GENERAL ASSEMBLY

DIMENSIONALITY REDUCTION IN NLP

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OUR PROGRESS SO FAR

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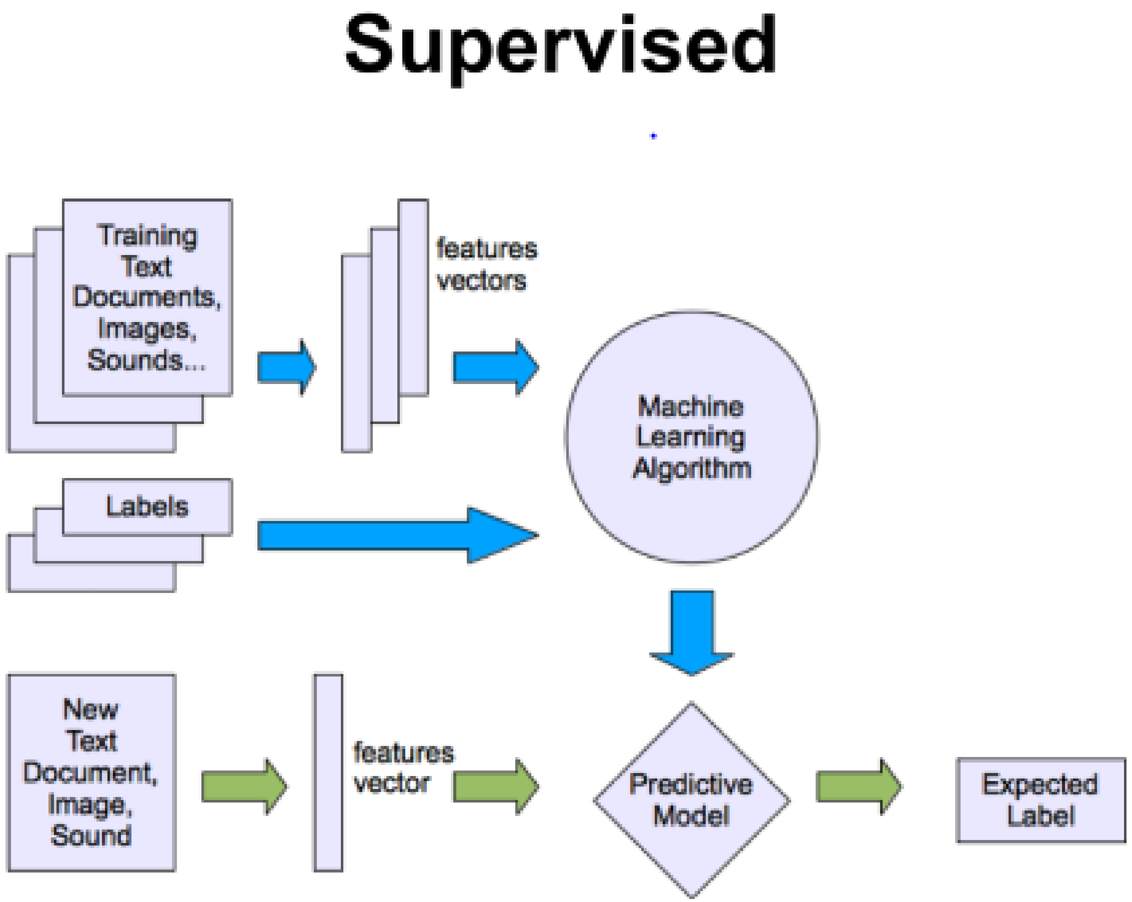
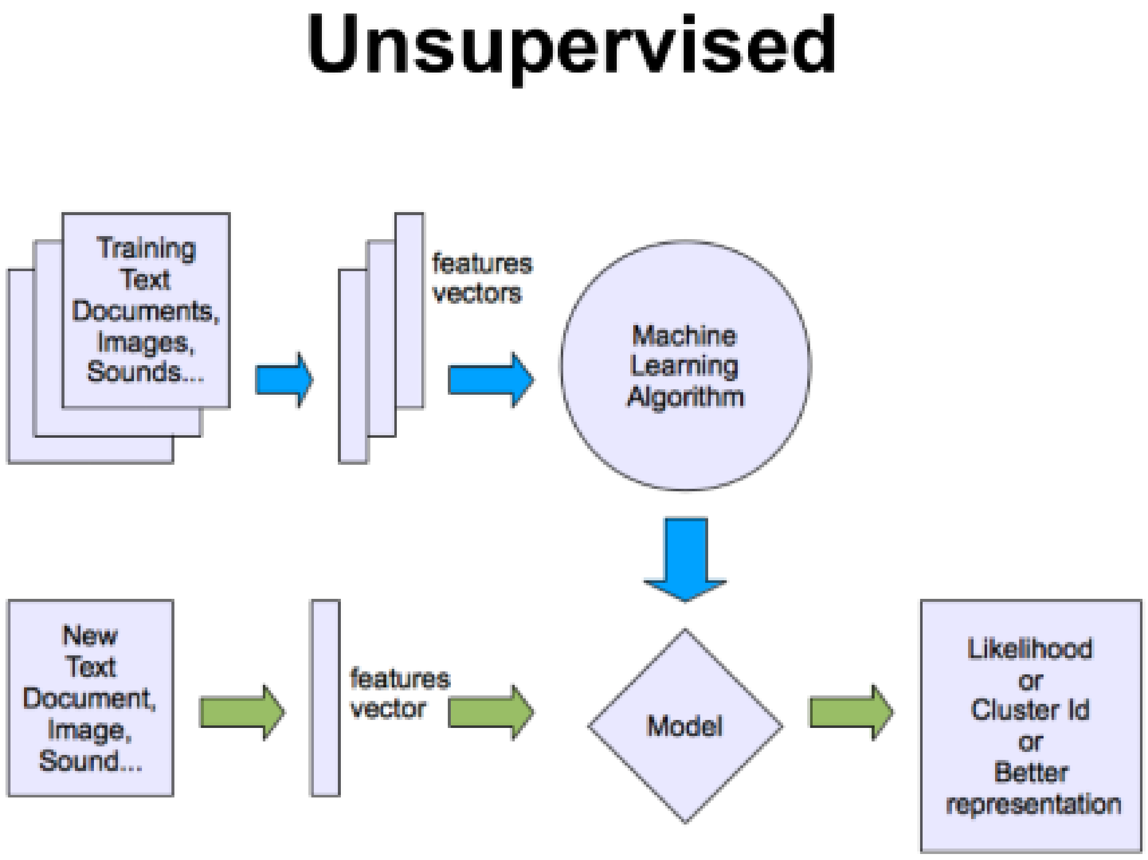
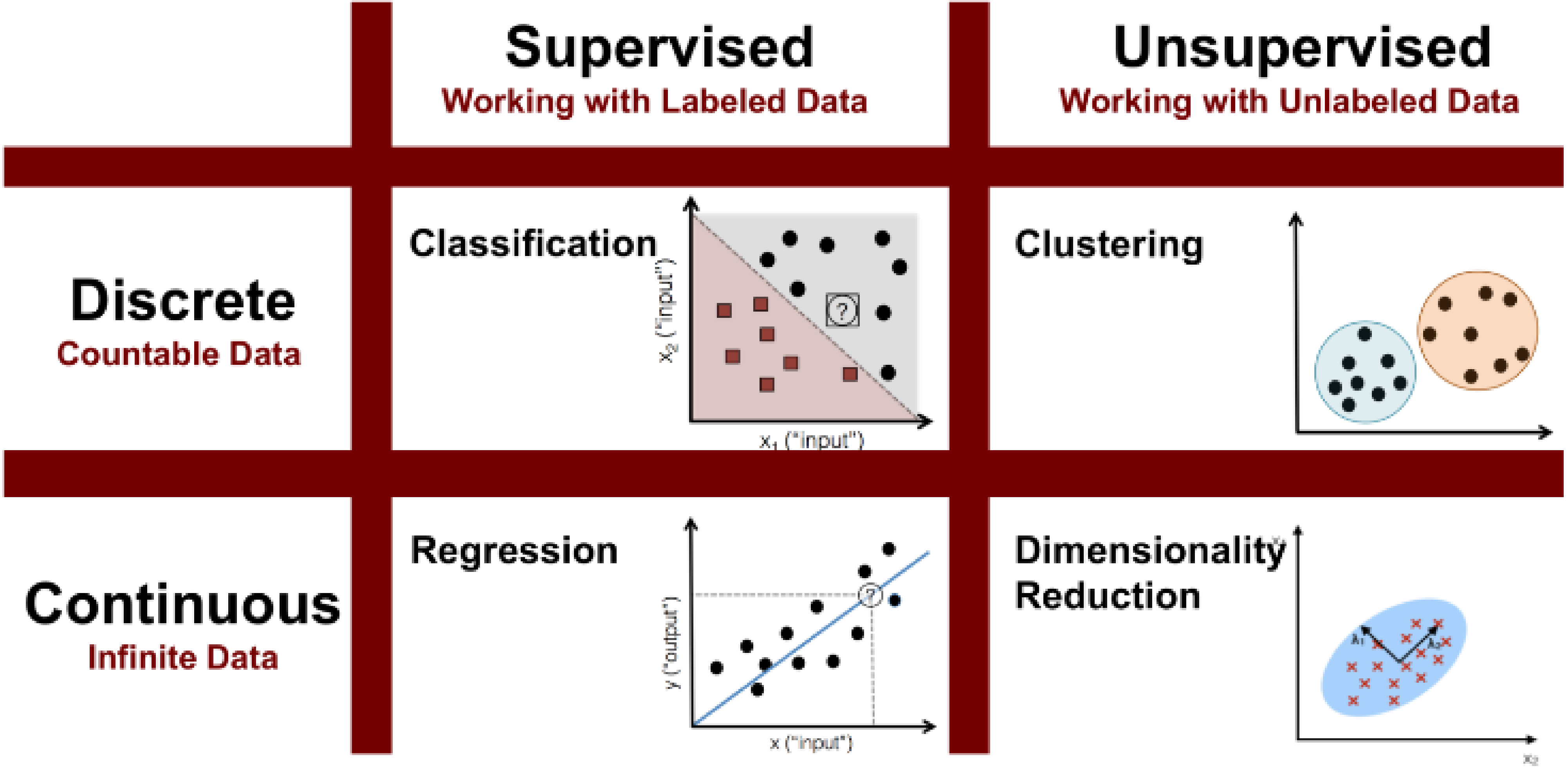
Today's Class

