CS6120: Lecture 12
Web Search
Machine Translation

Kenneth Church

https://kwchurch.github.io/

Your Projects

- Oral:
  - 20-40 minutes
- Written
  - 5-20 pages
  - lots of references
- Say everything three times
  - Winston: How to Speak
  - https://www.youtube.com/watch?v=Unzc731iCUY
- Examples:
  - https://aclanthology.org/2022.acl-long.60
  - http://34.204.188.58/cgi-bin/similar?embedding=s2_recommendations&limit=20&search=An+Information-theoretic+Approach+to+Prompt+Engineering+Without+Ground+Truth+Labels
  - https://aclanthology.org/events/acl-2022/

Web Search & Information Retrieval

Information Retrieval

- Textbook
  - https://www-nlp.stanford.edu/IR-book/
- Term-by-doc matrix: M
  - Similarity of terms: $M\ M^T$
  - Similarity of doc: $M^T M$
- Index: Inverted file (postings)
  - Rows of M
- Solitaire → Multiplayer Game
  - Solitaire: users lose to library (casino)
  - Multiplayer Game: Ecosytems
    - Readers, writers, advertizers, market makers

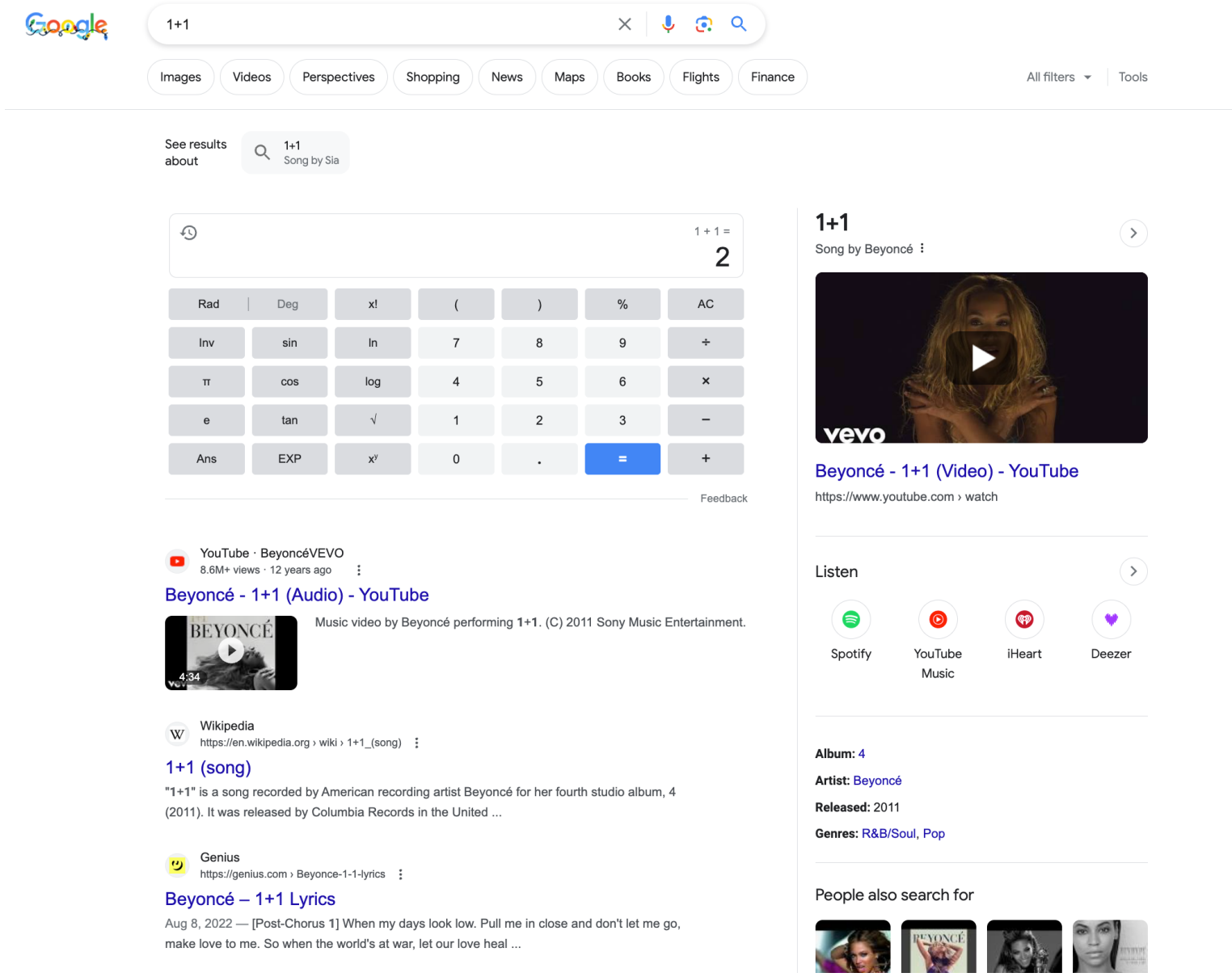
Web Search

- Left rail (algo) vs. right rail (ads)
  - Instant Answers
- Crawl: wget
  - Seed URLs → sample of ``everything''
  - Deep web
  - WayBack Machine
    - https://web.archive.org/
- User logs: queries, clicks
  - Larger than crawls
    - Healthy ecosystem → more readers than writers
  - Behavioral signals
    - (super-important feedback)

