Continuous Representations of Words

a.k.a. word vectors
a.k.a. word embeddings
a.k.a. projection layers

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January 28, 2016

Words as Integers

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

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- We can have the plural form, '*monkeys*' be close in that vector space:

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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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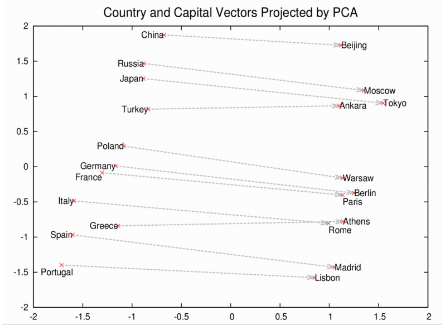

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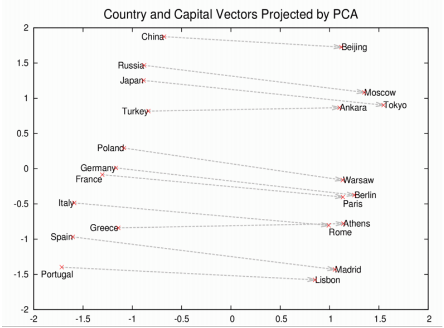

Japan – Tokyo ≈ Germany – Berlin

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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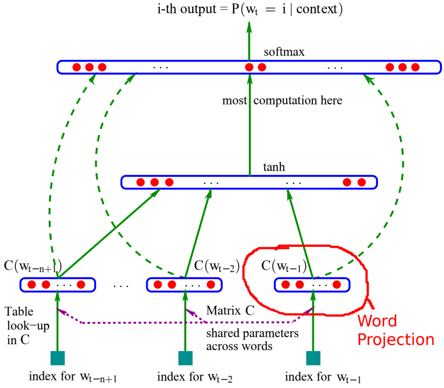
- Mikolov et al (2013b) selected the test word that best predicted the context

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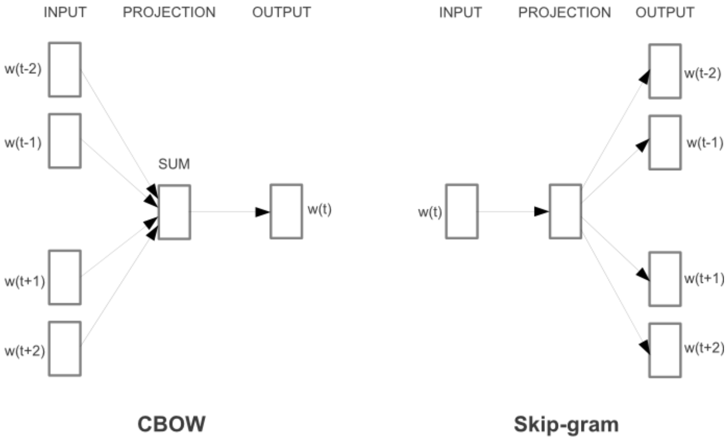
- In fact, you don't need a neural network at all. He removed the hidden layer, giving a traditional logistic regression model
- He developed a simplified form of training called negative sampling (derived from earlier NCE). It's a little like a binary MaxEnt classifier

word2vec: CBOW & Skip-gram

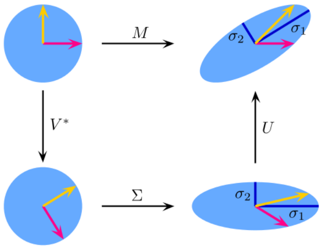


Hyperparameters

- 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



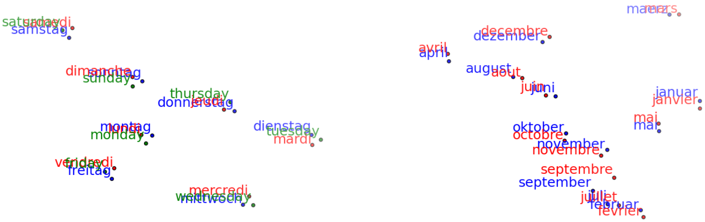
$$M = U \cdot \Sigma \cdot V^*$$

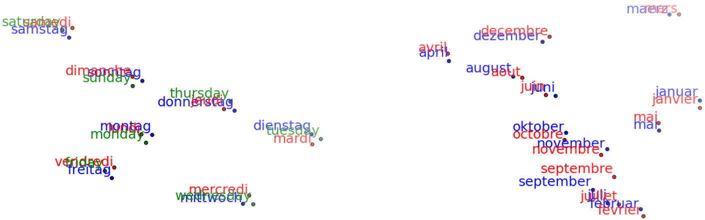
Unifying these Approaches

- 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





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