CSE440: Natural Language Processing II

Dr. Farig Sadeque
Associate Professor
Department of Computer Science and Engineering
BRAC University

Lecture 4: Word Representations

Outline

- Co-occurrence (SLP 6)
- TF-IDF (SLP 6)
- Embeddings (SLP 6 and lecture)

Intro

- Computers do not understand semantics
- Representation of text needs to include some sort of semantic information

Representation

- Sentence-level representation problems
- Co-occurrence
- TF-IDF
- Embeddings

Problems with BoW

- Too sparse
  - What’s wrong with sparsity?
- Completely ignores word order
- Almost no semantic information preserved
- But, works pretty well!

More problem with sentence-level representation

- Dogs chew snacks
- Canines eat treats

More problem with sentence-level representation

- Dogs chew snacks
- Canines eat treats

Documents	$f_{canines}$	f_{chew}	f_{dogs}	f_{eat}	f_{snacks}	f_{treats}
dogs chew snacks	0	1	1	0	1	0
canines eat treats	1	0	0	1	0	1

- No feature overlap whatsoever. If we try to calculate similarity, they are 100% dissimilar. But are they?
- Solution: instead of creating sentence level representations, let's go to smaller units i.e. words

A smarter sentence representation: TF-IDF

TF-IDF: Term Frequency - Inverse Document Frequency

Intuition: An informative term should:

- Occurs many times in some specific contexts (TF)
- Does not occur in every context (IDF)

Examples:

- high TF *vector* is informative; it's frequent in these slides
- high DF *the* is uninformative; it's frequent everywhere

TF-IDF

$$tf(w,d) = log(1 + f(w,d))$$

$$idf(w,D) = log(\frac{N}{f(w,D)})$$

w is a word, d is a document, D is the corpus, N = |D|

Intuitions:

- frequent in a single context is good
- avoid infinities
- appearing in every document is bad
- score of 100 (vs. 1) is not 100 times more relevant

Perfect word representations

- shared lemmas: mouse/mice, dormir/duermes, etc.
- different word senses: computer mouse vs. pet mouse, river bank vs. financial bank, etc.
- synonyms: couch/sofa, car/automobile, etc.
- antonyms: long/short, dark/light, etc.
- word similarity: dog/cat, doctor/nurse, etc.
- word relatedness: cup/coffee, scalpel/surgeon, etc.
- word valence: excited and relaxed are high valence, depressed and angry are low valence
- word arousal: excited and angry are high arousal, relaxed and depressed are low arousal

Neighboring words hint at semantics

- Imagine you didn’t know what ignite meant:

  . . . fusion fire does not ignite till temperatures . . .

  . . . plumes of flame ignite from the smokestacks . . .

  . . . over low heat. Ignite with a match …

- But you had seen another word in similar contexts:

  . . . the way the fire is lit or the heat source . . .

  ... flame couldn’t have lit a cigarette . . .

  . . . kiln-dried logs that lit with a match ...

Intuition: if two words are semantically similar, they will appear in text with similar surrounding words

Term-term matrix

A term-term co-occurrence matrix X is a |V|x|V| matrix where:

- |V| is the number of words in the vocabulary
- each cell $X_{i,j}$ records how often word j occurred in the context of word i
- each row X_i is the vector representation for word i

Context may be defined in different ways:

- The same document
- The same sentence
- Within ±n words of each other

V is typically the 10,000 - 50,000 most frequent words)

- Each word is represented by a large vector

Easy way to build a term-term matrix

- Build a binary BoW for the sentences
- Transpose it
- Multiply it with the original matrix
- Voila
- Try it: docs = ["any big cat", "big cat", "cat dog cat"]

Comparing word vectors

- How do you know the vectors you built make any sense?
- You need to compare these vectors
- What techniques do we have?

