Distributional Semantics

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(some slides from Marine Carpuat, Nathan Schneider)

ENLP Lecture 13
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Topics

- **Lexical Semantics**
  - Word Similarity
  - Distributional Hypothesis
  - Vector Representations
  - Evaluation
- **Document Semantics**
  - Topic Modeling

Lexical Semantics

Semantic similarity: Intuition

- **Identify word closest to target:**

- **Accidental**
  - Abominate
  - Meander
  - Inadvertent
  - inhibit

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- **FedEx**
  - car
  - UPS
  - rotate
  - Navy

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- **Identify word closest to target:**

- **Millennial**
  - octopus
  - fork
  - water
  - avocado

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  - fork
  - water
  - avocado

Semantic Similarity

What drives semantic similarity?

- **Meaning**
  - The two concepts are close in terms of meaning
  - e.g. ‘inadvertent’ and ‘accidental’
- **World Knowledge**
  - The two concepts have similar properties, often occur together, or occur in similar contexts
  - e.g. ‘spinach’ and ‘kale,’ or ‘UPS’ and ‘FedEx’
- **Psychology**
  - The two concepts fit together within an over-arching psychological schema or framework
  - e.g. ‘money’ and ‘bank’, or ‘millennial’ and ‘avocado’

Semantic Similarity

What drives semantic similarity?

- **Meaning**
  - The two
  - e.g. 'inac
- **World K**
  - The two ccur in similar c
  - e.g. 'spir
- **Psychol**
  - The two schema or framework
  - e.g. 'money' and 'bank', or 'millennial' and 'avocado'

Automatic computation of semantic similarity

Why would such a thing be useful?

- **Semantic similarity gives us a way to generalize beyond word identities**
- **Lots of practical applications**
  - Information retrieval
  - Machine translation
  - Ontological hierarchies
  - Etc.

Distributional Hypothesis

Idea: Similar linguistic objects have similar contents (for documents, paragraphs, sentences) or contexts (for words)

➔ "Differences of meaning correlates with differences of distribution" (Harris, 1970)

➔

➔ "You shall know a word by the company it keeps!" (Firth, 1957)

Example

- He handed her a glass of bardiwac
- Beef dishes are made to complement the bardiwac
- Nigel staggered to his feet, face flushed from too much bardiwac.
- Malbec, one of the lesser-known bardiwac grapes, responds well to Australia's sunshine
- I dined off bread and cheese and this excellent bardiwac
- The drinks were delicious: bold bardiwac as well as light, sweet Rhenish.

Word Vectors

- A word type may be represented as a vector of features indicating the contexts in which it occurs in a corpus.

$$\vec{w} = (f_1, f_2, f_3, \cdots f_N)$$

Context Features

Word Co-occurrence within a window:

	arts	boil	data	function	large	sugar	summarized	water
apricot	0	1	0	0	1	1	0	1
pineapple	0	1	0	0	1	1	0	1
digital	0	0	1	1	1	0	1	0
information	0	0	1	1	1	0	1	0

Grammatical Relations:

	subj-of, absorb	*subj-of*, adapt	*subj-of*, behave	::	*pobj-of*, inside	*pobj-of*, into	::	*nmod-of*, abnormality	*nmod-of*, anemia	*nmod-of*, architecture	::	*obj-of*, attack	*obj-of*, call	*obj-of*, come from	*obj-of*, decorate	::	*nmod*, bacteria	*nmod*, body	*nmod*, bone marrow
cell	1	1	1		16	30		3	8	1		6	11	3	2		3	2	2

Context Features

Feature Values:

- ➔Boolean
- ➔Raw Counts
- ➔ Weighting Scheme (e.g. tf-idf)
- ➔Association Values

Association Value: Pointwise Mutual Information

- Measures how often a target word *w* and a feature *f* occur together compared to what we would expect if the two were independent

$$\text{association}_{\text{PMI}}(w, f) = \log_2 \frac{P(w, f)}{P(w)P(f)}$$

➔ PMI ranges from *-inf* to *+inf*, but negative values are generally unreliable (Jurafsky & Martin, 2017:275).

