Word Embedding

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Outline

- Word embedding
  - Skipgram learning
  - Pre-trained embeddings
- Recurrent neural networks
  - LSTM
  - Extensions
- State-of-the-art

Word Embedding

Slides are partly based on the word embedding lecture by Dong Nguyen in the Applied Text Mining Utrecht summer school (linkToRCourse, linkToPythonCouse)

Word representations

How can we represent the meaning of words?

So, we can ask:

- How similar is cat to dog, or Paris to London?
- How similar is document A to document B?

Word as vectors

Can we represent words as vectors?

The vector representations should:

- capture semantics
  - similar words should be close to each other in the vector space
  - relation between two vectors should reflect the relationship between the two words
- be efficient (vectors with fewer dimensions are easier to work with)
- be interpretable

Word as vectors

How similar are the following two words? (not similar 0–10 very similar)

smart and **intelligent:**
easy and **big**:
easy and **difficult**:
hard and **difficult**:

Word as vectors

How similar are the following two words? (not similar 0–10 very similar)

smart and **intelligent:** 9.20
easy and **big**: 1.12
easy and **difficult**: 0.58
hard and **difficult**: 8.77

(SimLex-999 dataset, https://fh295.github.io/simlex.html)

Words as Vectors

One-hot encoding

Map each word to a unique identifier

e.g. cat (3) and dog (5).

- Vector representation: all zeros, except 1 at the ID

cat	0	0	1	0	0	0	0
dog	0	0	0	0	1	0	0
car	0	0	0	0	0	0	1

One-hot encoding

Map each word to a unique identifier

e.g. cat (3) and dog (5).

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cat	0	0	1	0	0	0	0
dog	0	0	0	0	1	0	0
car	0	0	0	0	0	0	1

What are limitations of one-hot encodings?

One-hot encoding

Map each word to a unique identifier

e.g. cat (3) and dog (5).

• Vector representation: all zeros, except 1 at the ID

cat	0	0	1	0	0	0	0
dog	0	0	0	0	1	0	0
car	0	0	0	0	0	0	1

Even related words have distinct vectors!

High number of dimensions

Distributional hypothesis: Words that occur in similar contexts tend to have similar meanings.

You shall know a word by the company it keeps. (Firth, J. R. 1957:11)

Word vectors based on co-occurrences

documents as context
word-document matrix

	doc_1	doc_2	doc_3	doc_4	doc_5	doc_6	doc_7
cat	5	2	0	1	4	0	0
dog	7	3	1	0	2	0	0
car	0	0	1	3	2	1	1

Word vectors based on co-occurrences

documents as context
word-document matrix

	doc_1	doc_2	doc_3	doc_4	doc_5	doc_6	doc_7
cat	5	2	0	1	4	0	0
dog	7	3	1	0	2	0	0
car	0	0	1	3	2	1	1

neighboring words as context
word-word matrix

	cat	dog	car	bike	book	house	tree
cat	0	3	1	1	1	2	3
dog	3	0	2	1	1	3	1
car	0	0	1	3	2	1	1

Word vectors based on co-occurrences

There are many variants:

- Context (words, documents, which window size, etc.)
- Weighting (raw frequency, etc.)

Vectors are sparse: Many zero entries.

Therefore: Dimensionality reduction is often used (e.g., SVD)

These methods are sometimes called **count-based** methods as they work directly on **co-occurrence** counts.

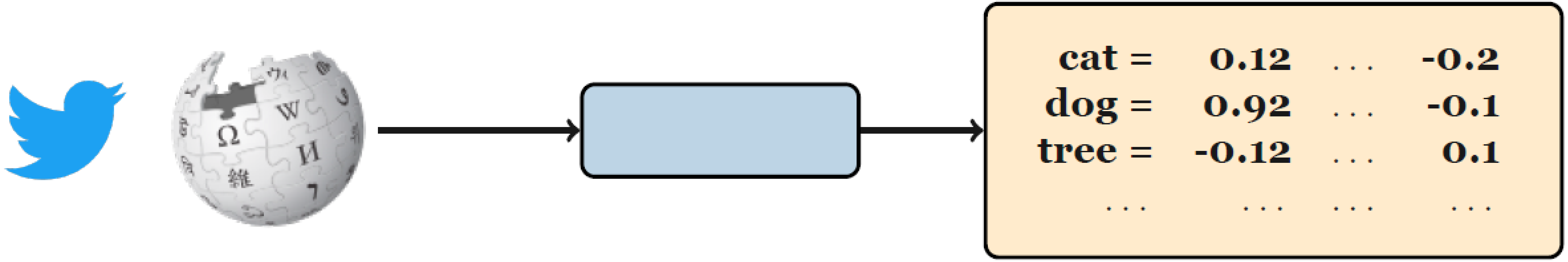
Word embeddings

- Vectors are short; typically 50-1024 dimensions ☺
- Vectors are dense (mostly non-zero values)
- Very effective for many NLP tasks ☺
- Individual dimensions are less interpretable ☹