Cosine similarity

- Most common similarity measure

$$cosine(\mathbf{v},\mathbf{w}) = \frac{\mathbf{v}^\top \mathbf{w}}{|\mathbf{v}||\mathbf{w}|} = \frac{\overbrace{\sum_i v_i w_i}^{\text{dot product}}}{\underbrace{\sqrt{\sum_i v_i^2}}_{\text{length of } \mathbf{v}} \underbrace{\sqrt{\sum_i w_i^2}}_{\text{length of } \mathbf{w}}}$$

Cosine similarity: Why?

- Range is between 1 and -1
- Why not Euclidean distance? $\sqrt{\sum_{i=1}^{n}(v_i - w_i)^2}$

Let’s try this for this three vectors: u = [0, 1, 0, 1] v = [1, 0, 1, 0] w = [3, 0, 3, 0]

What is the cosine similarity? What is the Euclidean distance? Which one makes more sense?

What’s wrong with term term matrix?

- Sparse. Very sparse.
- Does not carry any contextual information
- Does not represent how important a word is in a sentence

Using word vectors

For word tasks:

- finding synonyms via cosine
- as classifier features when the input is one word

For sentence/document tasks:

- First, combine all word vectors
- You can combine yourself (using centroid technique): usually needed for classical ML models; or
- You can let an RNN handle things
- These vectors can then be used for classification

Sparse vs. dense vectors

Vectors we studied are very sparse

Advantages of small, dense word vectors:

- fewer feature weights to learn in machine learning
- fewer features can reduce overfitting
- forces sharing; there are not enough dimensions for
- each word to be completely independent

Word embeddings

- Rather than count co-occurrence, let's try to predict it
- We can do it in two ways
  - Predict the target word given the neighboring words: CBOW

  - Predict the neighboring words given the target word: Skip-gram

- CBOW is easy, but…
- We will focus on Skip-gram

Skip-gram embeddings

- Input: a word, taken from some text
- Output: the 5 preceding and 5 following words
- Try it!
- Input: hippopotamus
- Output: [?, ?, ?, ?, ?, hippopotamus, ?, ?, ?, ?, ?]

Skip-gram embeddings

- Input: a word, taken from some text
- Output: the 5 preceding and 5 following words
- Try it!
- Input: hippopotamus
- Output: [?, ?, ?, ?, ?, hippopotamus, ?, ?, ?, ?, ?]
- This task is impossible! But that’s okay because
    - Creating training data is easy
    - We’ll only use word vectors learned as part of training

