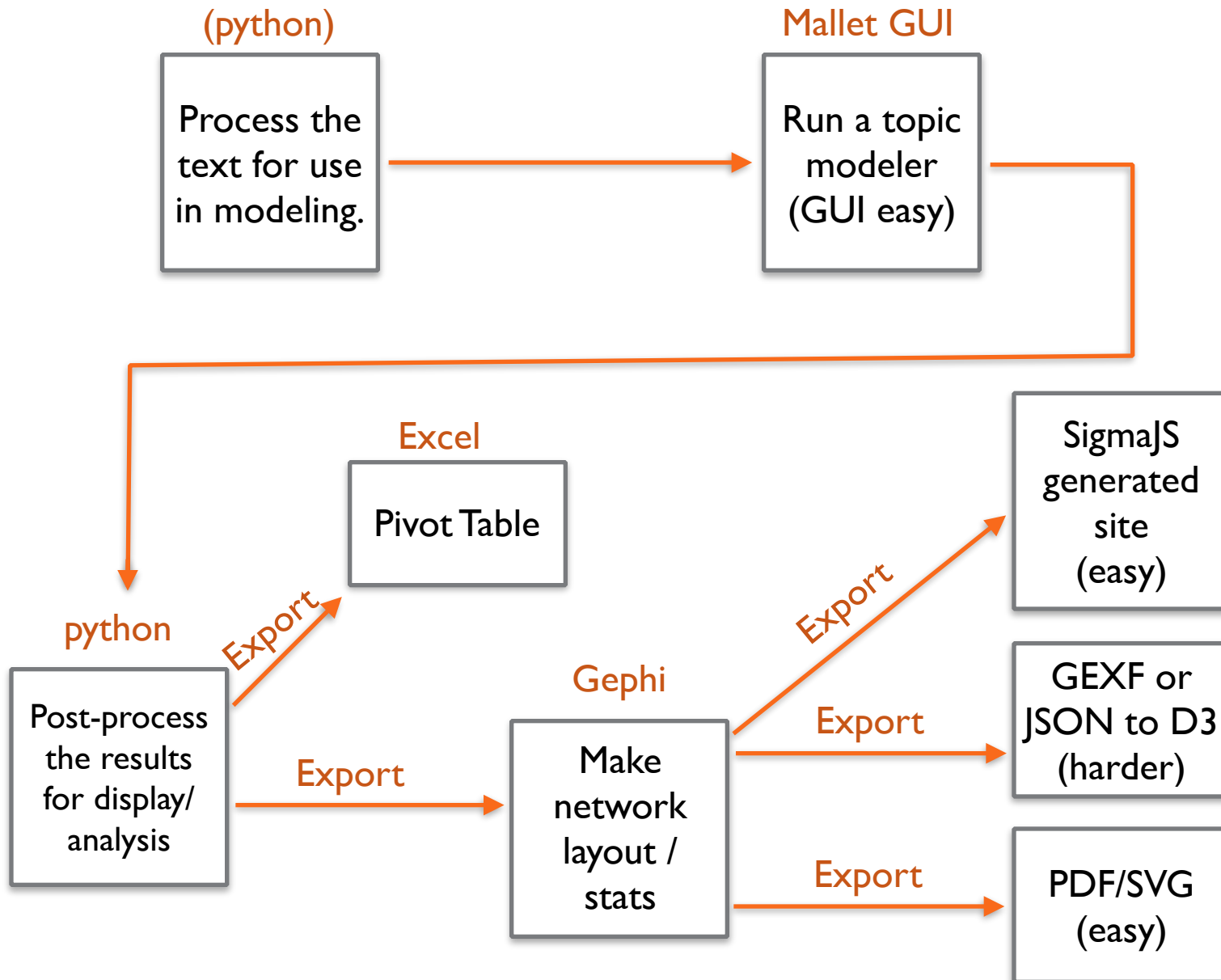


**WHAT IS TOPIC ANALYSIS?**

# 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

# Workflow for Today



# 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

## 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, a Uppsala University in Sweden researcher 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

