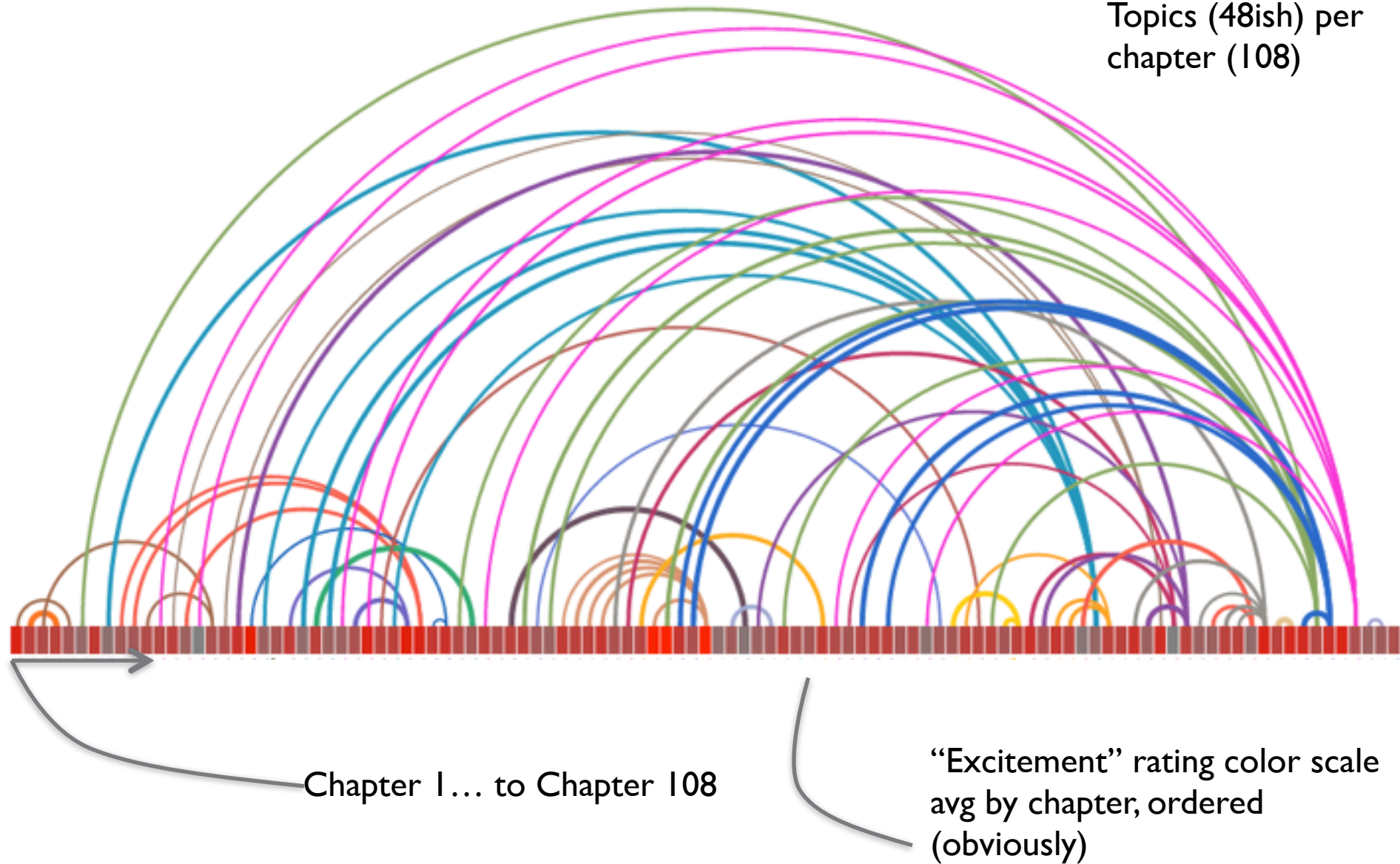
Filtered to only the
“exciting” nodes...

Small
“constellations”
show shared
words (an
accident that’s
useful!)