Creating Training Data is Easy

thou	shalt	not	make	a	machine	in	the	…

thou	shalt	not	make	a	machine	in	the	…

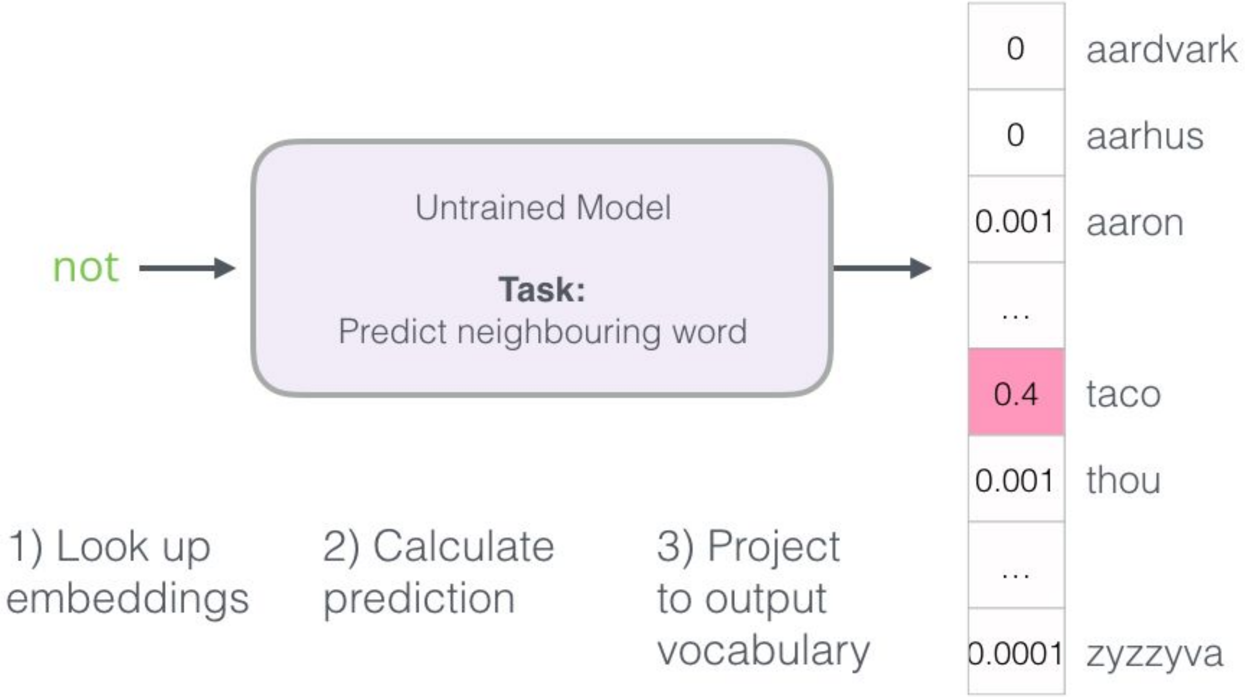
thou	shalt	not	make	a	machine	in	the	…

thou	shalt	not	make	a	machine	in	the	…

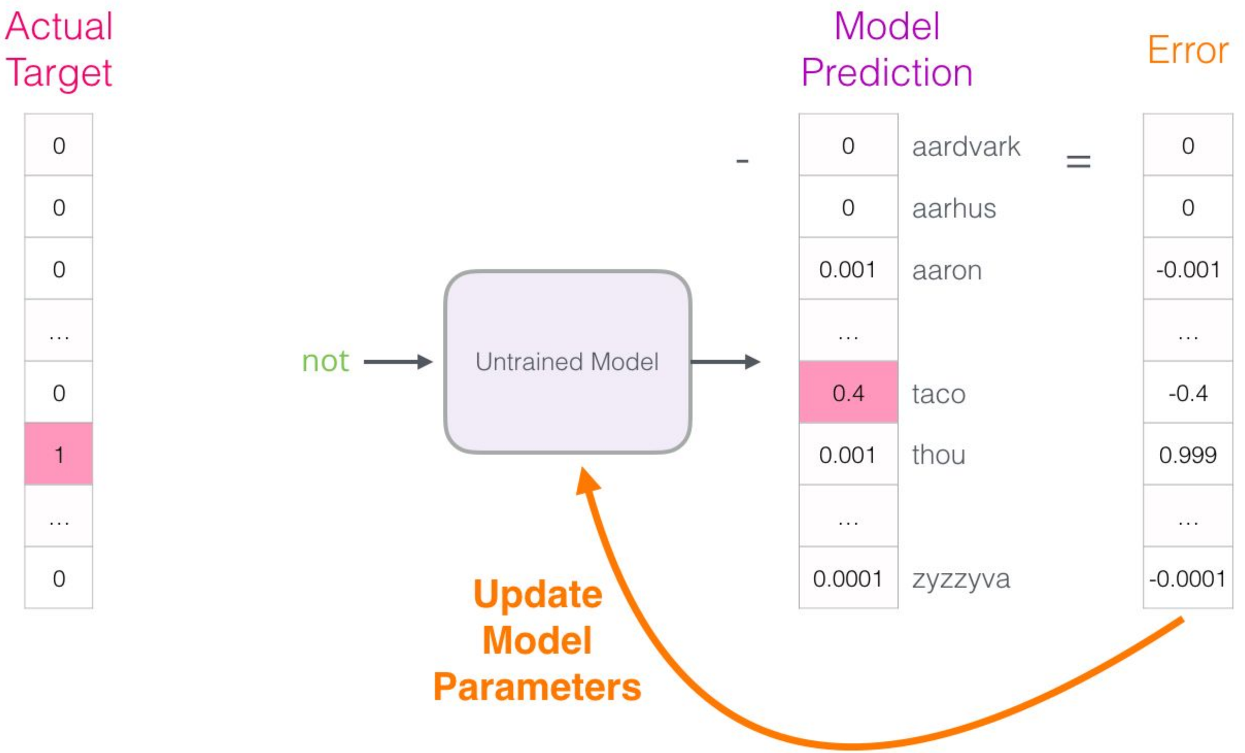
thou	shalt	not	make	a	machine	in	the	…

input word	target word
not	thou
not	shalt
not	make
not	a
make	shalt
make	not
make	a
make	machine
a	not
a	make
a	machine
a	in
machine	make
machine	a
machine	in
machine	the
in	a
in	machine
in	the
in	likeness

Training an embedding model



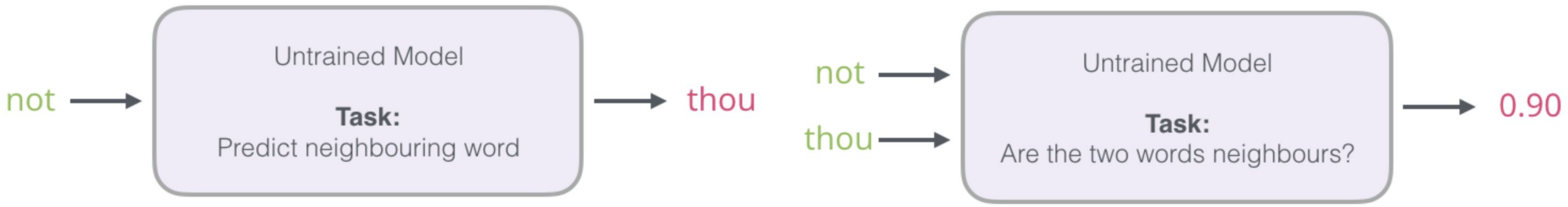
Training an embedding model



Problem with this model

- Step 3 is very expensive as we have to project the output into the entire vocabulary space
  - Especially, we have to do it for every single step