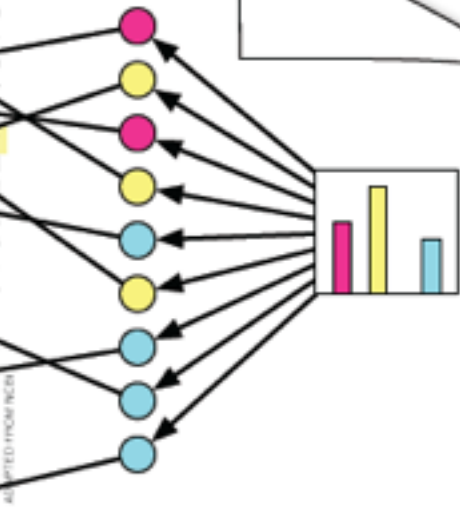


\* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

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

SCIENCE • VOL. 272 • 24 MAY 1996

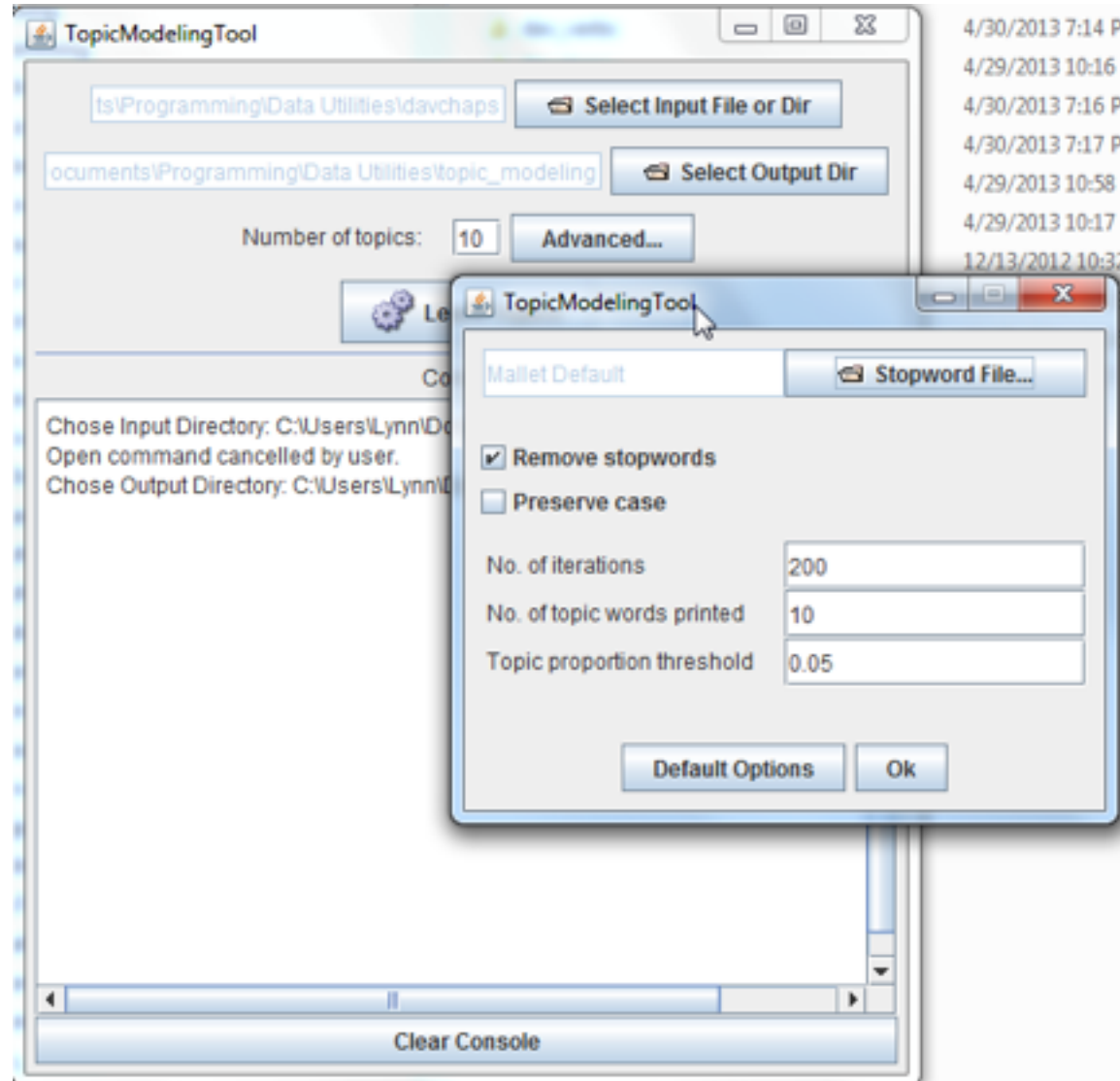
## Topic proportions and assignments



# David Newman's Topic Modeling GUI

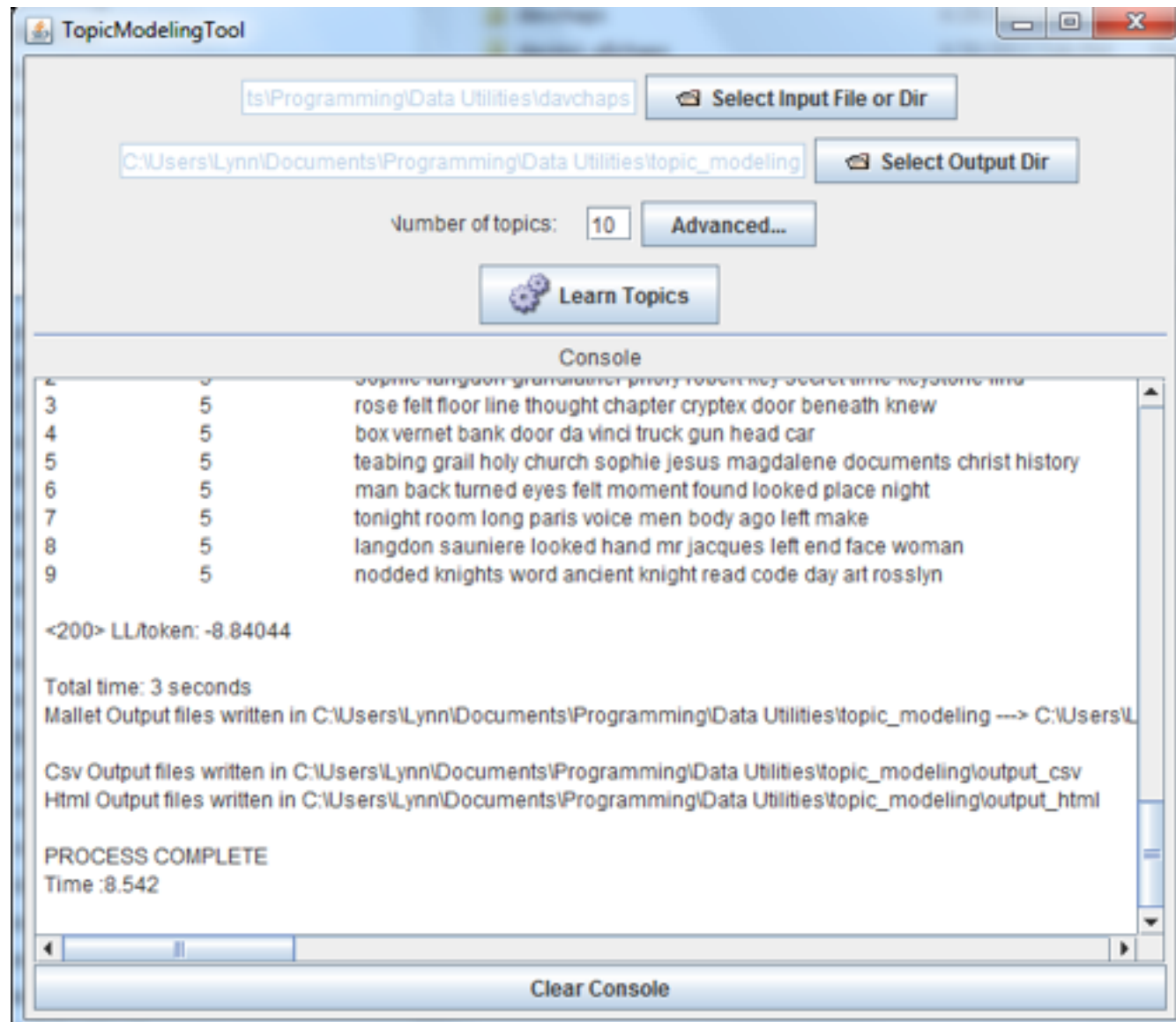
- Make a tool available for non-technical audiences! A GUI wrapper on the state-of-the-art `mallet` (java-based app by David Mimno).
- His overview slides:
- More of his work: <http://www.ics.uci.edu/~newman/>

# Topic Modeling Tool (GUI)





# 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), web site browser

## output\_csv

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

## output\_html

all\_topics.html

# Mallet command line

- You could also run mallet from the command line:
  - <http://programminghistorian.org/lessons/topic-modeling-and-mallet>
- Or use a Python wrapper:
  - <http://radimrehurek.com/2014/03/tutorial-on-mallet-in-python/>
  - To do the rest of this workshop, you'll need to process the output files yourself (assume \t seps, not csv)

# Pros/Cons vs CMD-Line Mallet

## Pros of GUI




- Allows stopword file specifying
- Produces csv and html output in a near dir structure
- Has a GUI (simpler to just get going without code and help)

## Cons of GUI

- Runs with defaults, so no optimize-interval or other cmd line options
- No diagnostic output (a command-line option)

# 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 |    |       |   |       |   |

# Notice a horrible thing here:

| docId | filename   | top topics | and contribution to doc ... |    |       |
|-------|--|------------|-----------------------------|----|-------|
| 1     | C:\Users\Lynn\Documents\Programming\Data Utilities\davchaps\chap_0.txt   | 9          | 0.21                        | 4  | 0.188 |
| 2     | C:\Users\Lynn\Documents\Programming\Data Utilities\davchaps\chap_1.txt   | 8          | 0.232                       | 9  | 0.21  |
| 3     | C:\Users\Lynn\Documents\Programming\Data Utilities\davchaps\chap_10.txt  | 4          | 0.274                       | 1  | 0.212 |
| 4     | C:\Users\Lynn\Documents\Programming\Data Utilities\davchaps\chap_100.txt | 1          | 0.442                       | 7  | 0.106 |
| 5     | C:\Users\Lynn\Documents\Programming\Data Utilities\davchaps\chap_101.txt | 6          | 0.175                       | 3  | 0.165 |
| 6     | C:\Users\Lynn\Documents\Programming\Data Utilities\davchaps\chap_102.txt | 1          | 0.333                       | 8  | 0.235 |
| 7     | C:\Users\Lynn\Documents\Programming\Data Utilities\davchaps\chap_103.txt | 1          | 0.222                       | 2  | 0.197 |
| 8     | C:\Users\Lynn\Documents\Programming\Data Utilities\davchaps\chap_104.txt | 4          | 0.242                       | 10 | 0.18  |
| 9     | C:\Users\Lynn\Documents\Programming\Data Utilities\davchaps\chap_105.txt | 9          | 0.252                       | 3  | 0.187 |
| 10    | C:\Users\Lynn\Documents\Programming\Data Utilities\davchaps\chap_106.txt | 4          | 0.353                       | 8  | 0.155 |
| 11    | C:\Users\Lynn\Documents\Programming\Data Utilities\davchaps\chap_11.txt  | 2          | 0.214                       | 0  | 0.24  |

