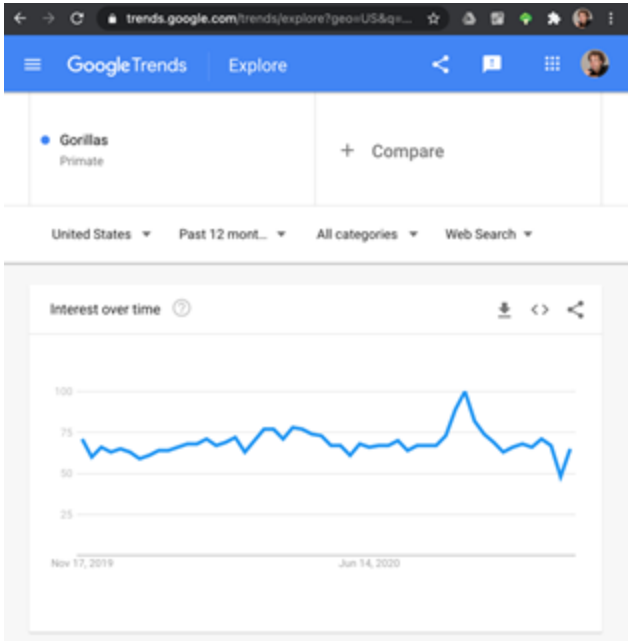
Introduction to Data Science and Analytics (DSC510)

Handling Text

George Pallis

Textual data

- Much of modern data is unstructured text
  - Web
  - Social media
  - News
  - …
- Frequently, “clean” datasets can be derived from “dirty” textual data
  - e.g., search queries are short texts;
    Google Trends time series for concepts
    (e.g., *Gorillas*) are obtained by aggregating
    all search queries referring to the concept
    (e.g., “gorilla”, “big black Rwandan apes”, “are gorillas humans?”)



Outline

- 4 typical tasks on text data:
  - Document retrieval
  - Document classification
  - Sentiment analysis
  - Topic detection
- How to phrase these tasks as machine learning problems
- How to preprocess text so it can be fed to ML algorithms
- Natural Language Processing

Typical task 1: document retrieval

- Given:
  - Document collection (a.k.a. corpus)
  - Query document (can be short query string)
- Task:
  - Rank all docs in collection by similarity to query
- An old problem (e.g., libraries)
- Document retrieval is the core task solved by Web search engines (“10 blue links”)

Document retrieval

- Straightforward approach: neighbor search (as in kNN)
- Define a distance function between documents
- Given query q, find the k docs with smallest distance to q
- k=10, docs sorted by distance, blue links, ads → G
- The hard part: craft/learn a distance function (and scale it to the Web…)

Typical task 2: document classification

- Given:
  - Document d
  - Set of classes (e.g., topics: news, sports, tech, music, romance)
- Task:
  - Decide to which one of the classes document d belongs
- Example scenario:
  - Find news articles about sports events in a large Web corpus

Document classification

- Supervised learning
- Obtain a large collection of documents
- Label each doc with the class it belongs to
- Represent docs as feature vectors
- Train a supervised classifier based on the labeled docs:
  - kNN, logistic regression, decision tree, random forest, support vector machine, neural network, …

Typical task 3: sentiment analysis

- Given:
  - Document d (e.g., product review)
- Task:
  - “Sentiment” score capturing how positive/negative d is
- Example scenario:
  - Infer what people think about a product from text only (i.e., without explicitly given ratings)
  - Historical opinion analysis; e.g., how has people’s attitude toward certain politicians changed over time?

Sentiment analysis

- Supervised learning
  - Regression
  - Classification
- Same setup as for document classification:
  - Label a training set with ground-truth sentiment scores
  - Represent documents as feature vectors
  - Train supervised model: linear/logistic regression, kNN, …

Typical task 4: topic detection

- Given:
  - Unlabeled document collection
- Task:
  - Determine a set of prevalent topics in the docs
  - Determine for each document to which topics it belongs
- Example scenario:
  - Detection of trending topics in social media (e.g., X)
  - Detection of polarized viewpoints on a political subject
  - Exploratory analysis of a large doc collection

Topic detection

- Clustering
- Represent documents as feature vectors
- Run hierarchical or point-assignment clustering algorithm
  - Hierarchical: agglomerative or divisive
  - Point-assignment: e.g., k-means, DBSCAN
- Alternative: matrix factorization

Feature vectors

- Nearly all ML methods work with feature vectors
  - E.g., previous slides: document retrieval; document classification; sentiment analysis; topic detection
- Text is not immediately a feature vector
  - Variable length
  - Even for fixed length (e.g., tweet…): Positions don't correspond to meaningful features

Feature vectors

- Need to transform arbitrarily long string to fixed-length vector
  - Traditional and vetted: bag of words
  - More recent: *learn* a mapping from strings to vectors (buzzword: “text embedding”)

