

CSC321 Lecture 7: Distributed Representations

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Overview

- Today's lecture: learning distributed representations of words
- Let's take a break from the math and see a real example of a neural net.
 - We'll see a lot more neural net architectures later in the course.
- This lecture also introduces the model used in Programming Assignment 1.

Language Modeling

Motivation: suppose we want to build a speech recognition system.

We'd like to be able to infer a likely sentence \mathbf{s} given the observed speech signal \mathbf{a} . The **generative** approach is to build two components:

- An **observation model**, represented as $p(\mathbf{a} | \mathbf{s})$, which tells us how likely the sentence \mathbf{s} is to lead to the acoustic signal \mathbf{a} .
- A **prior**, represented as $p(\mathbf{s})$, which tells us how likely a given sentence \mathbf{s} is. E.g., it should know that “recognize speech” is more likely than “wreck a nice beach.”

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Given these components, we can use **Bayes' Rule** to infer a **posterior distribution** over sentences given the speech signal:

$$p(\mathbf{s} | \mathbf{a}) = \frac{p(\mathbf{s})p(\mathbf{a} | \mathbf{s})}{\sum_{\mathbf{s}'} p(\mathbf{s}')p(\mathbf{a} | \mathbf{s}')}.$$

Language Modeling

In this lecture, we focus on learning a good distribution $p(\mathbf{s})$ of sentences. This problem is known as **language modeling**.

Assume we have a corpus of sentences $\mathbf{s}^{(1)}, \dots, \mathbf{s}^{(N)}$. The **maximum likelihood** criterion says we want our model to maximize the probability our model assigns to the observed sentences. We assume the sentences are independent, so that their probabilities multiply.

$$\max \prod_{i=1}^N p(\mathbf{s}^{(i)}).$$

Language Modeling

In maximum likelihood training, we want to maximize $\prod_{i=1}^N p(\mathbf{s}^{(i)})$.

The probability of generating the whole training corpus is vanishingly small — like monkeys typing all of Shakespeare.

- The **log probability** is something we can work with more easily. It also conveniently decomposes as a sum:

$$\log \prod_{i=1}^N p(\mathbf{s}^{(i)}) = \sum_{i=1}^N \log p(\mathbf{s}^{(i)}).$$

- Let's use *negative* log probabilities, so that we're working with positive numbers.

Language Modeling

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Better trained monkeys are slightly more likely to type *Hamlet*!

Language Modeling

- Probability of a sentence? What does that even mean?

Language Modeling

- Probability of a sentence? What does that even mean?
 - A sentence is a sequence of words w_1, w_2, \dots, w_T . Using the **chain rule of conditional probability**, we can decompose the probability as

$$p(s) = p(w_1, \dots, w_T) = p(w_1)p(w_2 | w_1) \cdots p(w_T | w_1, \dots, w_{T-1}).$$

- Therefore, the language modeling problem is equivalent to being able to predict the next word!
- We typically make a **Markov assumption**, i.e. that the distribution over the next word only depends on the preceding few words. I.e., if we use a context of length 3,

$$p(w_t | w_1, \dots, w_{t-1}) = p(w_t | w_{t-3}, w_{t-2}, w_{t-1}).$$

- Such a model is called **memoryless**.
 - Now it's basically a supervised prediction problem. We need to predict the conditional distribution of each word given the previous K .
 - When we decompose it into separate prediction problems this way, it's called an **autoregressive model**.

N-Gram Language Models

- One sort of Markov model we can learn uses a **conditional probability table**, i.e.

| | cat | and | city | ... |
|------------|--------|--------|--------|-----|
| the fat | 0.21 | 0.003 | 0.01 | |
| four score | 0.0001 | 0.55 | 0.0001 | ... |
| New York | 0.002 | 0.0001 | 0.48 | |
| ⋮ | | ⋮ | | |

- Maybe the simplest way to estimate the probabilities is from the **empirical distribution**:

$$p(w_3 = \text{cat} \mid w_1 = \text{the}, w_2 = \text{fat}) = \frac{\text{count}(\text{the fat cat})}{\text{count}(\text{the fat})}$$

- This is the maximum likelihood solution; we'll see why later in the course.
- The phrases we're counting are called **n-grams** (where n is the length), so this is an **n-gram language model**.
 - Note: the above example is considered a 3-gram model, not a 2-gram model!