This workshop has lots of code to process these files...  
see the .ipynb files and make\_gephi\_file.py

```
def read_doctopics(filename):  
    from collections import defaultdict  
    """ Takes topic_docs and outputs a dict style of topic assignment |"""  
    docs = defaultdict(list) # set because you  
    with open(filename, 'rb') as csvfile:  
        spamreader = csv.reader(csvfile, delimiter=',', quotechar='"')  
        for row in spamreader:  
            if spamreader.line_num > 1:  
                docid = stripdir(row[1]) # beware not to use docid from the file in row[0]  
                topics = row[2:]  
                topics_dict = dict(zip(topics[:2], topics[1::2]))  
                print docid, topics_dict  
                docs[docid] = (topics_dict)  
    return docs
```

```
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 default HTML output is a little lacking...

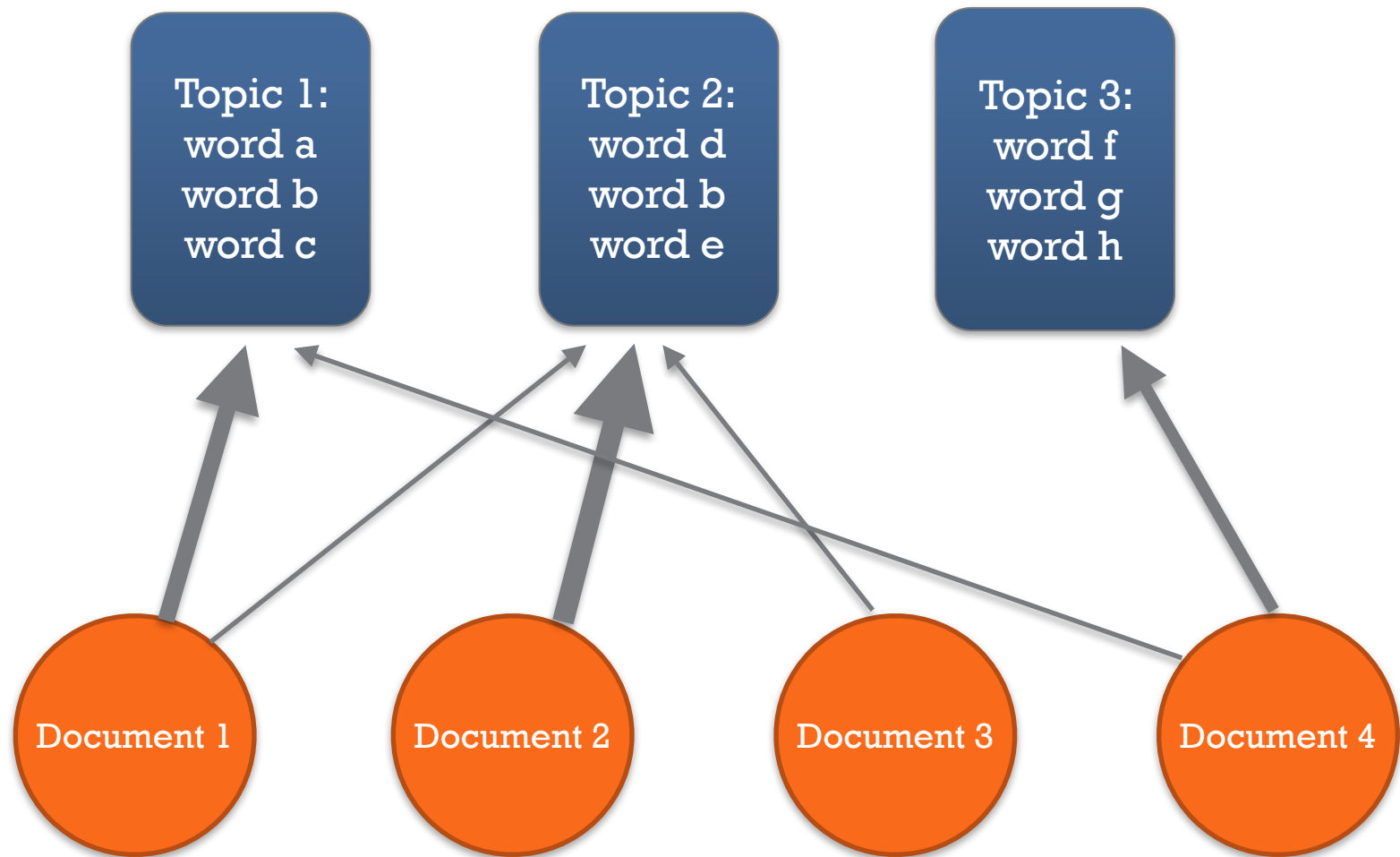
**TOPIC : man back turned felt eyes moment found looked place night ...**

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....

# The results of topic modeling



# Going to D3

- Raw nodes-edges json
  - export json from gephi
  - or post-process and create the json
- Export gexf and use Elijah Meeks' code to process and display it:
  - <http://bl.ocks.org/emeeks/9357371>

# Network JSON for D3.js, this format:

```
nodes[0:10]
```

```
[{'name': 'chap_28', 'other': '1', 'type': 'doc'},  
 {'name': 'chap_29', 'other': '1', 'type': 'doc'},  
 {'name': 'chap_20', 'other': '0.714285714', 'type': 'doc'},  
 {'name': 'chap_21', 'other': '1.1', 'type': 'doc'},  
 {'name': 'chap_22', 'other': '0.333333333', 'type': 'doc'},  
 {'name': 'chap_23', 'other': '1', 'type': 'doc'},  
 {'name': 'chap_24', 'other': '0.5', 'type': 'doc'},  
 {'name': 'chap_25', 'other': '0.5', 'type': 'doc'},  
 {'name': 'chap_26', 'other': '0.75', 'type': 'doc'},  
 {'name': 'chap_27', 'other': '1.5', 'type': 'doc'}]
```

```
links[0:10]
```

```
[{'source': 'chap_28', 'strength': '0.073', 'target': 'top10'},  
 {'source': 'chap_28', 'strength': '0.108', 'target': 'top3'},  
 {'source': 'chap_28', 'strength': '0.077', 'target': 'top5'},  
 {'source': 'chap_28', 'strength': '0.083', 'target': 'top4'},  
 {'source': 'chap_28', 'strength': '0.071', 'target': 'top7'},  
 {'source': 'chap_28', 'strength': '0.183', 'target': 'top6'},  
 {'source': 'chap_28', 'strength': '0.270', 'target': 'top9'},  
 {'source': 'chap_28', 'strength': '0.073', 'target': 'top8'},  
 {'source': 'chap_29', 'strength': '0.090', 'target': 'top10'},  
 {'source': 'chap_29', 'strength': '0.110', 'target': 'top1'}]
```

# Making the objects:

Make objects of nodes, links, and any extra data values on each that you want...