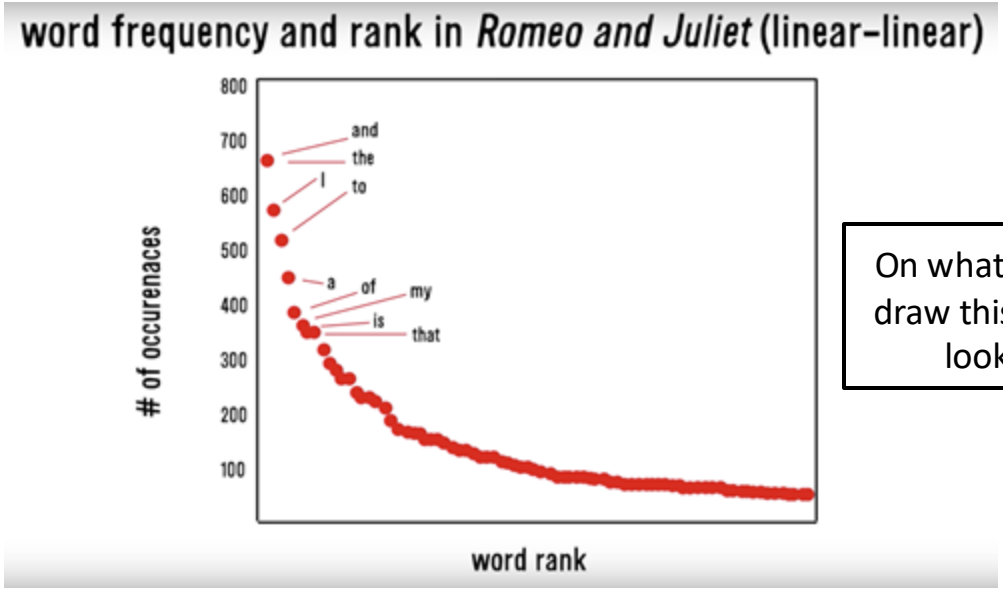
Bag of words

Tom Mitchell (CMU)

- Bag == multiset
  - “multi-”: Keep multiplicity of words
  - “-set”: Don’t keep order of words
  - E.g., document “what you see is what you get”
    → bag of words {get:1, is:1, see:1, what:2, you:2}
- To have fixed-length representation for all documents:
  - One entry for each unique word in vocabulary
  - Bag-of-word vectors are very high-dimensional (typically 1e5 or 1e6) and very sparse
  - E.g., above: [0…0 1 0…0 1 0…0 1 0…0 2 0…0 2 0…0]

Reason for sparsity: Zipf's law

A famous power law



On what axes would you need to draw this plot in order to make it look like a straight line?

The probability of observing a word scales inversely with its frequency rank:

$p(w_i) \propto 1/i$ (where w_i is the i-th most frequent word)

Bag-of-words matrix

- Combine document vectors as rows in a matrix
  - One row per doc
  - One column per word in vocabulary
- This matrix is huge!
  - E.g., Wikipedia: 5M docs, 2M words → 10 trillion entries
- Use a sparse matrix format
  - Triples: (doc_idx, word_idx, count)
  - E.g., Wikipedia, assuming 2000 words per article on avg.: 10 billion non-zero entries (fits in memory)
- With matrix representation, you're ready to use any ML model

… are you?

- In theory, yes
- In practice: “garbage in, garbage out”
- Be careful when mapping raw text to bag-of-words matrix!
  - Character encoding
  - Language identification
  - Tokenization
  - Stopword removal
  - Word normalization
- Tweaking the matrix a bit can lead to much better performance
  - Reweight/normalize rows and/or columns of matrix

Character encoding

- Mapping from (abstract) characters to bytes
- Old school: ASCII, Latin-1
- New school: Unicode (e.g., UTF-8, UTF-16, UTF-32)
- E.g., W → 0x57
- Reading text from file:
  - Need to read with encoding that was used to write file
  - Especially important for non-English text: à, ê, ü, ß, …
- Writing to file: Always use UTF-16; hard-code the output format!

```
file = codecs.open("temp", "w", "utf-8")
file.write(codecs.BOM_UTF8)
file.close()
```

- Otherwise, your future self will be very angry at you (example)

Language identification

- Typically, you're interested in text from a single language
- Increasingly, content is multilingual (e.g., Twitter, Wikipedia)
- Ideally, language code is specified (e.g., headers in HTML; JSON field in Twitter API results)
- But not always…
- There are great libraries (e.g., this)
  - Most commonly based on letter trigrams (e.g., "eau", "ghi", "ijs", "sch", "eiß", "ção")
  - Much harder if you messed up character encoding…

Tokenization

- Maps character string into sequence of tokens (≈ words)
- E.g., “Hello! How are you?” → Hello_!_How_are_you_?
- Tempting to do this yourself by splitting at whitespaces and punctuation
- But many corner cases:
  - “Hello, Mr. President! How are you?! :-)”
    → Hello_,_Mr._President_!_How_are_you_?!_:-)
- Don’t do it yourself, use libraries instead; e.g.,
  - Python: nltk; Java: Stanford CoreNLP
  - Rule-based, deterministic, fast

Tokenization

- Optimal tokenizer different for different languages (e.g., Swedish “Saint Peter” → “S:t Peter”), but English tokenizer often good enough
- Tokenization straightforward in English
- Hard in, e.g., Chinese: no whitespace between words
- Compound words, e.g. in German:
  - Advanced models can split “Donaudampfschifffahrtskapitän” into “Donau dampf schiff fahrts kapitän”
  - But what to keep together…? “Schiff fahrt” or “Schifffahrt”?

Stopword removal

- Very frequent, “small” words carry little information for most tasks and can “drown out” information contained in real content words
- E.g., “a”, “the”, “is”, “you”, “I”, punctuation marks
- Many stopword lists online, but be careful!
  - Different tasks require removing different stopwords
  - Good heuristic: remove words appearing in at least p% of all documents (but what should p be…?)
  - Sometimes stopword removal hurts!
    - Author identification, psychological modeling; punctuation can be useful as well: e.g., “!!!”, “:-)”

Word normalization: casefolding

- E.g., “I love yams. Yams are yummy.”
- Should “yams” and “Yams” really be different features?
- Simple solution: make everything lower-case (“casefolding”)
- But then: “I’d rather have an apple than an Apple.”
- Hand-code exceptions?
- In practice (especially when dataset is large), typically best to **not** do casefolding
- But when dataset is small, might help because less sparsity

Word normalization: Stemming

- Map different forms of same word to same, normalized form, by stripping affixes
- E.g., “walking”, “walks”, “walked” → “walk”
  “business”, “busy” → “busi”
- Typically done in hacky, heuristic way (e.g., Porter stemmer)
- Pro: decreases sparsity in bag-of-words matrix
- Con: discards information
  - E.g., “business” vs. “busy”; “operating” (as in “op. system”)
- In English (esp. with big data) typically not done anymore
- Still very useful in morphologically richer languages (e.g., German, Finnish, Bantu languages)

