Words vs. Terms

Words vs. Terms

- Information Retrieval cares about "terms"
- You search for 'em, Google indexes 'em
- Query:
  - `What kind of monkeys live in Costa Rica?`

Words vs. Terms

- `What kind of monkeys live in Costa Rica?`
  - words?
  - content words?
  - word stems?
  - word clusters?
  - multi-word phrases?
  - thematic content? (this is a "habitat question")

Finding Phrases ("collocations")

- kick the bucket
- directed graph
- iambic pentameter
- Osama bin Laden
- United Nations
- real estate
- quality control
- international best practice
- … have their own meanings, translations, etc.

Finding Phrases ("collocations")

- Just use common bigrams?
- Doesn't work:
  - 80871 of the
  - 58841 in the
  - 26430 to the
  - ...
  - 15494 to be
  - ...
  - 12622 from the
  - 11428 New York
  - 10007 he said
- Possible correction – just drop function words!

Finding Phrases ("collocations")

- Just use common bigrams?
- Better correction - filter by tags: A N, N N, N P N ...
  - 11487 New York
  - 7261 United States
  - 5412 Los Angeles
  - 3301 last year
  - ...
  - 1074 chief executive
  - 1073 real estate
  - ...

Finding Phrases ("collocations")

- Still want to filter out "new companies"
- These words occur together reasonably often but only because both are frequent
- Do they occur **more** often [among A N pairs?] than you would expect by chance?
  - Expect by chance: p(new) p(companies)
  - Actually observed: p(new companies) = p(new) p(companies | new)
  - mutual information
  - binomial significance test

data from Manning & Schütze textbook (14 million words of NY Times)

(Pointwise) Mutual Information

	new ___	¬new ___	TOTAL
___ companies	8	4,667 ("old companies")	4,675
___ ¬companies	15,820	14,287,181 ("old machines")	14,303,001
TOTAL	15,828	14,291,848	14,307,676

- p(new companies) = p(new) p(companies) ?
- MI = $\log_2$ p(new companies) / p(new)p(companies)
  = $\log_2$ (8/N) /((15828/N)(4675/N)) = $\log_2$ 1.55 = 0.63
- MI > 0 if and only if p(co's | new) > p(co's) > p(co's | ¬new)
- Here MI is positive but small. Would be larger for stronger collocations.

N

data from Manning & Schütze textbook (14 million words of NY Times)

Significance Tests

	new ___	¬new ___	TOTAL
___ companies	1	583 ("old companies")	584
___ ¬companies	1978	1,785,898 ("old machines")	1,787,876
TOTAL	1979	1,786,481	1,788,460

- Sparse data. In fact, suppose we divided all counts by 8:
  - Would MI change?
  - No, yet we should be less confident it's a real collocation.
  - Extreme case: what happens if 2 novel words next to each other?
- So do a significance test! Takes sample size into account.

data from Manning & Schütze textbook (14 million words of NY Times)

Binomial Significance ("Coin Flips")

	new ___	¬new ___	TOTAL
___ companies	8	4,667	4,675
___ ¬companies	15,820	14,287,181	14,303,001
TOTAL	15,828	14,291,848	14,307,676

- Assume we have 2 coins that were used when generating the text.
- Following new, we flip coin A to decide whether companies is next.
- Following ¬new, we flip coin B to decide whether companies is next.
- We can see that A was flipped 15828 times and got 8 heads.
  - Probability of this: $p^8 (1-p)^{15820} * {}^{15828!}/_{8!\ 15820!}$
- We can see that B was flipped 14291848 times and got 4667 heads.
- Our question: **Do the two coins have different weights?** (equivalently, are there really two separate coins or just one?)

data from Manning & Schütze textbook (14 million words of NY Times)

Binomial Significance ("Coin Flips")

	new ___	¬new ___	TOTAL
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TOTAL	15,828	14,291,848	14,307,676

- **Null hypothesis:** same coin
  - assume p_{null}(co's | new) = p_{null}(co's | ¬new) = p_{null}(co's) = 4675/14307676
  - p_{null}(data) = p_{null}(8 out of 15828)*p_{null}(4667 out of 14291848) = .00042
- **Collocation hypothesis:** different coins
  - assume p_{coll}(co's | new) = 8/15828, p_{coll}(co's | ¬new) = 4667/14291848
  - p_{coll}(data) = p_{coll}(8 out of 15828)*p_{coll}(4667 out of 14291848) = .00081
- So collocation hypothesis doubles p(data).
  - We can sort bigrams by the log-likelihood ratio: log p_{coll}(data)/p_{null}(data)
  - i.e., how *sure* are we that "companies" is more likely after "new"?