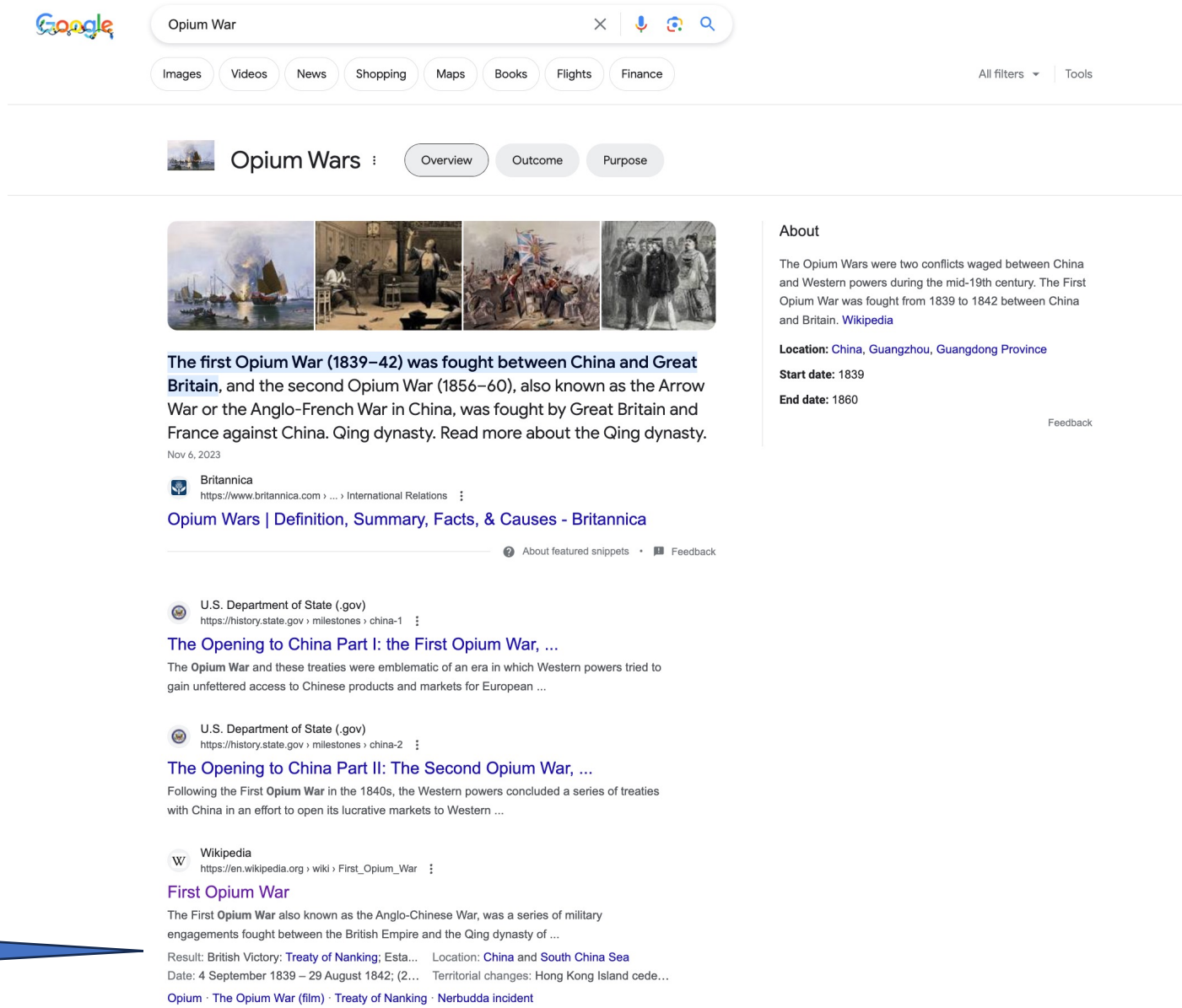
Types of Answers

- Left Rail: 10 blue links
  - algo search
  - learning to rank: https://en.wikipedia.org/wiki/Learning_to_rank
- Right Rail: ads
  - auction: https://en.wikipedia.org/wiki/Sponsored_search_auction
- Instant Answers
  - Internal groups compete for types of queries

