GENERAL ASSEMBLY

LATENT VARIABLES AND NATURAL LANGUAGE PROCESSING

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LEARNING OBJECTIVES

- Understand what *latent* variables are
- Understand the uses of *latent variables* in language processing
- Use the *word2vec* and *LDA* algorithms of `genism`

COURSE

PRE-WORK

PRE-WORK REVIEW

- Install `gensim` with `pip install gensim`
- Recall and apply *unsupervised learning* techniques
- Recall probability distributions, specifically discrete multinomial distributions
- Recall NLP essentials, including experience with `spacy`

OPENING

LATENT VARIABLE MODELS vs TRADITIONAL NLP

LATENT VARIABLE MODELS

- This lesson will continue on natural language processing with an emphasis on *latent variables models*.
- Mining and Refining data is a key part of the data science workflow.
- During the previous lessons, we saw many techniques for mining the data, including preprocessing, building linguistic rules to uncover patterns, and creating classifiers from unstructured data.
- In this class, we'll continue with methods to Refine our understanding of the text by attempting to uncover structure or organization in the text.

LATENT VARIABLE MODELS

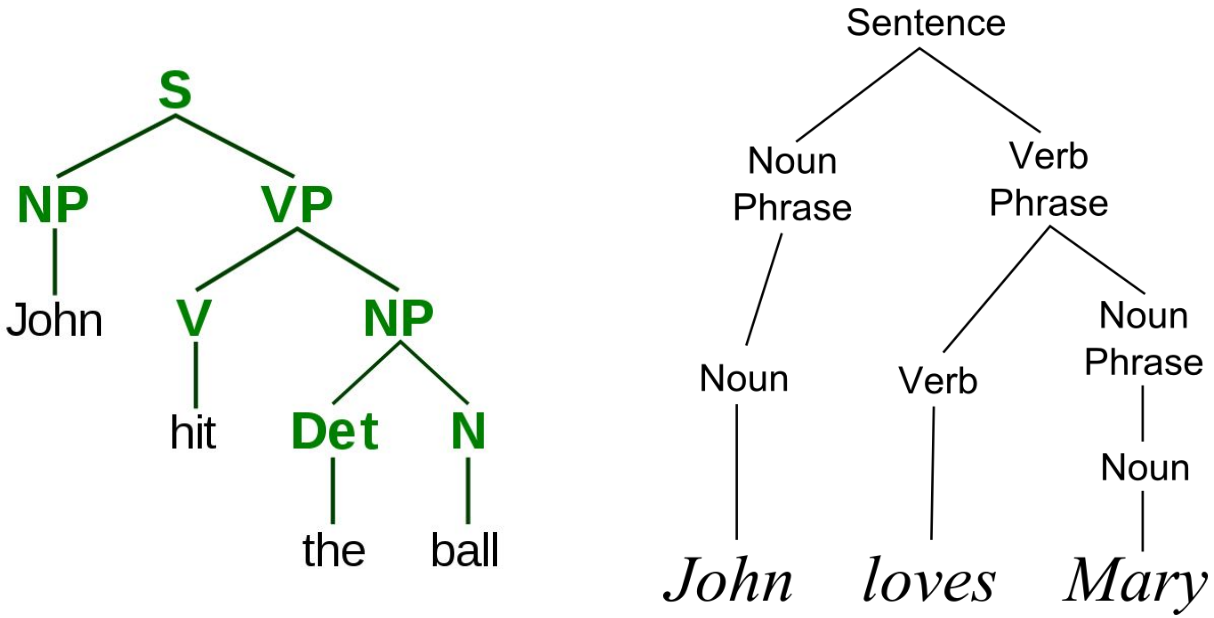
- Many advances in NLP are based on using data to learn rules of grammar and language. We saw these tools in our last class.
  - Tokenization
  - Stemming or lemmatization
  - Parsing and tagging
- Each of these are based on a classical or theoretical understanding of language.

LATENT VARIABLE MODELS

- Tokenization:
  - John hit the ball → [John, hit, the, ball]
  - Where did you go → [Where, did, you, go]

- Stemming or lemmatization: shouted → shout, better → good

- Parsing and tagging:



LATENT VARIABLE MODELS

- *Latent variable models* are different in that they try to understand language based on **how** the words are used.
- For example, instead of learning that ‘bad’ and ‘badly’ are related because they share the same root, we’ll determine that they are related because they are often used in the same way often or near the same words.
- We’ll use *unsupervised* techniques (discovering patterns or structure) to extract the information.