data from Manning & Schütze textbook (14 million words of NY Times)

Binomial Significance ("Coin Flips")

	new ___	¬new ___	TOTAL
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___ ¬companies	1978	1,785,898	1,787,876
TOTAL	1979	1,786,481	1,788,460

- **Null hypothesis:** same coin
  - assume p_{null}(co's | new) = p_{null}(co's | ¬new) = p_{null}(co's) = 584/1788460
  - p_{null}(data) = p_{null}(1 out of 1979)*p_{null}(583 out of 1786481) = .0056
- **Collocation hypothesis:** different coins
  - assume p_{coll}(co's | new) = 1/1979, p_{coll}(co's | ¬new) = 583/1786481
  - p_{coll}(data) = p_{coll}(1 out of 1979)*p_{coll}(583 out of 1786418) = .0061
- Collocation hypothesis still increases p(data), but only slightly now.
  - If we don't have **much** data, 2-coin model can't be **much** better at explaining it.
  - Pointwise mutual information as strong as before, but based on much less data. So it's now reasonable to believe the null hypothesis that it's a coincidence.

data from Manning & Schütze textbook (14 million words of NY Times)

Binomial Significance ("Coin Flips")

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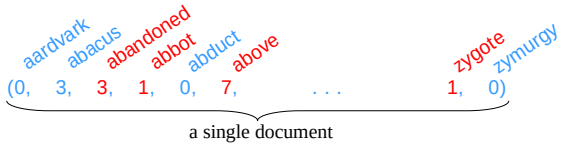
  - p_{coll}(data) = p_{coll}(8 out of 15828)*p_{coll}(4667 out of 14291848) = .00081
- Does this mean that collocation hypothesis is twice as likely?
  - No, as it's far less probable *a priori* ! (most bigrams ain't collocations)
  - Bayes: p(coll | data) = p(coll) * p(data | coll) / p(data) isn't twice p(null | data)

Function vs. Content Words

- Might want to eliminate function words, or reduce their influence on a search
- Tests for content word:
  - If it appears rarely?
    - no: c(beneath) < c(Kennedy) ≈ c(aside) « c(oil) in WSJ
  - If it appears in only a few documents?
    - better: Kennedy tokens are concentrated in a few docs
    - This is traditional solution in IR
  - If its frequency varies a lot among documents?
    - best: content words come in bursts (when it rains, it pours?)
    - probability of Kennedy is increased if Kennedy appeared in preceding text – it is a "self-trigger" whereas beneath isn't

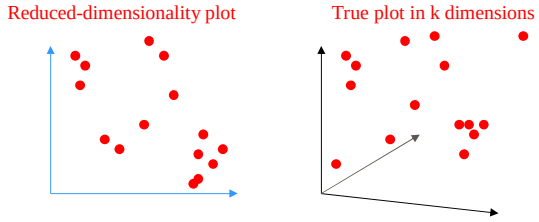
Latent Semantic Analysis

- A trick from Information Retrieval
  - Each **document** in corpus is a length-k vector
    - Or each paragraph, or whatever



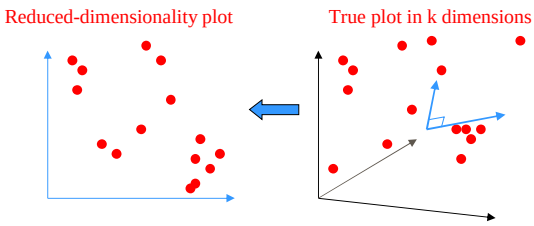
Latent Semantic Analysis

- A trick from Information Retrieval
  - Each **document** in corpus is a length-k vector
  - Plot all documents in corpus