Word normalization: Lemmatization

- Lemmatization == stemming++
- Map tokens to lexicon entries
- E.g., “U.S.A.”, “US” → “United States”
  “Grüße”, “Gruesse” → “Grüße”
  “You **lie** in the grass” vs. “You **lie** to me”
- Frequently omitted, as it requires complete lexicon and complex mapping rules
- Especially hard for non-English

Social media

A real tweet:

“ikr smh he asked fir yo last name so he can add u on fb lololol”

- Translation:
  - *"ikr"* means "I know, right?"
  - *"smh"* means "shake my head"
  - *"fb"* means "Facebook", a very common proper noun.
  - *"yo"* is being used as equivalent to *"your"*.
  - *"fir"* is a misspelling or spelling variant of the preposition *for*. (But who knows?!)
- Also common: repeating letters/syllables (“yeahhh”, “hahahaha”, “haha”)
- Good luck with traditional NLP tools…
- Need dedicated toolkits such as TweetNLP

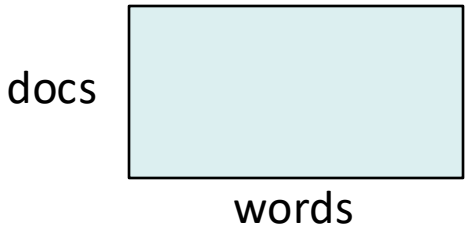
Tokens vs. n-grams

- So far: bag-of-words matrix
  - Rows: documents
  - Columns: tokens (a.k.a. unigrams, or 1-grams)
- Frequently, longer sequences belong together
  - E.g., “United States”, “operating system”
- Brute-force approach: use n > 1
  - E.g., all bigrams (n=2), all trigrams (n=3)
  - Using all 5-grams can beat neural networks (Table 1 here)
  - Problem: combinatorial explosion

Tokens vs. n-grams

- Smarter:
  - Feature selection (“multi-word expressions”, “phrase extraction”)
  - Simple approach for bigrams: keep bigram if *mutual information* between constituent tokens is large
  - How to generalize to n > 2?
    - Frequent itemset/sequence mining
    - Wikipedia anchor texts
    - Compressive feature learning (link)

Postprocessing the BOW matrix



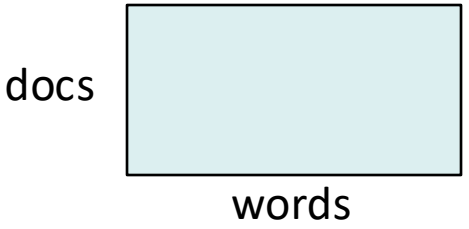
Inverse document frequency

- Not all words equally informative
- This is the reason for removing stopwords (“a”, “the”, “is”, …)
- Beyond discarding stopwords, want to give less weight to more common words
  - E.g., “permanent” vs. “perceptron”
- Standard way: **IDF = inverse document frequency**
  - docfreq(w): number of documents that contain word w
  - N: overall number of documents
  - idf(w) = -log(docfreq(w) / N) = log(N) - log(docfreq(w))

Inverse document frequency

- idf(w) = -log(docfreq(w) / N)
- Interpretation: information content (in terms of #bits) of event “randomly drawing a document that contains w”
- Beyond this theoretical justification, IDF weighting has been shown to work well in practice

TF-IDF matrix



- tf(w, d): term frequency of word w in doc d
  - This is what the bag of words captures
  - E.g., document “what you see is what you get”
    → bag of words {get:1, is:1, see:1, what:2, you:2}
- idf(w): inverse doc freq of w (computed on entire corpus)
- TF-IDF matrix:
  - Entry in row d and column w has value
    tf(w, d) * idf(w)
  - Amounts to multiplying column w with constant idf(w)

Row normalization of TF-IDF matrix

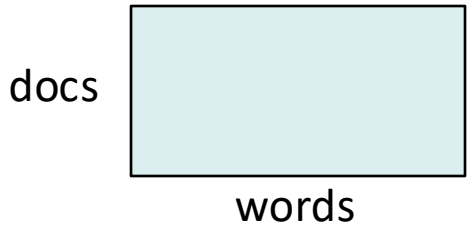
- Longer docs have more non-zero entries
- Interpreted as vectors, longer docs have longer vectors
- This may throw off ML algorithms
  - Long vectors far away from short vectors
  - Dot product: random vector has higher dot product with longer vector
- Fix: normalize doc vectors, i.e., rows of TF-IDF matrix
  - L2-normalization: all rows have Euclidean distance 1 from origin (all data points lie on a unit sphere)
  - L1-normalization: all rows sum to 1, i.e., can be interpreted as distribution
- How to know which one is better?

Column normalization

- IDF-scaling may be seen as column normalization
- Additionally, it may help to apply any of the normalization techniques
  - Min-max scale
  - Standardize: subtract mean; divide by standard deviation
- How to know which one (if any) to use?

Revisiting the 4 typical tasks

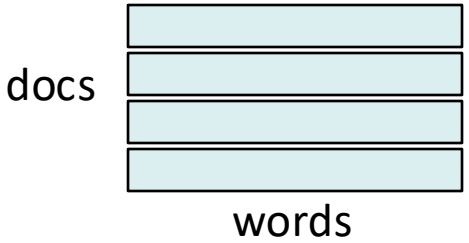
- Document retrieval
- Document classification
- Sentiment analysis
- Topic detection



- TF-IDF matrix to the rescue
  - Entry for doc d, word w:
    tf(w, d) * idf(w)

Typical task 1: document retrieval

- Nearest-neighbor method in spirit of kNN
- Compare query doc q to all documents in the collection (i.e., rows of the TF-IDF matrix)