TYPES OF MACHINE LEARNING





TYPES OF MACHINE LEARNING



LAST CLASS

WHAT DID WE LEARN?

- Define natural language processing
- List common tasks associated with
  - NLP Use-cases
  - Tokenization
  - Lemmatization and Stemming
  - Tagging and parsing
- Demonstrate how to classify text or documents using scikit-learn

LEARNING OBJECTIVES

- Understand what *latent* variables are
- Dimensionality Reduction (PCA, LSI, LDA)
- Understand the uses of *latent variables* in language processing
- Use the *word2vec* and *LDA* algorithms of `genism`

COURSE

PRE-WORK

PRE-WORK

- Install `gensim` with `conda install gensim`
- Recall and apply *unsupervised learning* techniques
- Recall NLP essentials, including experience with `spacy`

OPENING

LATENT VARIABLE MODELS

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.

- In our last class, 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

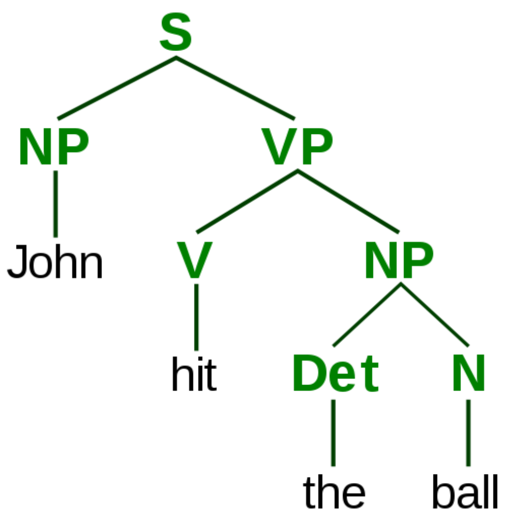
- Many advances in NLP are based on using data to learn rules of grammar and language. We saw these tools in our last class.
  - Tokenization
  - Stemming or lemmatization
  - Parsing and tagging
- Each of these are based on a classical or theoretical understanding of language.

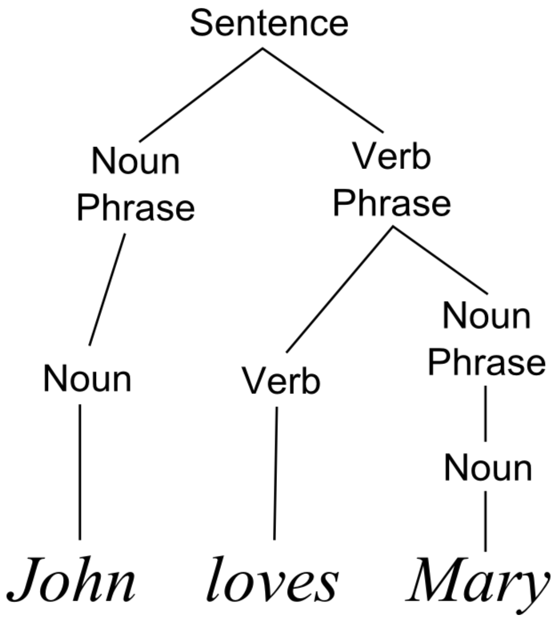
LATENT VARIABLE MODELS

- 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

‘bad’ and ‘badly’ are related because they share a common root.

‘Python’ and ‘C++’ are both programming languages because they are often a noun preceded by the verb ‘program’ or ‘code’.

Latent Variable Models

‘bad’ and ‘badly’ are related because they are used the same way or near the same words.