LATENT VARIABLE MODELS

Traditional NLP Models	Latent Variable Models
Focused on theoretical understanding of language	Focused on how the language is actually used in practice
Tries to learn the rules of a particular language	Infers meaning from how words are used together
Preprogrammed set of rules	Uses unsupervised learning to discover patterns or structure

LATENT VARIABLE MODELS

Traditional NLP Models	**Latent Variable Models**
‘bad’ and ‘badly’ are related because they share a common root.	‘bad’ and ‘badly’ are related because they are used the same way or near the same words.
‘Python’ and ‘C++’ are both programming languages because they are often a noun preceded by the verb ‘program’ or ‘code’.	‘Python’ and ‘C++’ are both programming languages because they are often used in the same context.

INTRODUCTION

LATENT VARIABLE MODELS

LATENT VARIABLE MODELS

- *Latent variable models* are models in which we assume the data we are observing has some **hidden, underlying structure** that we can't see, and which we'd like to learn.

- These hidden, underlying structures are the *latent* (i.e. hidden) variables we want our model to understand.

- Text processing is a common application of latent variables.

- The goal is to infer a model that would produce our text.

LATENT VARIABLE MODELS

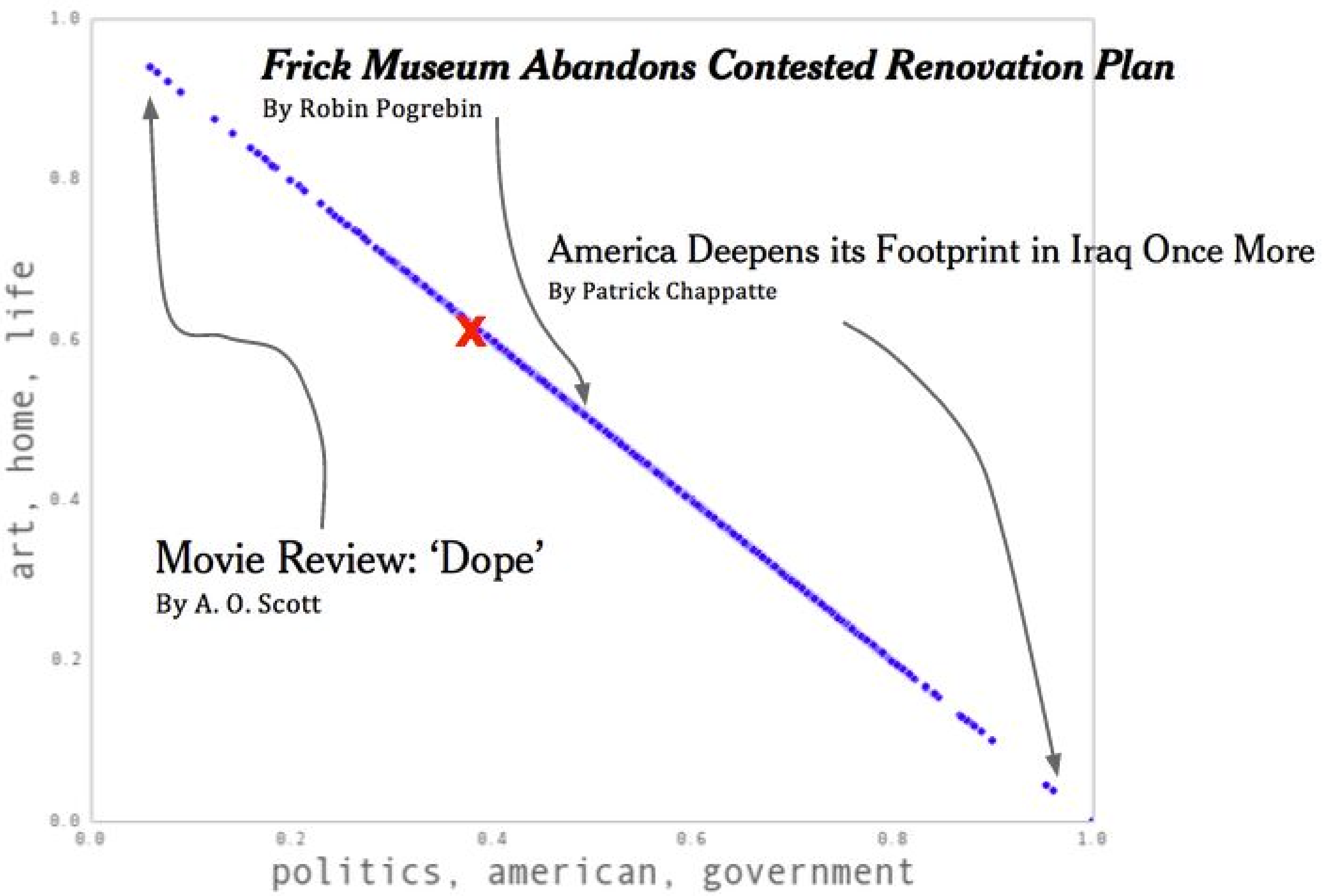
- While language (in the classical sense) is defined by a set of pre-structured grammar rules and vocab, we often break those rules and create new words (e.g. selfie).

