Word vectors of various kinds

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Jorge Luis Borges

An Argentinian philosopher and fiction writer. One of his stories mentions 'a certain Chinese Encyclopedia', the *Celestial Emporium of Benevolent knowledge.* It contains a classifcation of animals.

- those that belong to the emperor
- embalmed ones
- those that are trained
- suckling pigs
- mermaids
- fabulous ones
- stray dogs

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. . . actually, it goes on.

- those that are included in the present classification
- those that tremble as if they are mad
- innumerable ones
- those drawn with a very fine camelhair brush
- others
- those that have just broken a flower vase
- those that from a long way off look like flies

What words are

So far we've talked about words in order. But words have a relationship to each other.

- We use dictionaries in real life for a reason.
- We need to make fine-grained distinctions, draw connections, and so on.
- Humans make judgements about similarities.
    - You know that "motorcycle" can be used in most, but not all contexts that "car" can be used.
    - English-German bilinguals know that "pride" and "Stolz" are quite similar.

Define "chair"

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- A seat, especially for one person, usually having four legs for support and a rest for the back and often having rests for the arms.
- Something that serves as a chair or supports like a chair: “two men clasped hands to make a chair for their injured companion”.
- A position of authority, as of a judge, professor, etc.
- The person occupying a seat of office, especially the chairperson of a meeting: “the speaker addressed the chair”
- (in an orchestra) the position of a player, assigned by rank; desk: “first clarinet chair”.
- “the chair”, Informal. electric chair.

Words in terms of other words

That doesn't seem very helpful, but it gives us a place to start.
Define "chair" in terms of features:

- +one-person, +four-legs, +support, +backrest, +armrest
- +authority
- +occupies-chair
- +orchestra
- +execution

Words in terms of other words

OK, that gives us the definition of a chair in terms of (rather specific) features.

Define the noun "cockpit". Let's go to dictionary.com again. I get as features:

- +enclosed, +airplane, +controls, +panel, +seats
- +instrumentation, +automobile
- +pit, +cockfights
- +conflict

Very little overlaps.

So can we compare them?

Encode features as 1 or 0

	chair	cockpit
one-person	1	0
backrest	1	0?
four-legs	1	0
support	1	0?
armrest	1	0?
authority	1	0?
enclosed	0	1
airplane	0	1
seats	0?	1
...		

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- How can we measure the similarity between them? Common answer: cosine similarity.
- So what would the similarity of "chair" and "cockpit" be in our space? Probably zero!

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Now it's not so bad: we can get a non-zero similarity. Yay?

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  - More complex counts, such as POS tags, bits of parse trees.
- Sometimes raw counts aren't what you need: smoothing, reweighting.

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So now... "predict" vectors...

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- Either way, we're working with integers (. . . , -2, -1, 0, 1, 2, . . .)

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- We can also have a related word, like '*ape*' be close in that vector space, *but in different dimensions*:

0.38	**-1.33**	-0.55	**1.49**

Applications of Word Vectors

- **Word distances**. For example, closest words to '*Sweden*':

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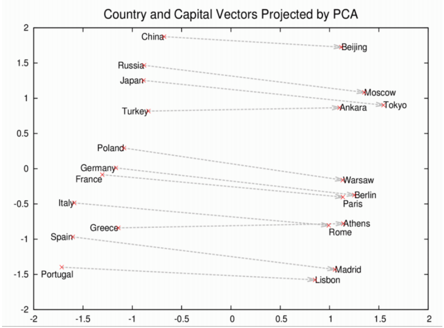
- **Analogy**. E.g., *Japan* is to *Tokyo* as *Germany* is to *Berlin*



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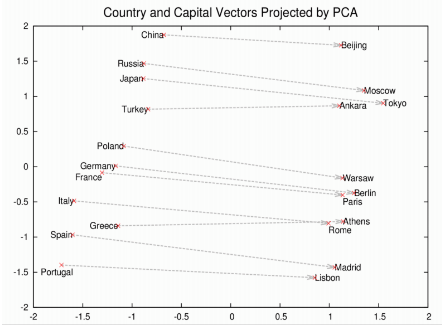

Japan − Tokyo ≈ Germany − Berlin

Applications of Word Vectors

- **Sentence Completion** (actually just restricted language modeling):
- "All red-headed men who are above the age of [800 | seven | twenty-one | 1,200 | 60,000] years , are eligible."
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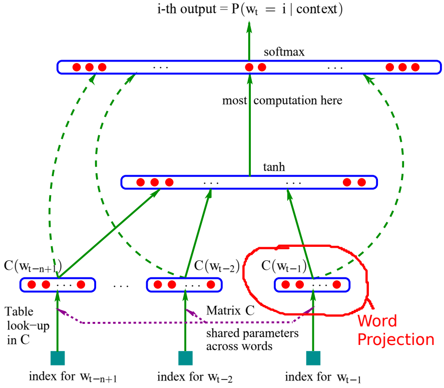
- "That is his [generous | mother's | successful | favorite | main] fault , but on the whole he's a good worker."
- Mikolov et al (2013b) selected the test word that best predicted the context