N-Gram Language Models

Shakespeare:

1
gram

–To him swallowed confess hear both. Which. Of save on trail for are ay device and rote life have

–Hill he late speaks; or! a more to leg less first you enter

2
gram

–Why dost stand forth thy canopy, forsooth; he is this palpable hit the King Henry. Live king. Follow.

–What means, sir. I confess she? then all sorts, he is trim, captain.

3
gram

–Fly, and will rid me these news of price. Therefore the sadness of parting, as they say, 'tis done.

–This shall forbid it should be branded, if renown made it empty.

4
gram

–King Henry. What! I will go seek the traitor Gloucester. Exeunt some of the watch. A great banquet serv'd in;

–It cannot be but so.

Jurafsky and Martin, *Speech and Language Processing*

N-Gram Language Models

Wall Street Journal:

| | |
|-----------|---|
| 1 gram | Months the my and issue of year foreign new exchange's september were recession exchange new endorsed a acquire to six executives |
| 2 gram | Last December through the way to preserve the Hudson corporation N. B. E. C. Taylor would seem to complete the major central planners one point five percent of U. S. E. has already old M. X. corporation of living on information such as more frequently fishing to keep her |
| 3 gram | They also point to ninety nine point six billion dollars from two hundred four oh six three percent of the rates of interest stores as Mexico and Brazil on market conditions |

Jurafsky and Martin, *Speech and Language Processing*

N-Gram Language Models

- Problems with n-gram language models

N-Gram Language Models

- Problems with n-gram language models
 - The number of entries in the conditional probability table is exponential in the context length.
 - **Data sparsity**: most n-grams never appear in the corpus, even if they are possible.

N-Gram Language Models

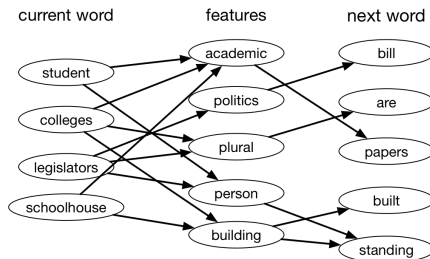
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- Ways to deal with data sparsity

N-Gram Language Models

- Problems with n-gram language models
 - The number of entries in the conditional probability table is exponential in the context length.
 - **Data sparsity**: most n-grams never appear in the corpus, even if they are possible.
- Ways to deal with data sparsity
 - Use a short context (but this means the model is less powerful)
 - Smooth the probabilities, e.g. by adding imaginary counts
 - Make predictions using an ensemble of n-gram models with different n

Distributed Representations

- Conditional probability tables are a kind of **localist representation**: all the information about a particular word is stored in one place, i.e. a column of the table.
- But different words are related, so we ought to be able to share information between them. For instance,



- Here, the information about a given word is distributed throughout the representation. We call this a **distributed representation**.
- In general, unlike in this cartoon, we won't be able to attach labels to the features in our distributed representation.

Distributed Representations

- We would like to be able to share information between related words.
E.g., suppose we've seen the sentence

The cat got squashed in the garden on Friday.

- This should help us predict the words in the sentence

The dog got flattened in the yard on Monday.

- An n-gram model can't generalize this way, but a distributed representation might let us do so.

