Lecture 2: Distributional Semantics

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Reading: J&M 19.1–19.5; Landauer and Dumais (1997).

The Meaning of "Bear"

PRINCETON UNIVERSITY

WordNet
A lexical database for English

bear → **carnivore**

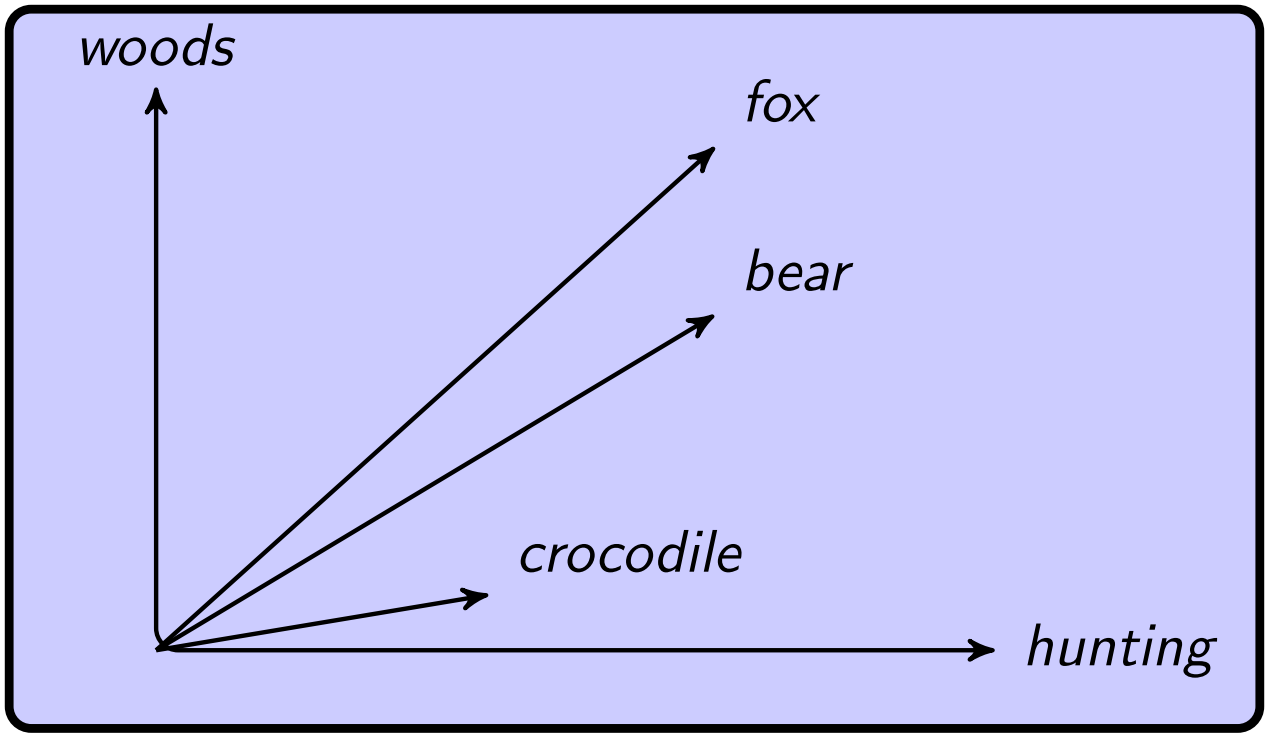
↓

predator, predatory animal

↓

animal, animate being, beast, brute, creature, fauna

The Meaning of "Bear"



Latent Semantic Analysis (LSA; Landauer and Dumais, 1997)
Latent Dirichlet Allocation (LDA; Griffiths et al., 2007)
Neural Language Model (NLM; Collobert and Weston 2008)