```
def make_nodes_links(results, otherdata=None):

    """ Write out dicts for later creating a json file of nodes/links from a results array of 'doc, topic, strength' values.
    Must make sure the 'otherdata' dict has the same keys as the chapter names here."""

    chapters = set()
    topics = set()

    for x in results:
        chapters.add(x[0])
        topics.add(x[1])

    chapters = list(chapters)
    topics = list(topics)

    nodes = []

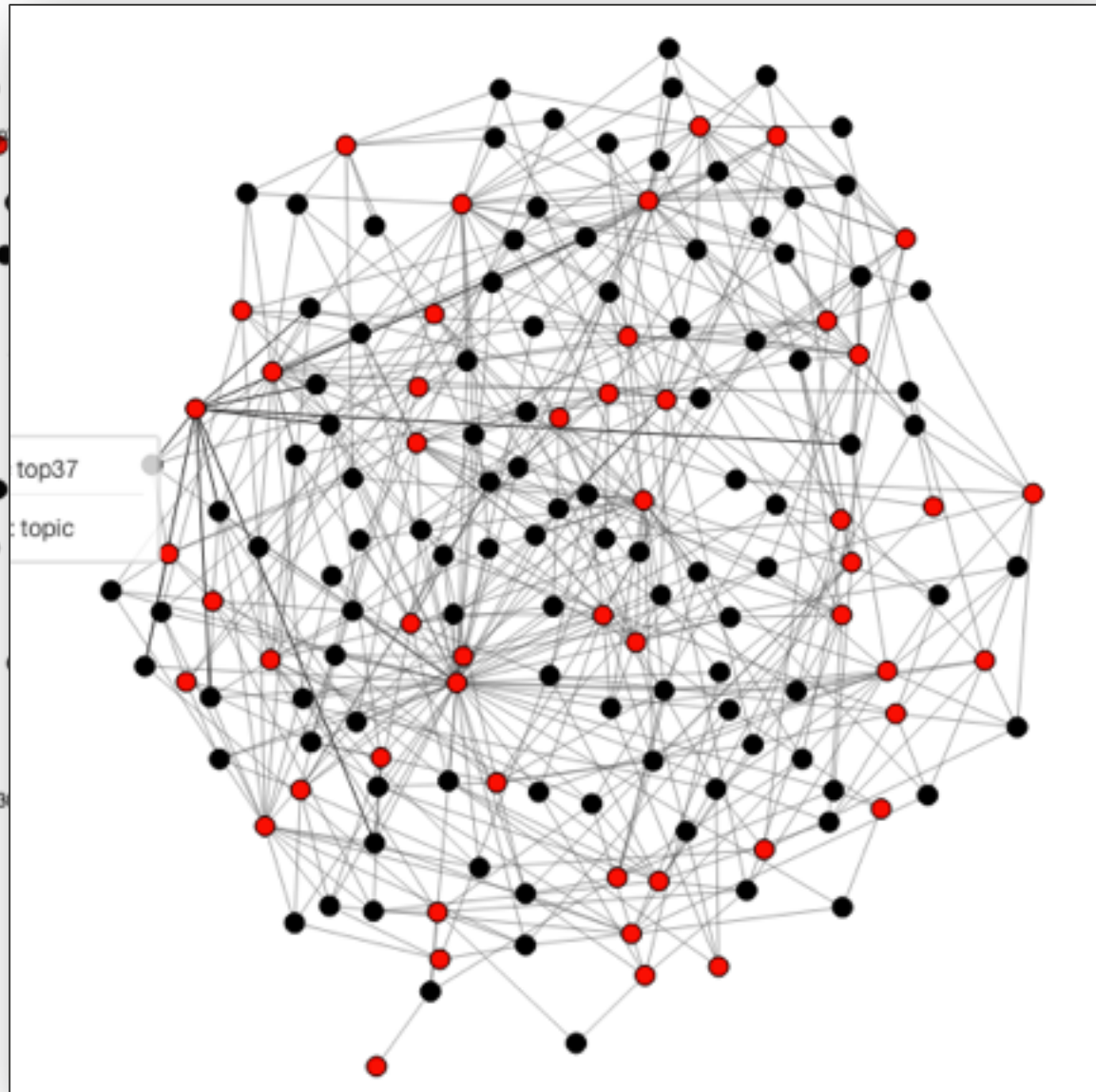
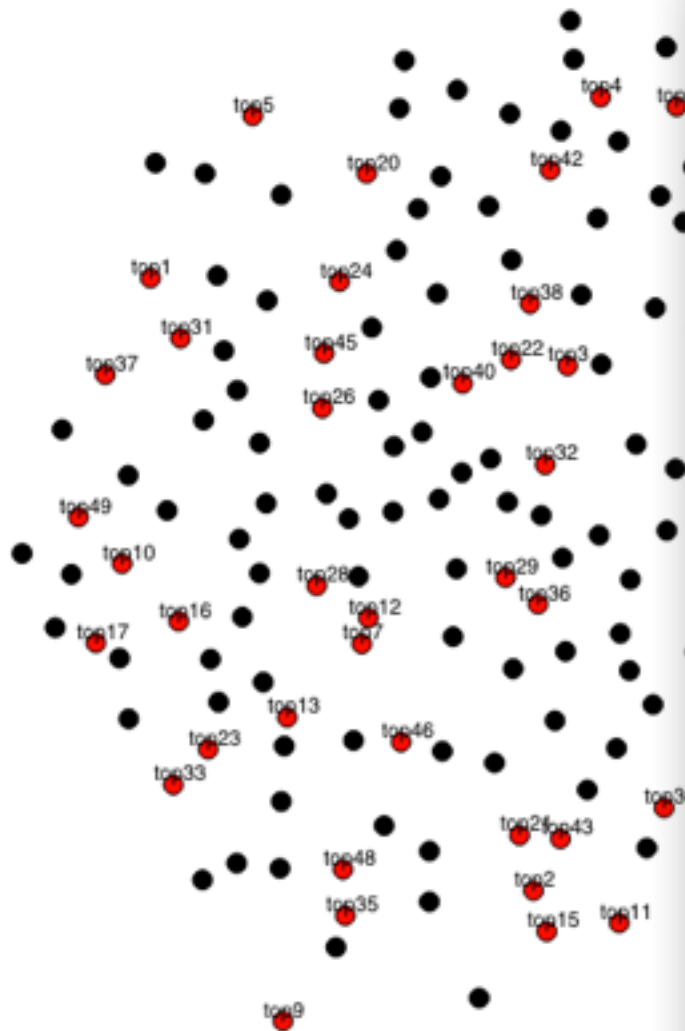
    for chapter in chapters:
        if otherdata:
            nodes.append({"name": chapter, "type": "doc", "other": otherdata[chapter]})
        else:
            nodes.append({"name": chapter, "type": "doc"})

    for topic in topics:
        nodes.append({"name": "top" + topic, "type": "topic"})