Neural Language Model

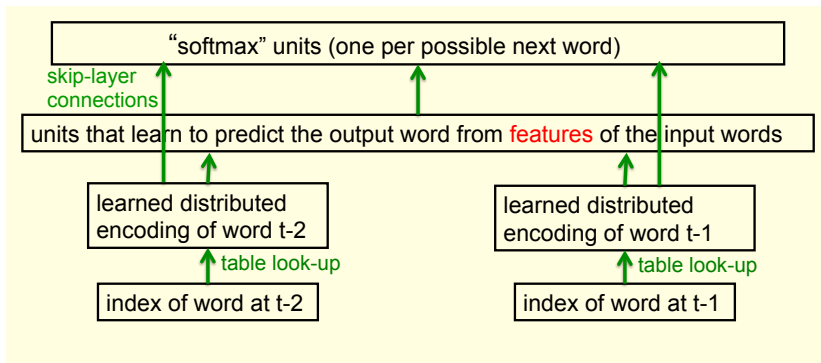
- Predicting the distribution of the next word given the previous K is just a multiway classification problem.
- **Inputs:** previous K words
- **Target:** next word
- **Loss:** cross-entropy. Recall that this is equivalent to maximum likelihood:

$$\begin{aligned} -\log p(\mathbf{s}) &= -\log \prod_{t=1}^T p(w_t \mid w_1, \dots, w_{t-1}) \\ &= -\sum_{t=1}^T \log p(w_t \mid w_1, \dots, w_{t-1}) \\ &= -\sum_{t=1}^T \sum_{v=1}^V t_{tv} \log y_{tv}, \end{aligned}$$

where t_{iv} is the one-of- K encoding for the i th word and y_{iv} is the predicted probability for the i th word being index v .

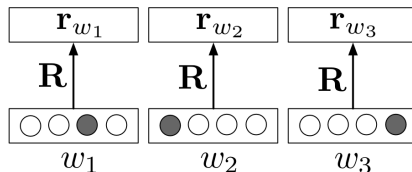
Neural Language Model

- Here is a classic **neural probabilistic language model**, or just **neural language model**:



Neural Language Model

- If we use a 1-of-K encoding for the words, the first layer can be thought of as a linear layer with **tied weights**.



- The weight matrix basically acts like a lookup table. Each column is the **representation** of a word, also called an **embedding**, **feature vector**, or **encoding**.
 - “Embedding” emphasizes that it’s a location in a high-dimensional space; words that are closer together are more semantically similar
 - “Feature vector” emphasizes that it’s a vector that can be used for making predictions, just like other feature mappings we’ve looked at (e.g. polynomials)

Neural Language Model

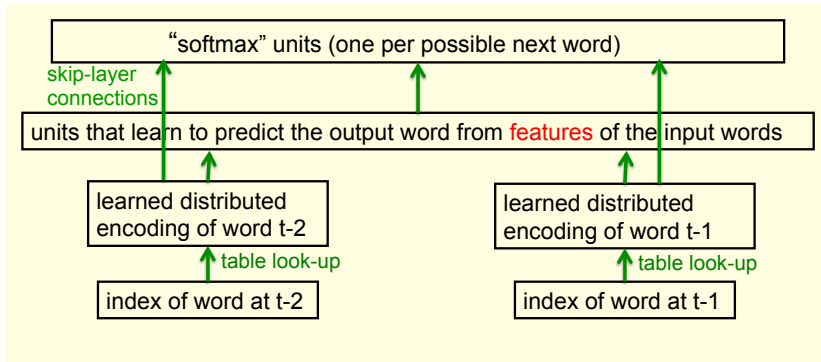
- We can measure the similarity or dissimilarity of two words using
 - the dot product $\mathbf{r}_1^\top \mathbf{r}_2$
 - Euclidean distance $\|\mathbf{r}_1 - \mathbf{r}_2\|$
- If the vectors have unit norm, the two are equivalent:

$$\begin{aligned}\|\mathbf{r}_1 - \mathbf{r}_2\|^2 &= (\mathbf{r}_1 - \mathbf{r}_2)^\top (\mathbf{r}_1 - \mathbf{r}_2) \\ &= \mathbf{r}_1^\top \mathbf{r}_1 - 2\mathbf{r}_1^\top \mathbf{r}_2 + \mathbf{r}_2^\top \mathbf{r}_2 \\ &= 2 - 2\mathbf{r}_1^\top \mathbf{r}_2\end{aligned}$$

- In this case, the dot product is called **cosine similarity**.

