CSE440: NATURAL LANGUAGE PROCESSING II

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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’s 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!

Luckily or not !!

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

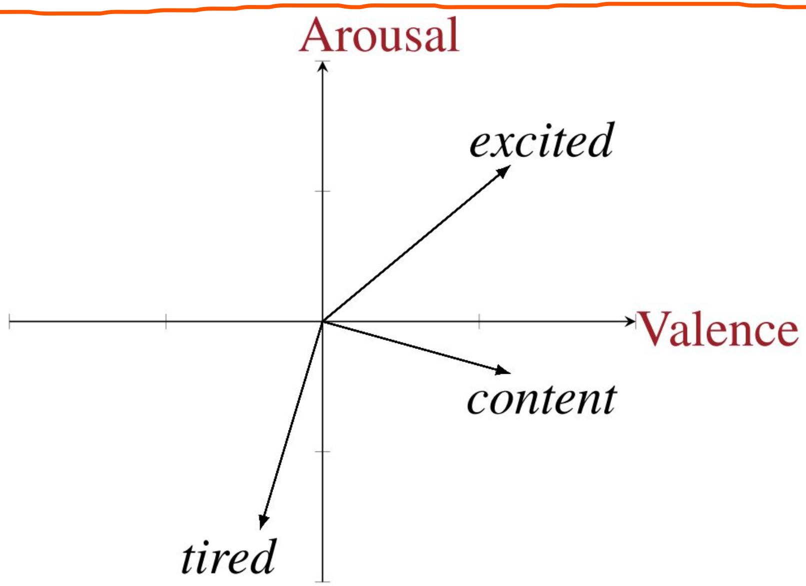
- No feature overlap whatsoever. If we try to calculate similarity, they are 100% dissimilar. But are they?
- Solution: instead of creating sentence level representations, let's go to smaller units i.e. words

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

Words as vectors

Words can be represented as vectors, where each entry in the vector represents a dimension of word meaning.



How to get numbers for each dimension of each word?

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

Word vectors from neighboring words

Example sentences:

the spinach artichoke dip

the leafy greens like spinach, kale, or collard greens

the bacon and spinach quiche

the collard greens and bacon

the cornbread and collard greens

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

Bad Cases —
(i) Very large
(ii) Sparse
(iii) not informative

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"]

Have to —

(i) reduce dimensions

(ii) make more contextual

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?

Semantic Similarities: Cosine similarity, Dot Product

Clustering: Euclidian & Manhattan Distⁿ

Sparse Representation: Jaccard Similarity

Probabilistic Data: KL Divergence -

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?

→ direction matters, not value
→ Capture semantic relationships
→ Valid for any non-zero vectors

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

→ considering length distant similarity measure
→ In higher dimensions, distn betn points tend to similar due to the effect of curse of dimensionality
→ normalisation issue

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

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

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, ?, ?, ?, ?, ?]