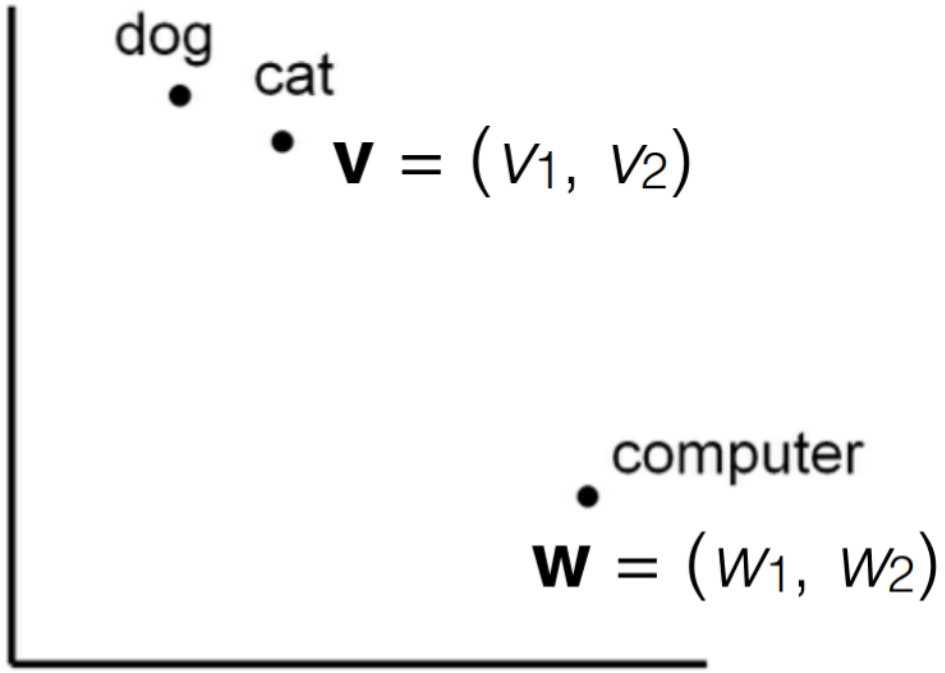
➔ Use positive PMI and clip at zero.

Computing Similarity

Semantic similarity boils down to computing some measure of spatial similarity between context vectors in vector space.

Words in a vector space

- **In 2 dimensions:**
  - V = ‘cat’
  - W = ‘computer’