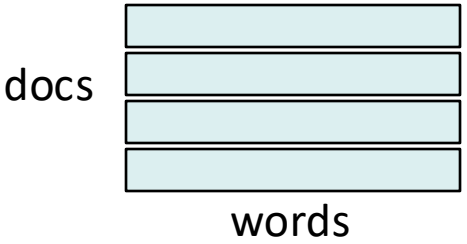
- Rank docs from collection in increasing order of distance
- Distance metrics
  - Typically cosine distance (= 1 - cosine similarity)
  - Recall: cosine similarity of q and v = <q/|q|, v/|v|>
  - If rows are L2-normalized, may simply take dot products <q,v>

Typical task 1: document retrieval

- This is just the most basic approach
- Google does much more…
  - Query-independent relevance: PageRank
  - Boost recent results
  - Personalization, contextualization
  - …
- For efficiency
  - Start by filtering documents by presence of query terms (use efficient full-text index)
  - Hugely narrows down set of documents to be ranked

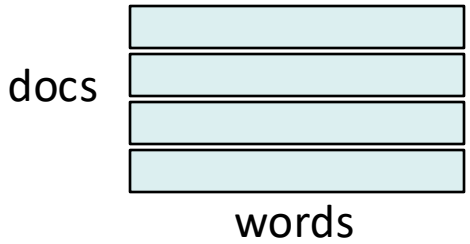
Typical task 2: document classification

- Use TF-IDF matrix as feature matrix for supervised methods
- Often more features (words) than documents
- What's the danger with this?
- High model capacity can lead to overfitting (high variance)
- Potential solutions:
  - Use more data (i.e., more labeled training docs)
  - Decrease model capacity:
    - Feature selection
    - Regularization (two slides from now)
    - Dimensionality reduction (a few slides from now)
  - Use ensemble methods such as random forests



Typical task 3: sentiment analysis

- Ctrl-C Ctrl-V previous slide



Regularization

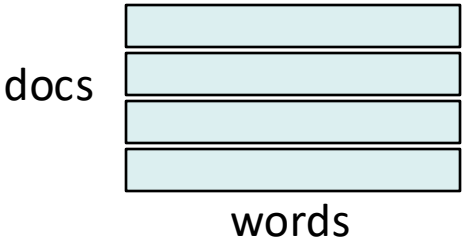
- E.g., linear regression:
  Find weight vector β that minimizes $\sum_{i=1}^{n}(y_i - \mathbf{z}_i^\top \boldsymbol{\beta})^2$

  (z_i: feature vector of *i*-th data point; y_i: label of *i*-th data point, i.e., here: sentiment [1-5 stars] in document *i*)
- If one word *j* appears only in docs with sentiment 5, we can obtain very small training error on these docs by making β_j large enough
- But doesn't generalize to unseen test data!
- Remedy: penalize very large positive and very large negative weights:

$$\sum_{i=1}^{n}(y_i - \mathbf{z}_i^\top \boldsymbol{\beta})^2 + \lambda \sum_{j=1}^{p} \beta_j^2$$

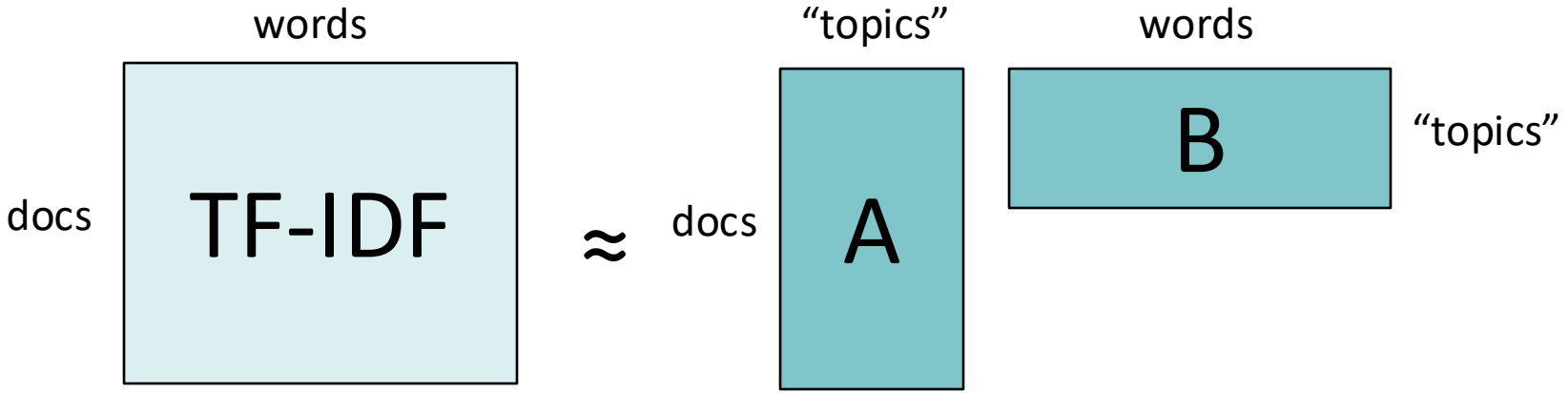
Typical task 4: topic detection

- Cluster rows of TF-IDF matrix (each row a data point)
- Manually inspect clusters and label them with descriptive names (e.g., “news”, “sports”, “romance”, “tech”, “politics”)
- Typically, use k-means or k-medoids algorithms
- Can be difficult if dimensionality is large (#words >> #docs)
  - “Curse of dimensionality”
  - Many outliers



Typical task 4: topic detection

- Alternative approach: **matrix factorization**



- #topics << #words (→ “dimensionality reduction”)
- Assume docs and words have representation in “topic space”
- Word frequency (IDF-weighted) modeled as dot product of doc’s vectors and word’s vectors in topic space
- Topics interpretable in doc space (A’s cols) and word space (B’s rows)

Typical task 4: topic detection

- Optimization problem:
  - Find A, B such that AB is as close to TF-IDF matrix as possible
  - Minimize $\sum_{d=1}^{N} \sum_{w=1}^{M} (T_{dw} - A_d^T B_w)^2$

    where T is TF-IDF matrix, A_d is d-th row of A, B_w is w-th column of B
- This is called **latent semantic analysis (LSA)**

