

Continuous Representations of Words

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

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Good Morning!

Words as Integers

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- Either way, we're working with integers ($\dots, -2, -1, 0, 1, 2, \dots$)



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

0.38	-1.33	-0.55	1.49
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Applications of Word Vectors

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

Word	Cosine Distance
Norway	0.75
Denmark	0.72
Finland	0.62
Switzerland	0.59
...	

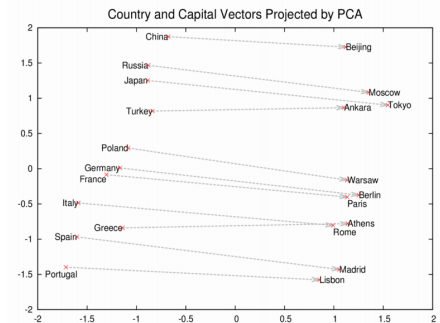
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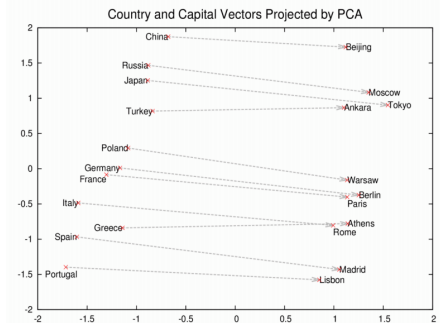
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$$\text{Japan} - \text{Tokyo} \approx \text{Germany} - \text{Berlin}$$

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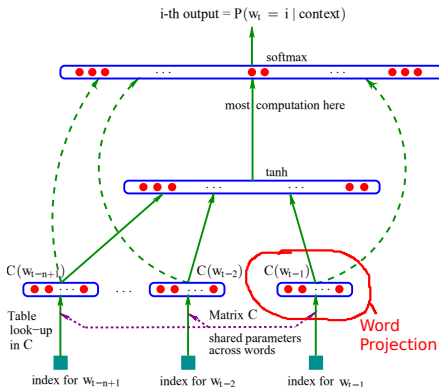
- **Sentence Completion** (actually just restricted language modeling):
- “All red-headed men who are above the age of [800 | seven | twenty-one | 1,200 | 60,000] years , are eligible.”
- “That is his [generous | mother’s | successful | favorite | main] fault , but on the whole he’s a good worker.”

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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



Word2vec

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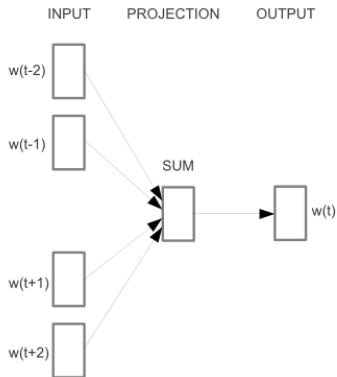
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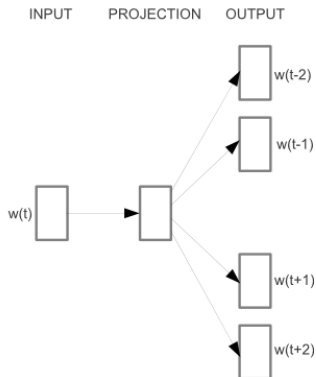
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- He developed a simplified form of training called negative sampling (derived from earlier NCE). It's a little like a binary MaxEnt classifier

word2vec: CBOW & Skip-gram



CBOW



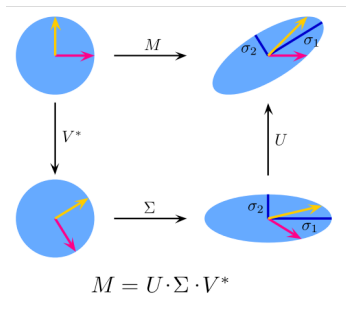
Skip-gram

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



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:

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

Try Them Out!

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