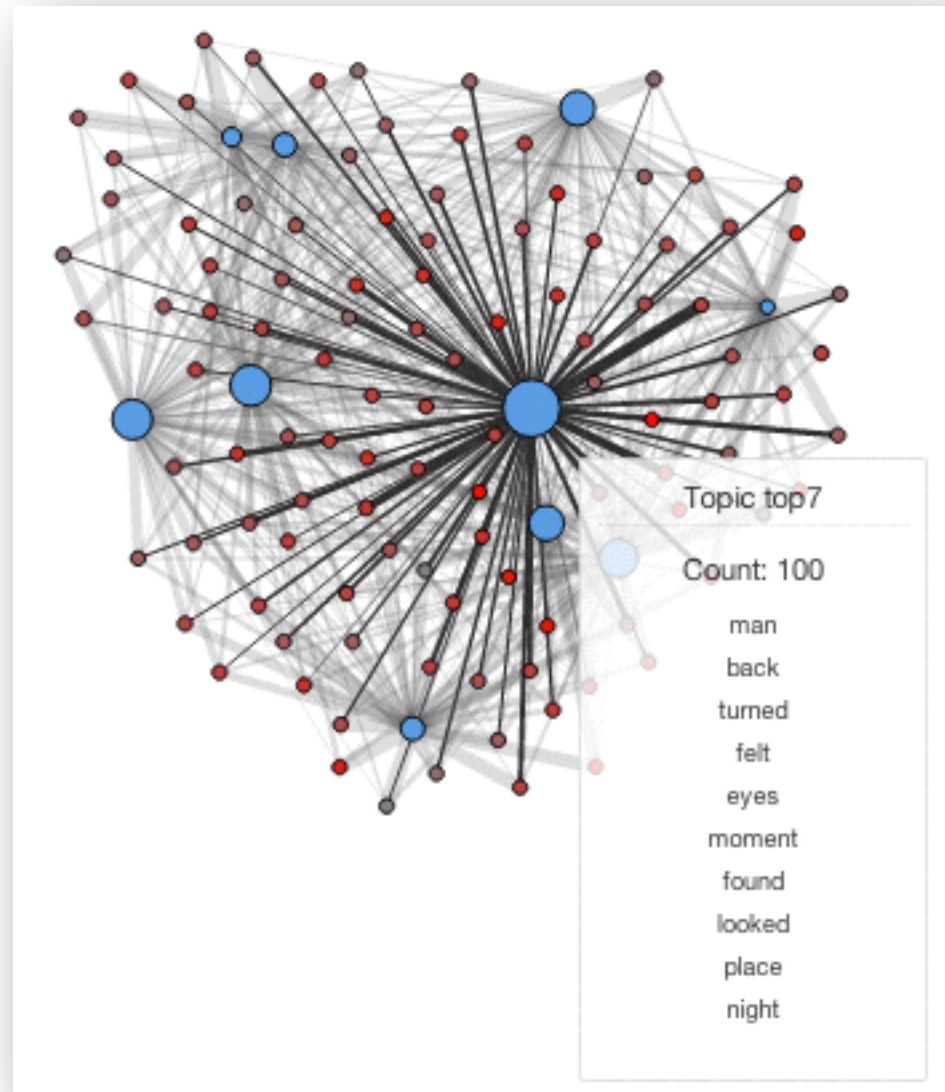
    links = []
    for x in results:
        doc = x[0]
        topic = x[1]
        strength = x[2]
        links.append({"source": doc, "target": "top" + topic, "strength": strength})

    return nodes, links
```

# Let's try a hairball!



# Improving the network's UI...



chap\_41

Excitement: 0.5

Demo:  
[http://www.ghostweather.com/essays/talks/openvisconf/topic\\_docs\\_network/index\\_better.html](http://www.ghostweather.com/essays/talks/openvisconf/topic_docs_network/index_better.html)

Adding strength, highlight effect, another variable, and informative tooltips.

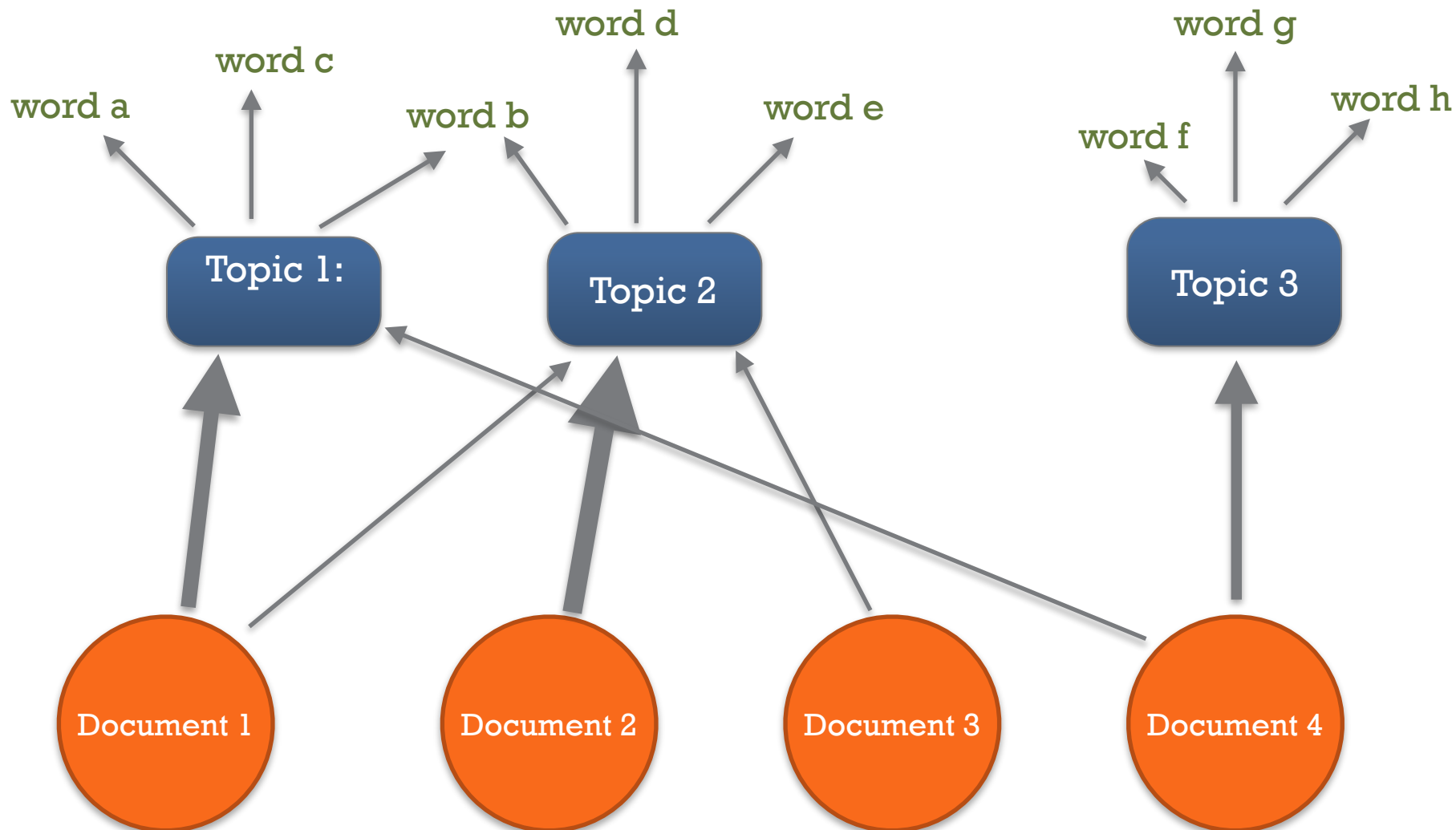
## Tricks in D3 – scales for sizing relatively:

```
countExtent = d3.extent(data.topics, (d) => +d.counts)
circleRadius = d3.scale.linear().range([5, 15]).domain(countExtent)