Typical task 4: topic detection

- You already know how to efficiently compute this, from your linear algebra class: singular-value decomposition (SVD)
  - $T = USV^T$
  - Freebie: columns of U and V are orthonormal bases (yay!)
  - S is diagonal and captures "importance" of topic (amount of variation in corpus w.r.t. topic)
  - If you want k topics, keep only the first k columns of U and V, and the first k rows and columns of S
    → U', S', V'
  - E.g., A = U', B = $S'V'^T$

Typical task 4: topic detection

- Recall potential problem with clustering and classification and regression: “curse of dimensionality”
- Matrix factorization via LSA solves these problems for you:
  - Use A instead of original TF-IDF matrix
  - That is, cluster (or learn to classify or regress) in topic space, rather than word space

- Topic representation from LSA is simply a vector, not a probability distribution over topics
- Probabilistic: LDA = Latent Dirichlet Allocation (p.t.o.)

LDA: probabilistic topic modeling

- **L**atent **D**irichlet **A**llocation (*not* Latent Discriminant Analysis!)
- Document := bag of words
- Topic := probability distribution over words
- Each document has a (latent) distribution over topics
- "Generative story" for generating a doc of length n:
  d := sample a topic distribution for the doc (← "Dirichlet")
  for i = 1, …, n
    t := sample a topic from topic distribution d
    w := sample a word from topic t
    Add w to the bag of words of the doc to be generated

Topics

gene	0.04
dna	0.02
genetic	0.01
. . .	

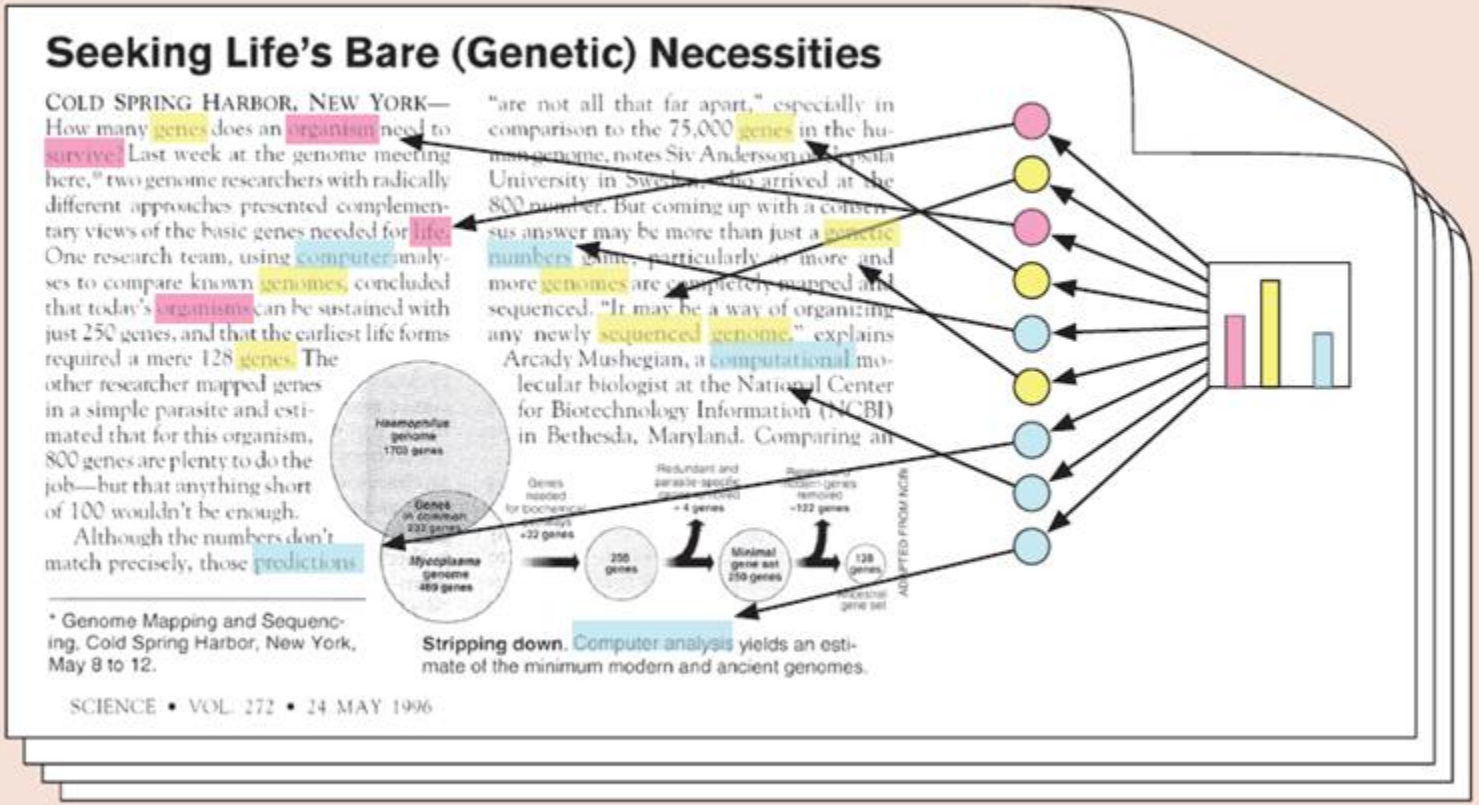
life	0.02
evolve	0.01
organism	0.01
. . .	

brain	0.04
neuron	0.02
nerve	0.01
. . .	

data	0.02
number	0.02
computer	0.01
. . .	