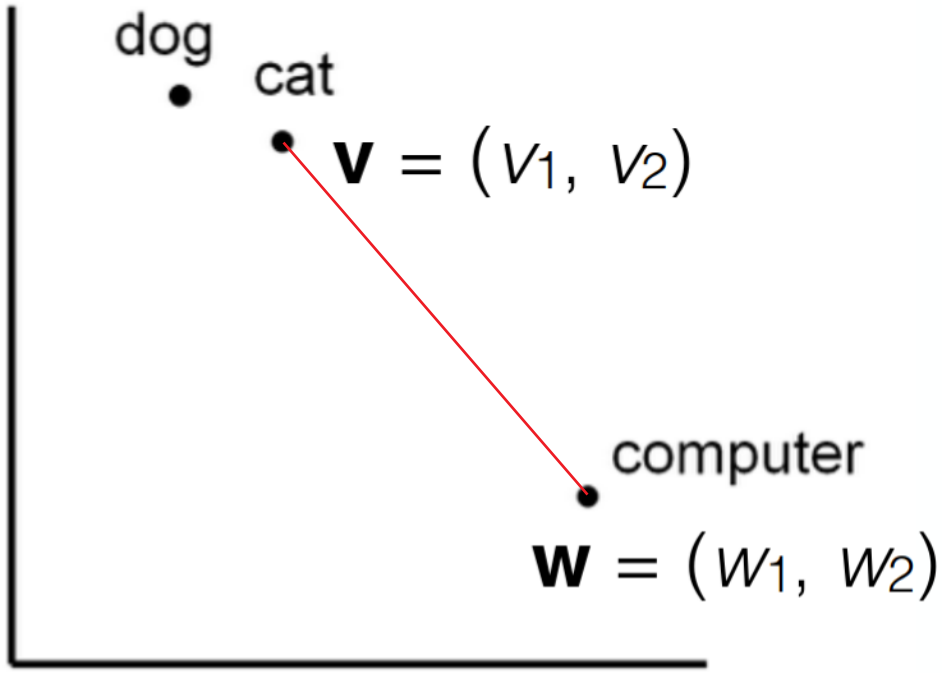


Euclidean Distance

- **Formula:**

$$\sqrt{\sum_i (v_i - w_i)^2}$$

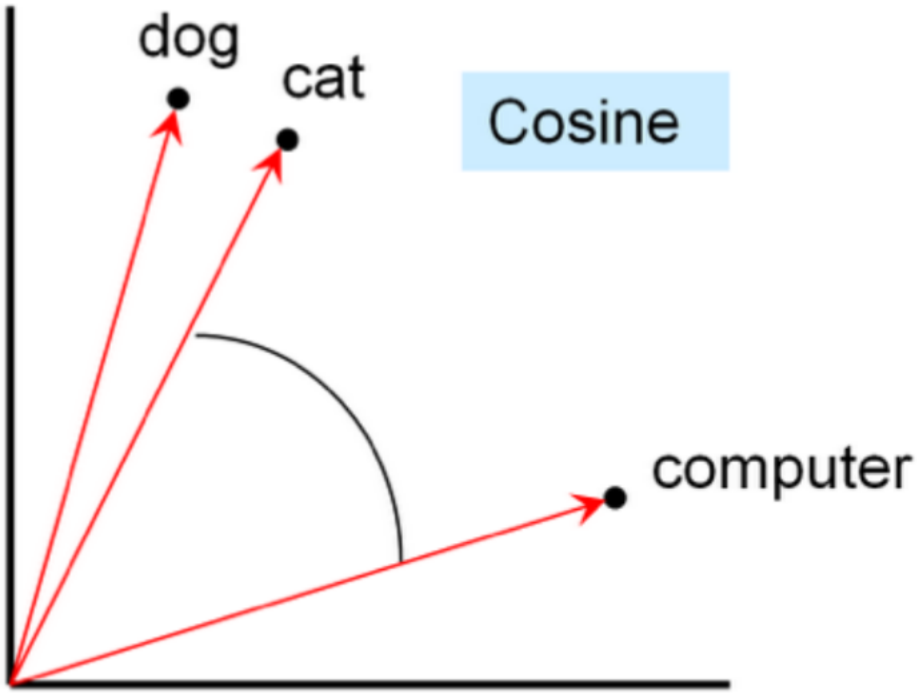
  - ➔ Can be oversensitive to extreme values



Cosine Similarity

- **Formula:**

$$\text{sim}_{\text{cosine}}(\vec{v},\vec{w}) = \frac{\vec{v}\cdot\vec{w}}{|\vec{v}||\vec{w}|} = \frac{\sum_{i=1}^{N} v_i \times w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$



➔ Typically better than Euclidean distance for vector space semantic

Vector Sparseness

- Co-occurrence based context vectors tend to very **long** and very **sparse**.
  - ➔ len(word_vec) == len(vocab)

- **short** (dim. of around 50-300) and **dense** context vectors are usually preferable.
  - ➔ Easier to include as features in machine learning systems
  - ➔ Fewer parameters = better generalization & less over-fitting
  - ➔ Better at capturing synonymy