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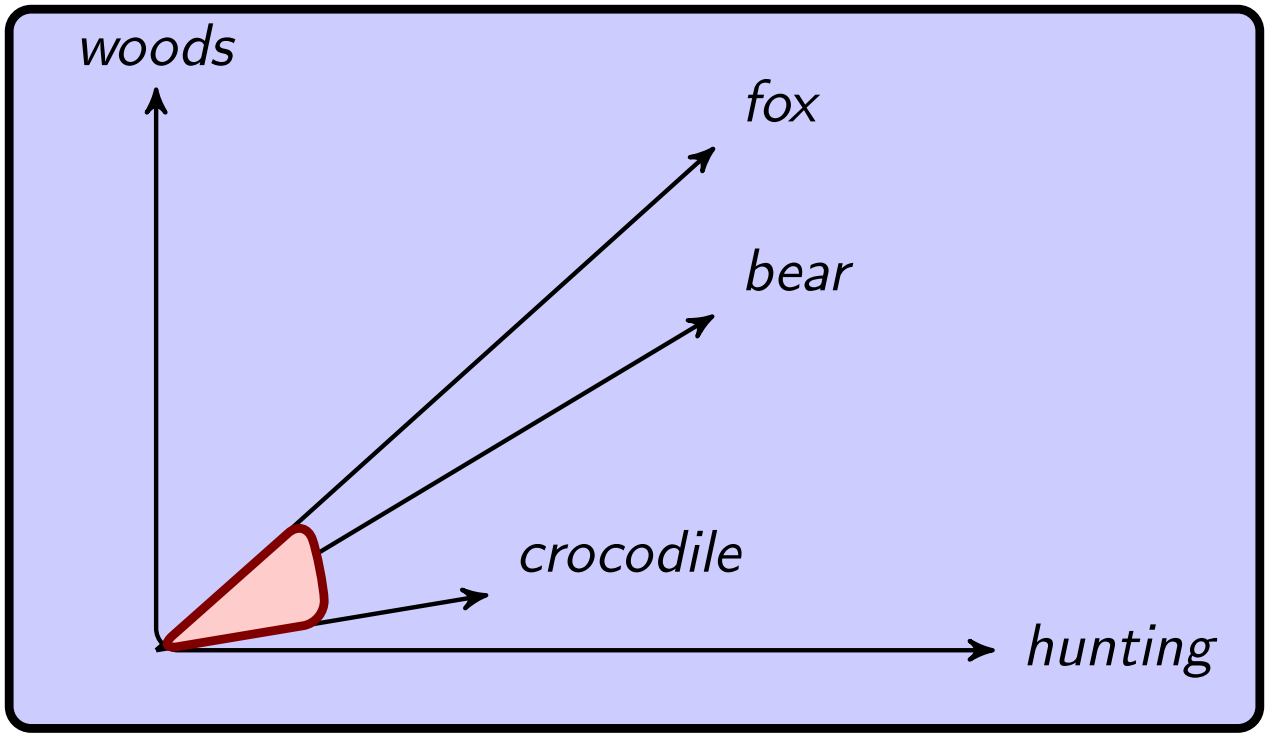