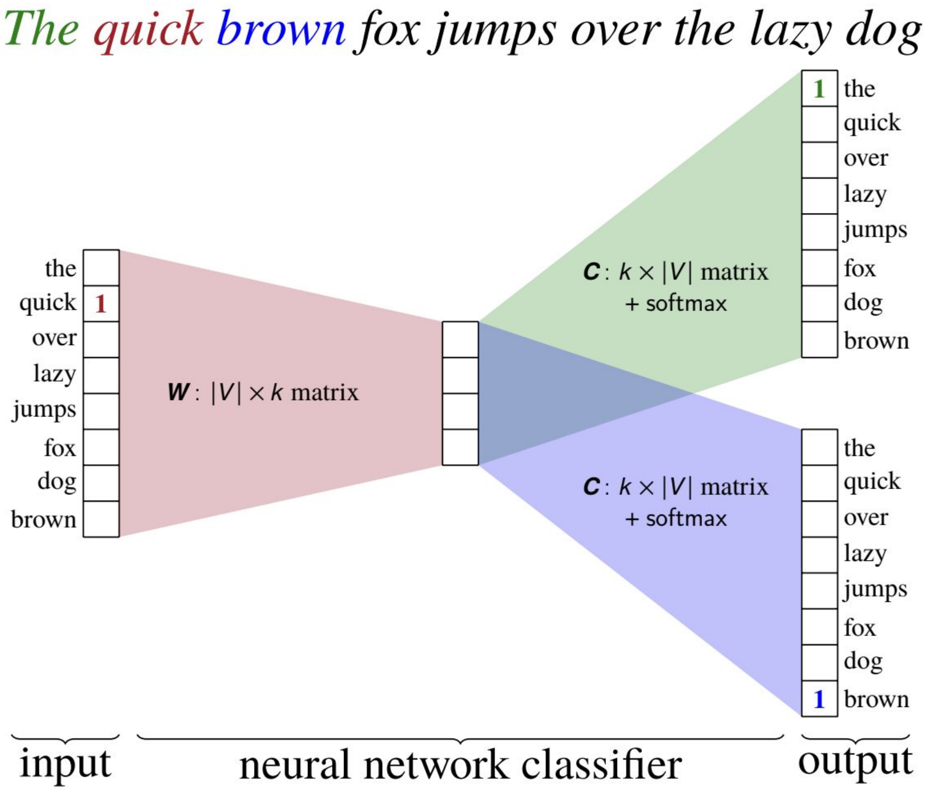
Skip-gram embeddings

- 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
  - We minimize cross-entropy loss, not classification error
  - We won't ever actually use the model for prediction
  - We'll only use word vectors learned as part of training

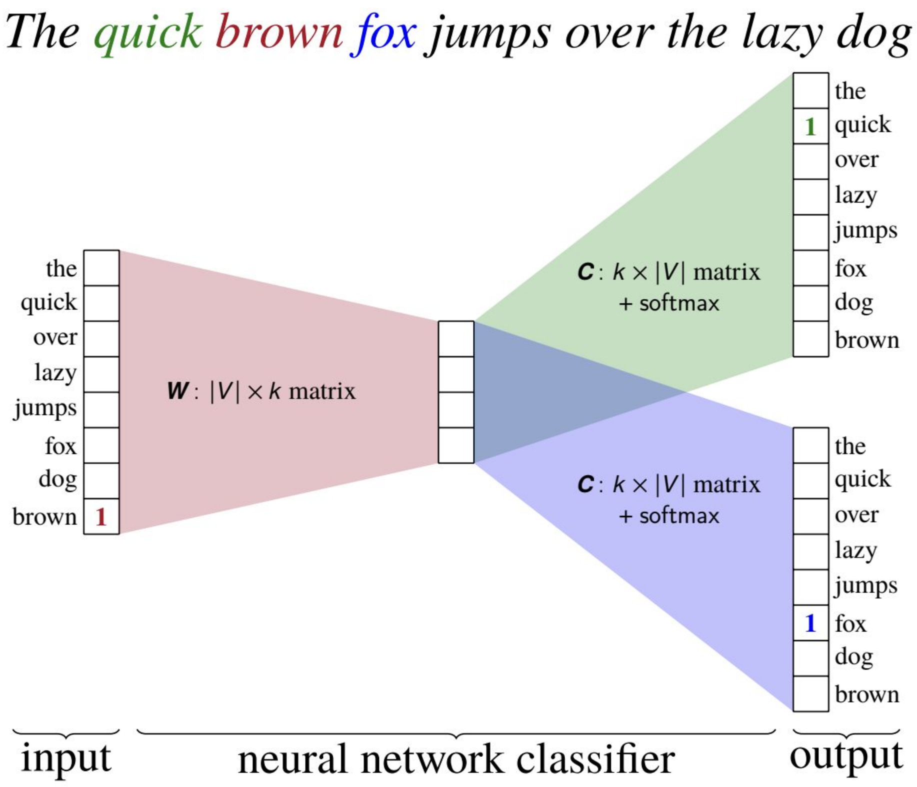
Skip-gram classifier

- We will use a feedforward neural network to predict the preceding and following words
- For simplicity's sake, we will only try to predict one preceding and one following word
- Steps:
    - Initialize all weights to random
    - Create one-hot vector for each of the words
    - Go from left to right
    - Predict the previous and the next word
    - Backpropagate the error and edit the weights
    - Continue