- Instead of attempting to train our model on the rules of proper grammar, we'll ignore grammar and seek to uncover alternate hidden structures.

LATENT VARIABLE MODELS

- Latent variable techniques are often used for recommending news articles or mining large troves of data to find commonalities.
- Topic modeling, a method we'll cover today, is used in the NY times recommendation engine.
- The New York Times attempts to map their articles to a latent space of topics using the content of the article.

LATENT VARIABLE MODELS



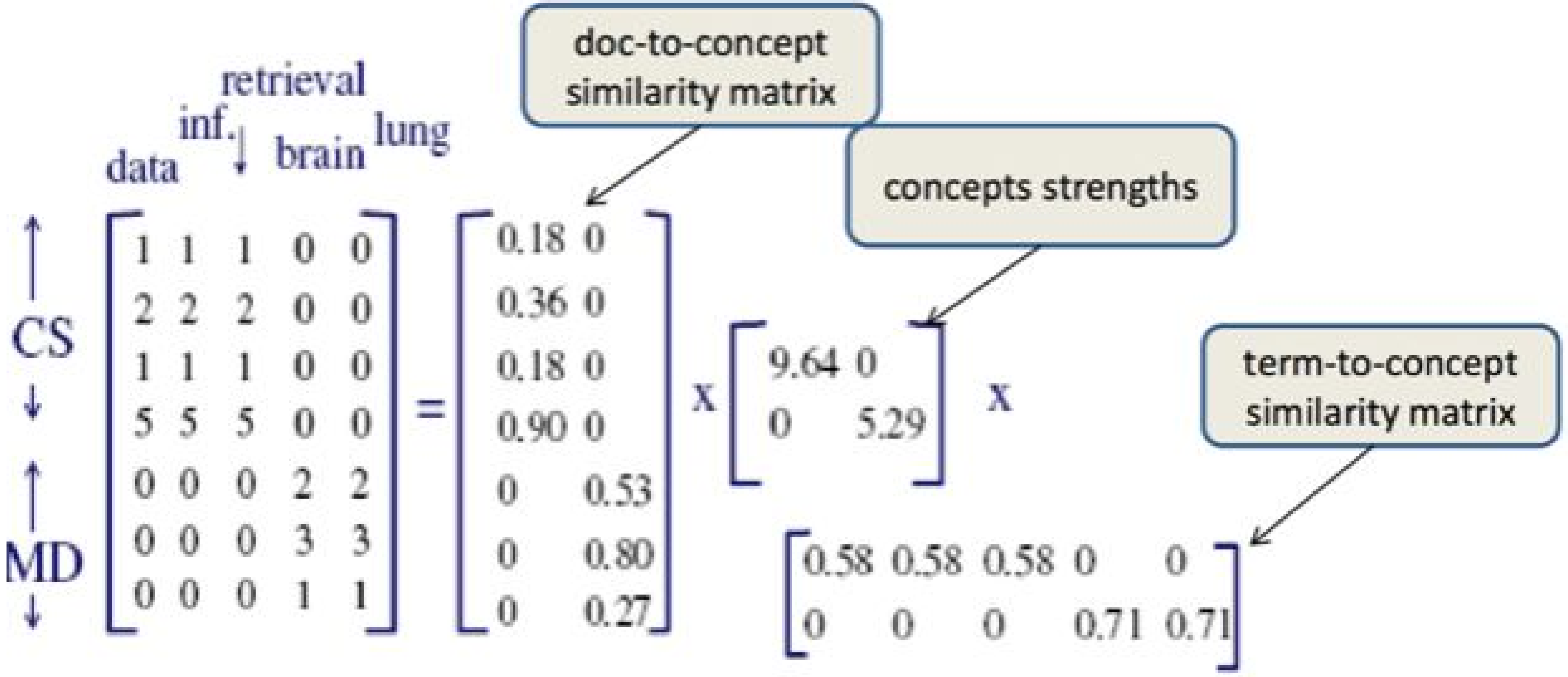
LATENT VARIABLE MODELS

- [Lyst](), an online fashion retailer, uses latent representations of clothing descriptions to find similar clothing.