Documents

Topic proportions and assignments



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

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

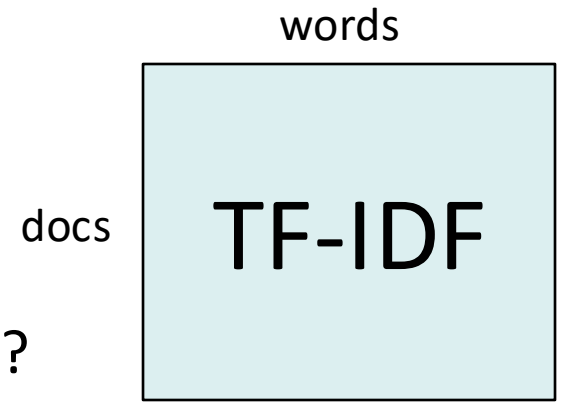
* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

Topic inference in LDA

- LDA is unsupervised (topics come out “magically”)
- Input:
  - Docs represented as bags of words
  - Number K of topics
- Output:
  - K topics (distributions over words)
  - For each doc: distribution over K topics
- How is this done?
  - Find distributions (i.e., topics, docs) that maximize the likelihood of the observed documents (maximum likelihood)

Question:

- “Which of these word pairs is more closely related?”
  - car, bus
  - car, astronaut
- How to quantify this?
- Detour:
  - How to quantify closeness of two docs?
  - E.g., cosine of **rows** of TF-IDF matrix
- Retour:
  - How to quantify closeness of two words?
  - E.g., cosine of **cols** of TF-IDF matrix



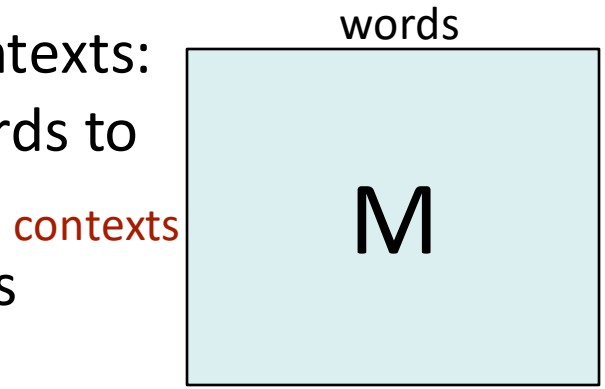
Sparsity in TF-IDF matrix

- Two docs (i.e., rows of TF-IDF matrix)
  - “Do you love men?”
  - “Adorest thou the likes of Adam?”
  - Cosine of row vectors == 0
- Solution:
  - Move from sparse to dense vectors
  - But how?
  - Latent semantic analysis (LSA)!

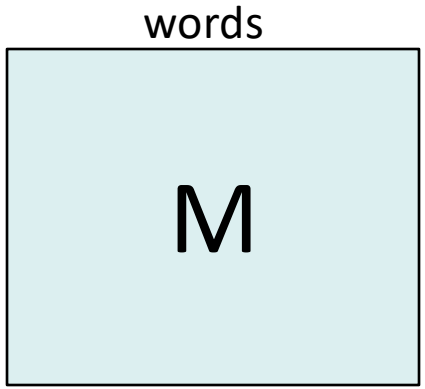
“Word vectors”

- Columns of TF-IDF matrix (sparse)
  or of word-by-topic matrix B (dense)

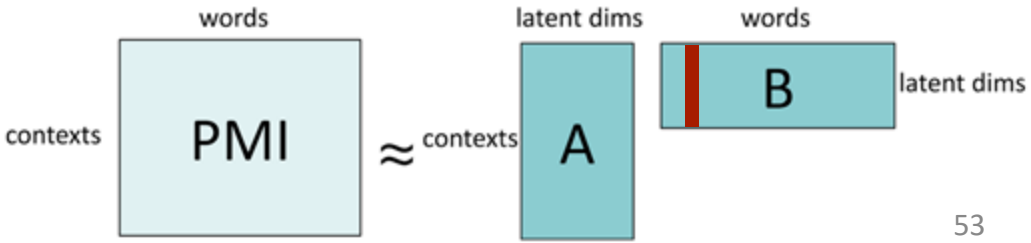
- Problem:
  - Entire doc treated as one bag of words
  - All information about word proximity, syntax, etc., lost
- Solution:
  - Instead of full docs, consider local contexts:
    windows of L (e.g., 3) consecutive words to
    left and right of the target word
  - Rows of matrix: not docs, but contexts



“Word vectors”



- What to use as entries of word/context matrix?
- Straightforward: same as TF-IDF, but with contexts as “pseudo-docs”: M[c,w] = TF-IDF(c,w)
- May use any other measures of statistical association
- E.g., pointwise mutual information (PMI):
  M[c,w] = PMI(c,w) = $\log \frac{\Pr(c,w)}{\Pr(c)\ \Pr(w)}$
  “How much more likely are c and w to occur together than if they were independent?”
- word2vec: factor PMI matrix and use columns of B as word vectors

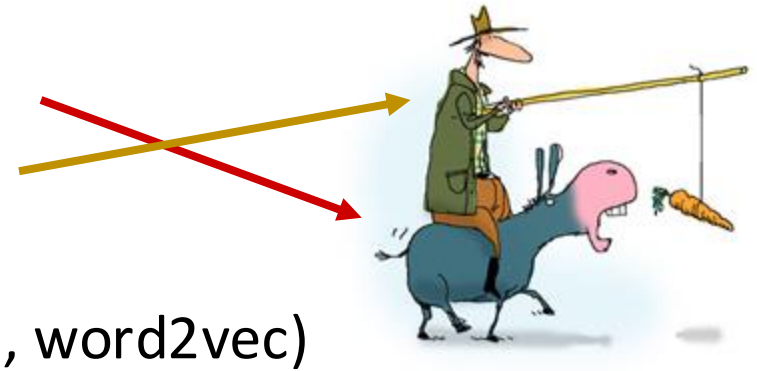


From words to texts

- Word vectors represent, well, words
- How to represent larger units, such as sentences, paragraphs, docs?
- Typical approach: take sum/average of word vectors
- Note: this is roughly also what bags of words are (when using “one-hot” encoding for words, i.e., vector with exactly one 1, rest 0)
- Current research: **learn** vectors for longer units
  - Cr5, sent2vec
  - Convolutional neural networks
  - Recurrent neural networks, e.g., LSTM, ELMo
  - Transformer-based models, e.g., BERT (next slide)