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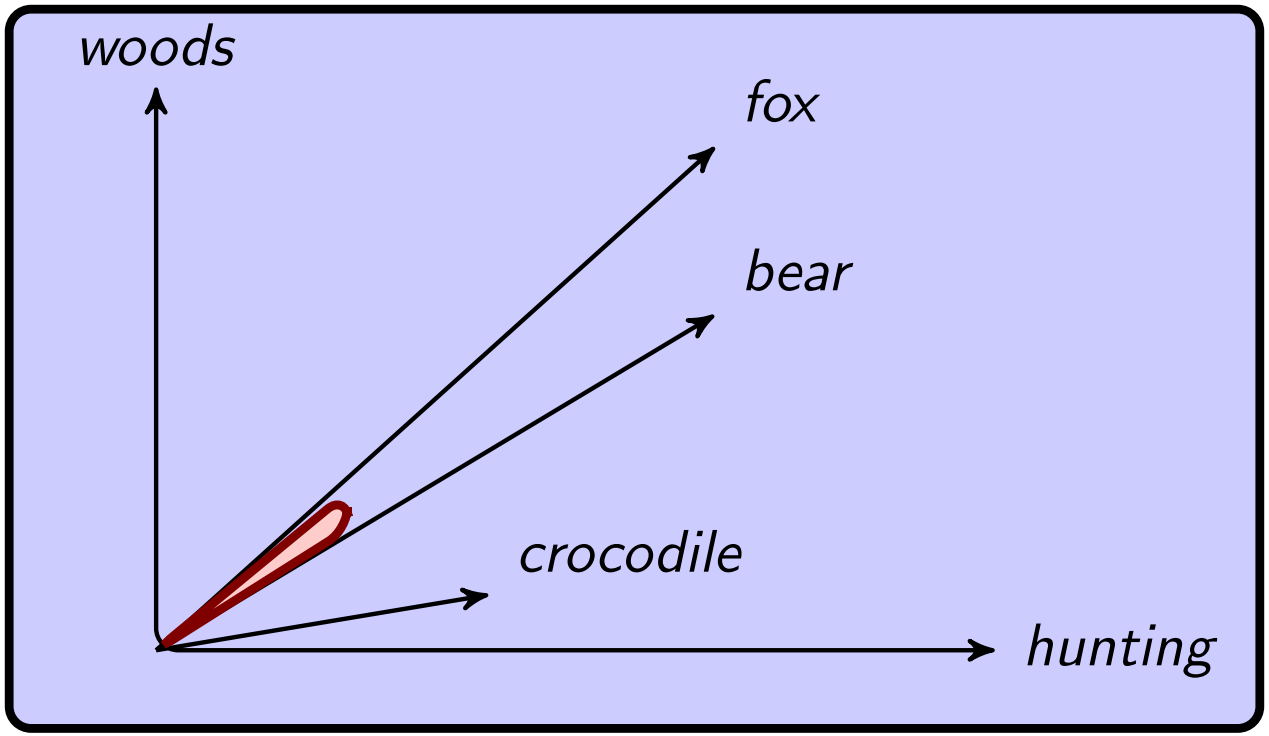

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Motivation

Goal: find a *representation* that succinctly describes the meaning of a word, phrase, sentence, document.

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Why is this a good thing?

- Retrieve documents relevant to a query.
- Use representations as features for entailment, sentiment, SRL, parsing, question answering, machine translation.
- Explain human learning and processing of words (word associations, speed of acquisition, etc).
- Theory neutral, few assumptions re word meaning.

Distributional Hypothesis

Linguists have long conjectured that the *context* in which a word occurs determines its meaning:

- You shall know a word by the company it keeps (Firth);
- The meaning of a word is defined by the way it is used (Wittgenstein).

This leads to the *distributional hypothesis* about word meaning:

- the context surrounding a given word provides information about its meaning;
- words are similar if they share similar linguistic contexts;
- semantic similarity $\approx$ distributional similarity.

Distributional Hypothesis

Distribution is represented using a *context vector*.

	pet	bone	fur	run	brown	screen	mouse	fetch
w_1	1	1	1	1	1	0	0	1
w_2	1	0	1	0	1	0	1	0
w_3	0	1	1	1	1	0	0	1

- Vector for w: all words that co-occur with w (here, binary).
- Vector dimensions = number of context words.
- Similar words should have similar vectors.

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Constructing Vector Spaces

Words occur in context:

car engine hood tires truck trunk

car emissions hood make model trunk

Chomsky corpus noun parsing tagging wonderful

Contexts can be obtained from corpora (large collections of text).

Note that we have already removed stop words (frequent words such as *the*, *of*, *although*).