Another tool: Sequential documents, with topic arcs.
DaVinci Code topics to chapters mapping

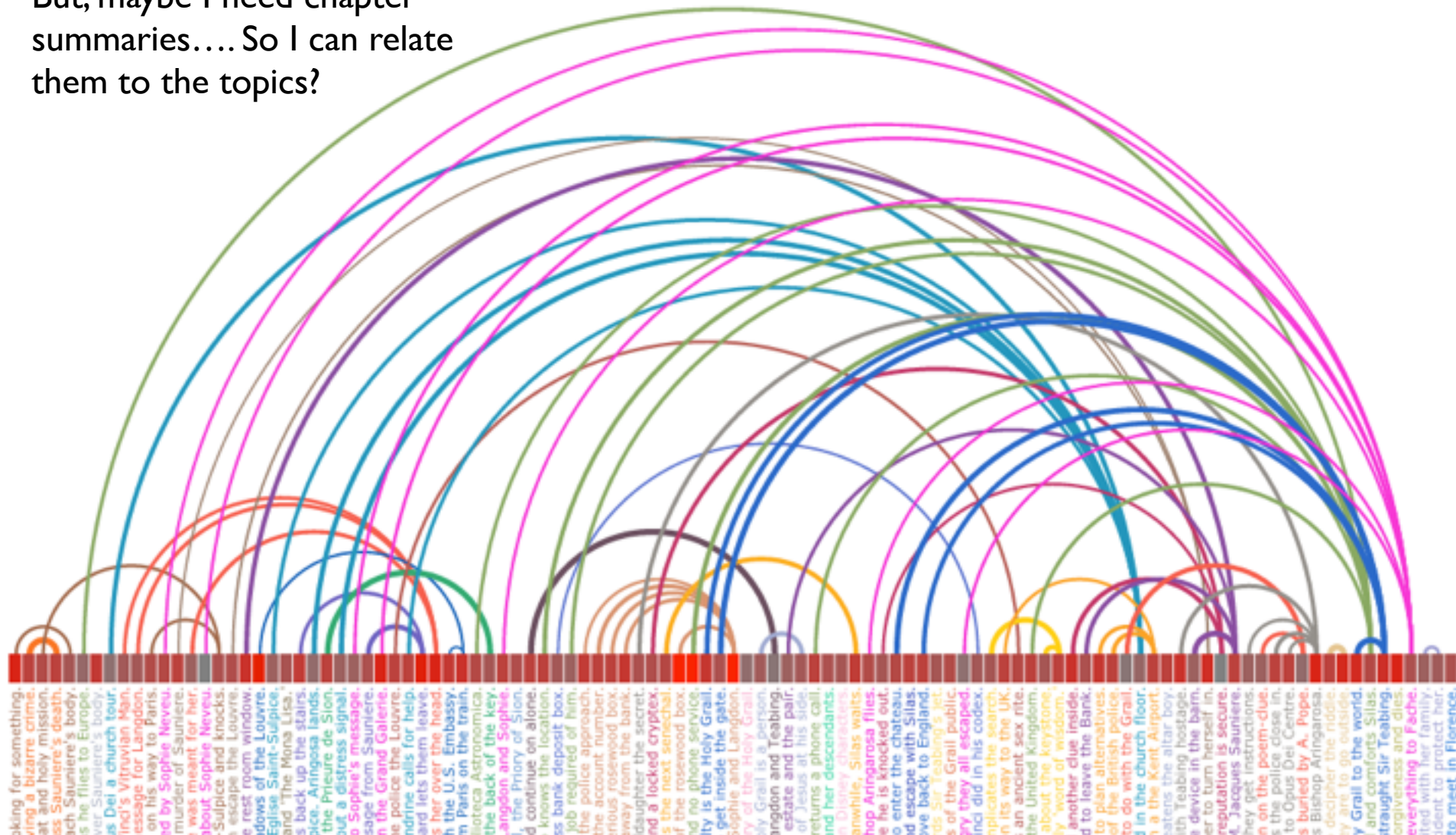
Topics (48ish) per
chapter (108)