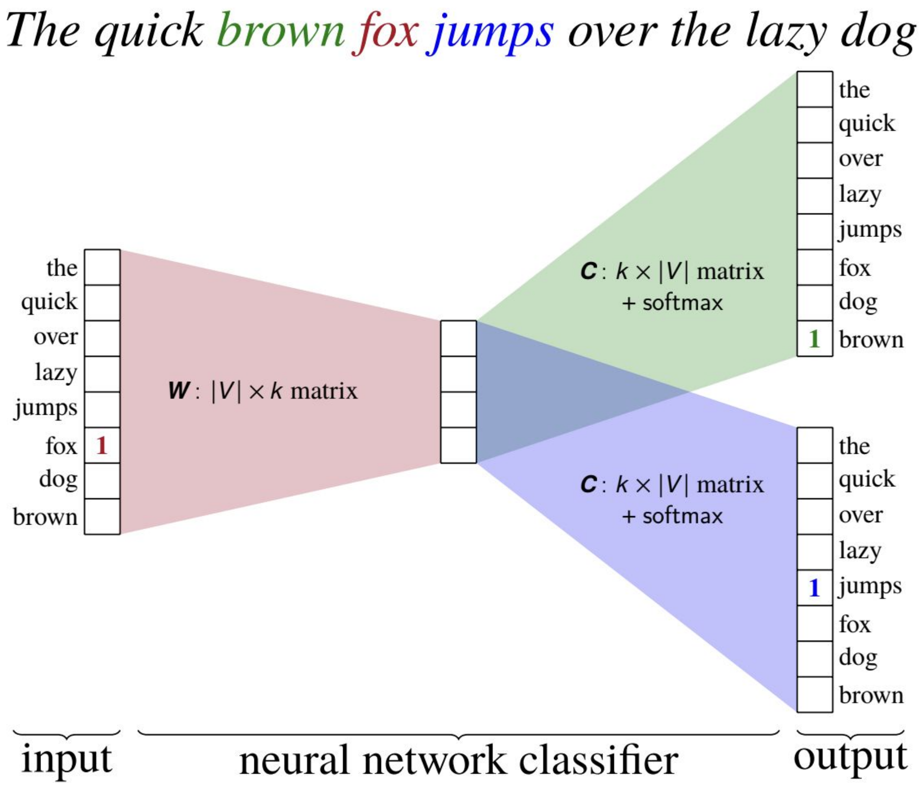
Skip-gram classifier



Skip-gram classifier



Skip-gram classifier



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/

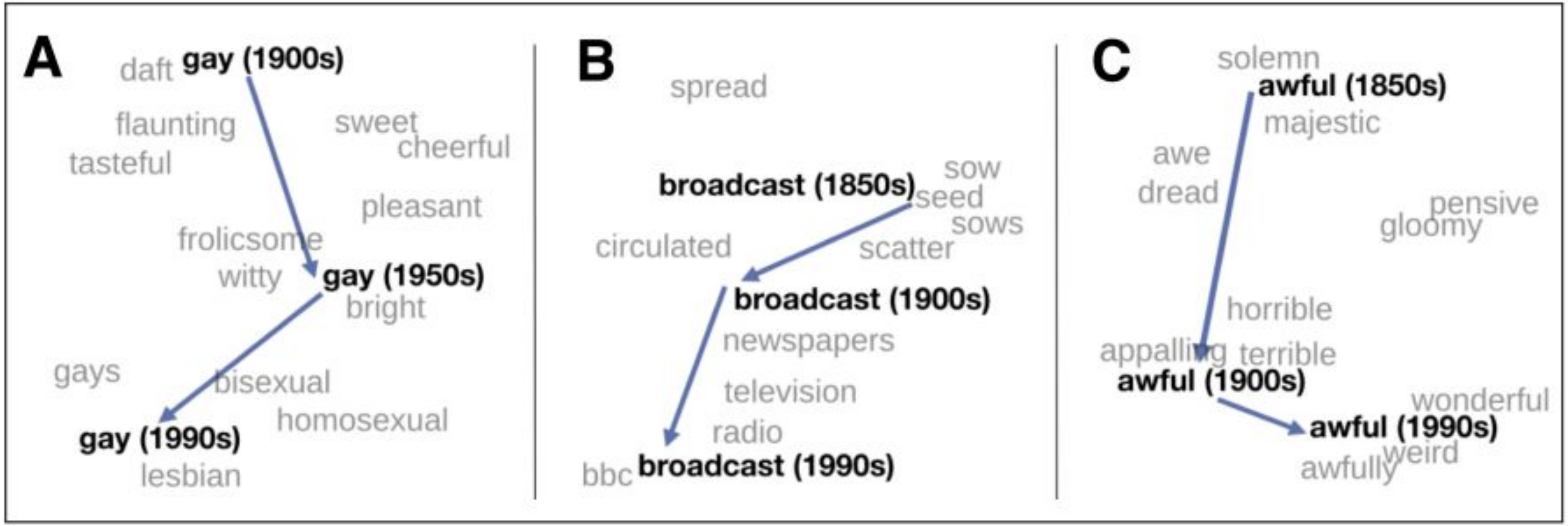
Many models provide pre-trained embeddings:
https://github.com/Hironsan/awesome-embedding-models