Constructing Vector Spaces

Select target words:

car engine hood tires truck trunk

car emissions hood make model trunk

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Constructing Vector Spaces

Define the context (here: symmetric, -5, $+5$):

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Constructing Vector Spaces

Create co-occurrence matrix:

	car	Chomsky	corpus	emissions	engine	hood	make	model	noun	parsing	tagging	tires	truck	trunk	wonderful
car	0	0	0	0	1	1	0	0	0	0	0	1	1	1	0
hood	1	0	0	1	0	0	1	1	0	0	0	0	0	1	0
Chomsky	0	0	1	0	0	0	0	0	1	1	1	0	0	0	1

Constructing Vector Spaces

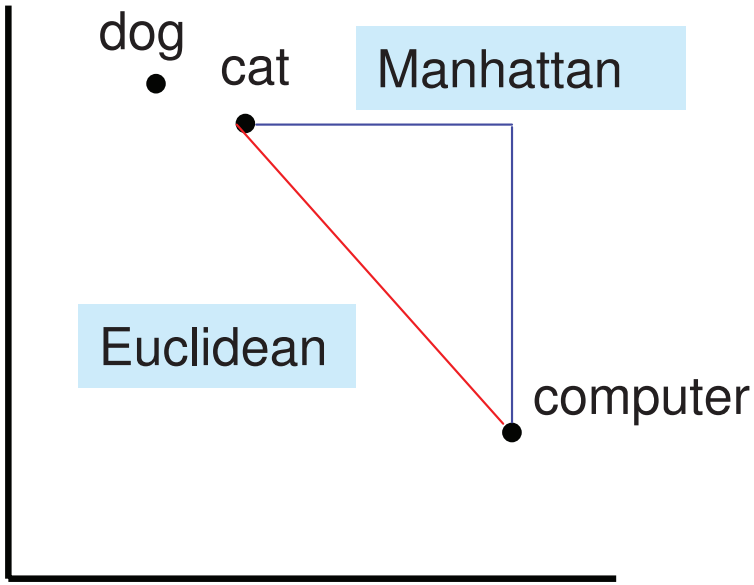
Informal algorithm for constructing vector spaces:

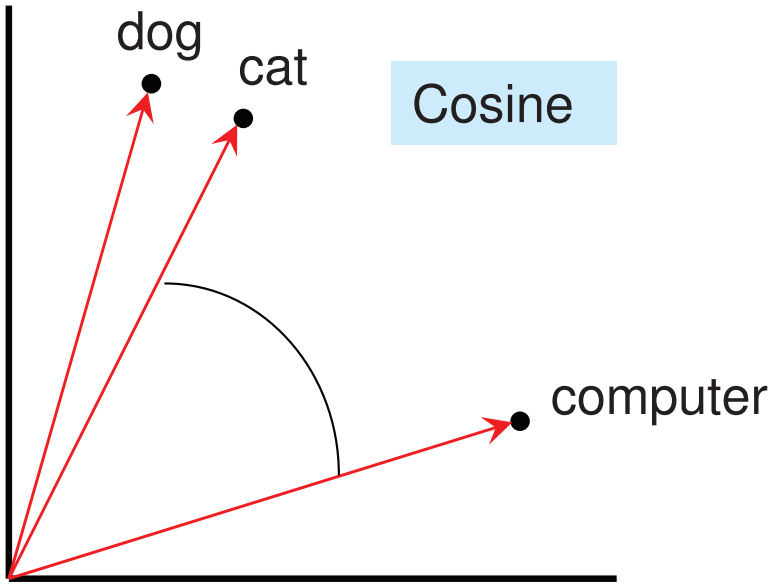
- pick the words you are interested in: *target words;*
- define number of words around target word: *context window;*
- count number of times target words co-occur with context words: *co-occurrence matrix.*

The context can also be defined in terms of documents, paragraphs, or sentences (rather than words around target word).

Constructing Vector Spaces

Measure the distance between vectors:





Measures of Distributional Similarity

The *cosine* of the angle between two vectors **x** and **y** is:

$$cos(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x} \cdot \mathbf{y}}{||\mathbf{x}|| \cdot ||\mathbf{y}||} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2} \sqrt{\sum_{i=1}^{n} y_i^2}}$$

The *Euclidean distance* of two vectors **x** and **y** is:

$$||\mathbf{x} - \mathbf{y}|| = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

Many more similarity measures exist.