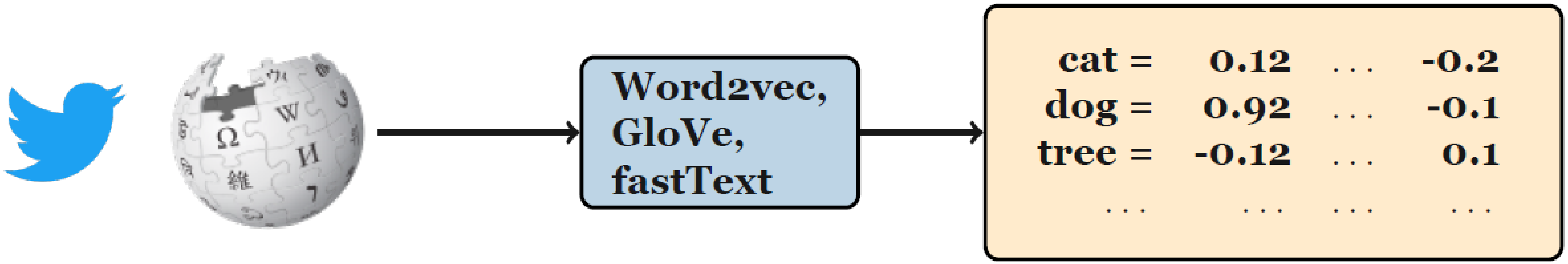
cat	0.52	0.48	-0.01	⋯	0.28
dog	0.32	0.42	-0.09	⋯	0.78

How do we learn word embeddings?

Learning word embeddings



Learning word embeddings



Training data for word embeddings

- Use **text itself** as training data for the model!
  - A form of self-supervision.
- Train a **classifier** (neural network, logistic regression, or SVM, etc.) to predict the next word given previous words.

Exercise: Word prediction task

Yesterday I went to the ?

A new study has highlighted the positive ?

Which word comes next?

Word2Vec

- Popular embedding method
- Very fast to train
- Idea: **predict** rather than **count**

- https://projector.tensorflow.org/

Word2Vec

The domestic **cat** is a small, typically furry carnivorous mammal

w_{-2} w_{-1} w_0 w_1 w_2 w_3 w_4 w_5

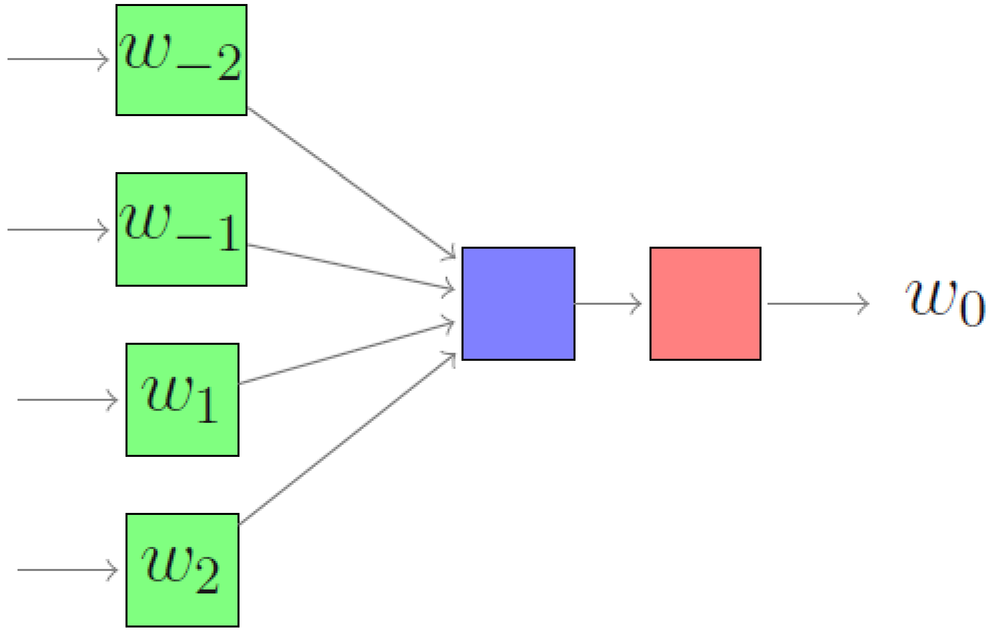
We have **target** words (cat) and **context** words (here: window size = 5).