	Term	Similarity
	"riding	" 0.962305
	"ankle"	0.888326
	"chelsea"	0.885039
	"gloss"	0.862084
	"combat"	0.861708

DIMENSIONALITY REDUCTION IN TEXT REPRESENTATION

- Our previous ‘representation’ of a set of text documents (articles) for classification was a matrix with one row per document and one column per word (or n-gram).



DIMENSIONALITY REDUCTION IN TEXT REPRESENTATION

- While this sums up most of the information, it does drop a few things, mostly structure and order.
- Additionally, many of the columns may be correlated.

DIMENSIONALITY REDUCTION IN TEXT REPRESENTATION

- For example, an article that contains the word 'IPO' is likely to contain the word 'stock' or 'NASDAQ'.

- Therefore, those columns are repetitive and likely to represent the same concept or idea.

- For classification, we may only care that there are finance-related words.

DIMENSIONALITY REDUCTION IN TEXT REPRESENTATION

- One way to deal with this is through regularization - L1/Lasso regularization tends to remove repetitive features by bringing their learned coefficients to 0.

- Another is to perform *dimensionality reduction* ,where we first identify the correlated columns and the replace them with a column that represents the concept they have in common.

- For instance, we could replace ‘IPO’, ‘stocks’, and ‘NASDAQ’ with a single column - ‘HasFinancialWords’ column.

DIMENSIONALITY REDUCTION IN TEXT REPRESENTATION

- There are many techniques to do this automatically and mostly follow a very similar approach.

  a. Identify correlated columns.

  b. Replace them with a new column that encapsulates the others.

Doc #	Car	Truck	Van	Dog
6344	1	1	1	0
6345	0	1	1	1
6346	1	1	1	0

Doc #	Vehicle	Dog
6344	1	0
6345	1	1
6346	1	0

DIMENSIONALITY REDUCTION IN TEXT REPRESENTATION

- The techniques vary in how they define correlation and how much of the relationship between the original and new columns you need to save.

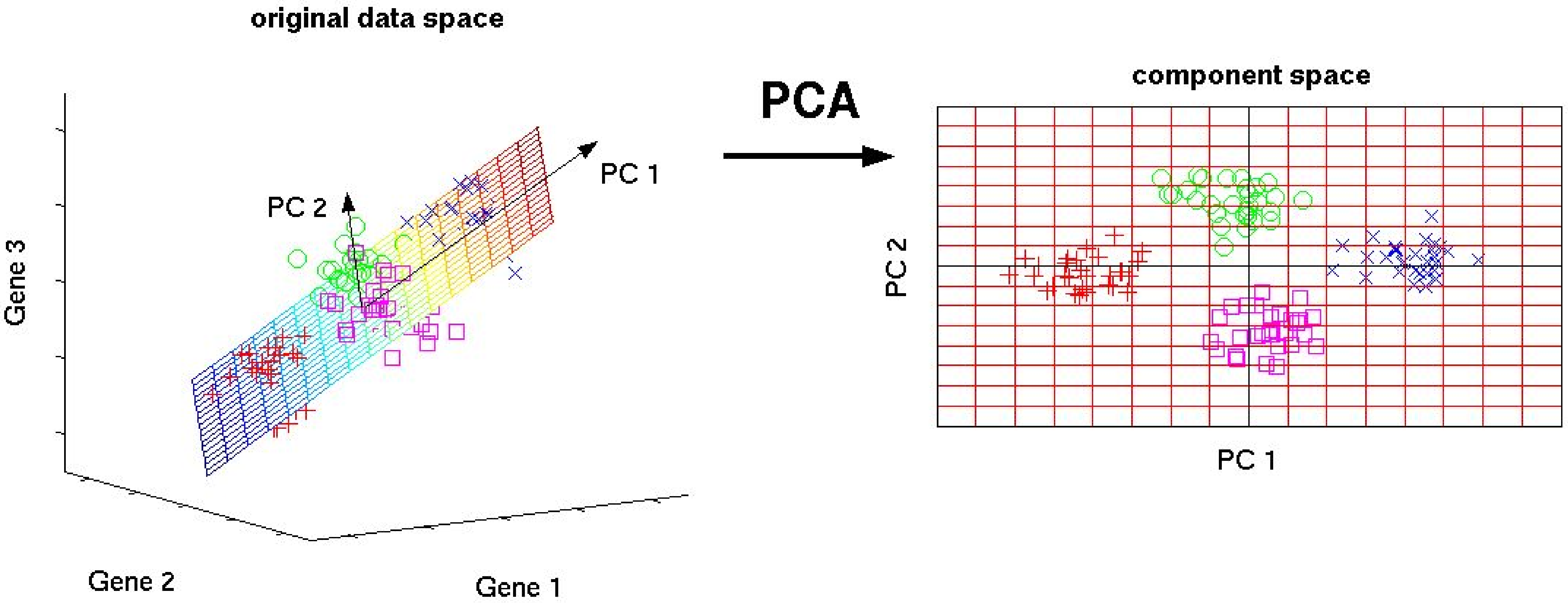
- Dimensionality techniques can vary between *linear* and *non-linear*.