Document similarity

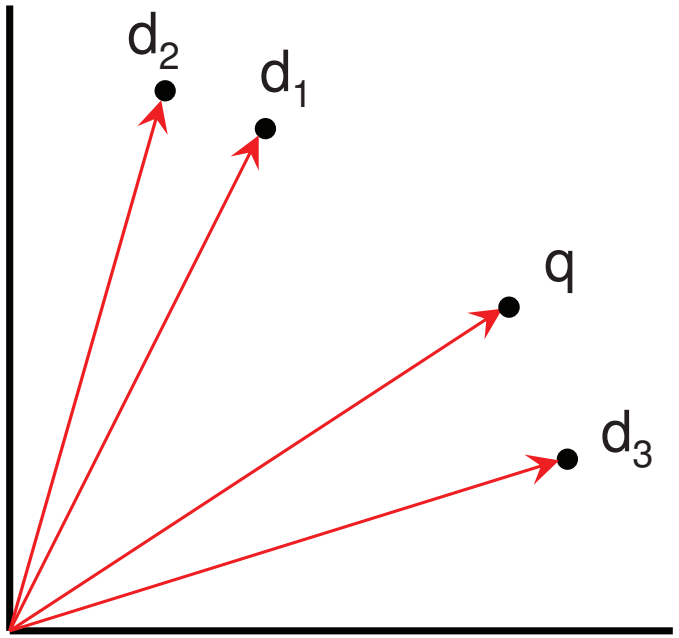
- We represent document semantics also using vectors.
- Bag-of-words (BOW) model: order of words is irrelevant.
- Naive version: represent documents by word counts.

	pet	bone	fur	run	brown	screen	mouse	fetch
d_1	0	2	0	3	5	0	0	1
d_2	1	0	1	0	8	0	0	0
d_3	0	0	0	1	0	3	6	2

Document-term co-occurrence matrix

Using the Vector Space Model

Can compute similarities between documents, or between documents and queries.



Query: "computer pointer"

Pointwise Mutual Information

- Co-occurrence frequency is not a good measure of association.
- How often two words x and y occur compared with what we would expect if they were independent.

The mutual information between two random variables X and Y

$$I(X,Y) = \sum_x \sum_y \log_2 \frac{P(x,y)}{P(x)P(y)}$$

The pointwise mutual information between events x and y

$$I(x,y) = \log_2 \frac{P(x,y)}{P(x)P(y)}$$

Applied to co-occurrence vectors (w target word; c context word):

$$PMI(w,c) = \log_2 \frac{P(w,c)}{P(w)P(c)}$$

TF-IDF

$$w_{t,d} = (1 + \log(tf_{t,d})) \log(\frac{N}{df_t})$$

- $tf_{t,d}$: frequency of word in document;
  idf: N number of documents in collection; df_t number of documents in which term t occurs;
- Words that occur more frequently in a document are often more central to its meaning.
- Words that occur frequently in all documents have little semantic value.
- Increases with the number of occurrences within a document.
- Increases with the rarity of the term in the collection.

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Problems

The co-occurrence matrix can be very **long** and **sparse** (many zeros) and **noisy** (e.g., due to words with the same meaning).