Word2Vec

- Instead of **counting** how often each word w occurs near a target word
  - Train a classifier on a binary **prediction** task:
    - Is w likely to show up near target?
- We don’t actually care about this task
  - But we'll take the learned classifier weights as the word embeddings
- Big idea: **self-supervision**
  - A word c that occurs near target in the corpus as the gold "correct answer" for supervised learning
  - **No need for human labels**
  - Bengio et al. (2003); Collobert et al. (2011)

Word2Vec algorithms

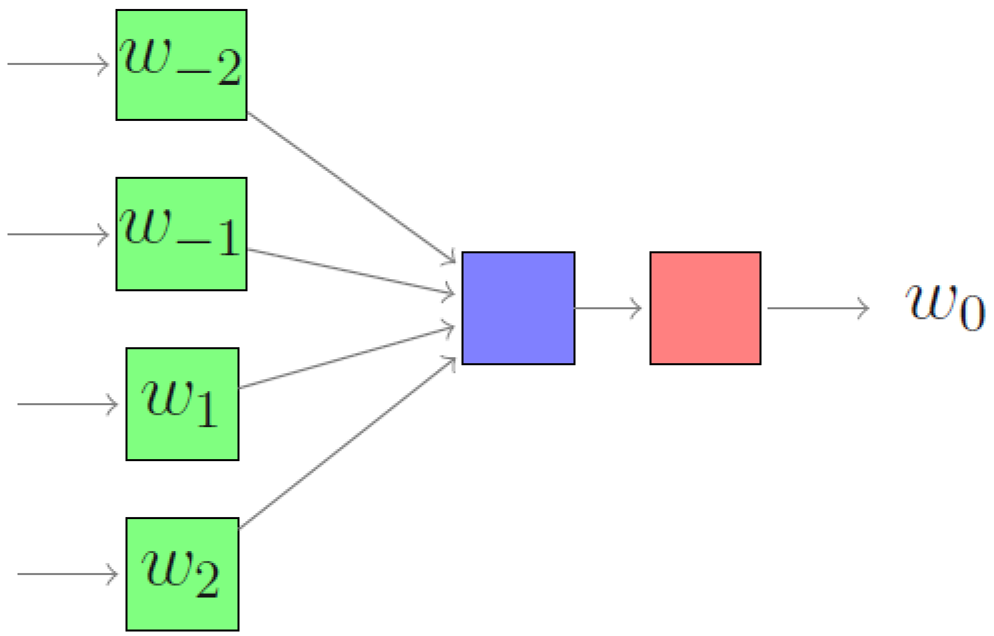
Continuous Bag-Of-Words (CBOW)



one snowy ? she went

Word2Vec algorithms

Continuous Bag-Of-Words (CBOW)



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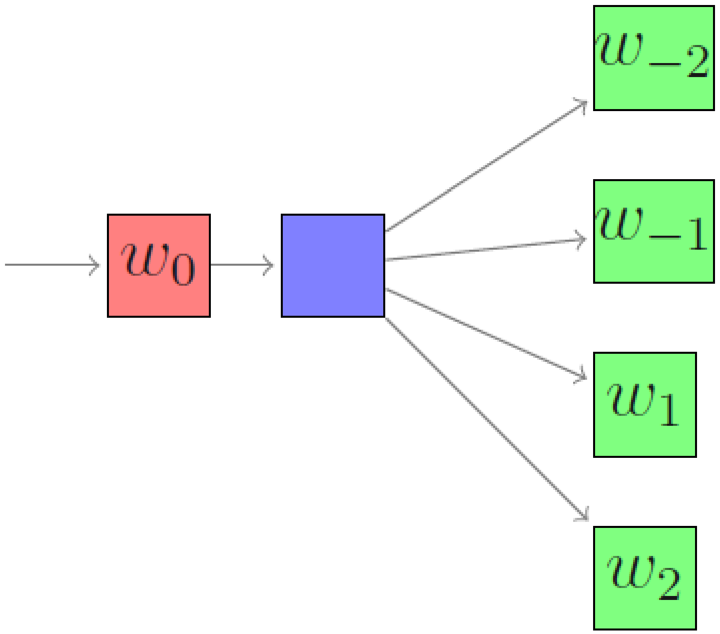
skipgram



? ? day ? ?