Let’s switch the task: Mikolov’s entry



This converts a complex neural learning task into a simple log-linear binary classification task

Converting the data for this task

input word	target word
not	thou
not	shalt
not	make
not	a
make	shalt
make	not
make	a
make	machine

input word	output word	target
not	thou	1
not	shalt	1
not	make	1
not	a	1
make	shalt	1
make	not	1
make	a	1
make	machine	1

Converting the data for this task

input word	target word
not	thou
not	shalt
not	make
not	a
make	shalt
make	not
make	a
make	machine

All one's is no good for learning

input word	output word	target
not	thou	1
not	shalt	1
not	make	1
not	a	1
make	shalt	1
make	not	1
make	a	1
make	machine	1

Negative sampling

Skipgram

shalt	not	make	a	machine

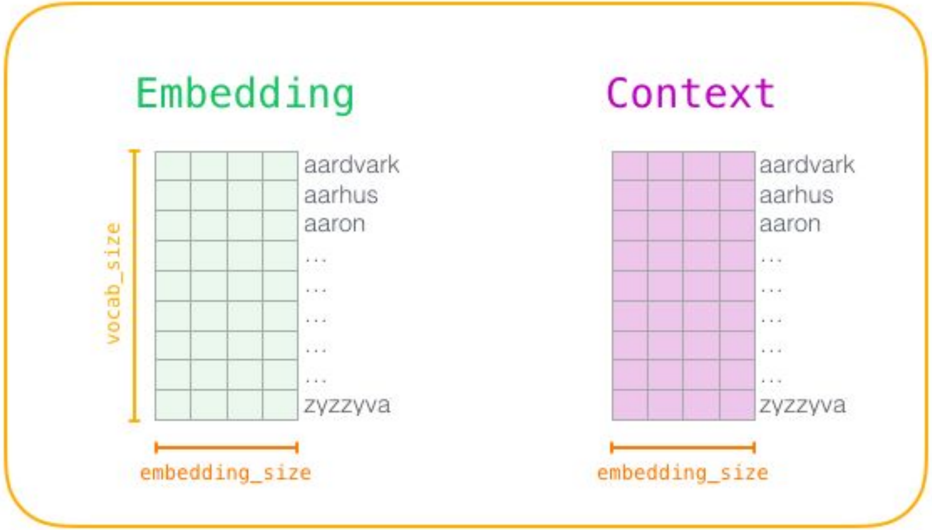
input	output
make	shalt
make	not
make	a
make	machine