Dense Vectors

2 Main methods of producing short, dense vectors:

(1) Dimensionality reduction

(2) Neural Language Models

Dimensionality Reduction

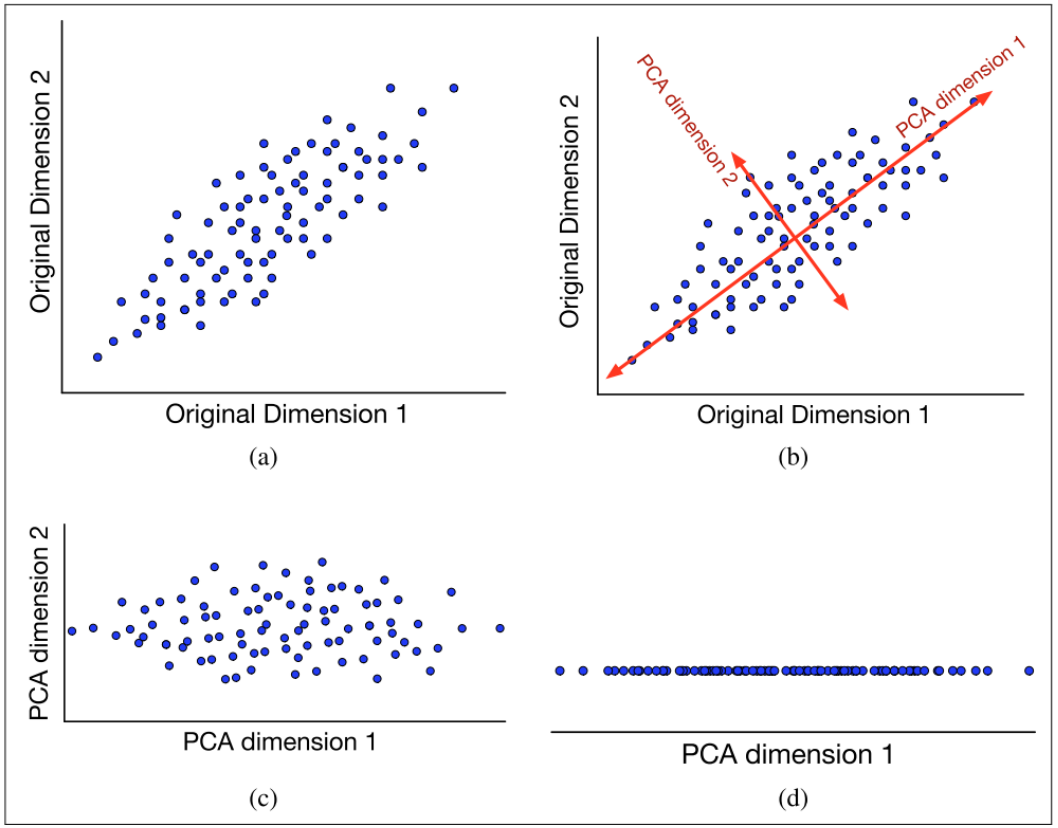
Methods:

➔Principal Component Analysis (PCA)

➔t-Distributed Stochastic Neighbor Embedding (t-SNE)

➔Latent Semantic Analysis (LSA)

➔...



Neural Network Embeddings

Idea: Train a neural network to predict context words based on current current 'target' word.