Skipgram overview

The domestic **cat** is a small, typically furry carnivorous mammal

1. **Create examples**
   - Positive examples: Target word and neighboring context
   - Negative examples: Target word and randomly sampled words from the lexicon (*negative sampling*)
2. Train a **logistic regression** model to distinguish between the positive and negative examples
3. The resulting **weights** are the embeddings!

word (w)	context (c)	label
cat	small	1
cat	furry	1
cat	car	0
...	...	...

Embedding vectors are essentially a byproduct!

Skipgram

The domestic **cat** is a small, typically furry carnivorous mammal

w_{-2} w_{-1} w_0 w_1 w_2 w_3 w_4 w_5

We have **target** words (cat) and **context** words (here: window size = 5).

The probability that c is a real context word, and the probability that c is not a real context word:

$$P(+|w, c)$$
$$P(-|w, c) = 1 - P(+|w, c)$$

Skipgram

Similarity is computed from dot product

- **Intuition**: A word *c* is likely to occur near the target *w* if its embedding is similar to the target embedding.

$$\approx w \cdot c$$

  - Two vectors are similar if they have a high dot product
  - Cosine similarity is just a normalized dot product

Turn this into a probability using the sigmoid function:

$$\begin{aligned} P(+|w,c) &= \sigma(c \cdot w) = \frac{1}{1+\exp(-c \cdot w)} \\ P(-|w,c) &= 1 - P(+|w,c) \\ &= \sigma(-c \cdot w) = \frac{1}{1+\exp(c \cdot w)} \end{aligned}$$

How Skipgram classifier computes P(+|w, c)

$$P(+|w,c) = \sigma(c \cdot w) = \frac{1}{1+\exp(-c \cdot w)}$$

This is for one context word, but we have lots of context words.
We'll assume independence and just multiply them:

$$P(+|w,c_{1:L}) = \prod_{i=1}^{L} \sigma(c_i \cdot w)$$

$$\log P(+|w,c_{1:L}) = \sum_{i=1}^{L} \log \sigma(c_i \cdot w)$$

Word2vec: how to learn vectors

- Given the set of positive and negative training instances, and an initial set of embedding vectors
- The goal of learning is to adjust those word vectors such that we:
- Maximize the similarity of the **target word, context word** pairs (w , c_{pos}) drawn from the positive data
- Minimize the similarity of the (w , c_{neg}) pairs drawn from the negative data.

Loss function for one *w* with c_{pos} , c_{neg1} ...c_{negk}

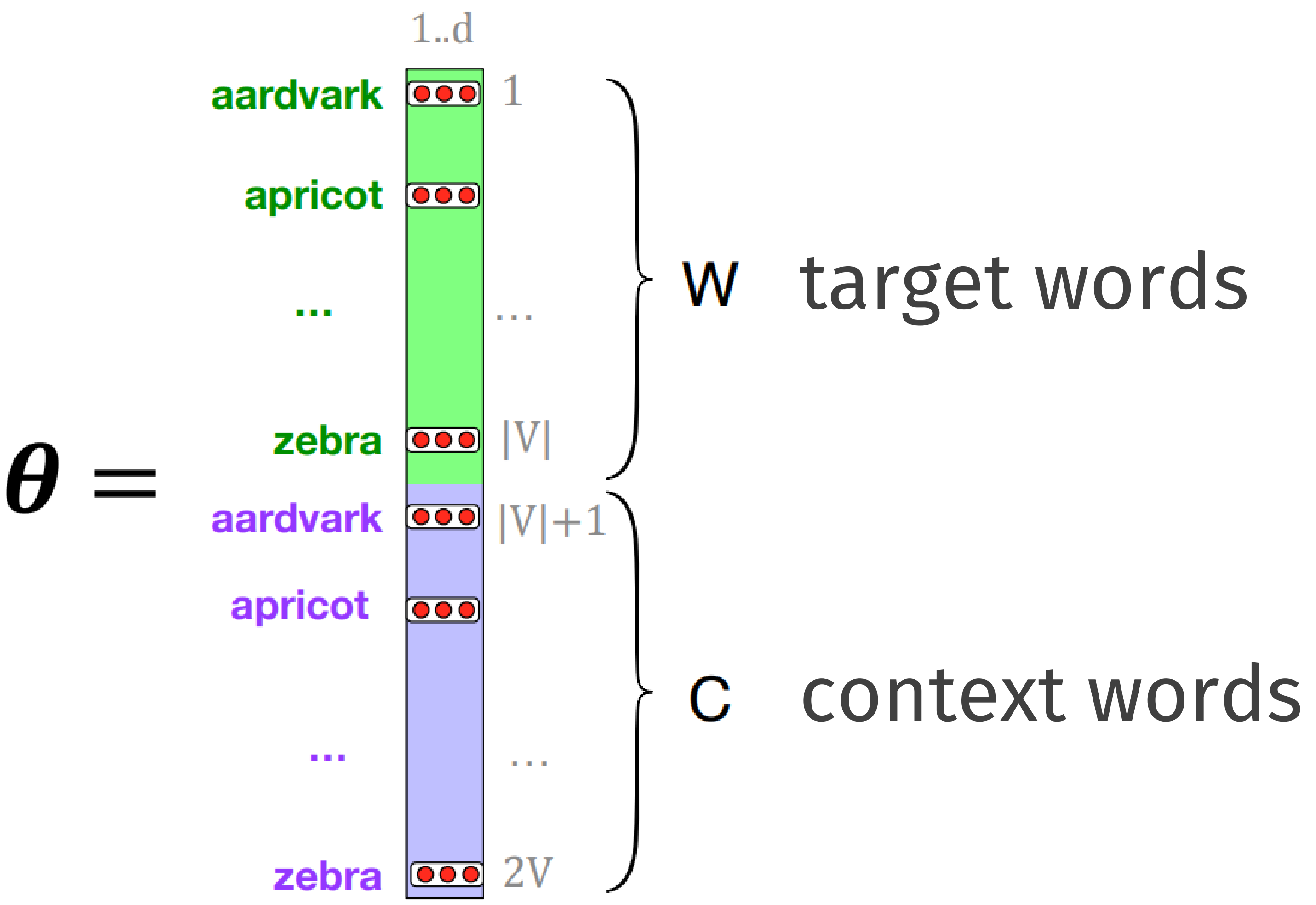
- Maximize the similarity of the target with the actual context words, and minimize the similarity of the target with the k negative sampled non-neighbor words.