Negative Sampling

input word	output word	target
make	shalt	1
make	aaron	0
make	taco	0

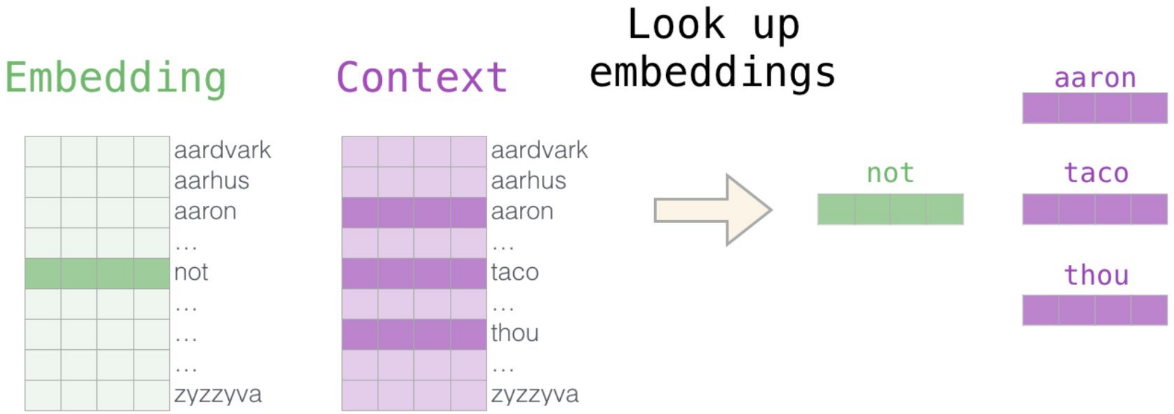
Word2vec Training

- we determine the size of our vocabulary
- create two matrices – an Embedding matrix and a Context matrix
- Initialize these matrices with random values



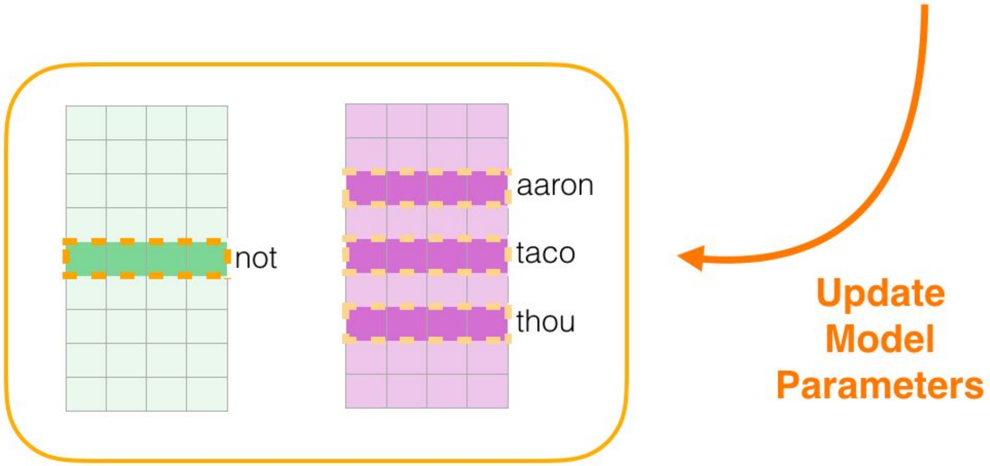
Word2vec Training

input word	output word	target
not	thou	1
not	aaron	0
not	taco	0
not	shalt	1
not	mango	0
not	finglonger	0
not	make	1
not	plumbus	0
...	...	...