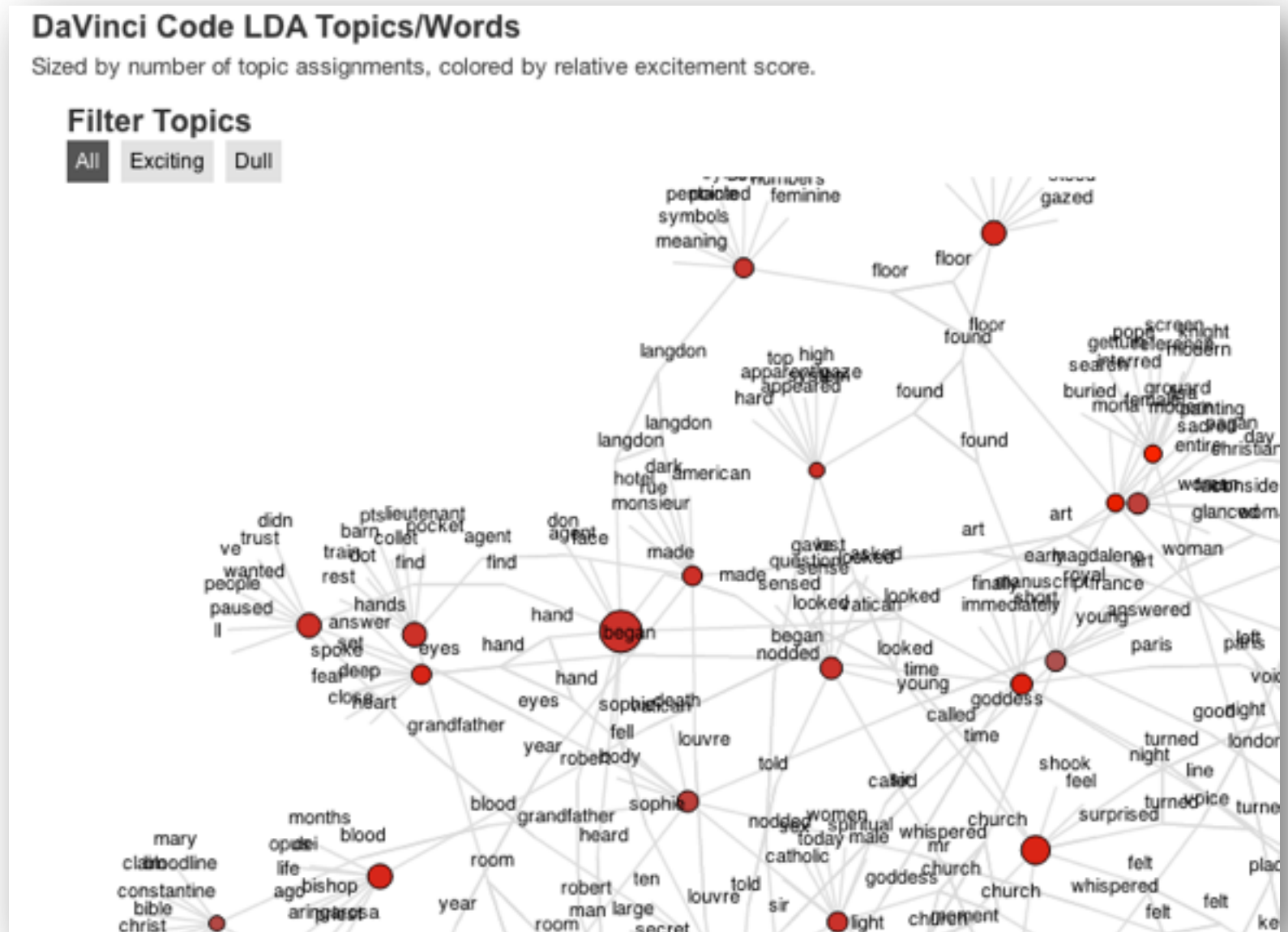
countStrength = d3.extent(data.links, (d) => +d.strength)
linkSize = d3.scale.linear().range([.5, 6]).domain(countStrength)
```



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



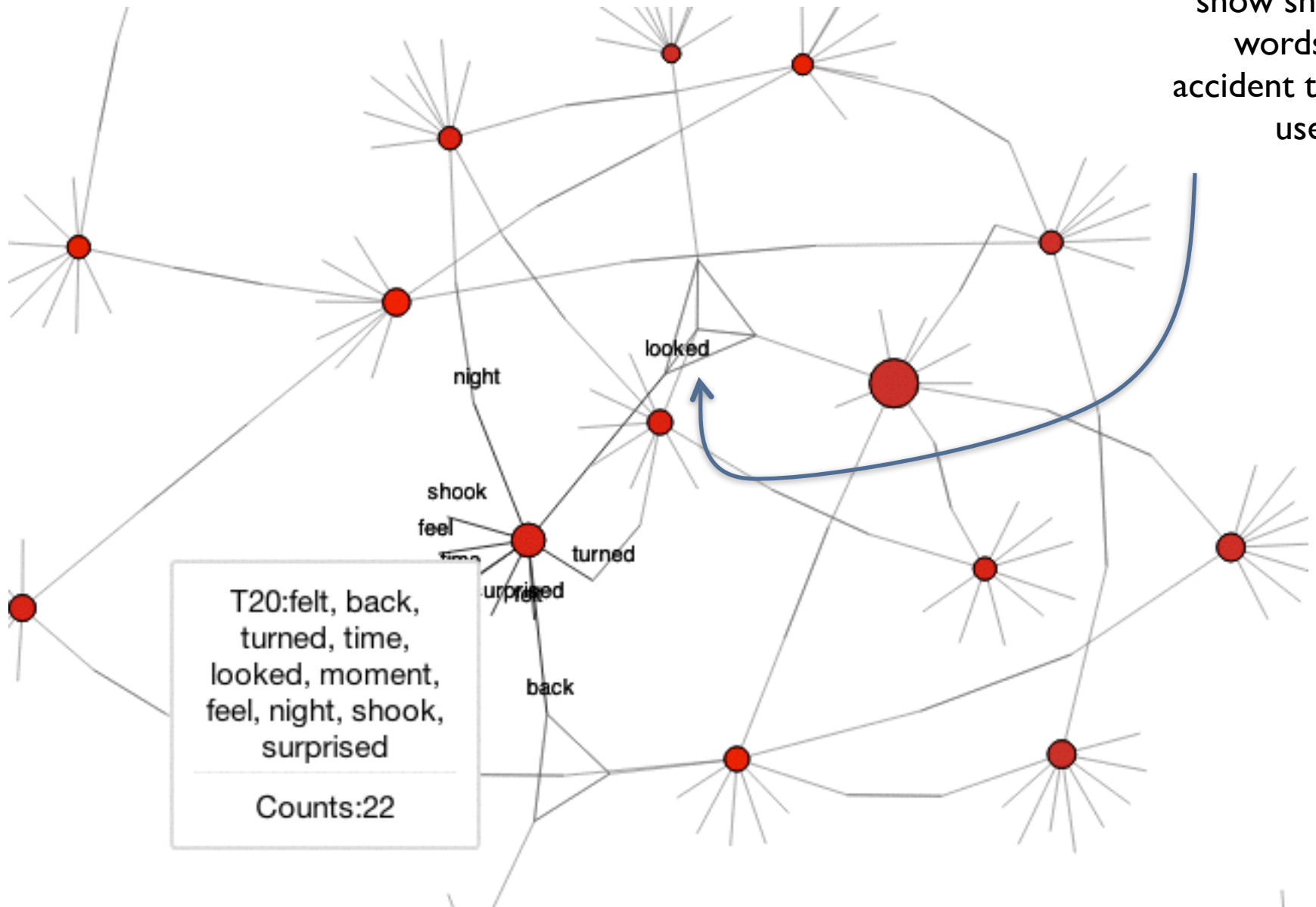
Maybe I need One More Tool. Any word relations of interest?  
Let's try another hairball...



Demo: [http://www.ghostweather.com/essays/talks/openvisconf/topic\\_words\\_network/index.html](http://www.ghostweather.com/essays/talks/openvisconf/topic_words_network/index.html)

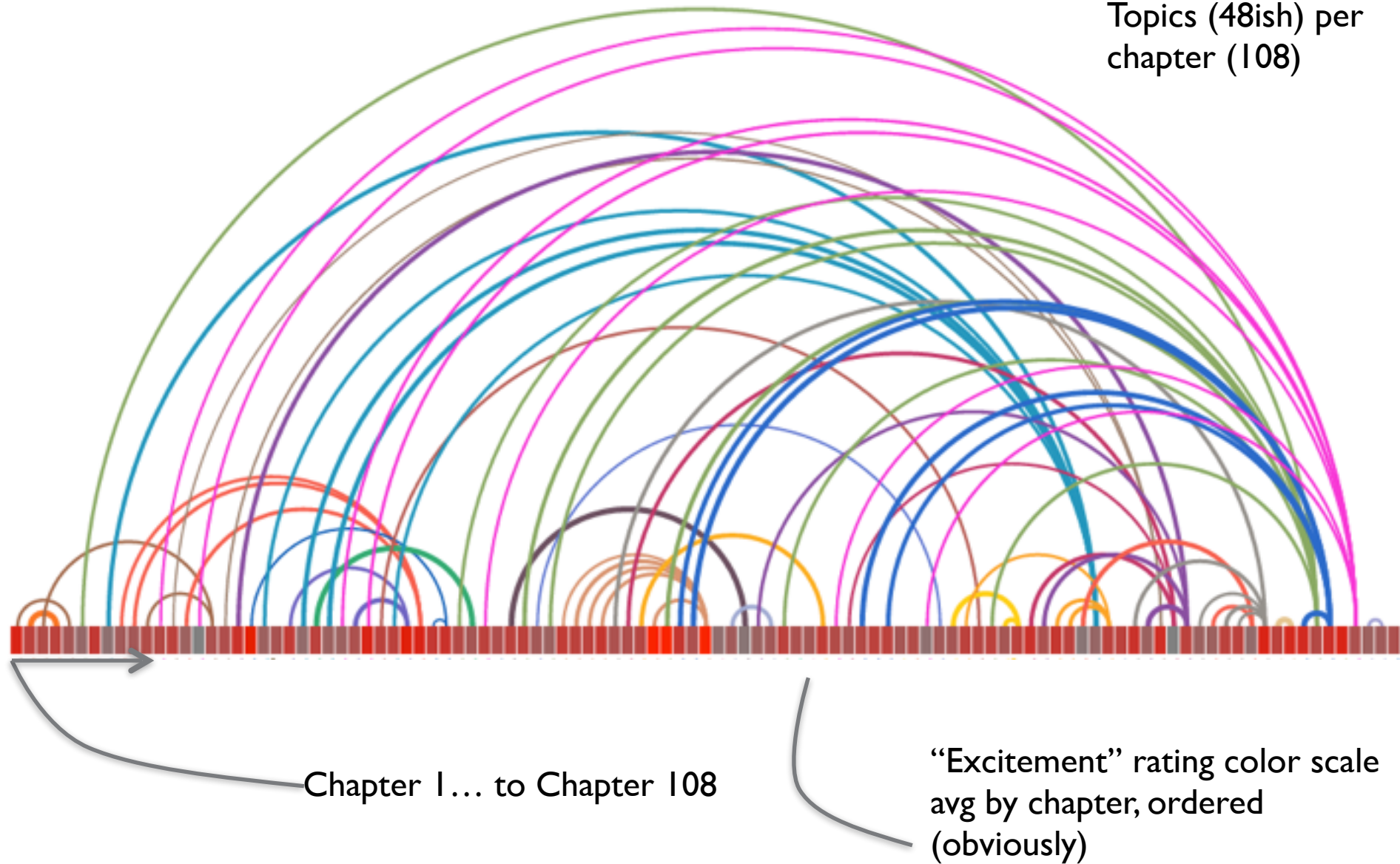