$$
\begin{aligned}
L_{\mathrm{CE}} &= -\log\left[P(+|w,c_{pos})\prod_{i=1}^{k}P(-|w,c_{neg_i})\right] \\
&= -\left[\log P(+|w,c_{pos})+\sum_{i=1}^{k}\log P(-|w,c_{neg_i})\right] \\
&= -\left[\log P(+|w,c_{pos})+\sum_{i=1}^{k}\log\left(1-P(+|w,c_{neg_i})\right)\right] \\
&= -\left[\log\sigma(c_{pos}\cdot w)+\sum_{i=1}^{k}\log\sigma(-c_{neg_i}\cdot w)\right]
\end{aligned}
$$

Learning the classifier

- How to learn?
  - **Stochastic gradient descent!**

Skipgram embeddings



Learning the classifier

- How to learn?
  - **Stochastic gradient descent!**

- SGNS learns two sets of embeddings
  - Target embeddings matrix W
  - Context embedding matrix C
- It's common to just add them together, representing word i as the vector Wi + Ci

Skipgram

1. Treat the target word t and a neighboring context word c as positive examples.
2. Randomly sample other words in the lexicon to get negative examples
3. Use logistic regression to train a classifier to distinguish those two cases
4. Use the learned weights as the embeddings

Skipgram classifier

- A probabilistic classifier, given
  - a test target word w
  - its context window of L words $c_{1:L}$
- Estimates probability that w occurs in this window based on similarity of w (embeddings) to $c_{1:L}$ (embeddings).

- To compute this, we just need embeddings for all the words.

Pre-trained Embeddings

Pre-trained embeddings

- I want to build a system to **solve a task** (e.g., sentiment analysis)
  - Use pre-trained embeddings. Should I **fine-tune**?
    - Lots of data: yes
    - Just a small dataset: no

- **Analysis** (e.g., bias, semantic change)
  - Train embeddings from scratch

Word embedding in Python

In Python

```
import numpy as np
#
```

Layer embedding in keras

```
layer_embedding(input_dim = max_words, output_dim = dim_size,
                input_length = maxlen,
                # put weights into list and do not allow training
                weights = list(word_embeds), trainable = FALSE)
```

State-of-the-art

State-of-the-art

- Recurrent neural networks
  - LSTM
  - GRU
  - Bi-directional network
- Transformers
- Contextual embeddings

We will discuss the details during the summer text mining courses:

- **Click to go to the Intro to Text Mining with R course**
- **Click to go to the Applied Text Mining course (Python)**

Practical
Word embedding

Questions?