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
- Analogy/relational similarity
    - Parallelogram model: Apple is to Tree as Grape is to _____
- Historical context

Historical semantic context



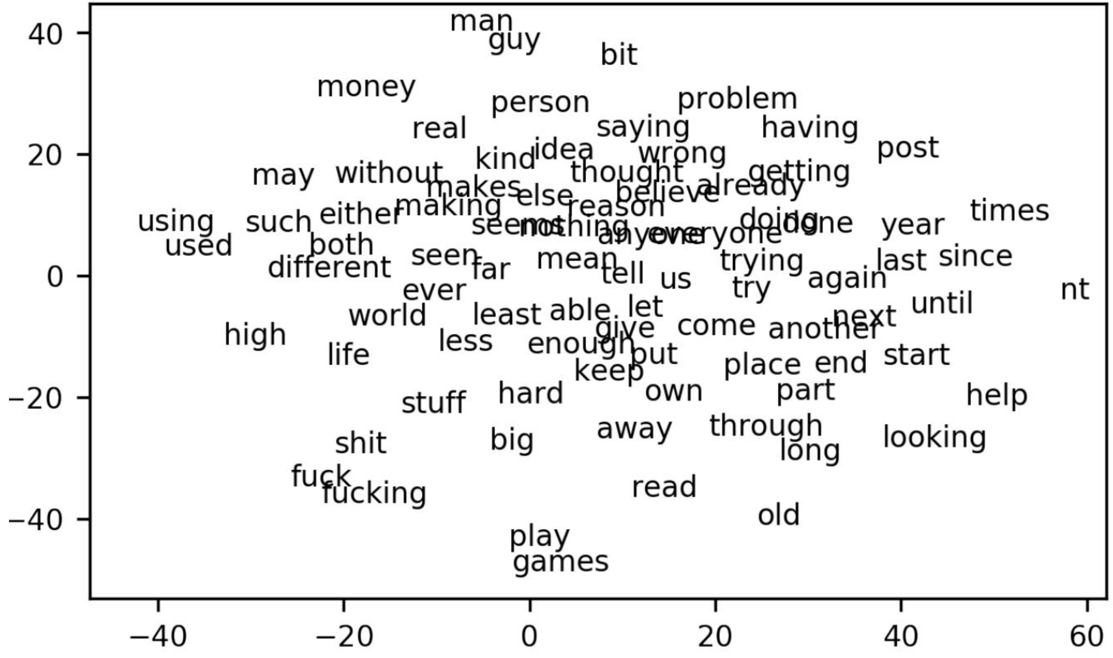
Inspecting embeddings

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]