Instant Answers

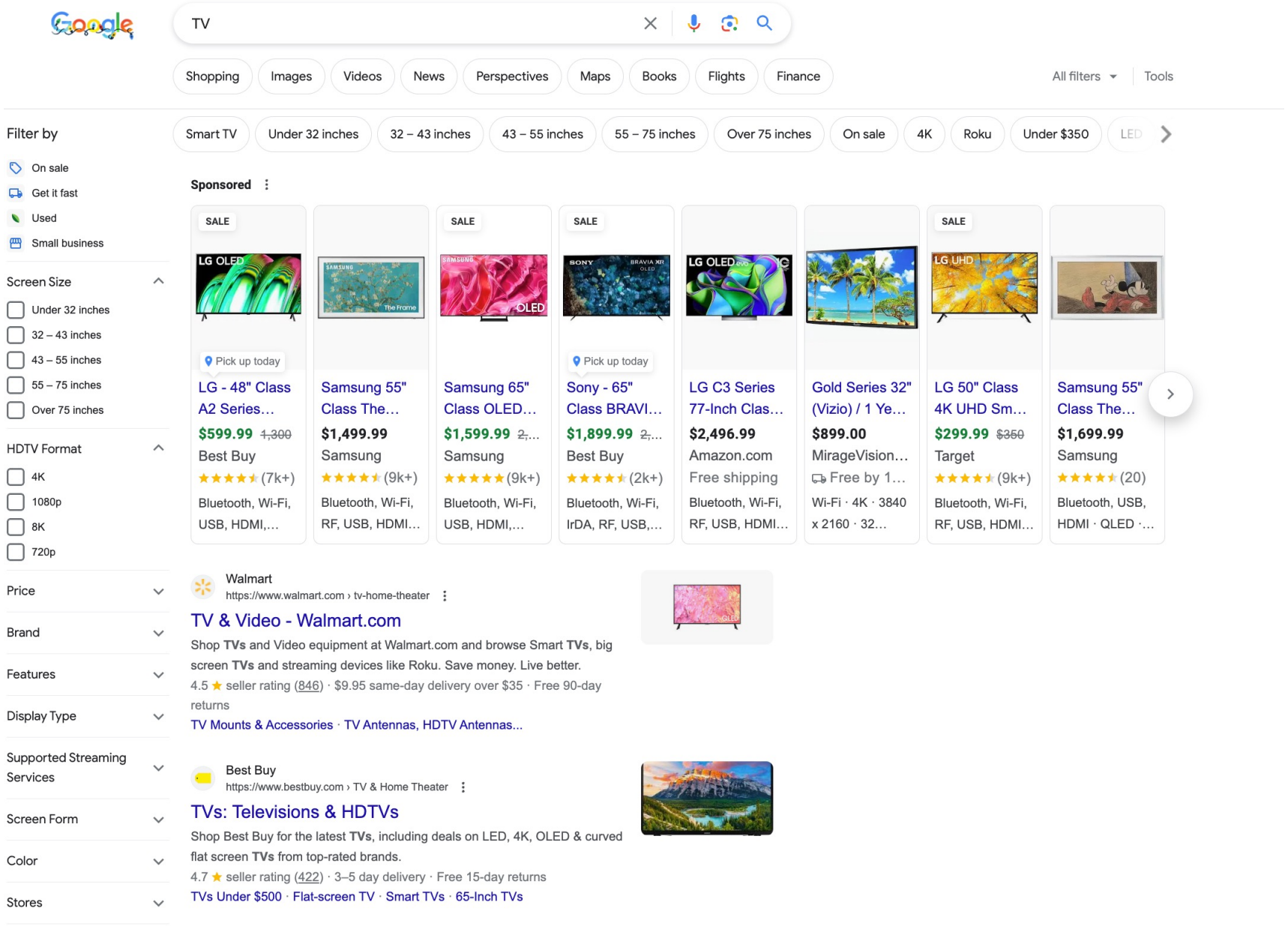


Instant Answers
10 Blue Links



Snippet

Ads


Google
TV
Shopping
Images
Videos
News
Perspectives
Maps
Books
Flights
Finance
All filters
Tools
Filter by
On sale
Get it fast
Used
Small business
Screen Size
Under 32 inches
32 – 43 inches
43 – 55 inches
55 – 75 inches
Over 75 inches
HDTV Format
4K
1080p
8K
720p
Price
Brand
Features
Display Type
Supported Streaming Services
Screen Form
Color
Stores
Smart TV
Under 32 inches
32 – 43 inches
43 – 55 inches
55 – 75 inches
Over 75 inches
On sale
4K
Roku
Under $350
Sponsored
SALE
Pick up today
LG - 48" Class A2 Series…
$599.99 1,300
Best Buy
(7k+)
Bluetooth, Wi-Fi, USB, HDMI,…
Samsung 55" Class The…
$1,499.99
Samsung
(9k+)
Bluetooth, Wi-Fi, RF, USB, HDMI…
Samsung 65" Class OLED…
$1,599.99
Samsung
(9k+)
Bluetooth, Wi-Fi, USB, HDMI,…
Sony - 65" Class BRAVI…
$1,899.99
Best Buy
(2k+)
Bluetooth, Wi-Fi, IrDA, RF, USB,…
LG C3 Series 77-Inch Clas…
$2,496.99
Amazon.com
Free shipping
Bluetooth, Wi-Fi, RF, USB, HDMI…
Gold Series 32" (Vizio) / 1 Ye…
$899.00
MirageVision…
Free by 1…
Wi-Fi · 4K · 3840 x 2160 · 32…
LG 50" Class 4K UHD Sm…
$299.99 $350
Target
(9k+)
Bluetooth, Wi-Fi, RF, USB, HDMI…
Samsung 55" Class The…
$1,699.99
Samsung
(20)
Bluetooth, USB, HDMI · QLED ·…
Walmart
https://www.walmart.com › tv-home-theater
TV & Video - Walmart.com
Shop TVs and Video equipment at Walmart.com and browse Smart TVs, big screen TVs and streaming devices like Roku. Save money. Live better.
4.5 ★ seller rating (846) · $9.95 same-day delivery over $35 · Free 90-day returns
TV Mounts & Accessories · TV Antennas, HDTV Antennas...
Best Buy
https://www.bestbuy.com › TV & Home Theater
TVs: Televisions & HDTVs
Shop Best Buy for the latest TVs, including deals on LED, 4K, OLED & curved flat screen TVs from top-rated brands.
4.7 ★ seller rating (422) · 3–5 day delivery · Free 15-day returns
TVs Under $500 · Flat-screen TV · Smart TVs · 65-Inch TVs

Evaluation

- Extract sample of queries from query logs
- Scrape 10 blue links from release candidates
  - (and competition)
  - (over time)
- Send Queries and candidate URLs to human judges
  - score 1-5 (plus perhaps offensive)
  - perfect, excellent, good, fair, poor, offensive/illegal/irresponsible
- Score scrapes with NDCG

- Learning to Rank
- Track scores over time
  - and hopefully get better and better over time
- Issues
  - Judges prefer Google Brand
    - Even when the links are the same
  - Learning to rank → Cheating
    - Watermarking
  - Now that Google is a monopoly
    - Little incentive to improve
    - Web search may be degrading
      - (creating opportunity for chat bots)
  - SEOs (Search Engine Optimization)

Ad Auction

https://moz.com/blog/understanding-google-ads-auction

- Bid
- Quality
  - Estimate of CTR (clicks)
- Market maker (Google)
  - Maximizing benefit to
    - Readers
    - Writers
    - Advertisers
- Economic Optimization
  - Different from learning to rank

	Max CPC Bid	x	Quality Score	=	Ad Rank	Ad Position
Advertiser 1	$3.00		8		24	1
Advertiser 2	$4.00		5		20	2
Advertiser 3	$6.00		2		12	3
Advertiser 4	$8.00		1		8	4

Vickrey auction

14 languages

Contents [hide]

From Wikipedia, the free encyclopedia

A **Vickrey auction** or **sealed-bid second-price auction** (**SBSPA**) is a type of sealed-bid auction. Bidders submit written bids without knowing the bid of the other people in the auction. The highest bidder wins but the price paid is the second-highest bid. This type of auction is strategically similar to an English auction and gives bidders an incentive to bid their true value. The auction was first described academically by Columbia University professor William Vickrey in 1961[1] though it had been used by stamp collectors since 1893.[2] In 1797 Johann Wolfgang von Goethe sold a manuscript using a sealed-bid, second-price auction.[3]

Vickrey's original paper mainly considered auctions where only a single, indivisible good is being sold. The terms *Vickrey auction* and *second-price sealed-bid auction* are, in this case only, equivalent and used interchangeably. In the case of multiple identical goods, the bidders submit inverse demand curves and pay the opportunity cost.[4]

Vickrey auctions are much studied in economic literature but uncommon in practice. Generalized variants of the Vickrey auction for multiunit auctions exist, such as the generalized second-price auction used in Google's and Yahoo!'s online advertisement programmes[5][6] (not incentive compatible) and the Vickrey–Clarke–Groves auction (incentive compatible).

Part of a series on

Auctions

Types

All-pay (Chinese) · Amsterdam · Anglo-Dutch · Barter double · Best/not best · Brazilian · Calcutta · Candle · Click-box bidding · Combinatorial · Common value · Deferred-acceptance · Discriminatory price · Double · Dutch · English · Forward · French · Generalized first-price · Generalized second-price · Japanese · Knapsack · Multi-attribute · Multiunit ·

Priors: Pr(URL)
Query-independent

- Page Rank
  - Prior: Pr(ULR)
  - Eigenvalue
  - Random Surfer Model
  - https://en.wikipedia.org/wiki/PageRank
- URL → Noisy Channel → Q
  - Pr(URL) = ARGMAX_U Pr(U) Pr(Q|U)
- Prior: Pr(URL)
- Channel: Pr(Q|URL)
- ProNE: Fast and Scalable Network Representation Learning
- https://en.wikipedia.org/wiki/Graph_neural_network

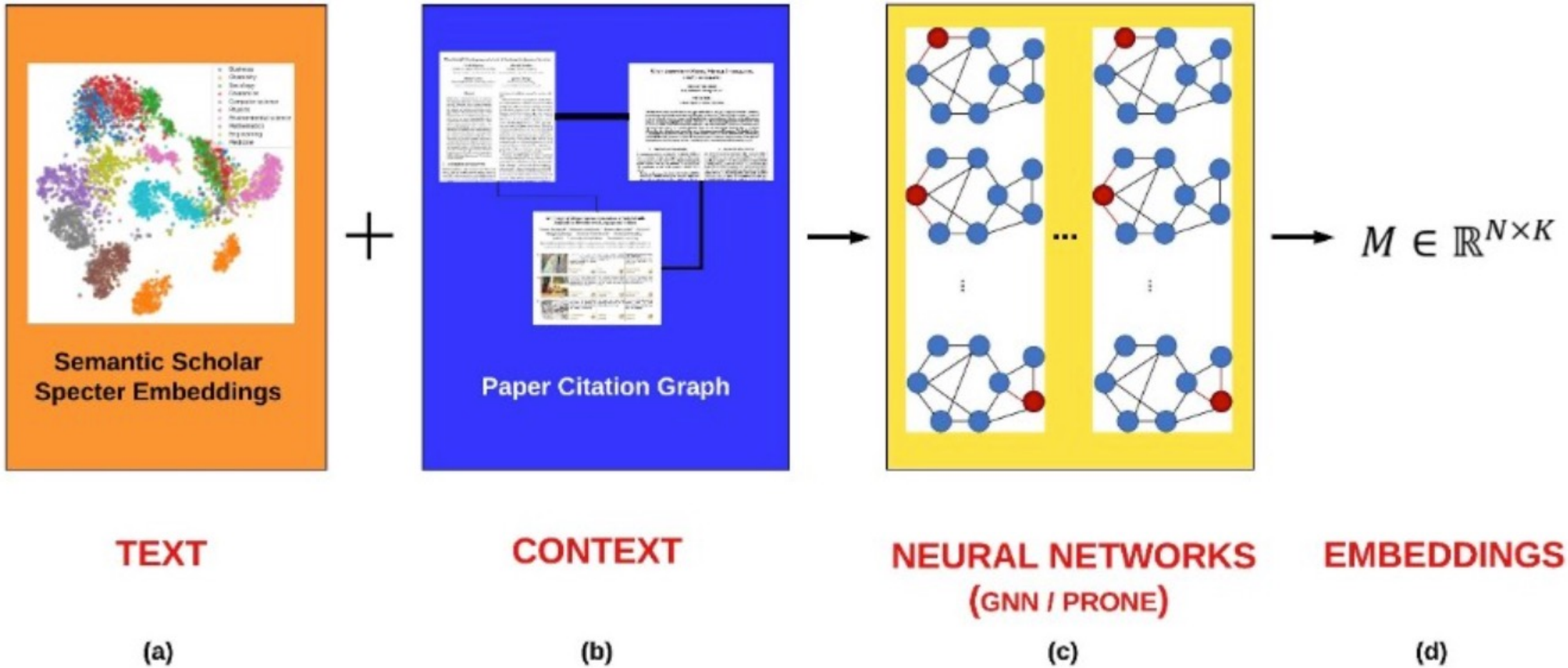
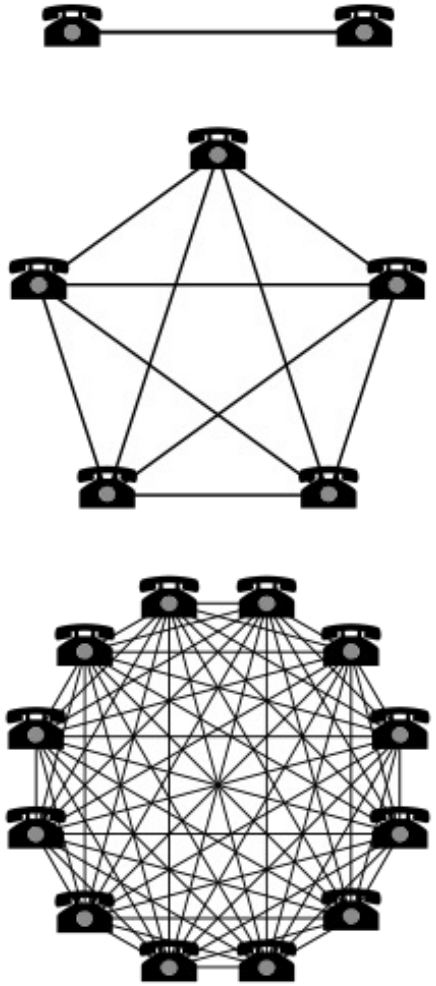