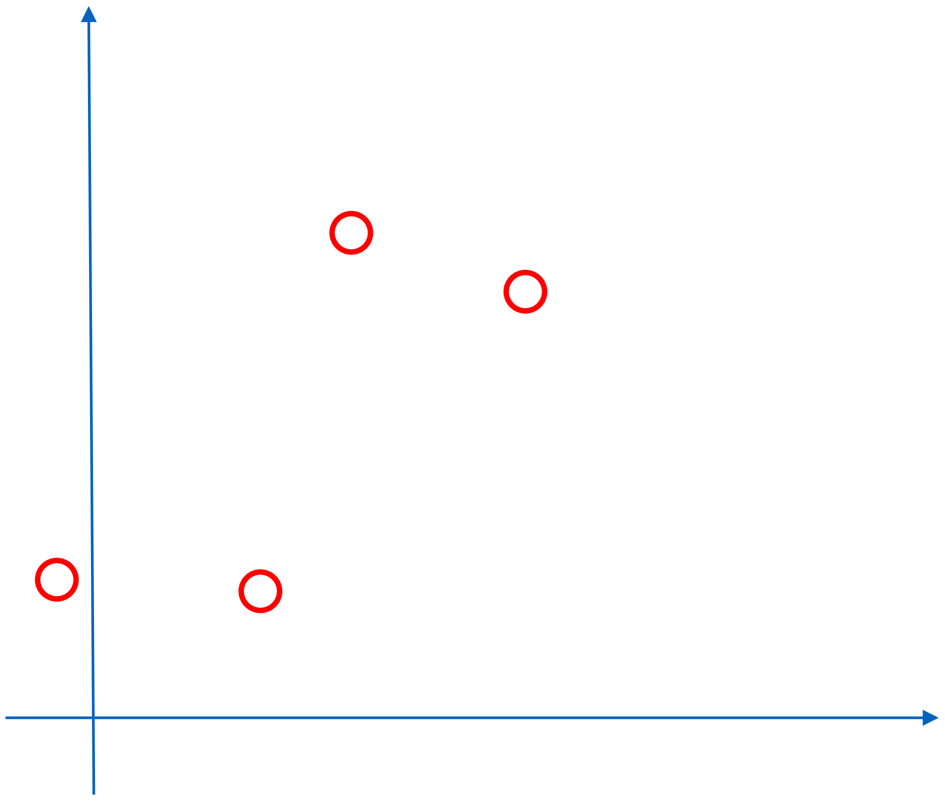
‘Python’ and ‘C++’ are both programming languages because they are often used in the same context.

INTRODUCTION

Dimensionality Reduction using PCA

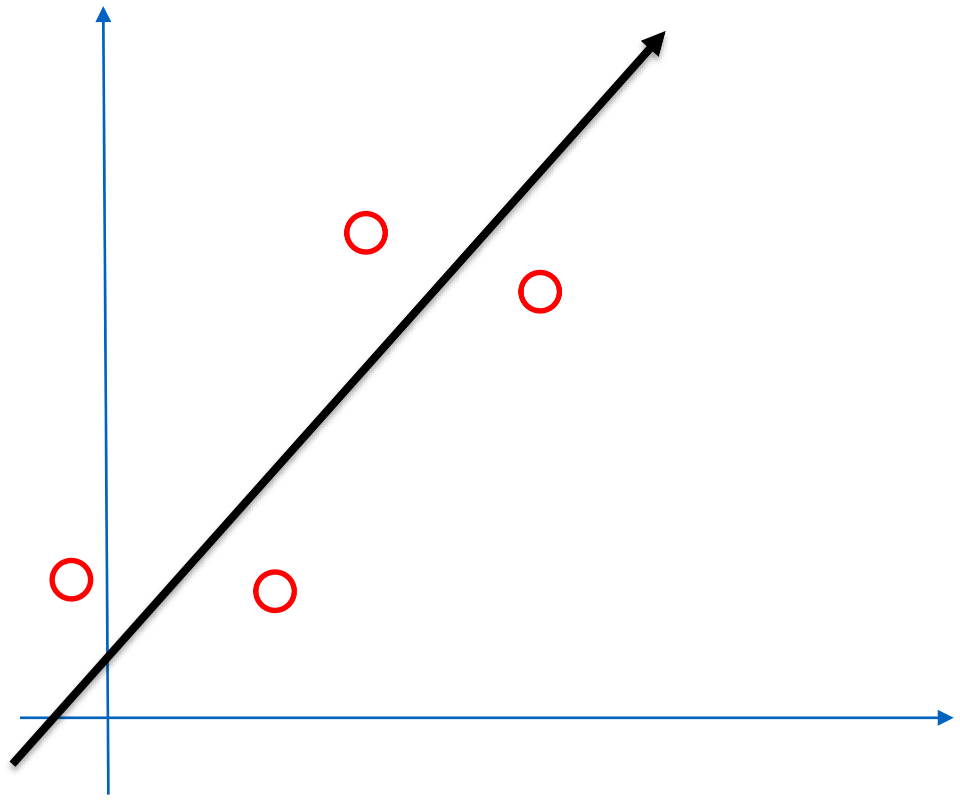
DIMENSIONALITY REDUCTION

How to reduce dimensionality (2D down to 1D) while keeping as much information as possible?