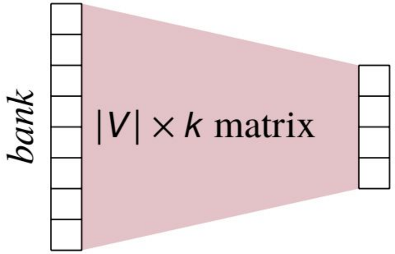
Should these two banks really have the same vectors?

Contextual word embeddings

Word embeddings

Input 1 word

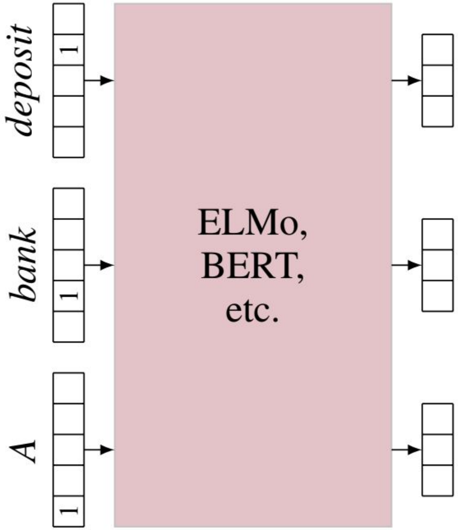
Output 1 embedding



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

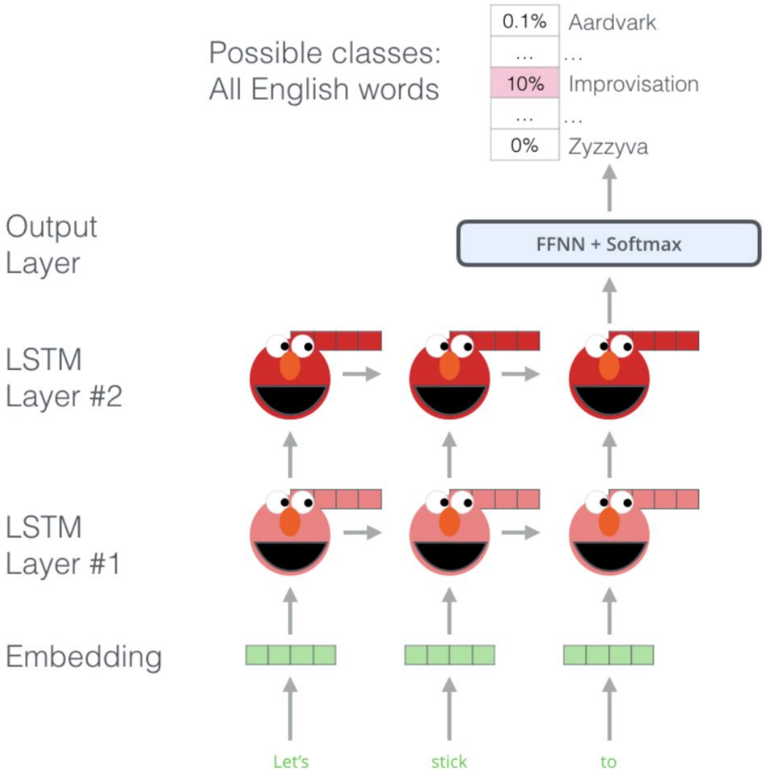
What is a language model?

- 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