auto engine bonnet tires lorry boot

car emissions hood make model trunk

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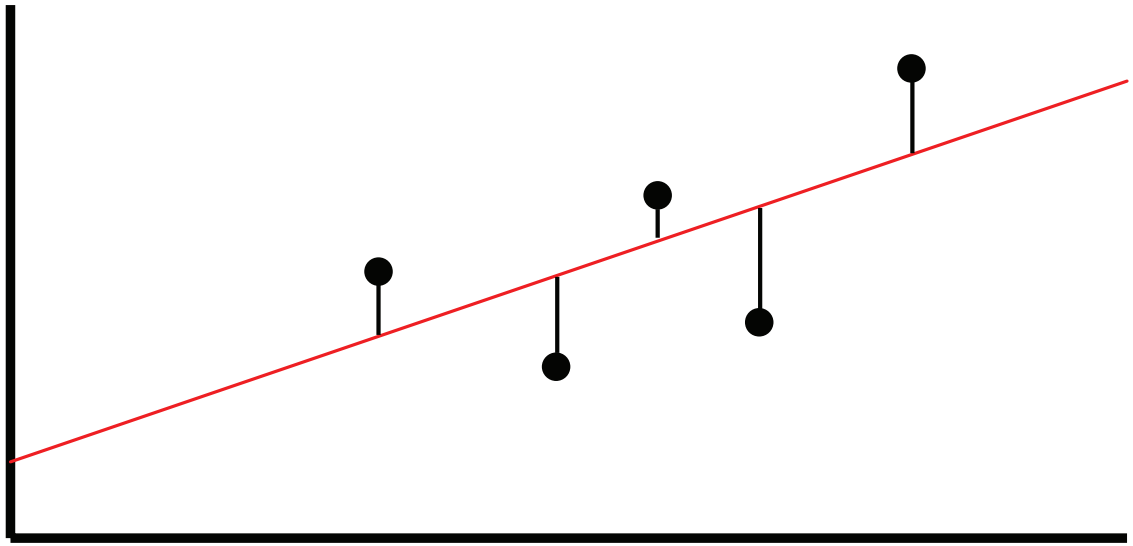
Dimensionality Reduction

In order to address these problems, reduce the *dimensionality* of the co-occurrence matrix A:

- *project* the word vectors into a different subspace so that vector cosines more accurately represent semantic similarity;
- in a *lower dimensional space,* synonym vectors may not be orthogonal;
- *singular value decomposition* is a widely used projection method;

Dimensionality Reduction



- Projecting from two dimensions to one:
- Single dimension (line) is chosen to follow direction of greatest variation.
- Fit using least squares regression, i.e., minimizing

$$\sum_{i=1}^{n} y_i - f(x_i)^2$$

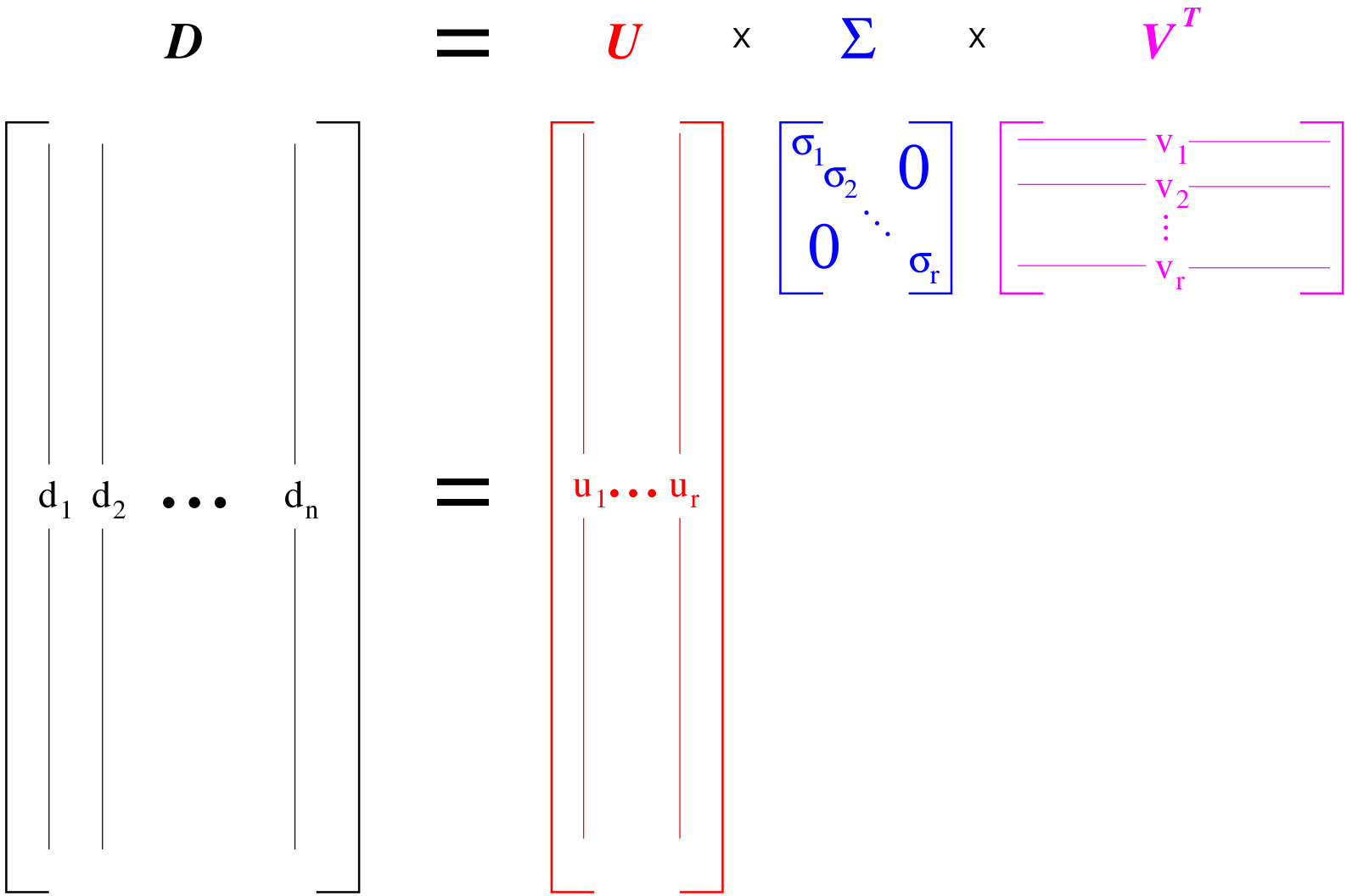
Singular Value Decomposition (SVD)

