Continuous Representations of Words

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

Jon Dehdari

November 30, 2015

Good Morning!

Words as Integers

- Our previous representations of words (and word classes) have been fairly flat
- For example, the word ‘*monkey*’ can be represented as an integer, such as ‘7’

Words as Integers

- Our previous representations of words (and word classes) have been fairly flat
- For example, the word '*monkey*' can be represented as an integer, such as '7'
- **One-hot encoding** represents that as:

0	0	0	0	0	0	1	0	0	0	...	0

Words as Integers

- Our previous representations of words (and word classes) have been fairly flat
- For example, the word '*monkey*' can be represented as an integer, such as '7'
- **One-hot encoding** represents that as:

0	0	0	0	0	0	1	0	0	0	...	0

- and the word class (eg. 2) containing '*monkey*':

0	1	0	0

Words as Integers

- Our previous representations of words (and word classes) have been fairly flat
- For example, the word '*monkey*' can be represented as an integer, such as '7'
- **One-hot encoding** represents that as:

0	0	0	0	0	0	1	0	0	0	...	0

- and the word class (eg. 2) containing '*monkey*':

0	1	0	0

- Both of these are sparse vectors of booleans, with just one entry having a 'true' value

Words as Integers

- Our previous representations of words (and word classes) have been fairly flat
- For example, the word '*monkey*' can be represented as an integer, such as '7'
- **One-hot encoding** represents that as:

0	0	0	0	0	0	1	0	0	0	...	0

- and the word class (eg. 2) containing '*monkey*':

0	1	0	0

- Both of these are sparse vectors of booleans, with just one entry having a 'true' value
- Either way, we're working with integers (..., -2, -1, 0, 1, 2, ...)

Words as $\mathbb{R}$eal Numbers

- We can do more with real numbers (eg. -1.5, 0.23, 55.01)

Words as ℝeal Numbers

- We can do more with real numbers (eg. -1.5, 0.23, 55.01)
- We can represent the word '*monkey*' as a dense vector of real numbers:

0.38	-1.27	-0.55	1.44

Words as $\mathbb{R}$eal Numbers

- We can do more with real numbers (eg. -1.5, 0.23, 55.01)
- We can represent the word '*monkey*' as a dense vector of real numbers:

0.38	-1.27	-0.55	1.44

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

0.31	-1.27	**-0.61**	1.44

Words as ℝeal Numbers

- We can do more with real numbers (eg. -1.5, 0.23, 55.01)
- We can represent the word '*monkey*' as a dense vector of real numbers:

0.38	-1.27	-0.55	1.44

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

0.31	-1.27	**-0.61**	1.44

- 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*':

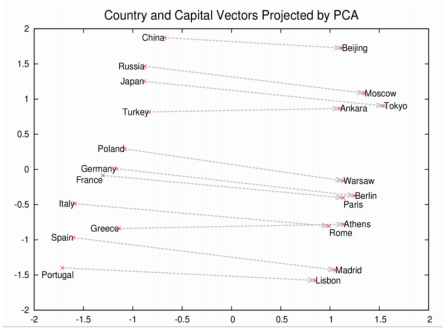
Word	**Cosine Distance**
Norway	0.75
Denmark	0.72
Finland	0.62
Switzerland	0.59
...	

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
...	

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

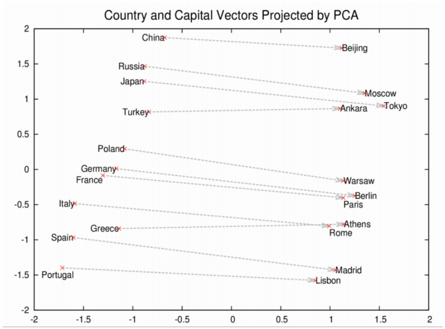


Applications of Word Vectors

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

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

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



Japan − Tokyo ≈ Germany − Berlin

Applications of Word Vectors

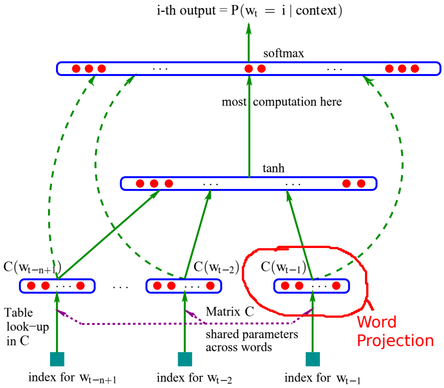
- **Sentence Completion** (actually just restricted language modeling):
- "All red-headed men who are above the age of [800 | seven | twenty-one | 1,200 | 60,000] years , are eligible."
- "That is his [generous | mother's | successful | favorite | main] fault , but on the whole he's a good worker."

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."
- "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

- Tomáš Mikolov and colleagues found that you don't need the full neural-net language model to get useful word vectors

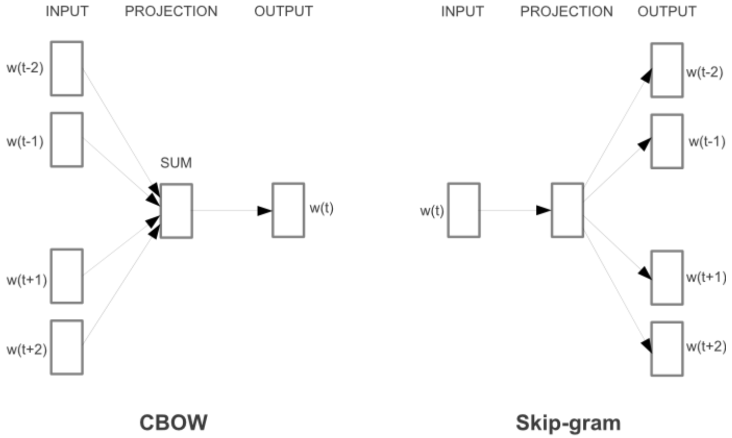
word2vec

- Tomáš Mikolov and colleagues found that you don't need the full neural-net language model to get useful word vectors
- In fact, you don't need a neural network at all. He removed the hidden layer, giving a traditional logistic regression model

word2vec

- Tomáš Mikolov and colleagues found that you don't need the full neural-net language model to get useful word vectors
- 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

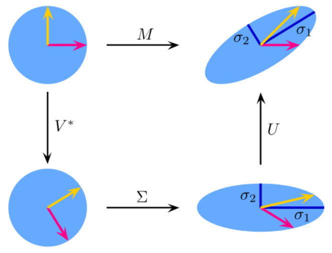


Hyperparameters

- 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:

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

Try Them Out!

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