Figure 1: Embeddings are typically based on text (titles and abstracts). We will create multiple embeddings based on combinations of text and context (citations).

Metcalfe's Law (Network Effects)



- History: 3Com was selling small networks
  - 3 = 1 printer + 2 computers
  - Metcalfe argued they should sell bigger networks
    - (and more 3Com products)
    - because of economies of scale
- Economy of Scale:
  - Benefits scale faster than costs
    - Benefits: $\sim n^2$
    - Costs: $\sim n$
- Law has been good for AT&T, Google, Social Media
- Hypo: also good for Academic Search
  - Consequently, we should experiment with large graphs

Linear Algebra & Term-by-Document Matrices

- Singular Value Decomposition (SVD)
- Principal Component Analysis (PCA)
- Dimension Reduction
- Rotations
- Approximate Nearest Neighbors (ANN)

Nearly Everything To Vectors (Embeddings) (VectorDB)

- "Everything"
  - Words (Terms): word2vec
  - Documents (Text Strings):
    - doc2vec, BERT, Specter
  - Graphs (GNNs)
    - Example: citation graph
  - Semantics ("Meaning")
  - All the world's languages
  - Audio (Speech, Music)
  - Pictures and Videos
- Embeddings
  - Similarity ≈ Cosine
    - Similar documents
      - Word Overlap
      - Nearby in citation graph
      - Similar topics, venues, authors
  - Latent (Hidden) Dimensions
- Computational Convenience
  - Dimension Reduction
  - Rotations
  - Approximate Nearest Neighbors

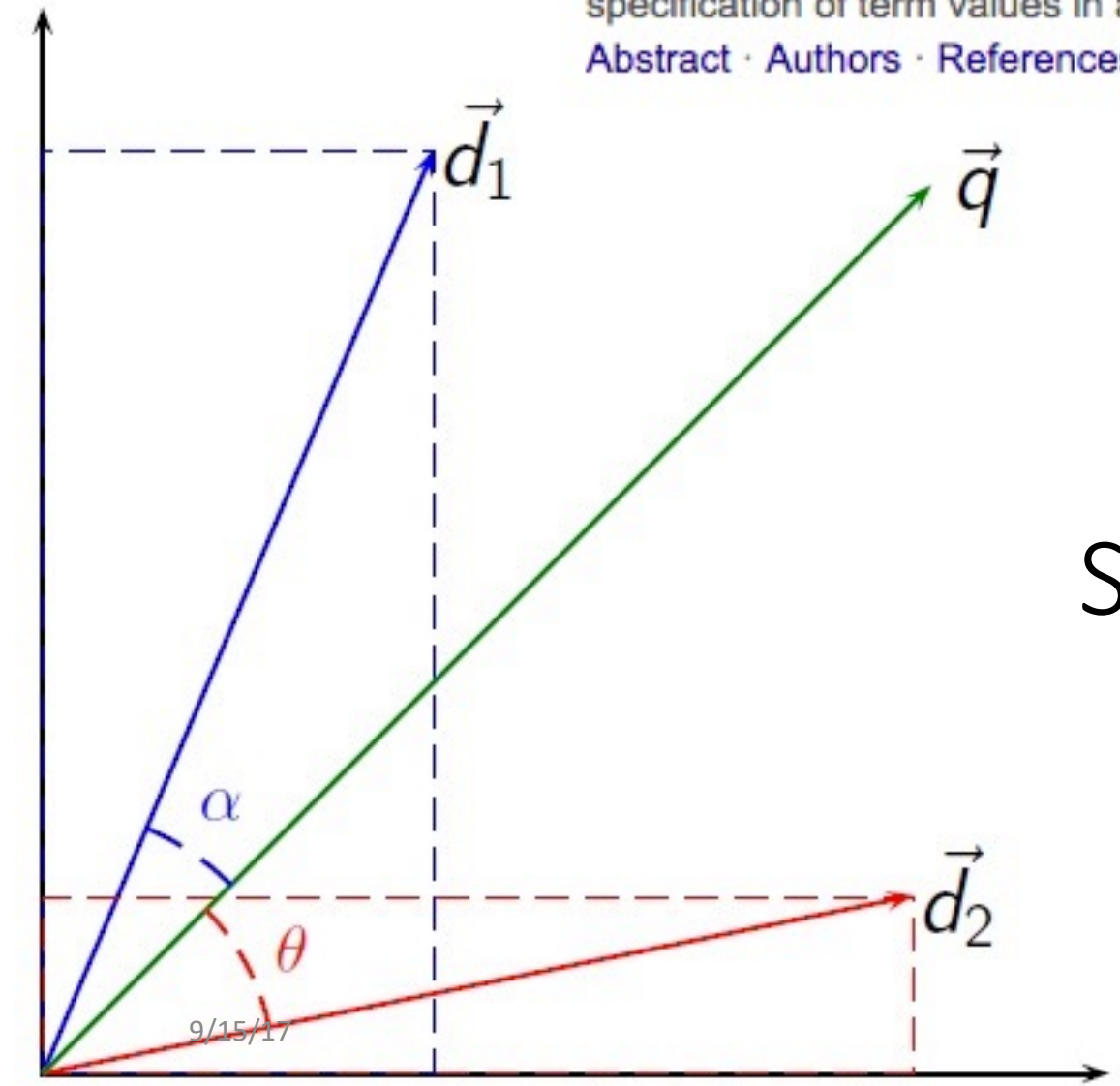
A vector space model for automatic indexing - ACM Digital Library

dl.acm.org/citation.cfm?id=361220 ▾

by G Salton - 1975 - Cited by 7464 - Related articles

A **vector space model** for automatic indexing, Published by ACM .... **Salton**, G., and Yang, C.S. On the specification of term values in automatic indexing.