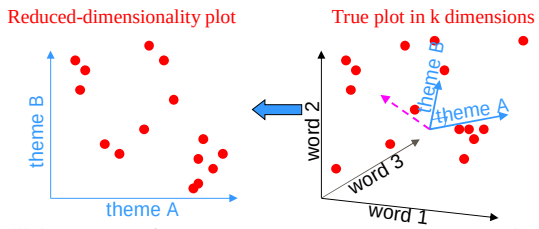
Latent Semantic Analysis

- Reduced plot is a perspective drawing of true plot
- It projects true plot onto a few axes
- ∃ a best choice of axes – shows most variation in the data.
  - Found by linear algebra: "Singular Value Decomposition" (SVD)



Latent Semantic Analysis

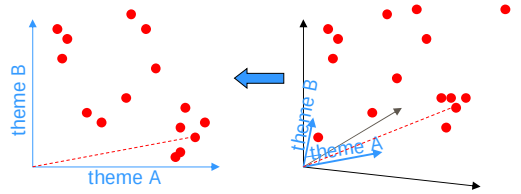
- SVD plot allows best possible reconstruction of true plot (i.e., can recover 3-D coordinates with minimal distortion)
- Ignores variation in the axes that it didn't pick
- Hope that variation's just noise and we **want** to ignore it



Latent Semantic Analysis

- SVD finds a small number of theme vectors
- Approximates each doc as linear combination of themes
- Coordinates in reduced plot = linear coefficients
  - How much of theme A in this document? How much of theme B?
  - Each theme is a collection of words that tend to appear together

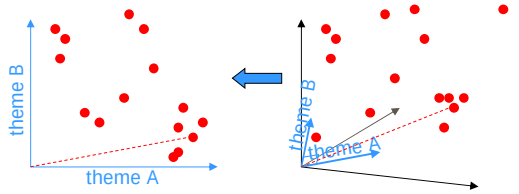
Reduced-dimensionality plot | True plot in k dimensions



Latent Semantic Analysis

- New coordinates might actually be useful for Info Retrieval
- To compare 2 documents, or a query and a document:
  - Project both into reduced space: do they have themes in common?
  - Even if they have no words in common!

Reduced-dimensionality plot | True plot in k dimensions

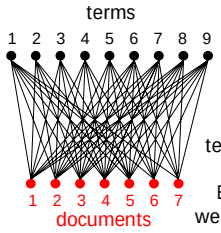


Latent Semantic Analysis

- Themes extracted for IR might help sense disambiguation
- Each word is like a tiny document: (0,0,0,1,0,0,...)
- Express word as a linear combination of themes
- Each theme corresponds to a sense?
  - E.g., "Jordan" has Mideast and Sports themes
    (plus Advertising theme, alas, which is same sense as Sports)
  - Word's sense in a document: which of its themes are strongest in the document?
- Groups senses as well as splitting them
  - One word has several themes and many words have same theme

Latent Semantic Analysis

- Another perspective (similar to neural networks):

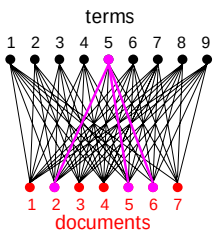


matrix of strengths (how strong is each term in each document?)

Each connection has a weight given by the matrix.

Latent Semantic Analysis

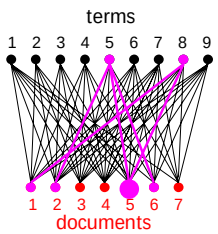
- Which documents is term 5 strong in?



docs 2, 5, 6 light up strongest.

Latent Semantic Analysis

- Which documents are terms 5 and 8 strong in?

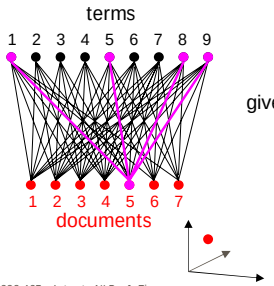


This answers a query consisting of terms 5 and 8!

really just matrix multiplication:
term vector (query) x strength matrix = doc vector

Latent Semantic Analysis

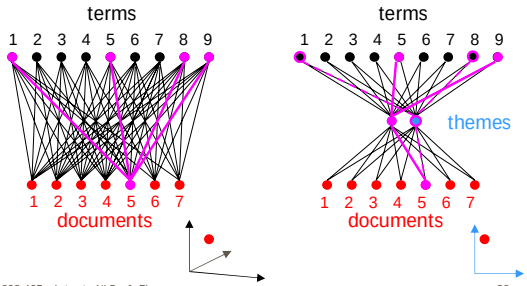
- Conversely, what terms are strong in document 5?



gives doc 5's coordinates!