Contextualized word vectors

- Motivating example:
  - “My ass likes carrots”
  - vs. “He’s such an ass”

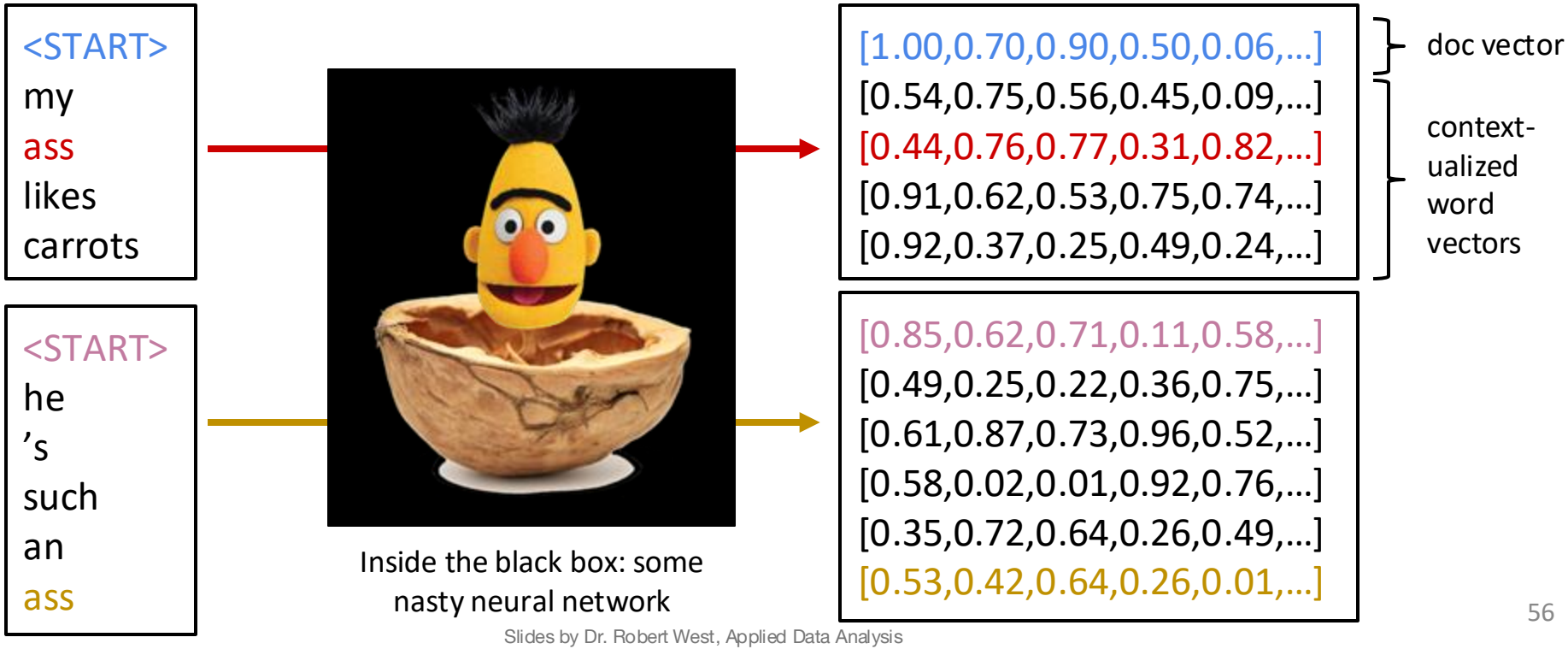


- Classic word vectors (e.g., word2vec) cannot distinguish these two cases; same vector used for both instances of “ass”

- Solution: contextualized word vectors
  - E.g., BERT

BERT in a nutshell

- Introduced on Oct 2018 by Google Research



BERT in a nutshell

1. What it is:

A **pre-trained language model** developed by Google in 2018.

Based on **Transformers** (attention mechanism).

Learns **contextual word representations** by looking at **both left and right context** (bidirectional).

2. Key Ideas:

Bidirectional: Unlike older models (e.g., Word2Vec, GPT-1), BERT reads the whole sentence simultaneously, capturing richer context.

Masked Language Modeling (MLM): Randomly masks some words in a sentence and predicts them.

Next Sentence Prediction (NSP): Learns relationships between sentences.

3. How it works:

Input: Sentence(s) → Tokenization → Add special tokens `[CLS]` and `[SEP]`

Pass through **Transformer encoder layers** → Output embeddings for each token

Fine-tune on downstream tasks (classification, QA, NER, etc.)