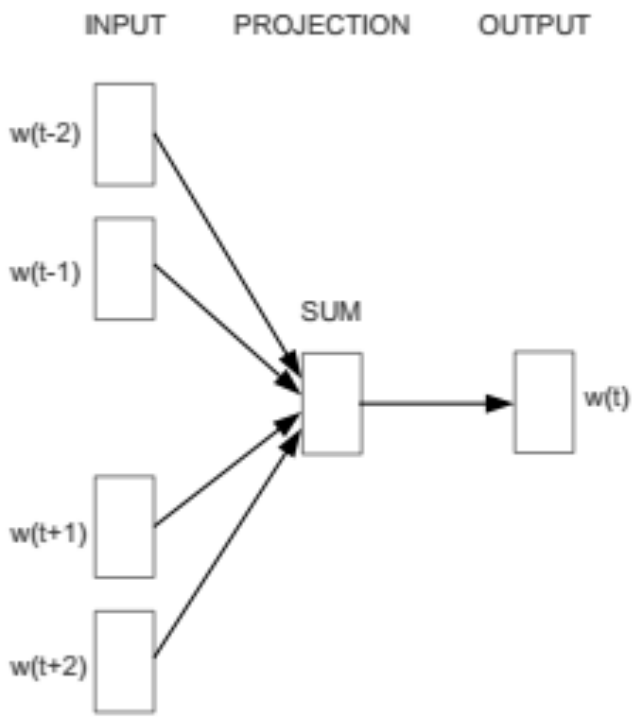
- Similar input words → similar context word prediction
- Similar input words → similar corresponding rows in the weight matrix of the trained network.

We don't actually care about context word prediction!

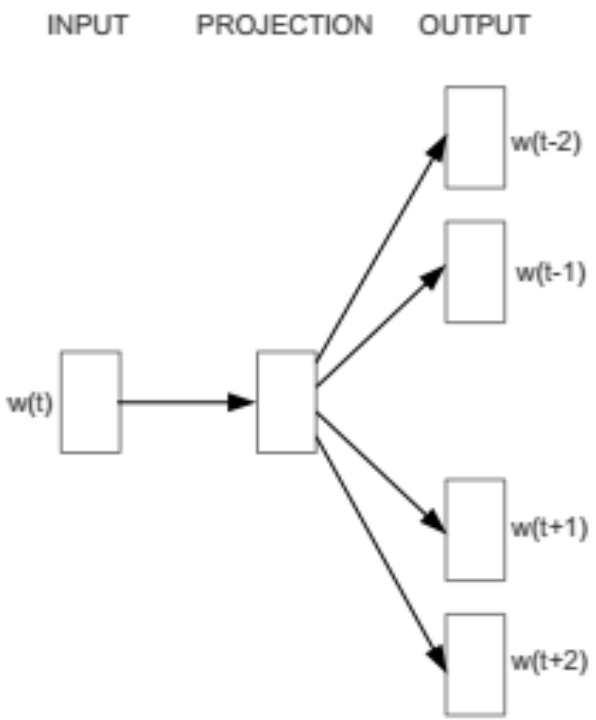
- Rows in the trained weight matrix become our context vectors (aka word vectors, aka word embeddings)

Neural Network Embeddings

Most popular family of methods: word2vec (Mikolov et al. 2013, Mikolov et al. 2013a)



CBOW



Skip-gram

Neural LM architectures: which to use?

- CBOW and Skip-Gram typically produce similar embeddings, but:
  - CBOW is several times faster to train, better accuracy for frequent words
  - Skip-Gram works well with small amounts of training data, and does well with representing rare words

- Mikolov: “Best practice is to try a few experiments and see what works the best for you”

- https://groups.google.com/forum/#!searchin/word2vec-toolkit/c-bow/word2vec-toolkit/NLvYXU99cAM/ESld8LcDxlAJ

Properties of dense word embeddings

Dense word embeddings encode:

- ➔ Semantic Relationships
- ➔ Syntactic Relationships

Can probe relations between words using vector arithmetic:

- ➔ king – male + female = ?
- ➔ walked – walk + fly = ?