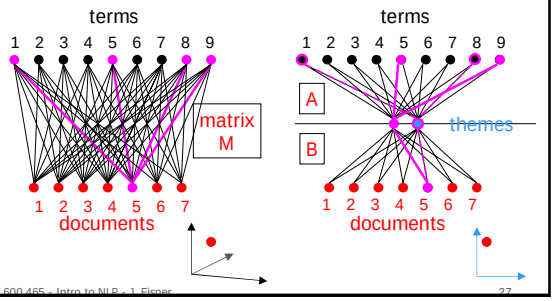
Latent Semantic Analysis

- SVD approximates by smaller 3-layer network
  - Forces sparse data through a bottleneck, smoothing it



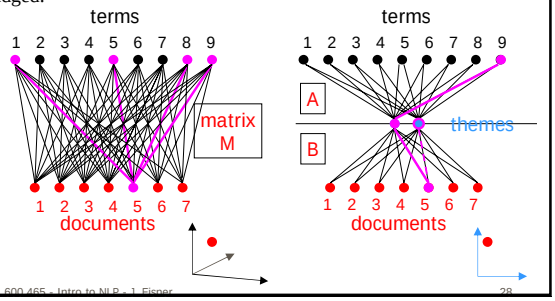
Latent Semantic Analysis

- I.e., smooth sparse data by matrix approx: **M ≈ A B**
  - A encodes camera angle, B gives each doc's new coords



Latent Semantic Analysis

Completely symmetric! Regard A, B as projecting terms and docs into a low-dimensional "theme space" where their similarity can be judged.

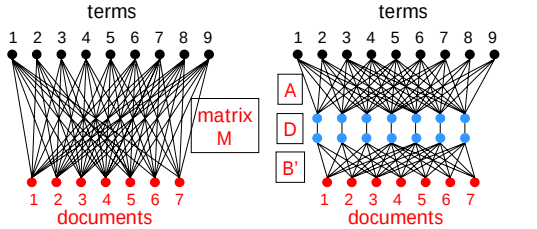


Latent Semantic Analysis

- Completely symmetric. Regard A, B as projecting terms and docs into a low-dimensional "theme space" where their similarity can be judged.
- Cluster documents (helps sparsity problem!)
- Cluster words
- Compare a word with a doc
- Identify a word's themes with its senses
  - sense disambiguation by looking at document's senses
- Identify a document's themes with its topics
  - topic categorization

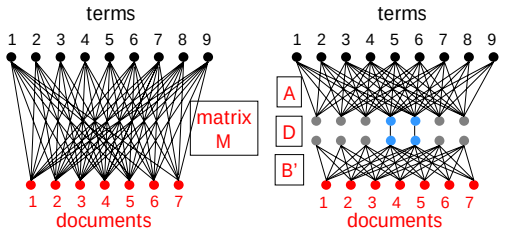
If you've seen SVD before ...

- SVD actually decomposes **M = A D B' exactly**
  - A = camera angle (orthonormal); D diagonal; B' orthonormal



If you've seen SVD before ...

- Keep only the largest j < k diagonal elements of D
  - This gives best possible approximation to M using only j blue units



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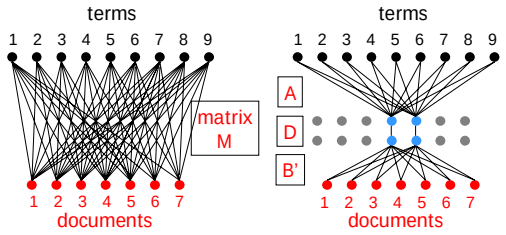
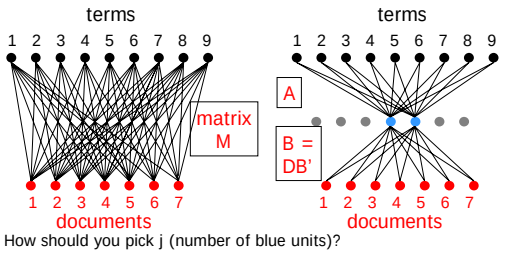


If you've seen SVD before ...

- To simplify picture, can write **M** ≈ A (DB') = AB



- How should you pick j (number of blue units)?
- Just like picking number of clusters:
  - How well does system work with each j (on held-out data)?