DIMENSIONALITY REDUCTION IN TEXT REPRESENTATION

- There are many techniques build into scikit-learn.
- One of the most common is **Principal Component Analysis** (**PCA**).
- PCA like techniques, when applied to text data, is sometimes known as **Latent Semantic Indexing (LSI)**.
- http://scikit-learn.org/stable/modules/decomposition.html#truncated-singular-value-decomposition-and-latent-semantic-analysis

DIMENSIONALITY REDUCTION IN TEXT REPRESENTATION

- PCA helps reduce the feature space into fewer dimensions.



MIXTURE MODELS AND LANGUAGE PROCESSING

- Mixture models (specifically **LDA** or **Latent Dirichlet Allocation**) take this concept further and generate more structure around the documents.
- Instead of just replacing correlated columns, we create clusters of common words and generate probability distributions to explicitly state how related words are.

MIXTURE MODELS AND LANGUAGE PROCESSING

- To understand this better, let's imagine that we generate text by:

   a. Start writing a document

      i. Choose a topic (sports, news, science).

      ii. Choose a random word from that topic.

      iii. Repeat.

   b. Repeat for the next document.

MIXTURE MODELS AND LANGUAGE PROCESSING

- This ‘model’ of text is assuming that each document is some *mixture* of topics.
- It may be mostly science but may contain some business information.
- The *latent* structure we want to uncover are the topics (or concepts) that generate that text.