Train your own word embeddings:

TensorFlow: https://www.tensorflow.org/tutorials/word2vec

Gensim: https://rare-technologies.com/word2vec-tutorial/

FastText: https://github.com/facebookresearch/fastText

Pretrained Word embeddings:

Word2Vec: https://code.google.com/archive/p/word2vec/

➔ Trained on 100 billion tokens from Google News corpus

GloVe: https://nlp.stanford.edu/projects/glove/

➔6B wikipedia, 42-840B tokens Common Crawl, 27B tokens Twitter

LexVec: https://github.com/alexandres/lexvec

➔ 58B tokens Common Crawl, 7B tokens Wikipedia + NewsCrawl

Word embeddings: Evaluation

How to judge the quality of embeddings?

- **'Relatedness' scores for given word pairs**
  - ➔ Compare model's relatedness scores to human relatedness scores
- **Analogy tests**
  - ➔ Find x such that x : y best resembles a sample relationship a : b
- **Categorization**
  - ➔ Recover a known clustering of words into different categories.

Document features

- So far: Features in word-vectors can be: context counts, PMI scores, weights from neural LMs…
- Can also be features of the docs in which the words occur.
- Document occurrence features are useful for topical/thematic similarity

Document-Term Matrix

	D1	D2	D3	D4
W1	23	17	0	0
W2	102	0	14	24
W3	14	57	0	2
W4	0	0	18	38

Term Frequency – Inverse Document Frequency (tf-idf)

- Common in IR tasks
- Popular method to weight term-document matrices in general

Tf: relative frequency of term in document

➔ tf(t,d) = f(t,d)

Idf: inverse of the proportion of docs containing the term

➔ N / n_t (N = total # of docs, n_t = # of docs term t appeared in)

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Tf-idf weighted Document-Term Matrix

	D1	D2	D3	D4
W1	.12	.16	0	0
W2	.21	0	.13	.11
W3	.03	.22	0	.01
W4	0	0	.39	.41

Tf-idf weighted Document-Term Matrix

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Word Vectors

Tf-idf weighted Document-Term Matrix

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Topic Models

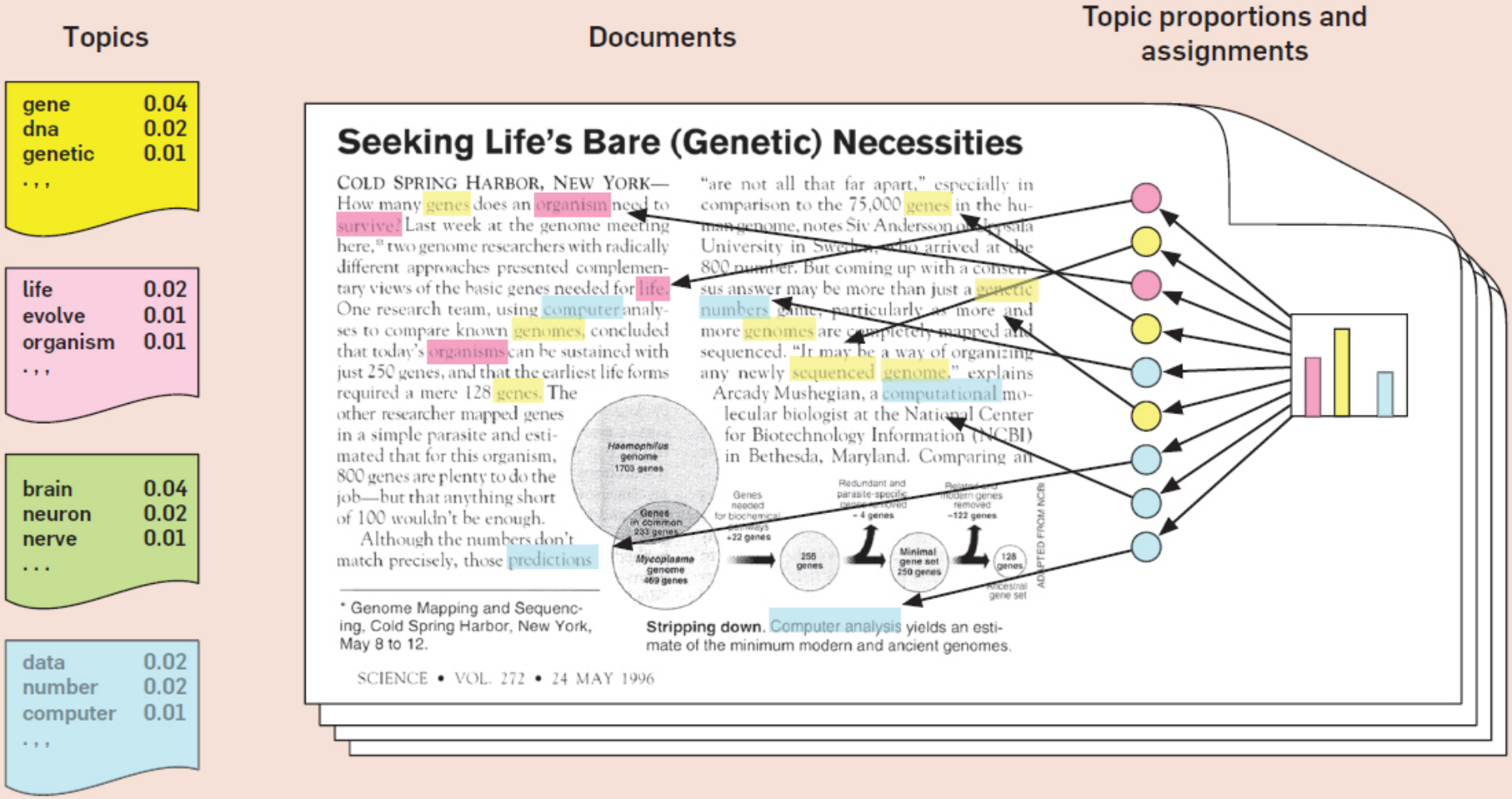
Latent Dirichlet Allocation (LDA) and variants known as topic models.