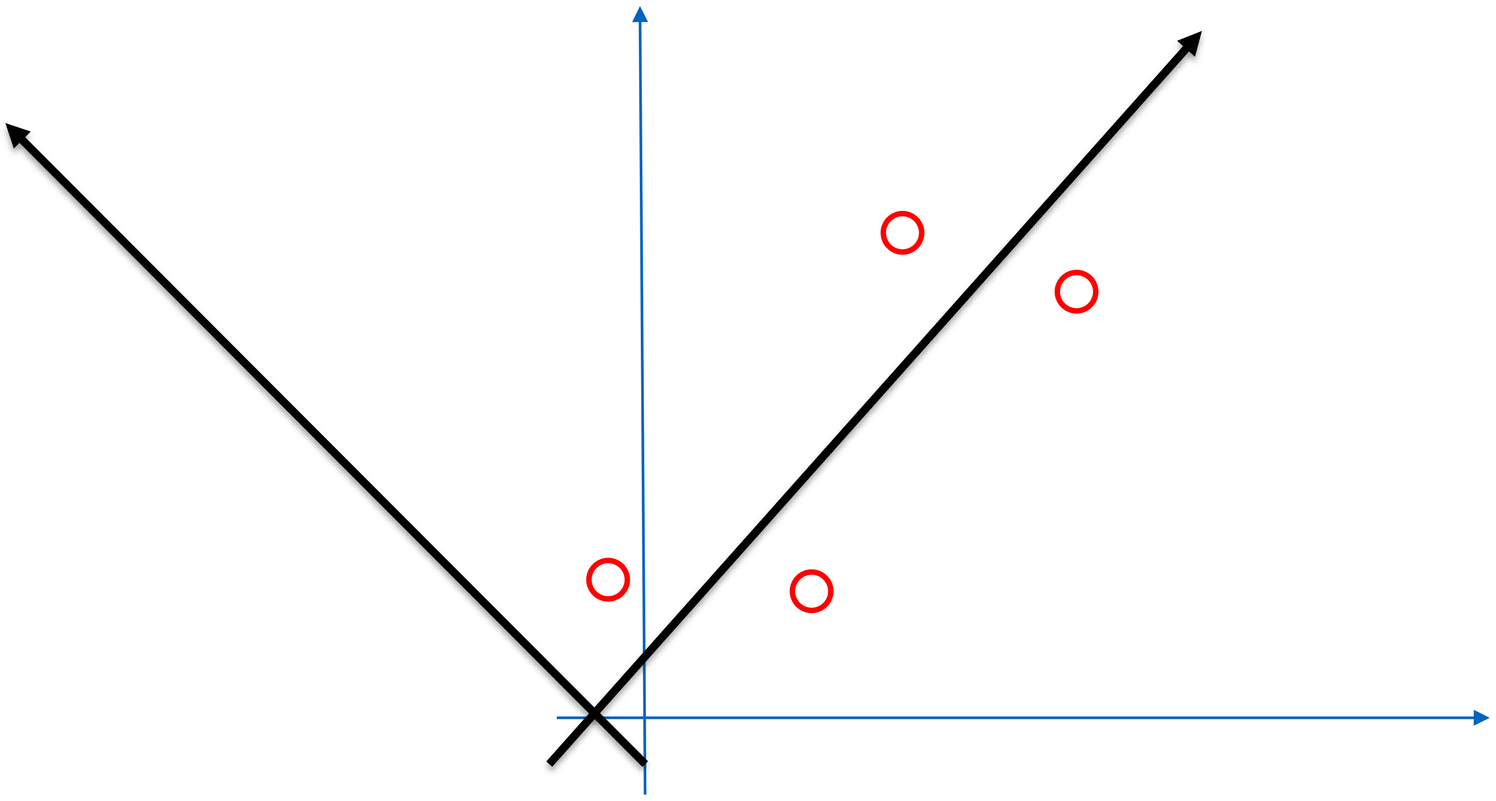
DIMENSIONALITY REDUCTION

Let's fit a "best" line



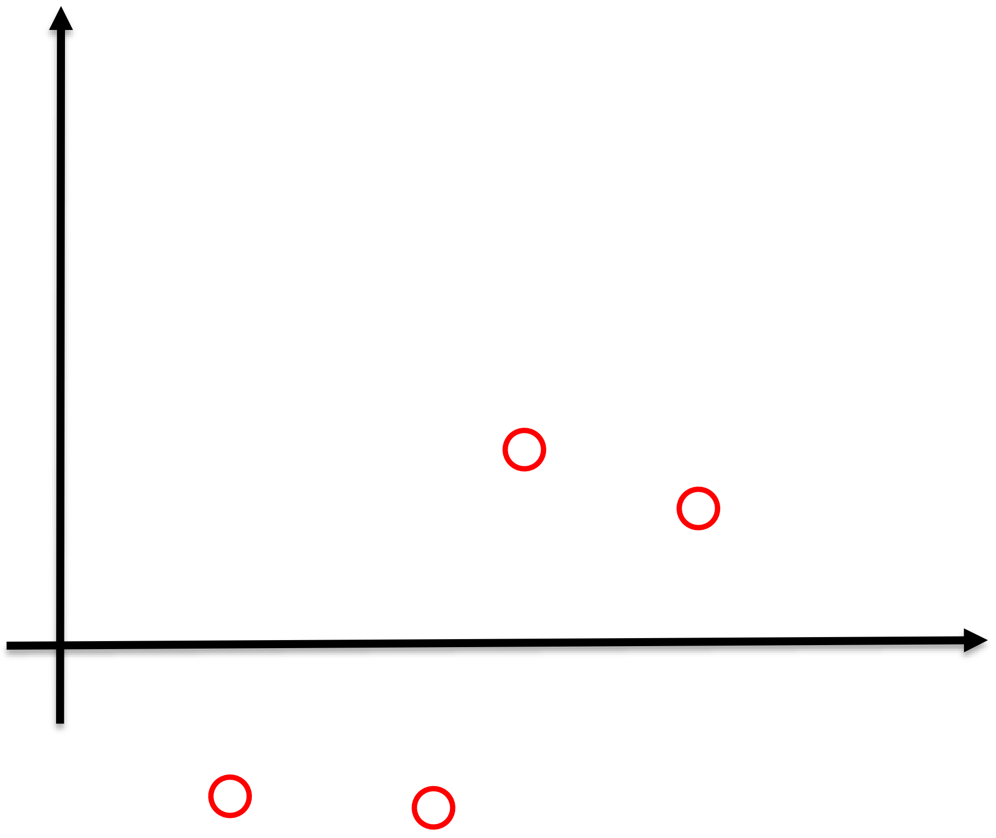
DIMENSIONALITY REDUCTION

This “best” line define a new coordinate system (x' along the line and y' orthogonal to x')



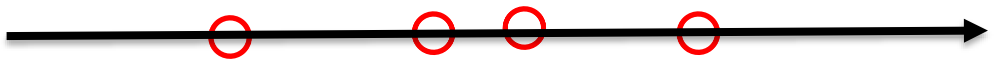
DIMENSIONALITY REDUCTION

Let's consider the new coordinate system (x', y')



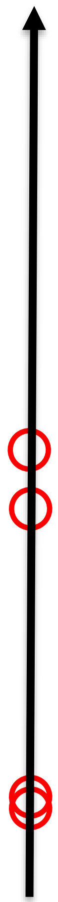
DIMENSIONALITY REDUCTION

Let's now project the data points into x' (cont.)