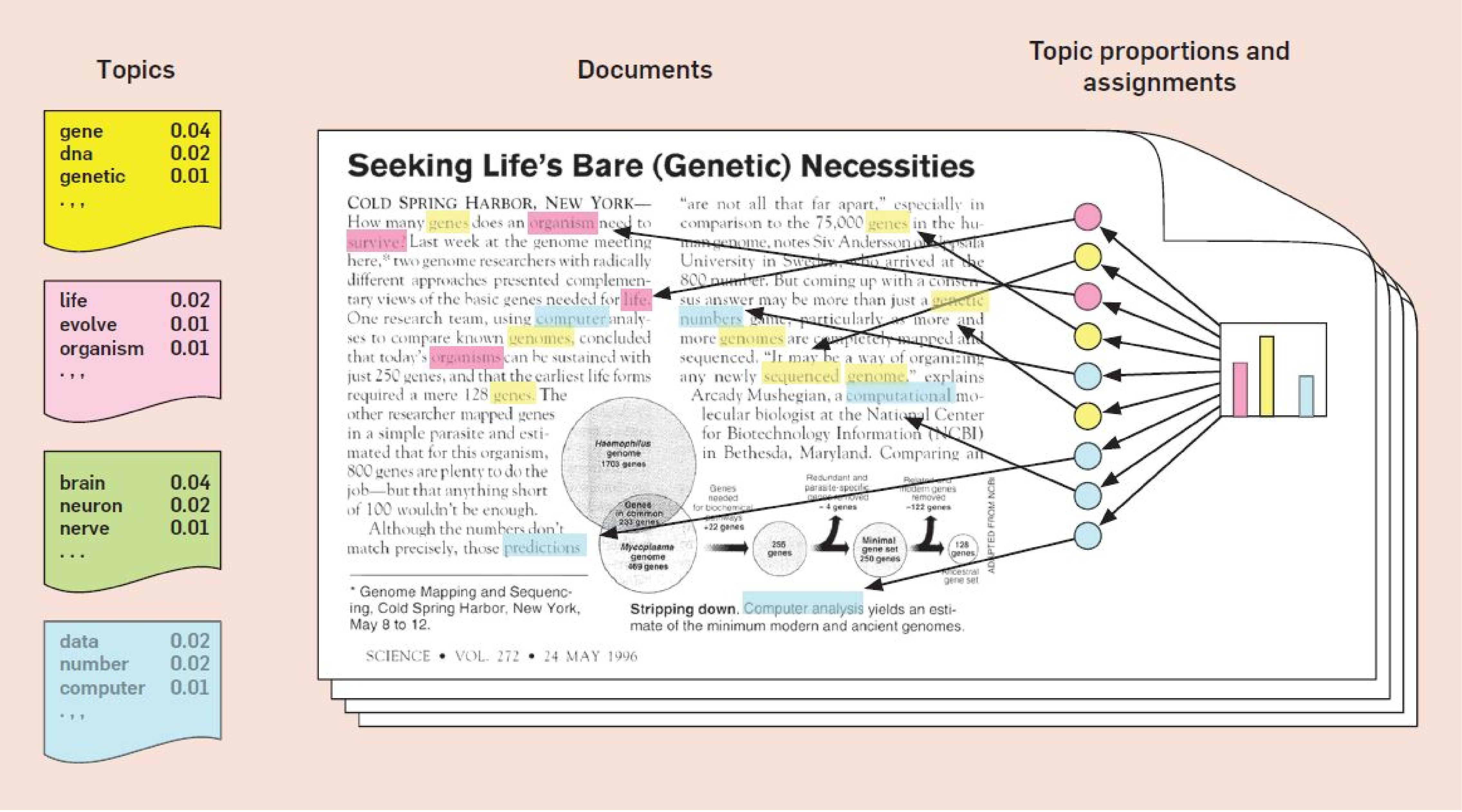
MIXTURE MODELS AND LANGUAGE PROCESSING

- *Latent Dirichlet Allocation* is a model that assumes this is the way text is generated and then attempts to learn two things:

  a. The word distribution of each topic

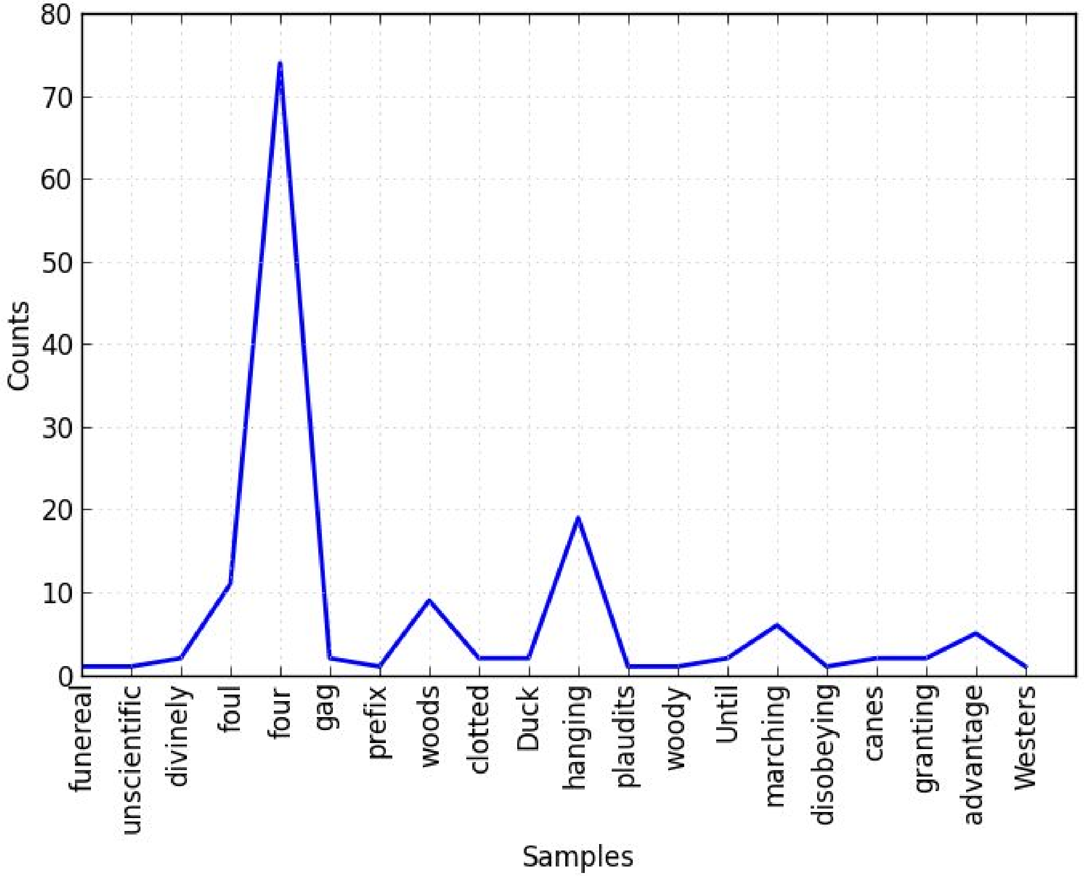
  b. The topic distribution of each document.