Abstract · Authors · References · Cited By



Salton's Vector Space Model

Word2vec (Embeddings)

Slide from JM3

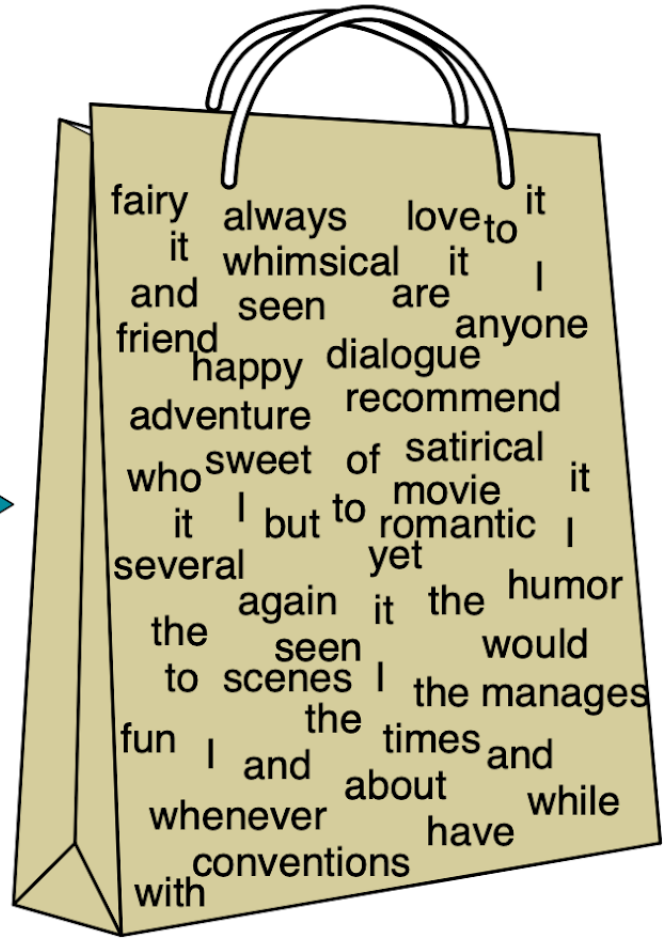
- $M \in \mathbb{R}^{V \times K}$ (tall-skinny matrix)
  - V: vocabulary size (≈ 500k)
  - K: hidden dimensions (≈ 300)
- $MM^T = cos(w_i, w_j) \propto PMI(w_i, w_j)$
  - Similarity of all pairs of words in V
  - It might be infeasible to materialize MM^T
    - But there are approximations (ANNs)
    - that find many/most of the large values
- Better for capturing collocations
  - Collocations: w_i & w_j appear near one another (more than chance)
- Less appropriate for other notions of similarity
  - Both synonyms and antonyms appear near one another
  - (But they don't mean the same thing)

For plotting purposes,

- use dimension reduction
- to reduce K down to 2D

The Bag of Words Representation

I love this movie! It's sweet, but with satirical humor. The dialogue is great and the adventure scenes are fun... It manages to be whimsical and romantic while laughing at the conventions of the fairy tale genre. I would recommend it to just about anyone. I've seen it several times, and I'm always happy to see it again whenever I have a friend who hasn't seen it yet!



it	6
I	5
the	4
to	3
and	3
seen	2
yet	1
would	1
whimsical	1
times	1
sweet	1
satirical	1
adventure	1
genre	1
fairy	1
humor	1
have	1
great	1
…	…

https://web.stanford.edu/~jurafsky/slp3/slides/7_NB.pdf

Information Retrieval (IR) notation
Term Weighting: tf * IDF

- t: term
- d: document
- D: # of documents in library

- Interpretation:
  - Entropy: $H = -\log(P)$
  - where $P = \Pr(t \in d)^{count(t,d)}$

- tf(t,d): term frequency
  - # of times that t appears in d
- df(t): document frequency
  - # of documents that contain t
  - (at least once)
- IDF(t): inverse doc frequency
  - $IDF(t) = -log_2 \frac{df(t)}{D}$
- tf * IDF weighting
  - Assumes (too much) indep

Bellcore Example

- Example of term by document matrix
  - A document ≈ a bag of words
  - A word ≈ a bag of documents
    - *You shall know a word by the company it keeps*
- Example of SVD for dimension reduction
  - Suggestion: reducing dimensions → better separation of classes of interest
- Motivate latent dimensions
  - as a method to embed both terms and documents
  - into a common (unified) vector space

Bellcore's Example: Bag of Words + SVD

http://wordvec.colorado.edu/papers/Deerwester_1990.pdf

c1 Human machine *interface* for Lab ABC *computer* applications

c2 A *survey* of *user* opinion of computer *system response time*

c3 The EPS *user interface* management *system*

c4 *System* and *human system* engineering testing of EPS

c5 Relation of *user*-perceived *response time* to error measurement

---

m1 The generation of random, binary, unordered *trees*

m2 The intersection *graph* of paths in *trees*

m3 *Graph minors* IV: Widths of *trees* and well-quasi-ordering

m4 *Graph minors*: A *survey*

Term by Documents Matrix

c1	Human machine interface for Lab ABC computer applications
c2	A survey of user opinion of computer system response time
c3	The EPS user interface management system
c4	System and human system engineering testing of EPS
c5	Relation of user-perceived response time to error measurement
m1	The generation of random, binary, unordered trees
m2	The intersection graph of paths in trees
m3	Graph minors IV: Widths of trees and well-quasi-ordering
m4	Graph minors: A survey

c1	c2	c3	c4	c5	m1	m2	m3	m4	
1			1						human
1		1							interface
1	1								computer
	1	1		1					user
	1	1	2						system
	1			1					response
	1			1					time
		1	1						EPS
	1							1	survey
					1	1	1		trees
						1	1	1	graph
							1	1	minors

Term by Document Matrix

c1	c2	c3	c4	c5	m1	m2	m3	m4	
1			1						human
1		1							interface
1	1								computer
	1	1		1					user
	1	1	2						system
	1			1					response
	1			1					time
		1	1						EPS
	1							1	survey
					1	1	1		trees
						1	1	1	graph
							1	1	minors

Singular Value Decomposition (SVD)

- $M \approx U\ D\ V^T$
- D is diagonal
  - Eigenvalues
  - Sorted from largest to smallest
- U and V are Eigenvectors
  - Orthogonal and unit length
    - $U^T U = I$
    - $V^T V = I$

- $\cos(M, M) = MM^T$
  - $U\ D\ V^T (U\ D\ V^T)^T$
  - $U\ D\ V^T (V\ D\ U^T)$
  - $UD^2\ U^T$
- $M \rightarrow UD$
  - Plus dimension reduction
  - Replace smaller Eigenvalues with 0