4. Use Cases:

Question Answering

Sentiment Analysis

Named Entity Recognition

Text Classification

5. Key Takeaways:

Context-aware word representations

Powerful for a variety of NLP tasks

Can be fine-tuned efficiently on small datasets

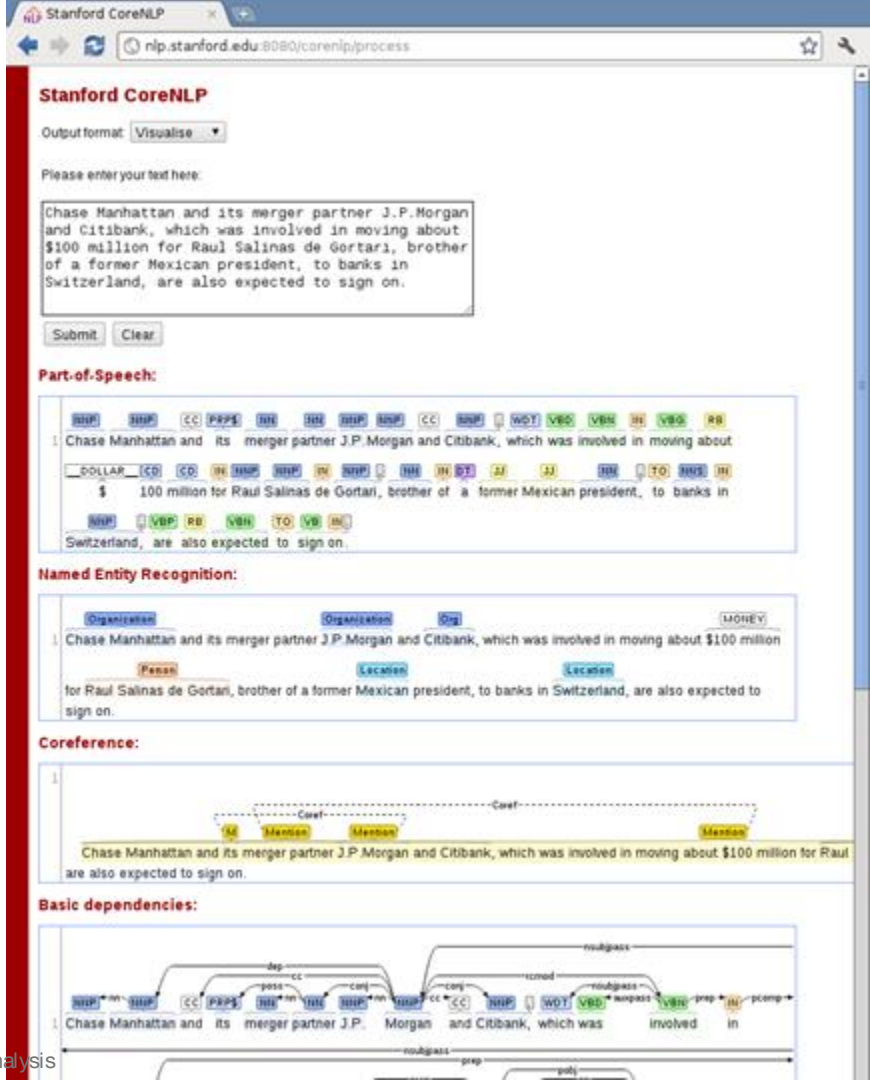
ChatGPT in a nutshell

1. What it is:
A **large language model (LLM)** developed by OpenAI.
Based on the **GPT-5 architecture**, optimized for **text understanding, generation, and reasoning**.
Designed to be **conversational, knowledgeable, and context-aware**.
2. Key Features:
Generative: Produces human-like text for a wide range of tasks.
Context-aware: Maintains coherence over long conversations.
Multi-modal (future/optional): Can handle text and potentially images in certain implementations.
Few-shot learning: Can adapt to new tasks with minimal examples.
3. How it works:
Uses **transformer architecture** with attention mechanisms.
Predicts the next token in a sequence based on prior context.
Fine-tuned with **reinforcement learning from human feedback (RLHF)** for safe and useful outputs.
4. Use Cases:
Conversational AI / Chatbots
Content generation (articles, summaries, code)
Question answering
Educational tutoring
Research assistance
5. Key Takeaways:
Powerful, versatile AI for **language understanding and generation**
Can **adapt to many domains** without retraining
Emphasizes **safety, alignment, and contextual reasoning**

Beyond bags of words

NLP pipeline

- Tokenization
- Sentence splitting
- Part-of-speech (POS) tagging
- Named-entity recognition (NER)
- Co-reference resolution
- Parsing
  - Shallow parsing (a.k.a. chunking)
  - Constituency parsing
  - Dependency parsing



Shallow Parsing (Chunking)

Definition: Identifies phrases (noun, verb, etc.) without full hierarchical structure.

Goal: Detect phrase boundaries. Shallow parsing (also chunking or light parsing) is an analysis of a sentence which first identifies constituent parts of sentences (nouns, verbs, adjectives, etc.) and then links them to higher order units that have discrete grammatical meanings (noun groups or phrases, verb groups, etc.).

Example:

```
Sentence: The quick brown fox jumps over the lazy dog
Chunks: [The quick brown fox] [jumps] [over the lazy dog]
```

Use Cases:

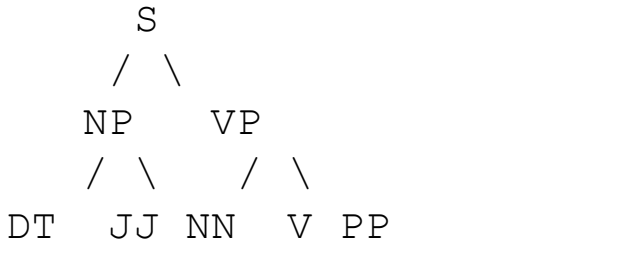
- Information extraction
- Named Entity Recognition

Constituency Parsing

Definition: Builds a hierarchical parse tree showing nested phrases.

Goal: Capture full syntactic structure - helps computers understand sentence structure for applications like machine translation and sentiment analysis

Example Tree (simplified):



- `S` = Sentence, `NP` = Noun Phrase, `VP` = Verb Phrase
- `DT` = Determiner, `JJ` = Adjective, `NN` = Noun, `V` = Verb

Use Cases:

- Grammar checking
- Machine translation
- Question answering

Dependency Parsing

Definition: Represents grammatical relationships between words (head → dependent).

Goal: Capture word-to-word syntactic relations.

Example:

•In the sentence "She eats an apple," "eats" is the root, "She" is its subject, and "apple" is its object.

Use Cases:

- Relation extraction
- Semantic role labeling
- Information retrieval

NLP pipeline

- Implemented by Stanford CoreNLP, nltk, spaCy, etc.
- Sequential model
  - Fixed order of steps
  - Early errors will propagate downstream
  - Fixed order not optimal for all cases (e.g., syntax usually done before semantics, but semantics might be useful for inferring syntax)
- Hence, current research: learn all tasks jointly (early example)
- To learn how all this magic is implemented
  - Take NLP course in the spring semester