➔Learned on large document collection (unsupervised)

➔Latent probabilistic clustering of words that tend to occur in the same document. Each 'topic' cluster is a distribution over words.

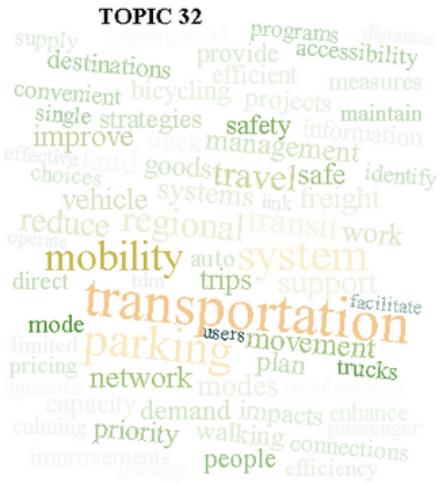
➔Generative Model: Each document is a sparse mixture of topics. Each word in the doc is chosen by sampling a topic from the doc-specific topic distribution, then sampling a word from that topic.

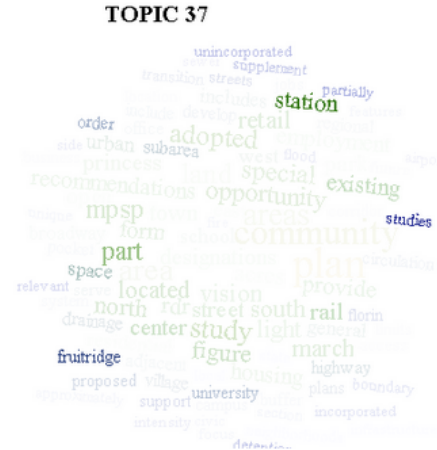
Topic Models



https://cacm.acm.org/magazines/2012/4/147361-probabilistic-topic-models/fulltext

Visualizing Topics





https://dhs.stanford.edu/algorithmic-literacy/using-word-clouds-for-topic-modeling-results/

Questions?