Dimension Reduction

- Standard Recipe
  - Set smaller Eigenvalues to 0
- Interpretation
  - L2 optimality (least squares)
- Recall that Eigenvalues are sorted from largest to smallest

- Motivation for dimension reduction
  - Computational resources:
    - Space
      - Specter: $M \in \mathbb{R}^{N \times K}$
      - N is 200M documents
      - K is 768 (BERT hidden layer)
      - $MM^T \in \mathbb{R}^{N \times N}$ (***very*** large)
    - Time
  - Statistical convenience:
    - Smoothing (soft thesaurus)
    - Replace zeros with small values
  - Computational convenience:
    - Approximate nearest neighbors
    - https://pypi.org/project/annoy/

SVD and PCA

SVD (Singular Value Decomposition)

- $M \approx U\ D\ V^T$
- D: Eigenvalues
- U: Eigenvectors
- M need not be square
  - (just non-singular)

PCA (Principal Componenet Analysis)

- $Q \propto X^T X = W \Lambda W^T$
- Q is square by construction
  - Λ: Eigenvalues
  - W: Covariances
    - Diagonal of W are variances

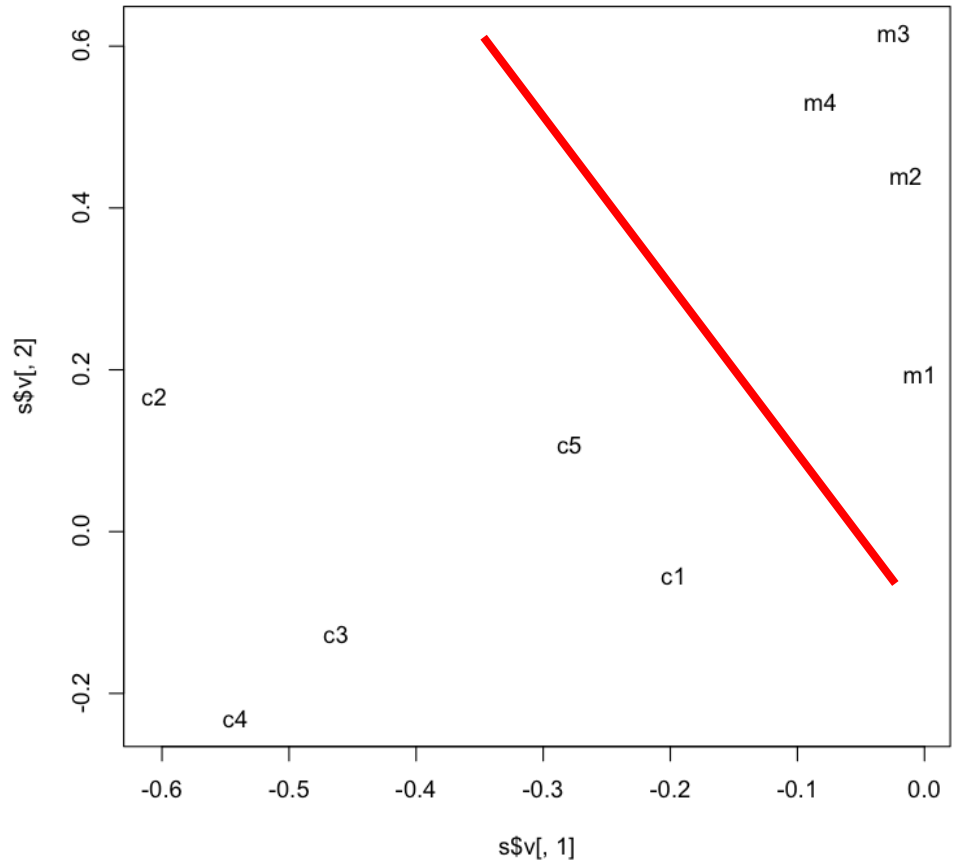
Dimension Reduction in R

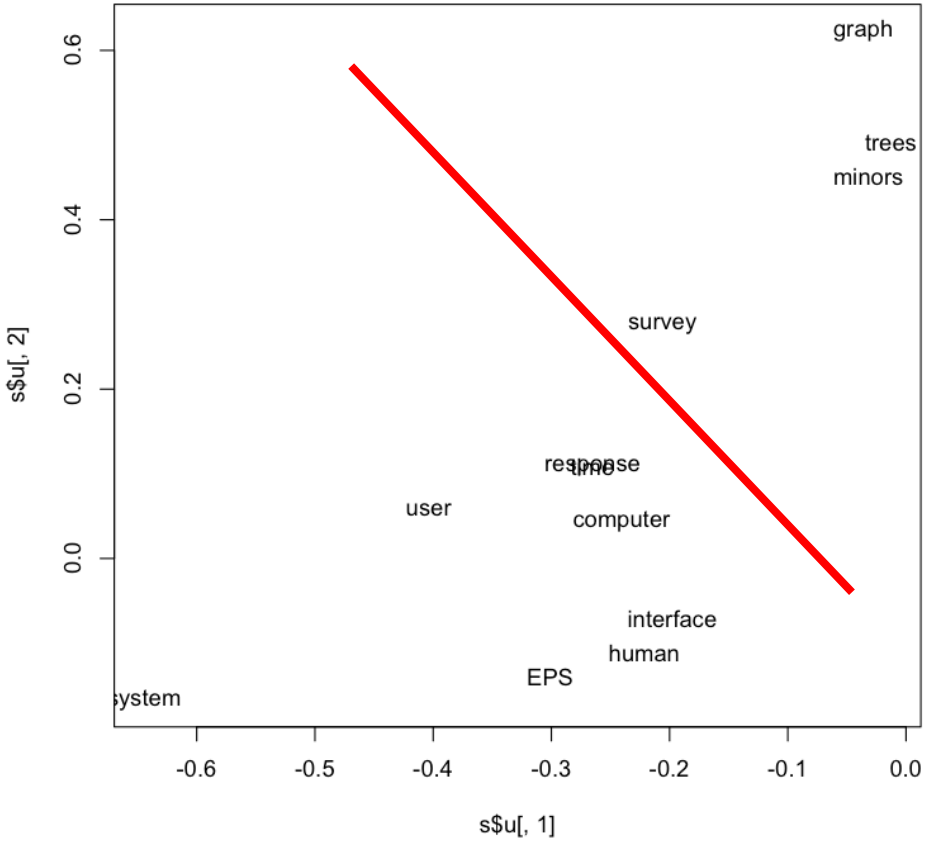
$$bellcore \approx U\ D\ V^T$$

```
bellcore =

structure(.Data = c(1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
    1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0,
    0, 1, 0, 0, 0, 2, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0,
    0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
    0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0,
    0, 0, 0, 0, 0, 0, 1, 0, 1, 1),

.Dim = c(12, 9),

.Dimnames = list(c("human", "interface", "computer",
    "user", "system", "response", "time", "EPS",
    "survey", "trees", "graph", "minors"),

c("c1", "c2", "c3", "c4", "c5", "m1", "m2", "m3",
    "m4")))
```

```
b = svd(bellcore)

b2 = b$u[,1:2] %*% diag(b$d[1:2]) %*%
   t(b$v[,1:2])

dimnames(b2) = dimnames(bellcore)

par(mfrow=c(2,2))

plot(hclust(as.dist(-cor(bellcore))))

plot(hclust(as.dist(-cor(t(bellcore)))))

plot(hclust(as.dist(-cor(b2))))

plot(hclust(as.dist(-cor(t(b2)))))
```