MIXTURE MODELS AND LANGUAGE PROCESSING



MIXTURE MODELS AND LANGUAGE PROCESSING

- The *word distribution* is a multinomial distribution of each topic representing what words are most likely from that topic.



MIXTURE MODELS AND LANGUAGE PROCESSING

- For example, let's say we have three topics: sports, business, and science.
- For each topic, we uncover the most likely words to come from them:

```
sports: [football: 0.3, basketball: 0.2, baseball: 0.2, touchdown: 0.02 ... genetics: 0.0001]
```

```
science: [genetics: 0.2, drug: 0.2, ... baseball: 0.0001]
```

```
business: [stocks: 0.1, ipo: 0.08,  ... baseball: 0.0001]
```

- For each word and topic pair, we learn some probability: `P(word|topic)`.

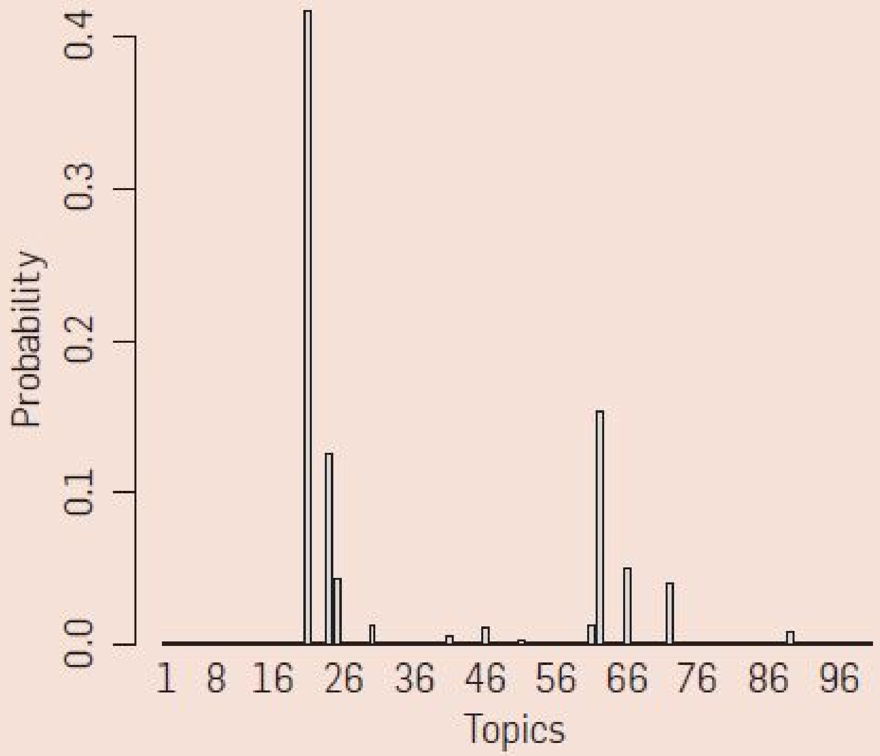
MIXTURE MODELS AND LANGUAGE PROCESSING

- The *topic distribution* is a multinomial distribution for each document representing what topics are most likely to appear in that document.
- For all our sample of documents, we have a distribution over {sports, science, business}.

```
ESPN article: [sports: 0.8, business: 0.2, science: 0.0]
Bloomberg article: [business: 0.7, science: 0.2, sports: 0.1]
```

- For each topic and document pair, we learn some probability, `P(topic|document)`.