Word2vec Training

input word	output word	target	input • output	sigmoid()	Error
not	thou	1	0.2	0.55	0.45
not	aaron	0	-1.11	0.25	-0.25
not	taco	0	0.74	0.68	-0.68



Using embeddings

It’s rarely necessary to train skip-gram or GloVe directly.

Download pre-trained word embeddings:

- Skip-gram https://code.google.com/archive/p/word2vec/
- GloVe https://nlp.stanford.edu/projects/glove/

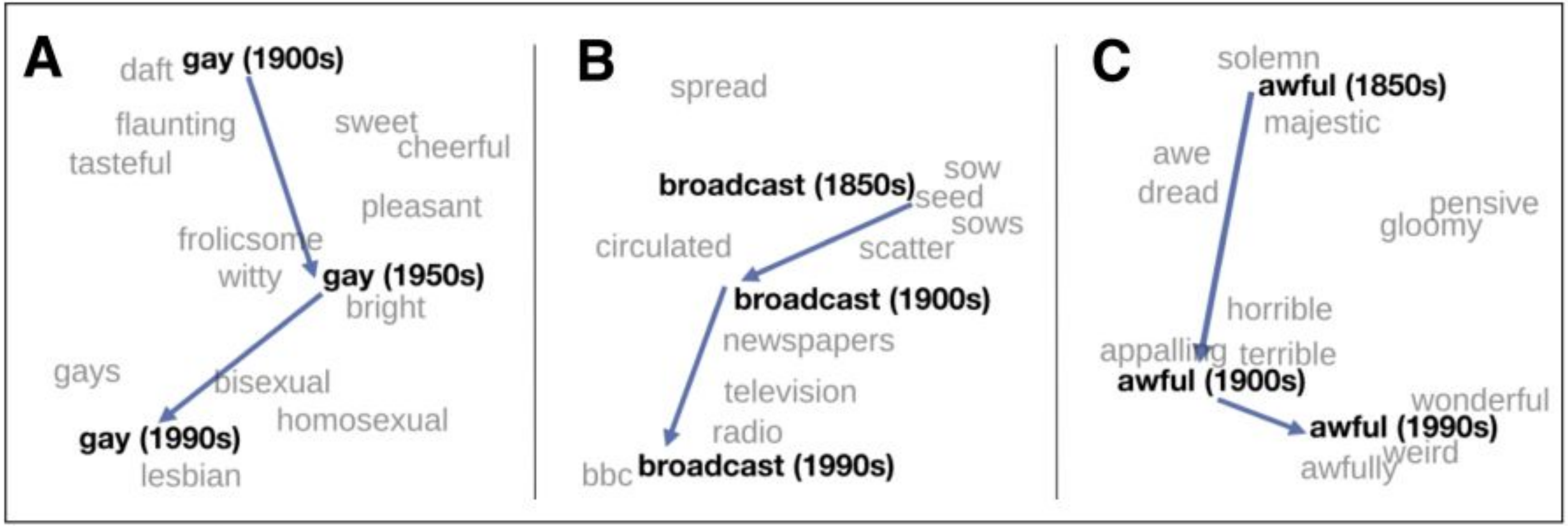
Many models provide pre-trained embeddings:
https://github.com/Hironsan/awesome-embedding-models

Which one should I choose? Try a few and see what works!

Semantic properties of embeddings

- Different types of similarity or association
    - Based on the context window, word association changes
    - smaller window sizes (2-15) lead to embeddings where high similarity scores between two embeddings indicates that the words are interchangeable
    - Larger window sizes (15-50, or even more) lead to embeddings where similarity is more indicative of relatedness of the words
- Analogy/relational similarity
    - Parallelogram model: Apple is to Tree as Grape is to _____
- Historical context