SVD maps terms & docs into internal dimensions





$bellcore \approx U\ D\ V^T$

c1	c2	c3	c4	c5	m1	m2	m3	m4	
1			1						human
1		1							interface
1	1								computer
	1	1		1					user
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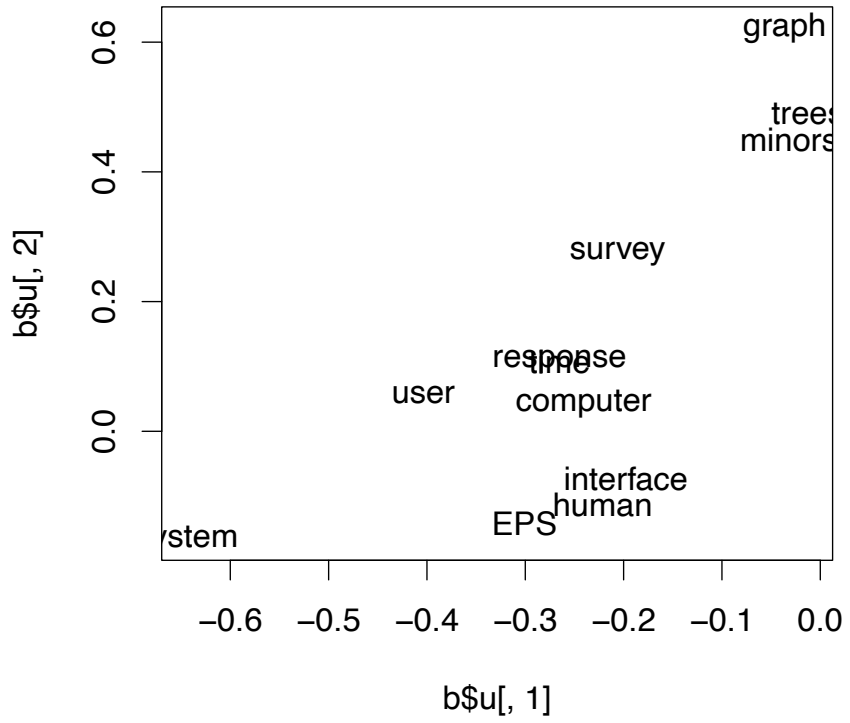
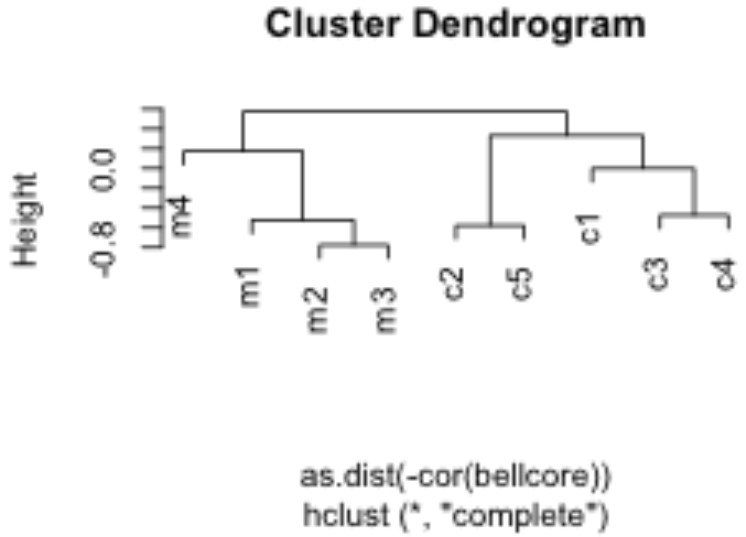
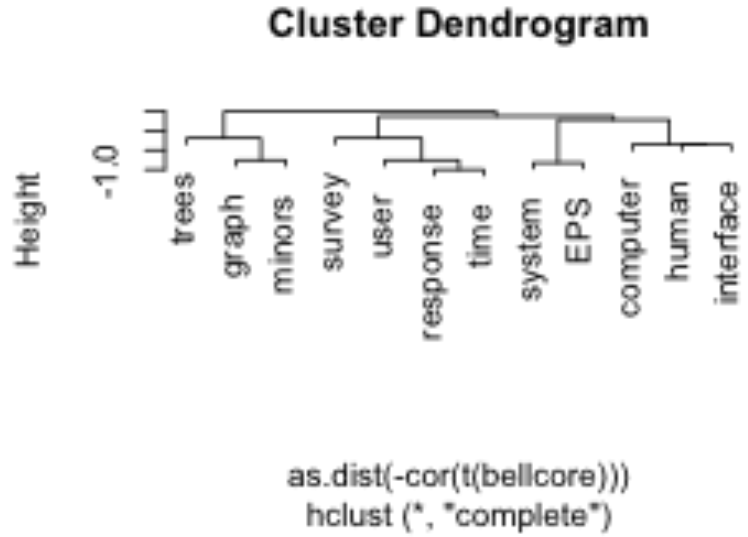


```
b = svd(bellcore)
b2 = b$u[,1:2] %*% diag(b$d[1:2]) %*% t(b$v[,1:2])
dimnames(b2) = dimnames(bellcore)
par(mfrow=c(2,2))
plot(hclust(as.dist(-cor(bellcore))))
plot(hclust(as.dist(-cor(t(bellcore)))))
plot(hclust(as.dist(-cor(b2))))
plot(hclust(as.dist(-cor(t(b2)))))
```