The singular value decomposition of an m-by-n matrix A is:

$$A_{mn} = U_{mm}\Sigma_{mn}V^T_{nn}$$

- an orthogonal matrix U, a diagonal matrix Σ, and the transpose of an orthogonal matrix V.
- m-dimensional vectors making up the columns of U are called left singular vectors
- the n-dimensional vectors making up the columns of V are called right singular vectors
- Σ contains the the square roots of eigenvalues from U or V in descending order
- A single value $A[i][j]$ in the matrix may be computed by the dot product of the i-th row vector and the j-th column vector, scaled by singular values

Singular Value Decomposition (SVD)



Latent Semantic Analysis

- Best known vector space model (Landauer and Dumais, 1997).
- Natural language engineering:
  - lexicon acquisition (e.g., synonyms), unsupervised morphology;
  - essay grading, text coherence;
  - information retrieval;
  - language modeling, summarization, etc.
- Cognitive science: TOEFL 2nd language learning test.

The TOEFL Task

Test of English as a Foreign Language tests non-native speakers' knowledge of English.

You will find the office at the main intersection.
(a) place
(b) crossroads
(c) roundabout
(d) building

This is a standard task in the cognitive modeling literature, and vectors space models are frequently used to solve it.

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The TOEFL Task

- 80 items: 1 word/4 alternative words.
- Compute semantic representations for probe and answer words
- Word with largest cosine to the probe is correct answer.
- LSA was trained on a 4.6 M corpus from encyclopedia.
- LSA answered 64.4% items correctly.
- Non-native speakers' average is 64.5%.
- This average is adequate for admission in many US universities.

What is the state of the art now?

https://www.aclweb.org/aclwiki/index.php?title=TOEFL_Synonym_Questions_%28State_of_the_art%29

Discussion

Strengths:

- fully automatic construction;
- representationally simple: all we need is a corpus and some notion of what counts as a word;
- language-independent, cognitively plausible.

Weaknesses:

- no underlying model, many ad-hoc parameters
- ambiguous words: their meaning is the average of all senses
- context words contribute indiscriminately to meaning;

> The author received much acclaim for his new **book**.
> For author acclaim his much received new **book**.

References

Landauer, T. K. and S. T. Dumais. 1997. A solution to Plato's problem: the latent semantic analysis theory of acquisition, induction and representation of knowledge. *Psychological Review* 104(2):211–240.