Historical semantic context



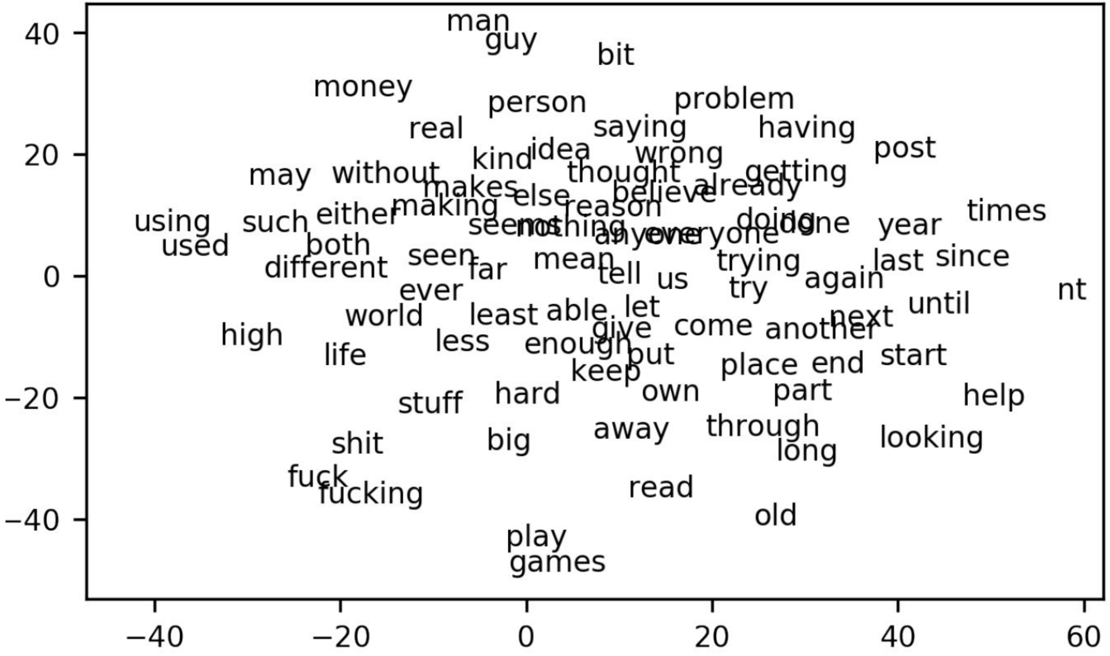
Inspecting embeddings

How do I know if my word embeddings make sense?

- Check by hands
- Project the words to a visible dimension
- Use linear algebra

Visualizing embeddings

We usually have very high-dimensional vectors for each words. t-SNE can project down to 2.



Algebra

```
>>> cosine(vector("queen"), vector("king"))
0.7252606
>>> cosine(vector("queen"),
...  vector("king")-vector("man")+vector("woman"))
0.7880841
>>> cosine(vector("Paris"), vector("Rome"))
0.58241177
>>> cosine(vector("Paris"),
...  vector("Rome")-vector("Italy")+vector("France"))
0.71733016
```

Other standard evaluations

Correlation with human judgments of similarity

- **WordSim-353** noun similarity, e.g., (plane, car, 5.77)
- **SimLex-999** adjective, noun, and verb similarities
- **SCWS** word similarity given sentential context
- **STS** sentence-level similarity

Accuracy at similarity-based task

- **TOEFL** e.g., Levied is closest in meaning to: imposed, believed, requested, correlated
- **analogies** e.g., Athens is to Greece as Oslo is to ____

Bias in embeddings

Embeddings reflect the language they were trained on

```
>>> cosine(vector("attractive"), vector("man"))
0.3085765
>>> cosine(vector("attractive"), vector("woman"))
0.41110972
>>> cosine(vector("dumb"), vector("American"))
0.41180187
>>> cosine(vector("dumb"), vector("European"))
0.26587355
```

Contextual word embeddings

Traditional word vectors ignore context

The river bank: [0.3, -0.1, -0.2] [0.1, -0.3, -0.2] [-0.6, 0.3, -0.1]

A bank deposit: [0.0 , 0.0 , -0.2] [-0.6, 0.3, -0.1] [-0.3, -0.3, 0.0]

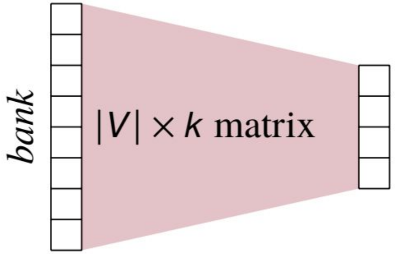
Should these two banks really have the same vectors?