Neural Language Model

- This model is very compact: the number of parameters is *linear* in the context size, compared with exponential for n-gram models.



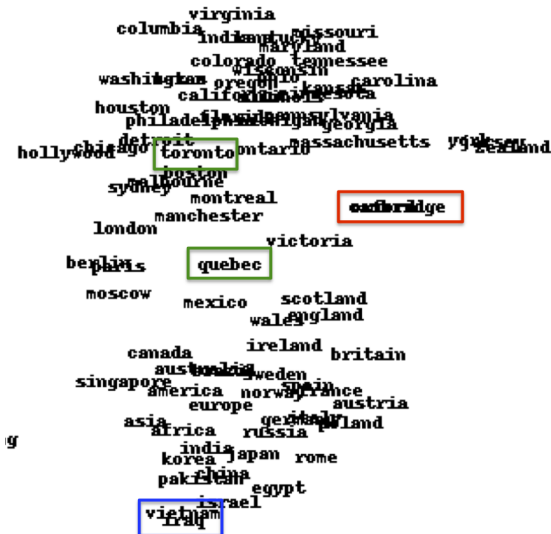
Neural Language Model

- What do these word embeddings look like?
- It's hard to visualize an n -dimensional space, but there are algorithms for mapping the embeddings to two dimensions.
- The following 2-D embeddings are done with an algorithm called tSNE which tries to make distances in the 2-D embedding match the original 30-D distances as closely as possible.
- Note: the visualizations are from a slightly different model.

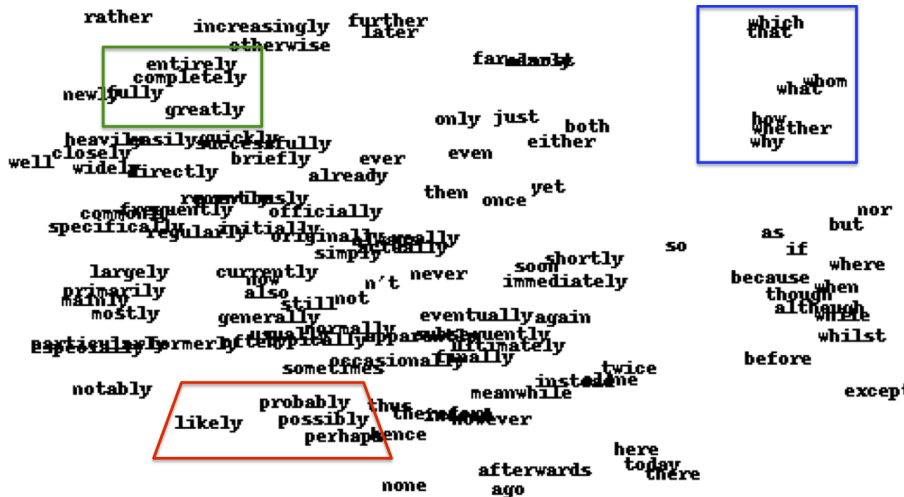
Neural Language Model



Neural Language Model



Neural Language Model



Neural Language Model

- Thinking about high-dimensional embeddings
 - Most vectors are nearly orthogonal (i.e. dot product is close to 0)
 - Most points are far away from each other
 - “In a 30-dimensional grocery store, anchovies can be next to fish and next to pizza toppings.” – Geoff Hinton
- The 2-D embeddings might be fairly misleading, since they can’t preserve the distance relationships from a higher-dimensional embedding. (I.e., unrelated words might be close together in 2-D, but far apart in 30-D.)

Neural language model

When we train a neural language model, is that supervised or unsupervised learning? Does it have elements of both?

Skip-Grams (Optional)

- Fitting language models is really hard:
 - It's really important to make good predictions about relative probabilities of rare words.
 - Computing the predictive distribution requires a large softmax.
- Maybe this is overkill if all you want is word representations.

Skip-Grams (Optional)

- **Skip-gram** model (Mikolov et al., 2013), also called **word2vec**
 - **Task:** given one word as input, predict (the distribution of) a word in its surrounding context.