Chapter 1... to Chapter 108

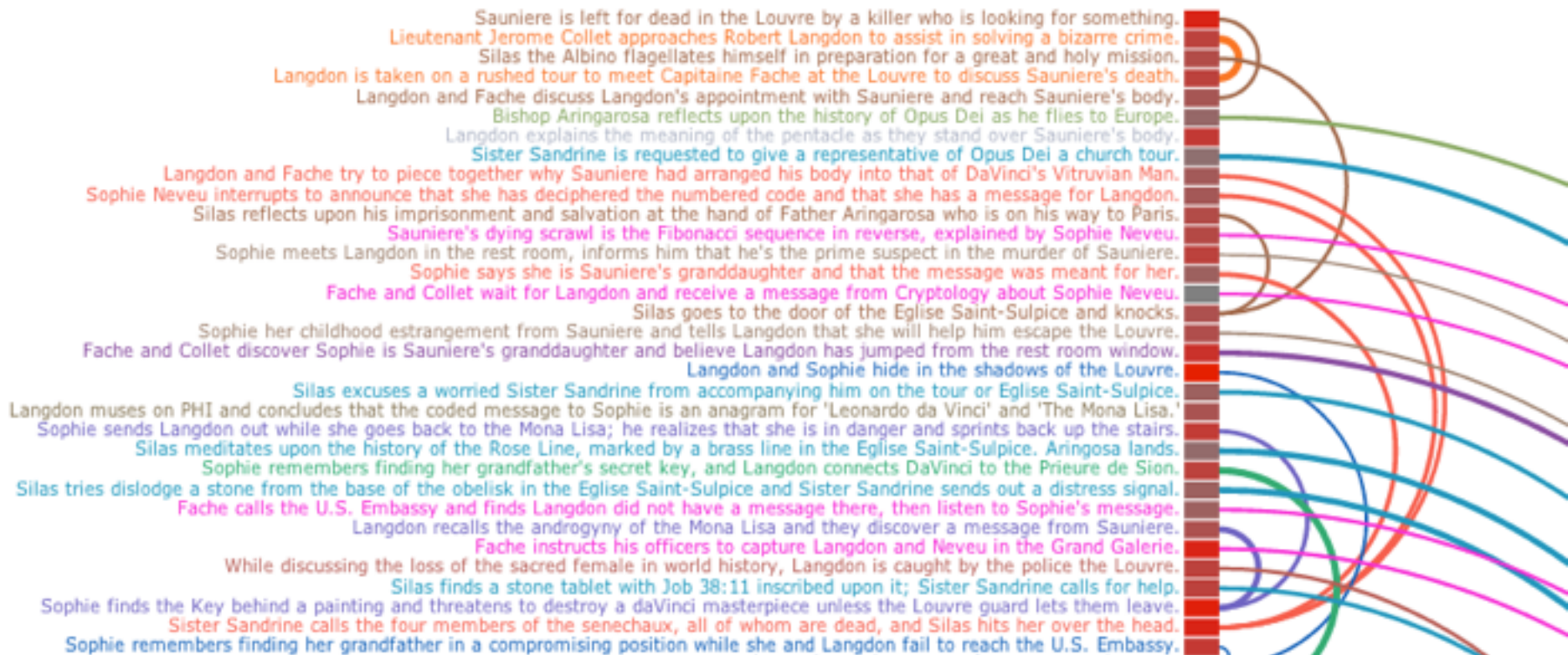
“Excitement” rating color scale
avg by chapter, ordered
(obviously)

But, maybe I need chapter summaries.... So I can relate them to the topics?