MIXTURE MODELS AND LANGUAGE PROCESSING



"Genetics"	"Evolution"	"Disease"	"Computers"
human	evolution	disease	computer
genome	evolutionary	host	models
dna	species	bacteria	information
genetic	organisms	diseases	data
genes	life	resistance	computers
sequence	origin	bacterial	system
gene	biology	new	network
molecular	groups	strains	systems
sequencing	phylogenetic	control	model
map	living	infectious	parallel
information	diversity	malaria	methods
genetics	group	parasite	networks
mapping	new	parasites	software
project	two	united	new
sequences	common	tuberculosis	simulations

MIXTURE MODELS AND LANGUAGE PROCESSING

- Topic models are useful for organizing a collection of documents and uncovering the main underlying concepts.

- There are many variants that attempt to add even more structure to the 'model':

  a. Supervised topic models guide the process with pre-decided topics.
  b. Position-dependent topic models ignore which words occur in which document and instead focus on *where* they occur.
  c. Variable number topic models test different numbers of topics to find the best model.

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

1. Take any recent news article and brainstorm which three topics this story is most likely to be made up of.

2. Next, brainstorm which words are most likely derived from which of those three topics.

DELIVERABLE

Topics and word-topic pairs

DEMO

LDA IN GENSIM

LDA IN GENSIM

- `gensim` is a library of language processing tools focused on latent variable models of text.
- It was originally developed by grad students dissatisfied with current implementations of latent models.
- Documentation and tutorials are available on the package's website.

LDA IN GENSIM

- Let’s first translate a set of documents (articles) into a matrix representation with a row per document and a column per feature (word or n-gram).

LDA IN GENSIM

```python
from sklearn.feature_extraction.text import CountVectorizer

cv = CountVectorizer(binary=False,
                     stop_words='english',
                     min_df=3)

docs = cv.fit_transform(data.body.dropna())

# Build a mapping of numerical ID to word
id2word = dict(enumerate(cv.get_feature_names()))
```

LDA IN GENSIM

- We want to learn which columns are correlated (i.e. likely to come from the same topic).

- This is the *word distribution*.

- We can also determine what topics are in each document, the *topic distribution*.

LDA IN GENSIM

```
from gensim.models.ldamodel import LdaModel
from gensim.matutils import Sparse2Corpus

# First we convert our word-matrix into gensim's format
corpus = Sparse2Corpus(docs, documents_columns = False)

# Then we fit an LDA model
lda_model = LdaModel(corpus=corpus, id2word=id2word, num_topics=15)
```

LDA IN GENSIM

- In this model, we need to explicitly specify the number of topic we want the model to uncover.

- This is a critical parameter, but there isn't much guidance on how to choose it. Try to use domain expertise where possible.

LDA IN GENSIM

- Now we need to assess the *goodness of fit* for our model.
- Like other unsupervised learning techniques, our validation techniques are mostly about interpretation.
- Use the following questions to guide you:
    - Did we learn reasonable topics?
    - Do the words that make up a topic make sense?
    - Is this topic helpful towards our goal?

LDA IN GENSIM

- We can evaluate fit by viewing the top words in each topic.
- `gensim` has a `show_topics` function for this:

```
num_topics = 25
num_words_per_topic = 5
for ti, topic in enumerate(lda.show_topics(num_topics = num_topics,
num_words_per_topic = n_words_per_topic)):
    print("Topic: %d" % (ti))
    print (topic)
    print()
```

LDA IN GENSIM

- Some topics will be clearer than others. The following topics represent clear concepts:

```
0.009*cup + 0.009*recipe + 0.007*make + 0.007*food + 0.006*sugar
→ Cooking and Recipes
```

```
0.013*butter + 0.010*baking + 0.010*dough + 0.009*cup + 0.009*sugar
→ Cooking and recipes
```

```
0.013*fashion + 0.006*like + 0.006*dress + 0.005*style
→ Fashion and Style
```

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

1. Demonstrate the code you used to generate the topics above.
2. Hypothesize other topic interpretations.

DELIVERABLE

Code and topics