Contextual word embeddings

Word embeddings

Input 1 word

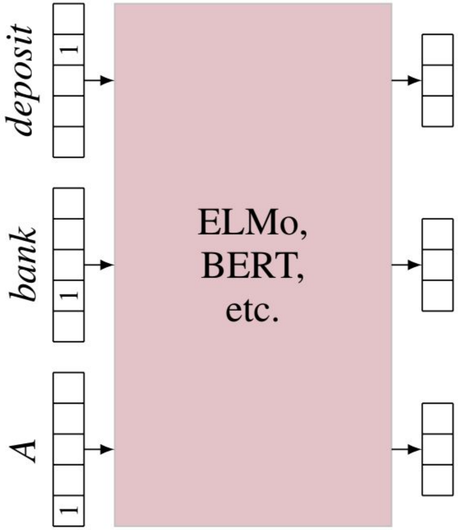
Output 1 embedding



Contextual word embeddings

Input n words

Output n embeddings



Learning contextual word embeddings

We need to make up a prediction task that

- takes n words as input
- produces n vectors as output
- requires only unlabeled data

ELMo’s task: language modeling

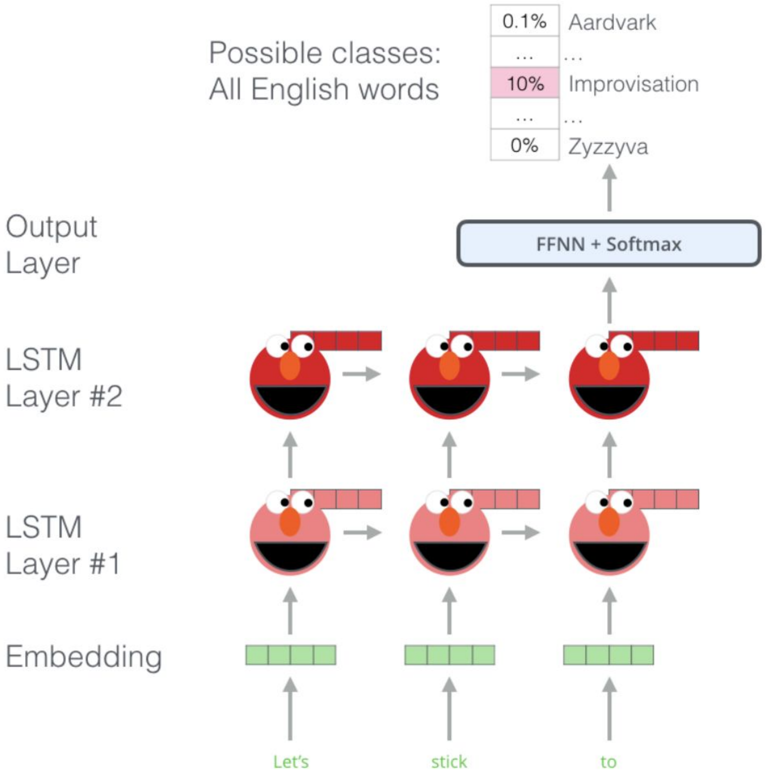
What is a language model?

- Given a sequence of words, what is the next most probable word?
- Unsupervised, great for learning representations

ELMo combines a forward language model and a backward language model.

Transformers use the same idea, but in a much larger canvas.

ELMo’s task: language modeling



How to use contextual word embeddings?

Contextual word embeddings are trained on unlabeled data. How do we use them on the task we care about?

- Extract word vectors, use as features
- Fine-tune contextual embedding model, i.e., continue training the model, but now on our labeled data instead of the unlabeled data