Filtered to only the  
“exciting” nodes...

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



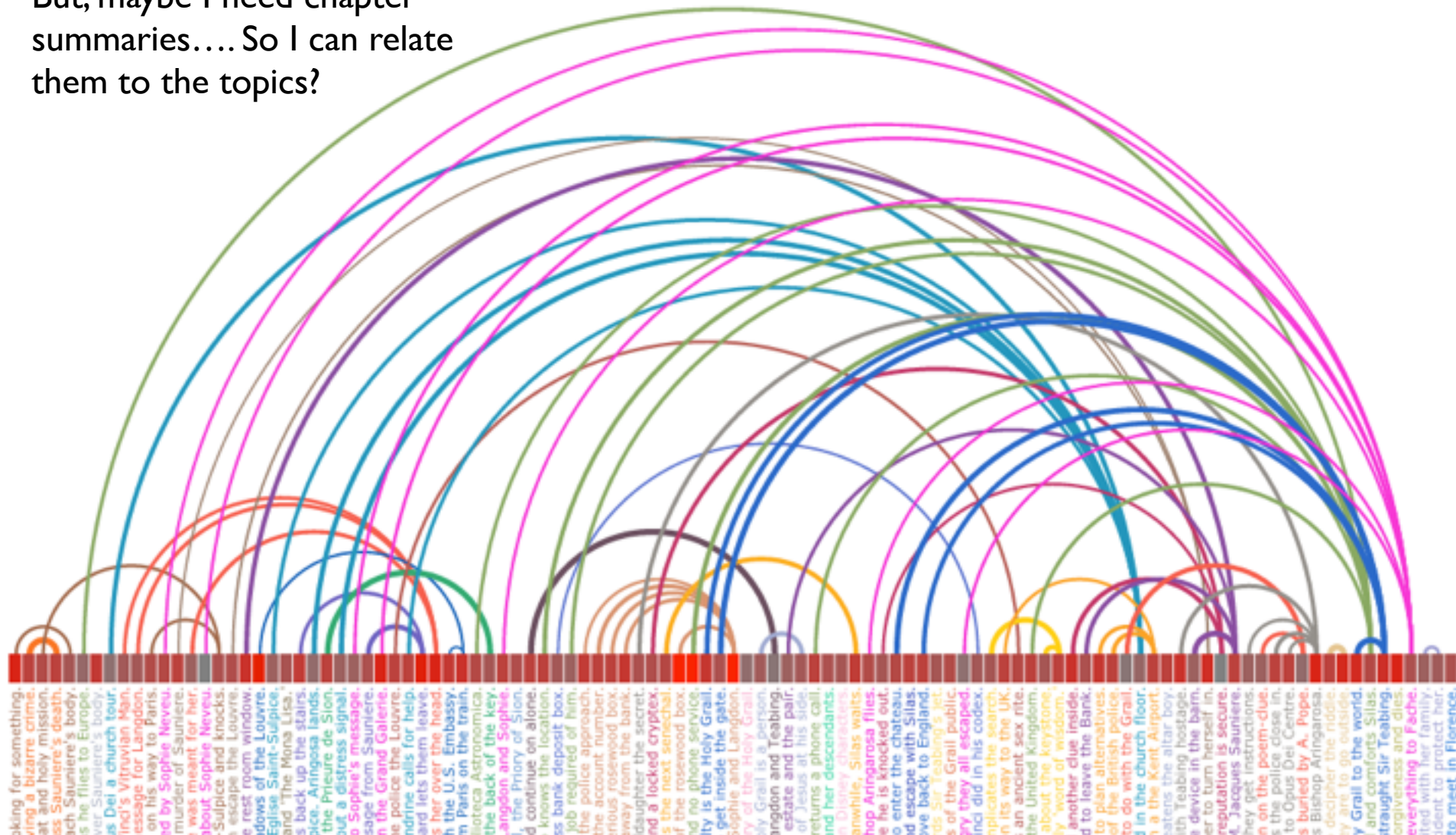
Another tool: Sequential documents, with topic arcs.  
DaVinci Code topics to chapters mapping

Topics (48ish) per  
chapter (108)



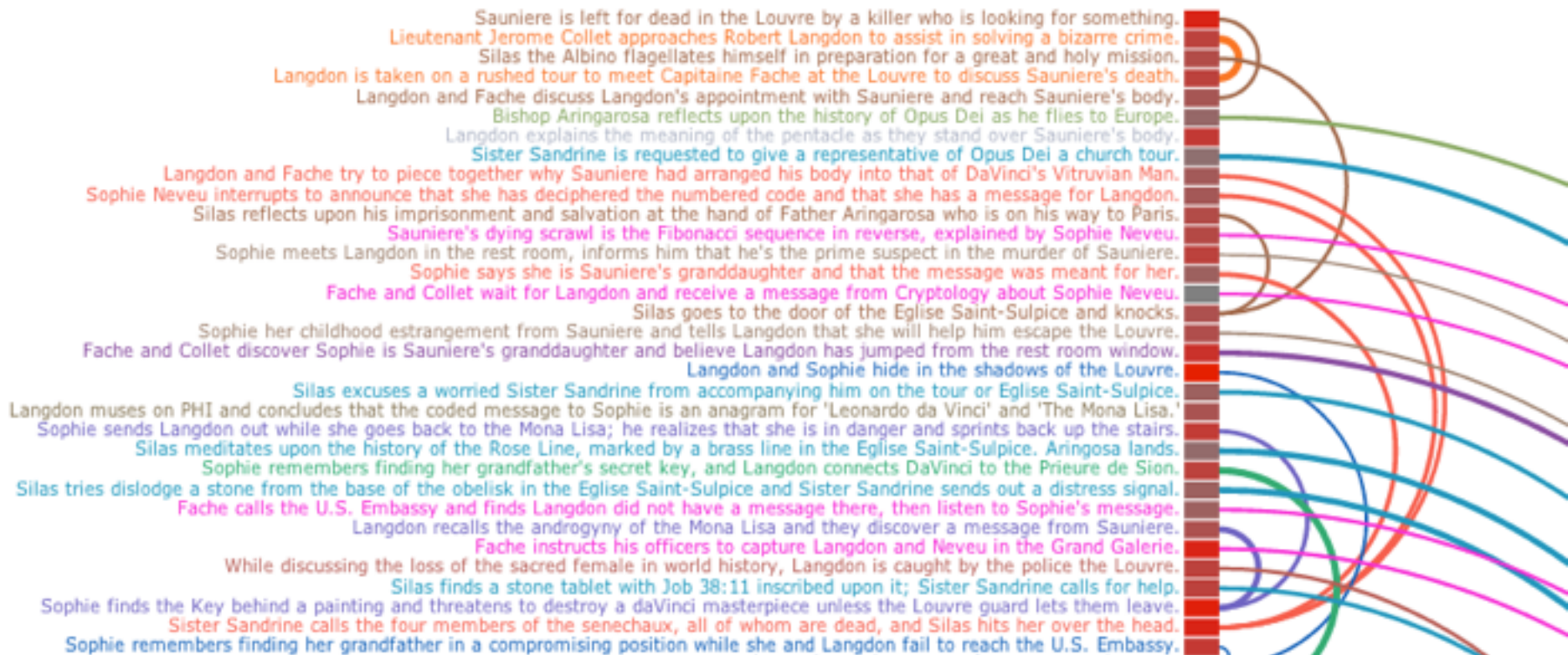


But, maybe I need chapter summaries.... So I can relate them to the topics?



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

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



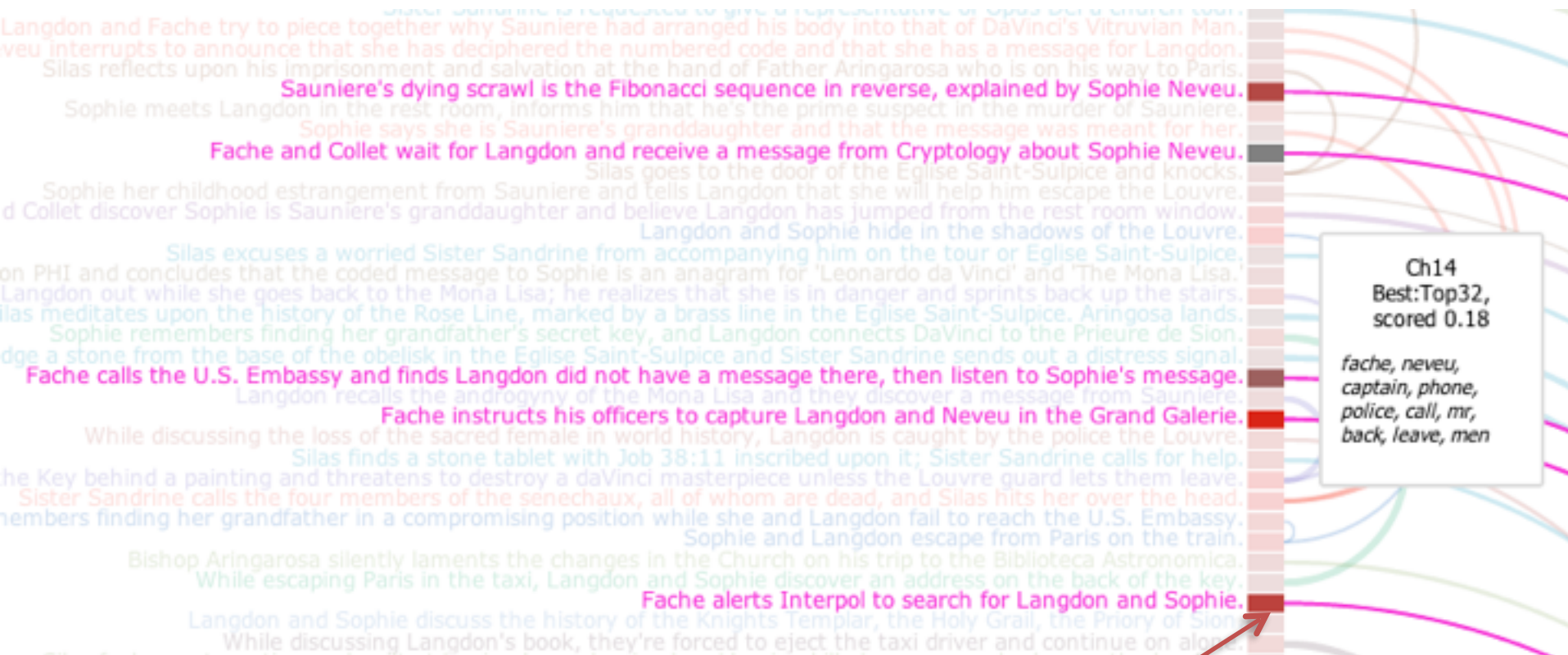
Add some topic-tooltips  
and fade-outs....





# 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)

# How can you improve on the results?

Topic modeling depends on the input:  
pre-process the documents differently:

- only verbs / nouns?
  - Read in a document, parse it, save out a new “document” of the POS you want
- use stop words tuned for your data set (don't want proper nouns? or only proper nouns?)
- iterate on the number of topics you output



# Improve the Results Display

- Visualize differently or more...
- 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>