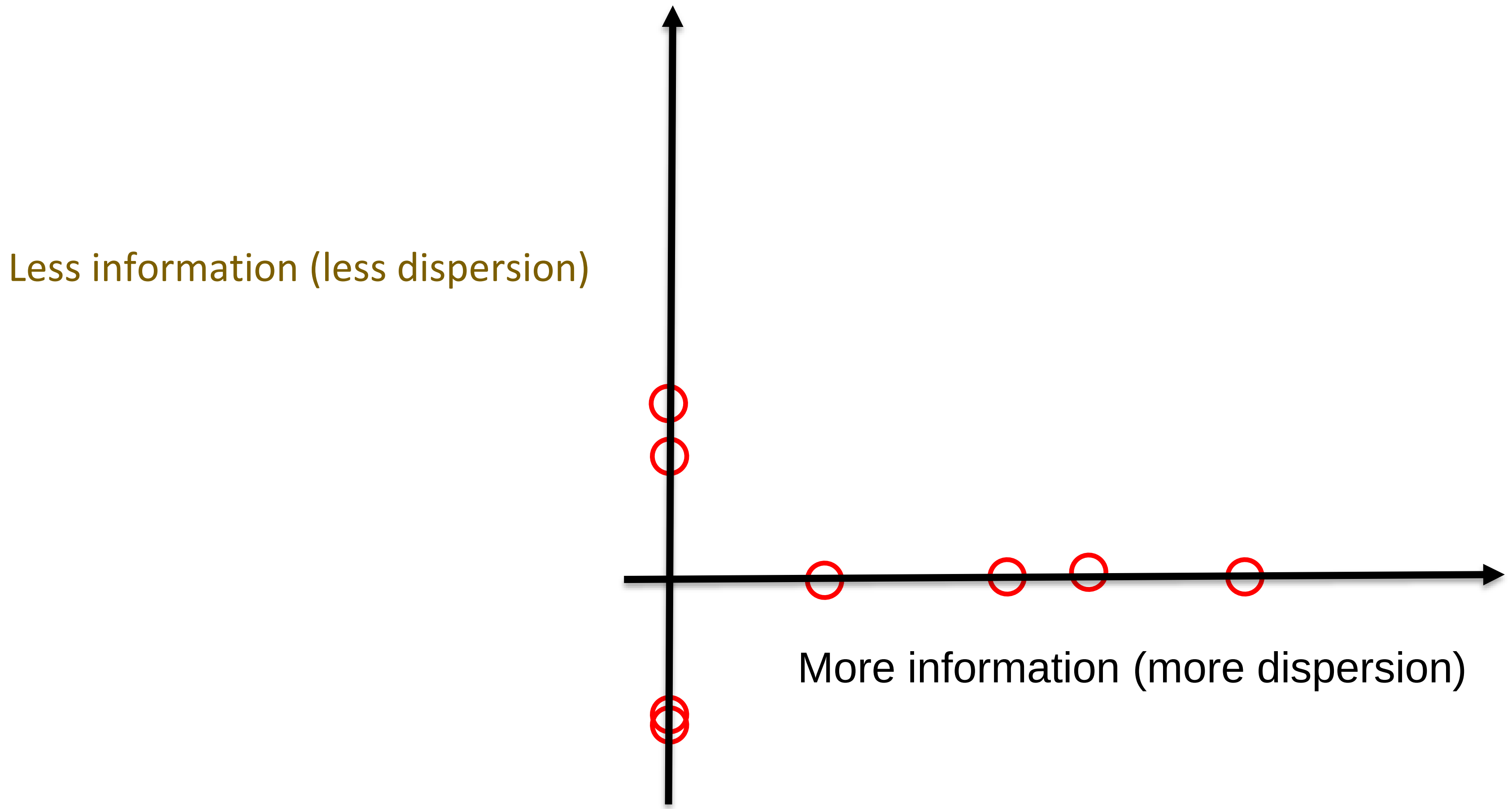
DIMENSIONALITY REDUCTION

Let's now project the data points into y′ (cont.)



DIMENSIONALITY REDUCTION

How much information have we "lost" when projecting the data points to (x', y')?

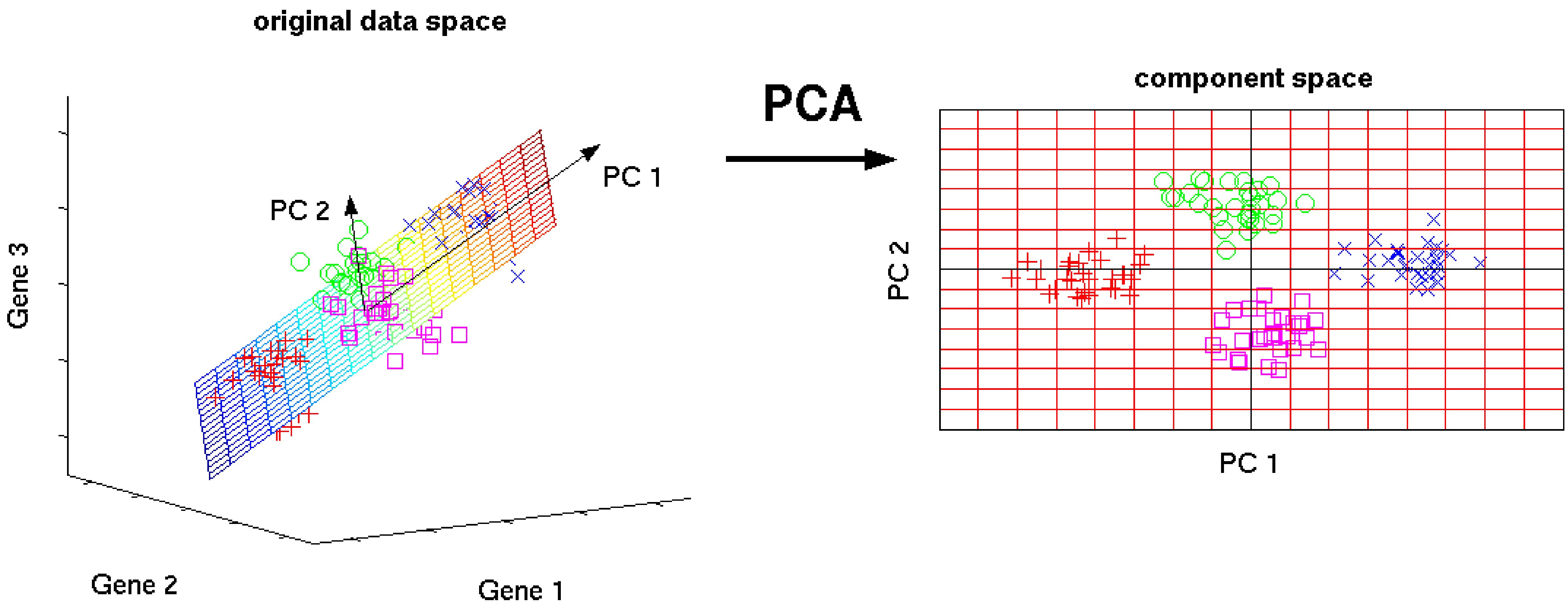


DIMENSIONALITY REDUCTION

Let's say we have a data set of dimension 300 (n) × 50 (p). n represents the number of observations (rows) and p represents number of predictors (columns).

In a data set, the maximum number of principal component loadings is a minimum of (n-1, p)

DIMENSIONALITY REDUCTION



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.

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.

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 most follow a very similar approach.

    a. Identify correlated columns.

    a. 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

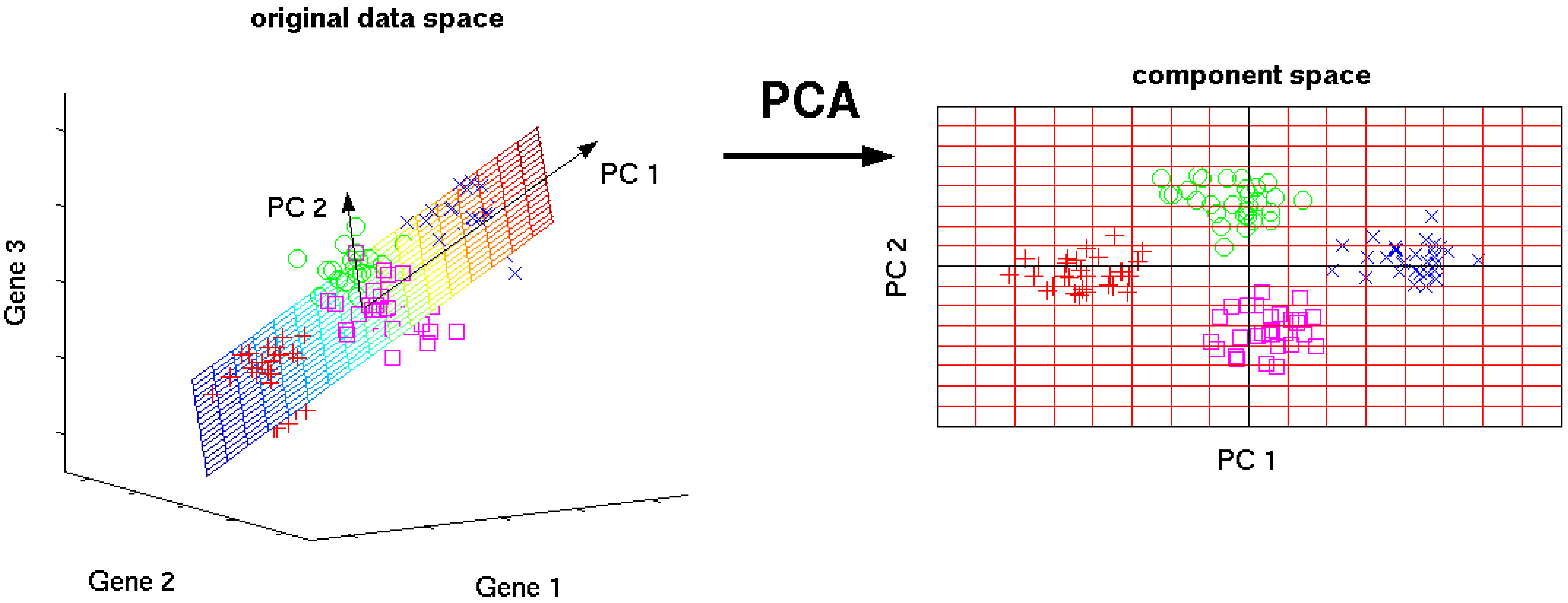
- There are many techniques build into scikit-learn.