Term by Document Matrix

c1	c2	c3	c4	c5	m1	m2	m3	m4	
1			1						human
1		1							interface
1	1								computer
	1	1		1					user
	1	1	2						system
	1			1					response
	1			1					time
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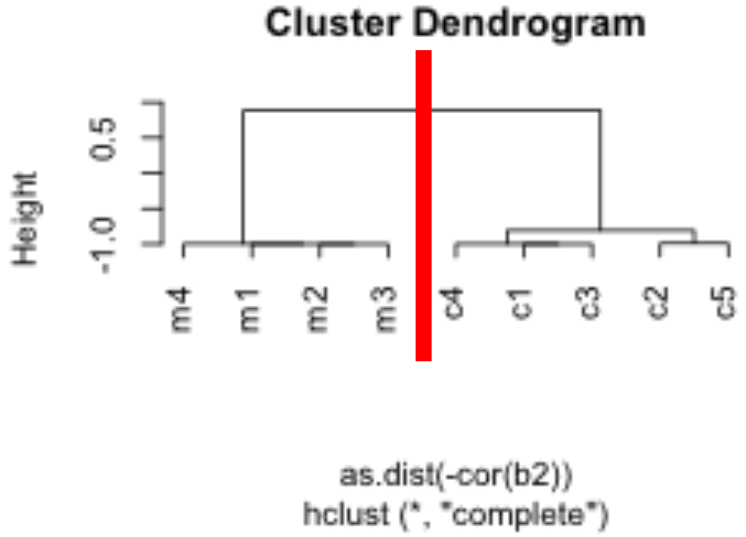
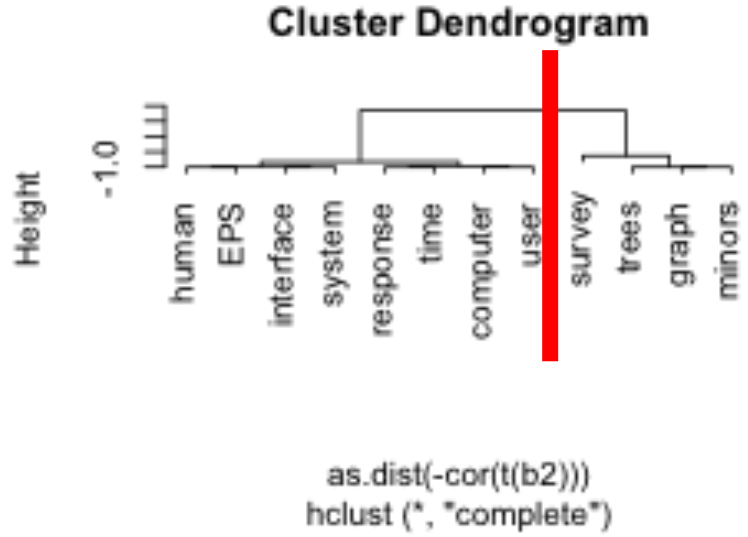
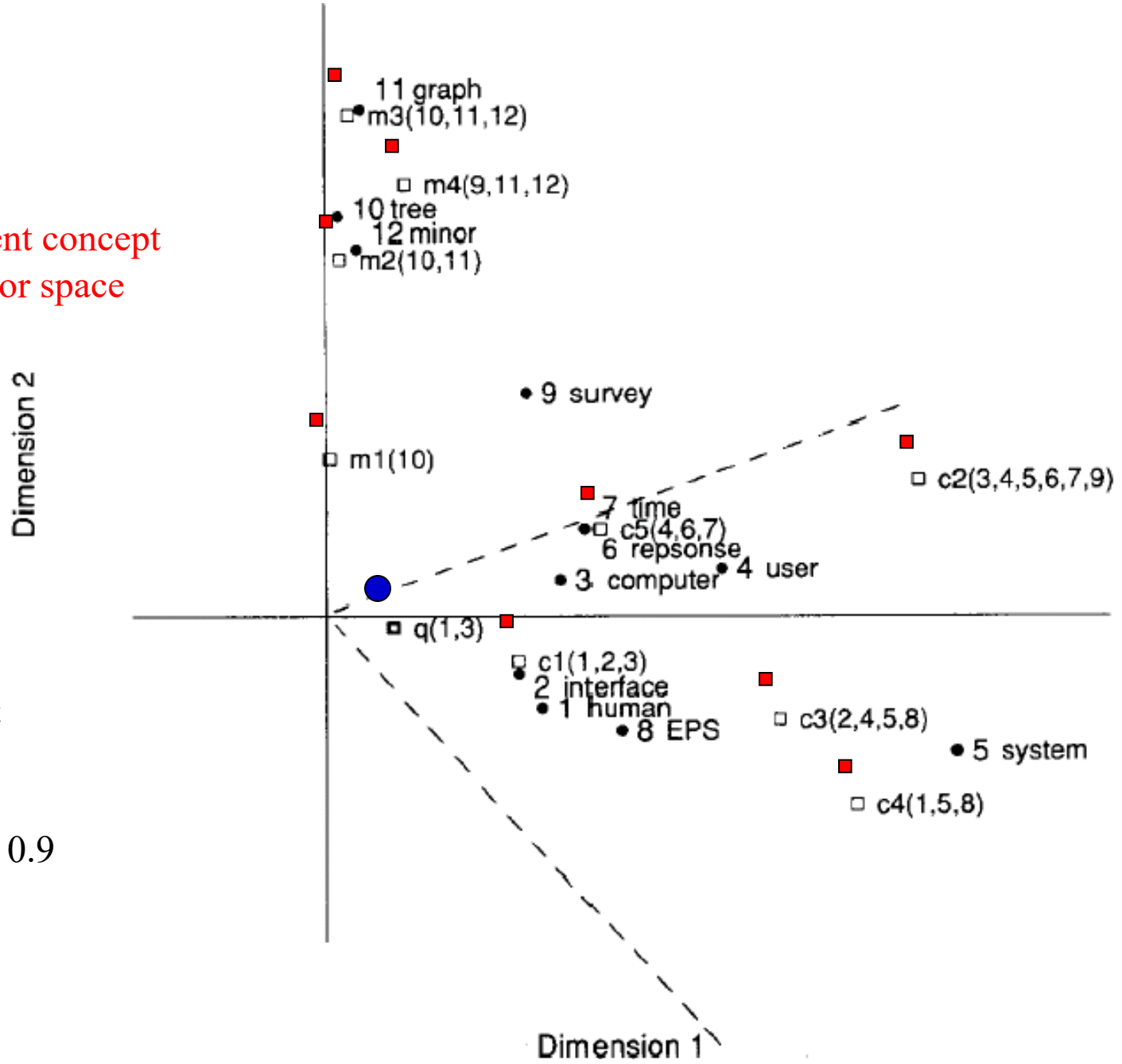
					1	1	1		trees
						1	1	1	graph
							1	1	minors





Latent concept vector space



- term
- document
- query
- cosine > 0.9

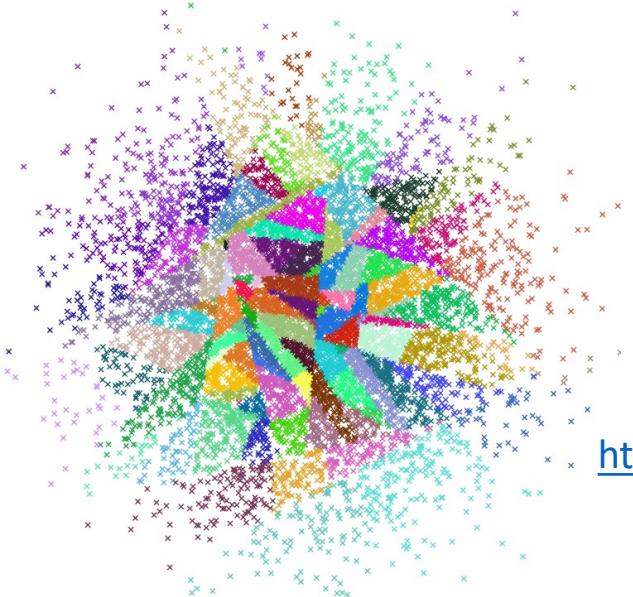
Approximate Nearest Neighbors (ANN)

- Indexing time:
  - Input: Embedding $M \in \mathbb{R}^{N \times K}$
  - Output: Indexes
- Query time:
  - Input:
    - Embedding, Indexes, query
  - Query: $q \in \mathbb{R}^{K}$
  - Output: candidates, $c \in \mathbb{R}^{K}$
    - where c is near q
    - sorted by $sim(q, c)$

```python
from gensim.similarities.annoy import AnnoyIndexer

# 100 trees are being used in this example
annoy_index = AnnoyIndexer(model, 100)
# Derive the vector for the word "science" in our model
vector = wv["science"]
# The instance of AnnoyIndexer we just created is passed
approximate_neighbors = wv.most_similar([vector], topn=11, indexer=annoy_index)
# Neatly print the approximate_neighbors and their corresponding cosine similarity values
print("Approximate Neighbors")
for neighbor in approximate_neighbors:
    print(neighbor)
```

https://radimrehurek.com/gensim/auto_examples/tutorials/run_annoy.html



https://pypi.org/project/annoy/