_____ *fish* _____ ?

- Learn separate embeddings for the input and target word.
- **Model:** softmax where the log odds are computed as the dot product:

$$p(w_{t+\tau} = a \mid w_t = b) = \frac{\exp(\tilde{\mathbf{r}}_a^\top \mathbf{r}_b)}{\sum_c \exp(\tilde{\mathbf{r}}_c^\top \mathbf{r}_b)}$$

- **Loss:** cross-entropy, as usual
- Predictions are efficient because it's just a linear model, i.e. no hidden units.
- Problem: this still requires computing a softmax over the entire vocabulary!
 - The original paper used a model called “hierarchical softmax” to get around this, but there's an easier way.

Skip-Grams (Optional)

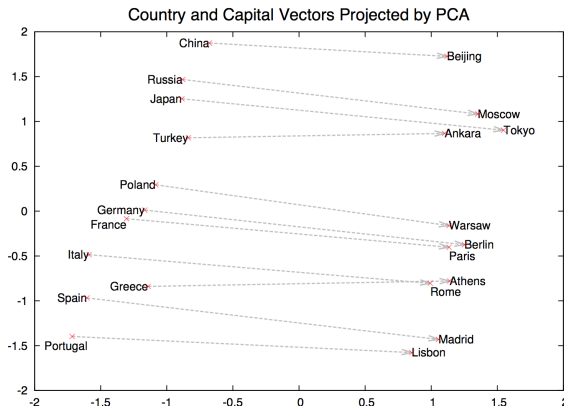
- Instead of predicting a distribution over words, switch to a binary prediction problem.
- **Negative sampling**: the model is given pairs of words, and needs to distinguish between:
 - real: the two words actually occur near each other in the training corpus
 - fake: the two words are sampled randomly from the training corpus
- Cross-entropy loss, with logistic activation function:

$$p(\text{real} \mid w_1 = a, w_2 = b) = \sigma(\tilde{\mathbf{r}}_a^\top \mathbf{r}_b) = \frac{1}{1 + \exp(-\tilde{\mathbf{r}}_a^\top \mathbf{r}_b)}$$

- This forces the dot product to be large for words which co-occur and small (or negative) for words which don't co-occur.
- Skip-grams with negative sampling can be trained very efficiently, so we can use tons of data.

Skip-Grams (Optional)

- Here's a linear projection of word representations for cities and capitals into 2 dimensions.
- The mapping city \rightarrow capital corresponds roughly to a single direction in the vector space:



Skip-Grams (Optional)

- In other words,
 $\text{vector}(\text{Paris}) - \text{vector}(\text{France}) \approx \text{vector}(\text{London}) - \text{vector}(\text{England})$
- This means we can analogies by doing arithmetic on word vectors:
 - e.g. “Paris is to France as London is to _____”
 - Find the word whose vector is closest to
 $\text{vector}(\text{France}) - \text{vector}(\text{Paris}) + \text{vector}(\text{London})$
- Example analogies:

| Relationship | Example 1 | Example 2 | Example 3 |
|----------------------|---------------------|-------------------|----------------------|
| France - Paris | Italy: Rome | Japan: Tokyo | Florida: Tallahassee |
| big - bigger | small: larger | cold: colder | quick: quicker |
| Miami - Florida | Baltimore: Maryland | Dallas: Texas | Kona: Hawaii |
| Einstein - scientist | Messi: midfielder | Mozart: violinist | Picasso: painter |
| Sarkozy - France | Berlusconi: Italy | Merkel: Germany | Koizumi: Japan |
| copper - Cu | zinc: Zn | gold: Au | uranium: plutonium |
| Berlusconi - Silvio | Sarkozy: Nicolas | Putin: Medvedev | Obama: Barack |
| Microsoft - Windows | Google: Android | IBM: Linux | Apple: iPhone |
| Microsoft - Ballmer | Google: Yahoo | IBM: McNealy | Apple: Jobs |
| Japan - sushi | Germany: bratwurst | France: tapas | USA: pizza |