Projection Layer in Neural Language Models

- **Neural Language Modeling** – this was actually one of the earliest uses of word vectors. We'll talk more about these later this semester



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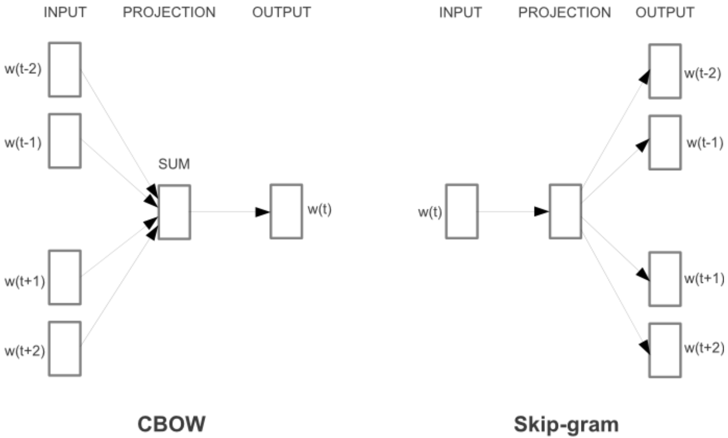
- In fact, you don't need a neural network at all. He removed the hidden layer, giving a traditional log-linear model
- He developed a simplified form of training called negative sampling (derived from earlier NCE). It's a little like a binary MaxEnt classifier

word2vec: CBOW & Skip-gram

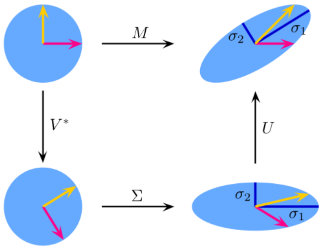


Hyperparameters

- Window size: how much surrounding context to use
- Normalization: softmax (traditional) vs. hierarchical softmax vs. negative sampling
- Vector dimensions: 100–500 common
- Number of negative samples: 3–10 common
- Number of training epochs, initial learning rate, negative sample distribution ($\alpha = 0.75$), model, ...

Matrix Factorization of Count Co-Occurrences

- Glove and Latent Semantic Analysis (LSA) count the co-occurrences of word pairs, then use matrix factorization techniques like singular value decomposition (SVD) for dimensionality reduction of this original matrix



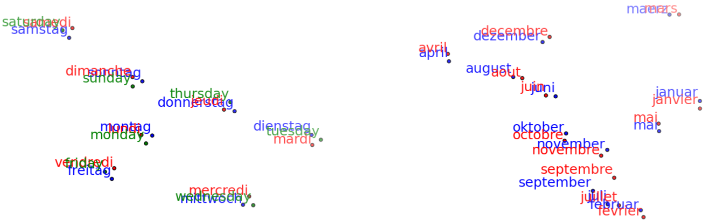
$$M = U \cdot \Sigma \cdot V^*$$

Unifying these Approaches

- Word2vec, Glove, and LSA all do matrix factorization (Levy & Goldberg, 2014), but the successful ones are weighted for word frequency
- Pointwise Mutual Information (PMI) is (implicitly) used by these:

$$\mathrm{PMI}(x, y) = log \frac{P(x, y)}{P(x)\, P(y)}$$

Bilingual Word Vectors



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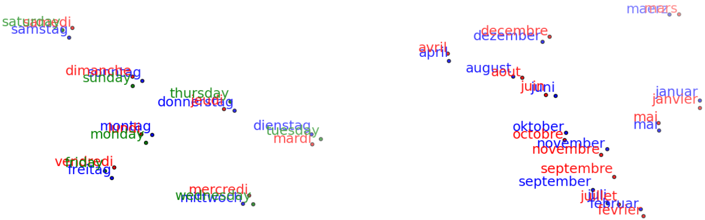

Monolingual objective: maximize likelihood of training set, where $P(w|c) = \sigma(\mathbf{w} \cdot \mathbf{c})$

Multilingual objective: maximize likelihood of both sentence-aligned training sets (s & t), based on: $\sigma(\mathbf{w_t} \cdot \mathbf{c_t}) + \sigma(\mathbf{w_t} \cdot \mathbf{c_s}) + \sigma(\mathbf{w_s} \cdot \mathbf{c_s}) + \sigma(\mathbf{w_s} \cdot \mathbf{c_t})$

Courtesy of Hermann & Blunsom (2013)

Bilingual Word Vectors Comparison

Method	No word alignments required	No prior on the mapping between target vectors	No explicit alignments of target vectors	Computationally efficient	Can leverage monolingual corpus	Free software
Klementiev et al (2012)	✓	×	✓	×	✓	×
BiCVM	✓	✓	×	✓	×	✓
Bilingual autoencoders	✓	✓	×	×	×	✓
BilBOWA	✓	✓	×	✓	✓	✓
Trans-gram	✓	✓	✓	✓	✓	×

Courtesy of Coulmance et al. (2015)

Try Them Out!

- Original word2vec code: `https://code.google.com/p/word2vec/` – includes nice illustrations
- Python version: Gensim
- Java version in DL4J
- Glove