- One of the most common is **Principal Component Analysis** (**PCA**).

- PCA, when applied to text data, is sometimes known as **Latent Semantic Indexing** (**LSI**).

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 a new way to generate text:

  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.

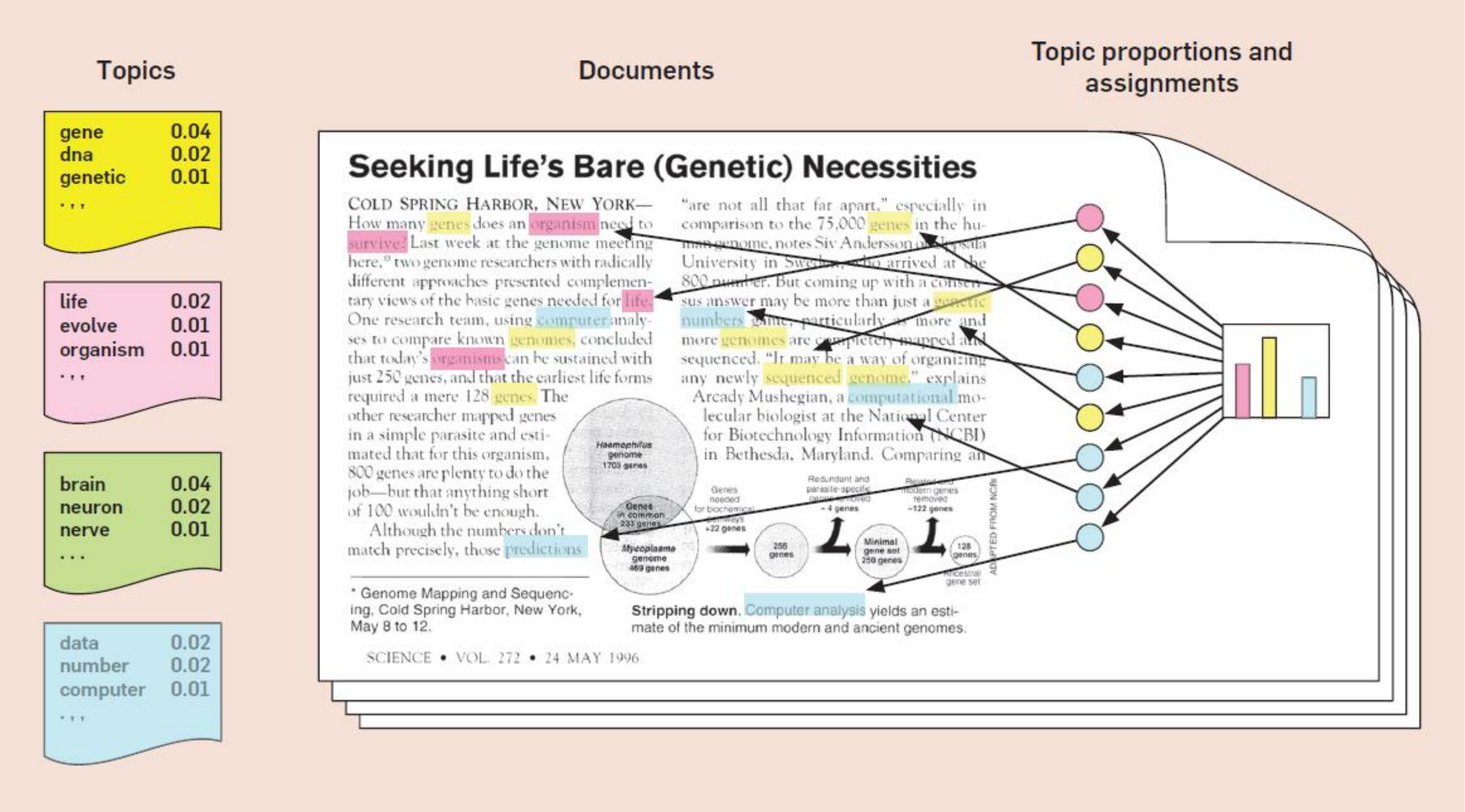
MIXTURE MODELS AND LANGUAGE PROCESSING

- *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

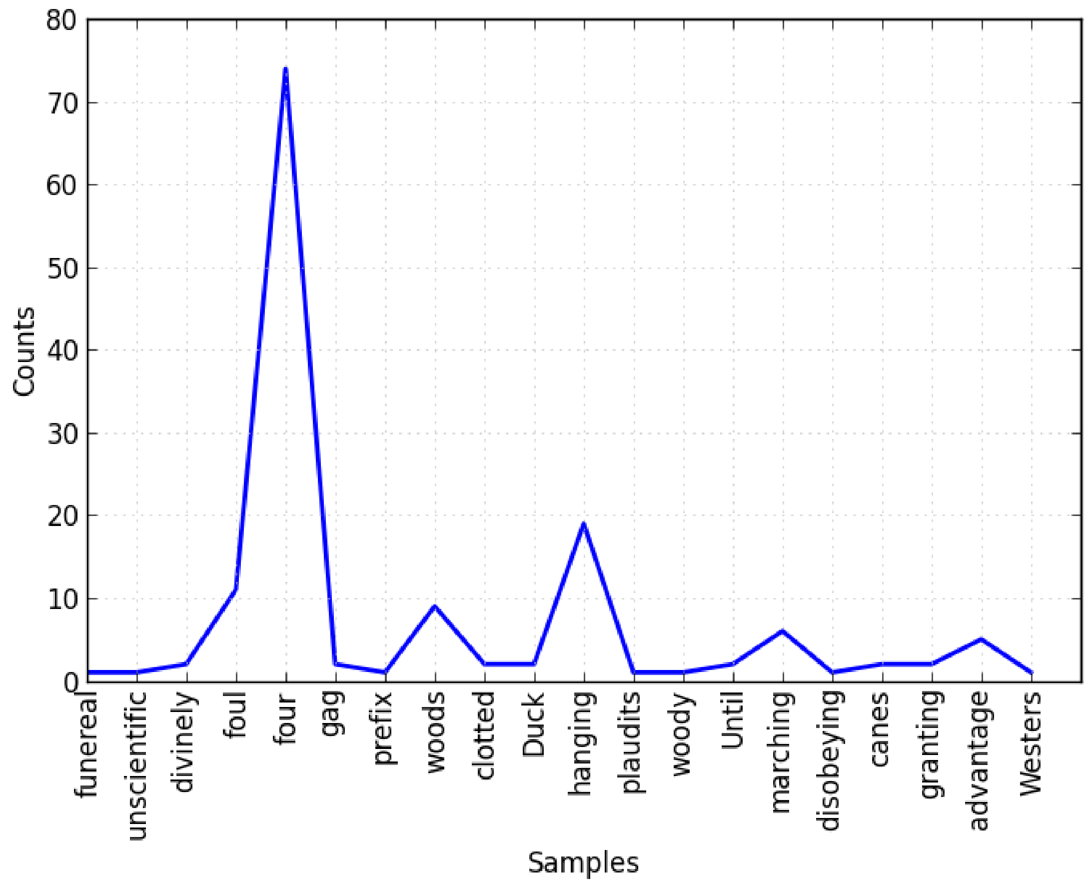
    a. The topic distribution of each document.