Ah, but since it's svg/d3...

```
var chart = chart.append("g").attr("translate", "0," +  
y).attr("transform", "rotate(90 600 600)");
```

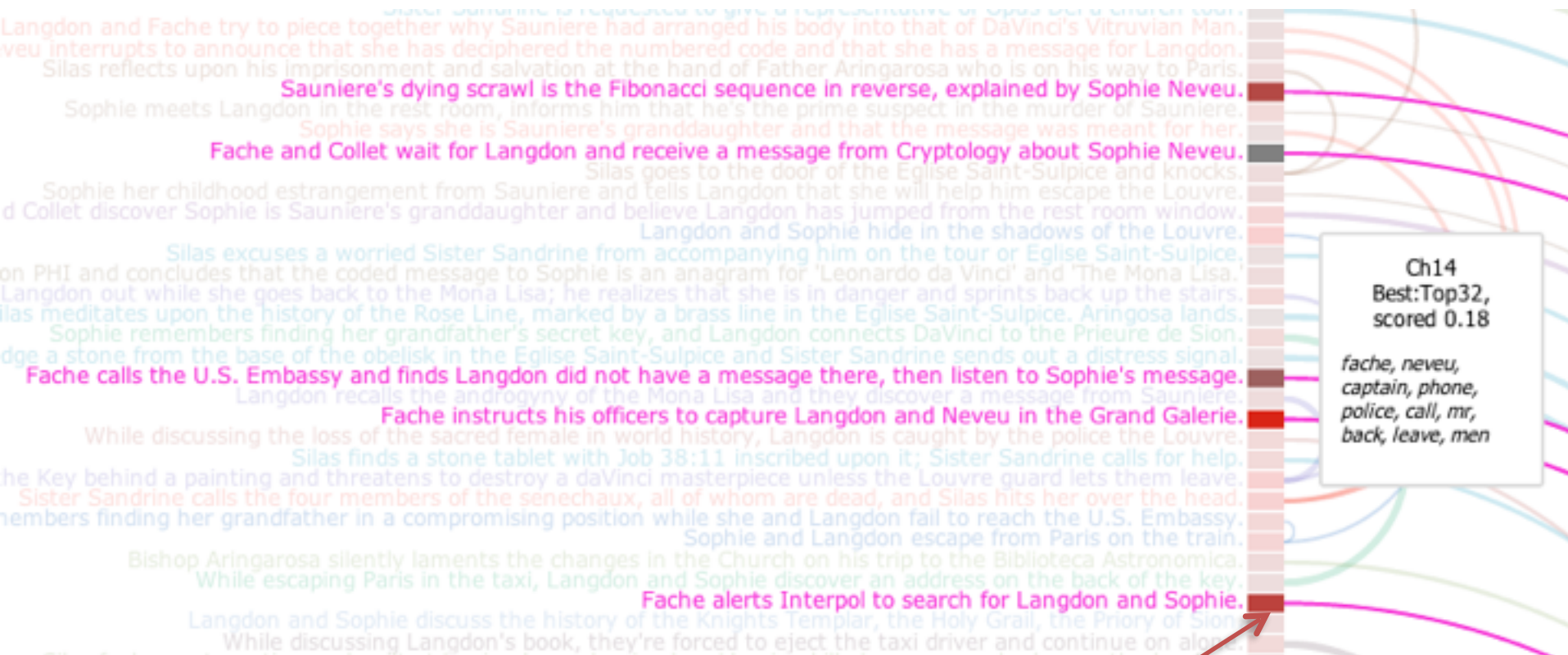


Add some topic-tooltips
and fade-outs....



But what did this show?

Some topics are just neither exciting nor dull – topic clustering (as I did it) had little to do with action scenes. It's slightly helpful for topics, though ☺



These nodes are shaded from
gray (dull) to red (exciting)

Improve the Results Display

- Visualize differently or more (chords, matrix...)
- Look for the topic words “in context” - find sentences with them and use those as part of your topic description
- Construct phrases from your topic words to make them “better” for descriptors
- Use only the interesting output words for a topic
- Don’t use the result immediately — use as input to other methods (it’s a data reduction technique like principal components analysis)

A Few More References

- Scott Weingart's nice overview of LDA Topic Modeling in Digital Humanities: <http://www.scottbot.net/HIAL/?p=221>
- Elijah Meeks' lovely set of articles on LDA & Digital Humanities vis: <https://dhs.stanford.edu/comprehending-the-digital-humanities/>
- Some pure python (and C) implementations (toy code, primarily) are listed on Blei's website: <http://www.cs.princeton.edu/~blei/topicmodeling.html>