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

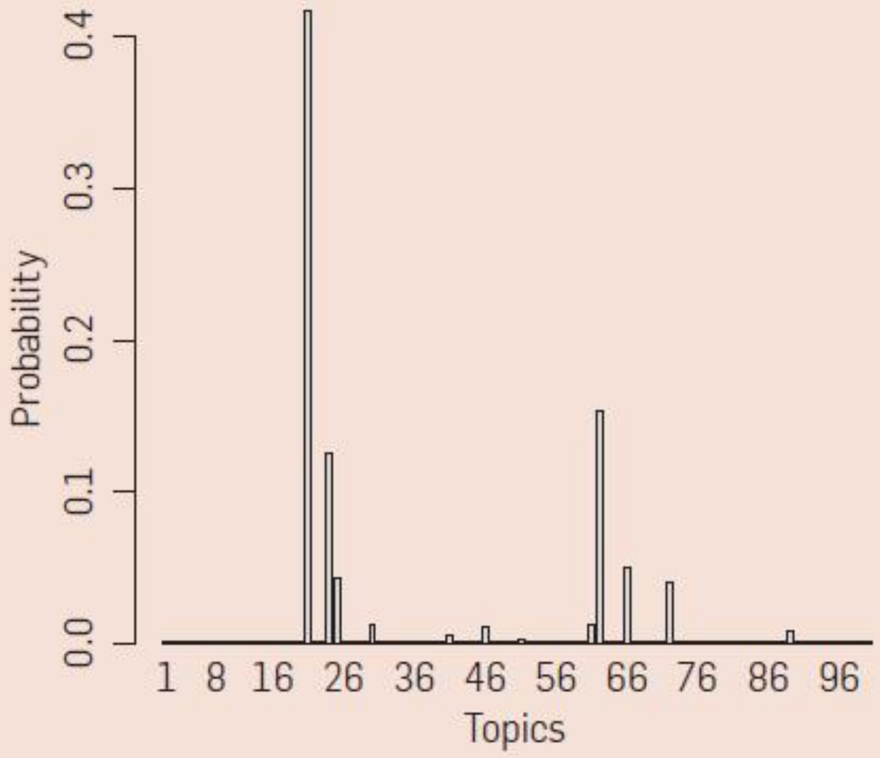
- The *topic distribution* is a multinomial distribution for each document representing what topics are most likely to appear in that document.

- For all our sample 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.

  a. Position-dependent topic models ignore which words occur in which document and instead focus on *where* they occur.

  a. Variable number topic models test different numbers of topics to find the best model.

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.
- Follow Lab 14 Demo

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

```
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

```python
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
```

INTRODUCTION

WORD2VEC

WORD2VEC

- *Word2Vec* is another unsupervised model for latent variable NLP.
- It was originally released by Google and further refined at Stanford.
- This model creates *word vectors*, multidimensional representations of words.

```
assembly → [0.12315, 0.23425, 0.89745324, 0.235234, 0.234234, …]
```

- This is similar to having a distribution of concepts or topics that the word may come from.

WORD2VEC

- If we take our usual document-word matrix and take its transpose, instead of talking about words as being features of a document, we can talk about *documents as being features of a specific word*.

- In other words, how do we define or characterize a single word?

    - We can do so by defining its dictionary definition.

    - Or we can enumerate all of the ways we might use it.

WORD2VEC

- Given the word ‘Paris’, we have many contexts or uses we may find it in:

```
['_ is the capital of', '_, France', 'the capital city _', 'the restaurant in _',]
```

- There are also a bunch of contexts we *don’t* expect to find it in:

```
['can I have a _', 'there's too much _ on this' ... and millions more]
```

- We could make a feature or column for each of these contexts.

- We could represent ‘Paris’ in a sparse feature with all possible contexts.

WORD2VEC

- Additionally, the first few examples represent the *same* concept:
  - Paris is a city like thing, so it contains shops and restaurants.
  - Paris is a capital city.
- We want to use **dimensionality reduction** to find a *few* concepts per word instead of *all* possible contexts.

WORD2VEC

- With **LDA**, we could do this by identifying the topics a word was most likely to come from.

- With **Word2Vec**, we will replace the overlapping contexts by some concept that represents them.

- Like other techniques, our goal is to identify correlated columns and replace them with a new column that represents those replaced columns.

- We can replace the [‘_ is a city’, ‘_ is a capital’, ‘I flew into _ today’] columns by a single column, ‘IsACity’.

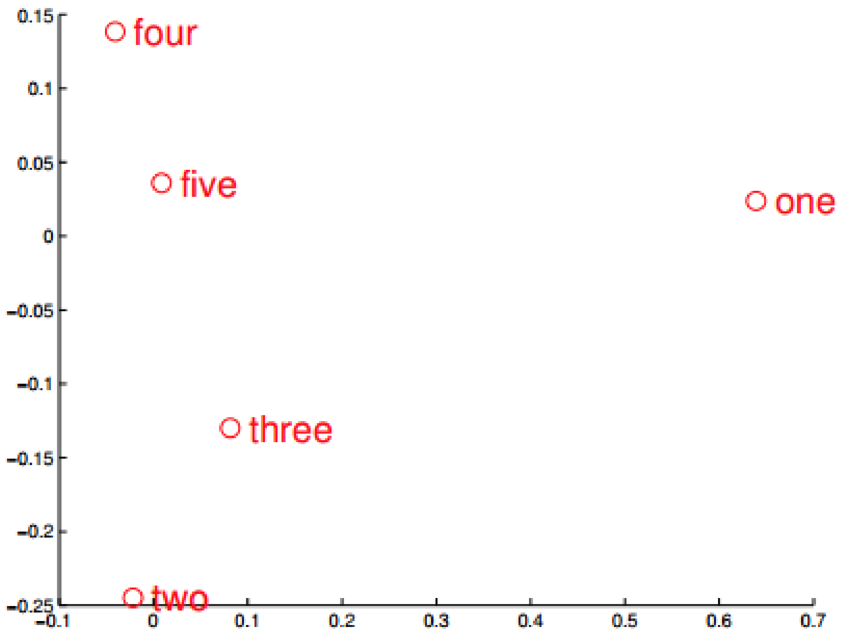
WORD2VEC

- With a trained model, Word2Vec can be used for many tasks.
- A commonly used feature of Word2Vec is being able to ask what words are similar to each other.
- For example, if you ask for words similar to ‘france’, you would get:

```
   spain       0.678515
belgium           0.665923
netherlands       0.652428
   italy       0.633130
switzerland       0.622323
luxembourg        0.610033
portugal          0.577154
```

WORD2VEC

- If we have data for other languages, Word2Vec could also be used for translation.



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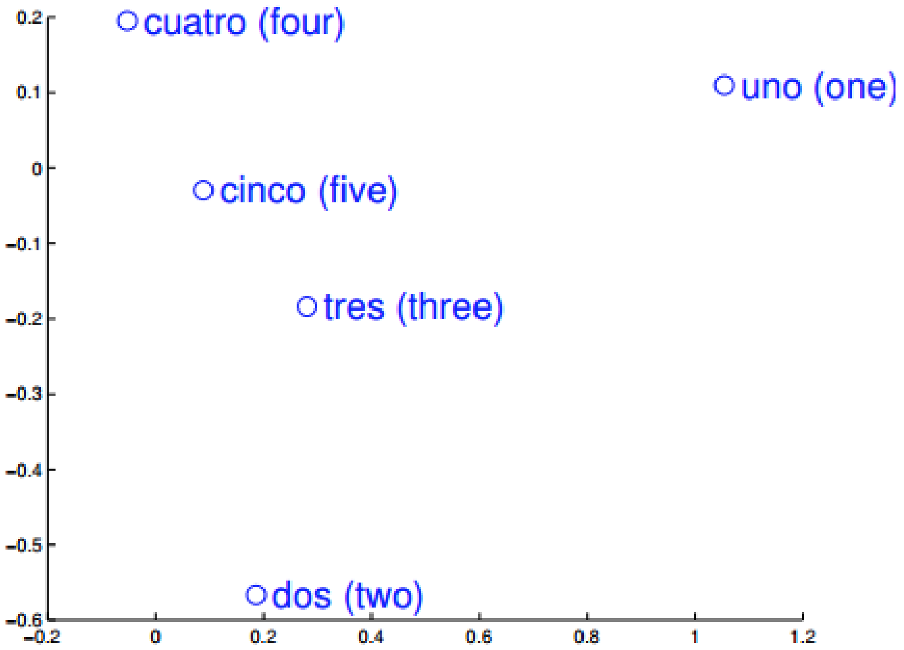

DEMO

WORD2VEC IN GENSIM

WORD2VEC IN GENSIM

- We will build a Word2Vec model using the body text of the articles available in the StumbleUpon dataset.

```
from gensim.models.word2vec import Word2Vec
```

```
# Setup the body text
text = data.body.dropna().map(lambda x: x.split())
```

```
from gensim.models import Word2Vec
model = Word2Vec(text, size=100, window=5, min_count=5, workers=4)
```

WORD2VEC IN GENSIM

- The `Word2Vec` class has many arguments.
    - `size` represents how many concepts or topics we should use.
    - `window` represents how many words surrounding a sentence we should use as our original feature.
    - `min_count` is the number of times that context or word must appear.
    - `workers` is the number of CPU cores to use to speed up model training.

WORD2VEC IN GENSIM

- The model has a most_similar function that helps find the words *most similar* to the one you queried.

- This will return words that are most often used in the same context:

```
model.most_similar(positive=['cookie', 'brownie'])
```

- It can easily identify words related to those from this dataset.

INDEPENDENT PRACTICE

TWITTER LAB

ACTIVITY: TWITTER LAB

EXERCISE

STARTER CODE

Refer to the starter code provided in the class repository for lesson-14.

LOADING THE DATA

```
tweets = [tweet for tweet in
open('../../assets/dataset/captured-tweets.txt', 'r')]
```

SETTING UP SPACY

```
from spacy.en import English
nlp_toolkit = English()
```

ACTIVITY: TWITTER LAB

EXERCISE

TASKS AND QUESTIONS

1. Build a word2vec model of the tweets we have collected using gensim.
   a. First take the collection of tweets and tokenize them using spacy.
      i. Think about how this should be done.
      ii. Should you only use upper-case or lower-case?
      iii. Should you remove punctuations or symbols?

   b. Build a word2vec model.
      i. Test the window size as well - this is how many surrounding words need to be used to model a word. What do you think is appropriate for Twitter?

   c. Test your word2vec model with a few similarity functions.
      i. Find words similar to 'Syria'.
      ii. Find words similar to 'war'.
      iii. Find words similar to "Iran".
      iv. Find words similar to 'Verizon'.

   d. Adjust the choices in (b) and (c) as necessary.

ACTIVITY: TWITTER LAB

EXERCISE

TASKS AND QUESTIONS

1. Filter tweets to those that mention 'Iran' or similar entities and 'war' or similar entities.
   a. Do this using just spacy.
   b. Do this using word2vec similarity scores.

DELIVERABLE

Working code and answers to the questions

EXTRA HOME PRACTICE

Mining Emails

ACTIVITY: TWITTER LAB

EXERCISE

TASKS AND QUESTIONS

1. Mine Emails in emails.csv and ceo-emails.csv

DELIVERABLE

Working code and answers to the questions

CONCLUSION

TOPIC REVIEW

CONCEPT REVIEW

- Latent variable models attempt to uncover structure from text.
- Dimensionality reduction is focused on replacing correlated columns.
- Topic modeling (or LDA) uncovers the topics that are most common to each document and then the words most common to those topics.
- Word2Vec builds a representation of a word from the way it was used originally.
- Both techniques avoid learning grammar rules and instead rely on large datasets. They learn based on how the words are used, making them very flexible.

COURSE

BEFORE NEXT CLASS

DUE DATE

- Project: Final Project, Deliverable 3 (next Tuesday)

OUR PROGRESS SO FAR

UNIT 1: RESEARCH DESIGN AND EXPLORATORY DATA ANALYSIS	~~What is Data Science~~	~~Lesson 1~~
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	~~Statistics Fundamentals II~~	~~Lesson 4~~
	~~Flexible Class Session~~	~~Lesson 5~~
UNIT 2: FOUNDATIONS OF DATA MODELING	~~Introduction to Regression~~	~~Lesson 6~~
	~~Evaluating Model Fit~~	~~Lesson 7~~
	~~Introduction to Classification~~	~~Lesson 8~~
	~~Introduction to Logistic Regression~~	~~Lesson 9~~
	~~Communicating Logistic Regression Results~~	~~Lesson 10~~
	~~Flexible Class Session~~	~~Lesson 11~~
UNIT 3: DATA SCIENCE IN THE REAL WORLD	~~Decision Trees and Random Forests~~	~~Lesson 12~~
	~~Natural Language Processing~~	~~Lesson 13~~
	~~Dimensionality Reduction~~	~~Lesson 14~~
	Time Series Data I	Lesson 15
	Time Series Data II	Lesson 16
	Database Technologies	Lesson 17
	Where to Go Next	Lesson 18
	Flexible Class Session	Lesson 19
	Final Project Presentations	Lesson 20

Next Class

LESSON

Q & A

LESSON

EXIT TICKET

DON'T FORGET TO FILL OUT YOUR EXIT TICKET