Natural Language Understanding, Generation, and Machine Translation

Lecture 3: Conditional Language Models (with n-grams)

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Based on slides by Adam Lopez.

Overview

- Revision
  - Language models
  - n-gram Language models
- Conditional language models
  - Modeling translation with n-grams
  - Parameter estimation
  - Decoding

Required, optional, and revision readings are listed on Opencourse.

Agenda for Today

Last lecture: should have given you some intuitions about how to model the problem of machine translation.

This lecture: see how to turn those intuitions into a probabilistic model that can be learned from data and used to translate new sentences.

Revision

Predict the next word!

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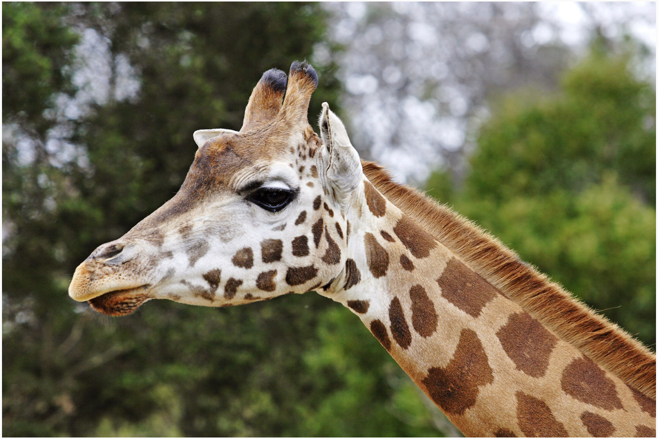
Summer is hot winter is ____

Predict the next word!

She is drinking a hot cup of ____

Predict the next word!

In the park I saw a ____



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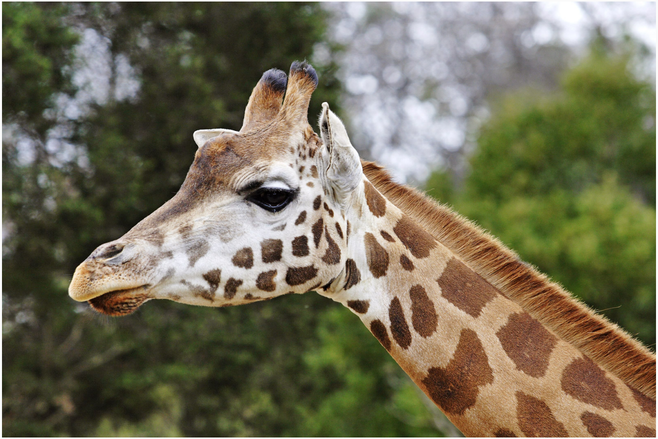

Image captioning

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Example: Train a probabilistic model from CNN Business Headlines.

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- More than 1 million people subscribe to this electric toothbrush startup
- Heart drug recall expanded again

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- Star Wars Episode IX Has New Lime Blazer
- Coca-Cola is Scanning Your Messages for Big Chinese Tech
- Amazon is Recalling 1 Trillion Jobs

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Conditional language models have many uses

There are many, many applications where we want to predict words *conditioned on some input*:

- speech recognition: condition on speech signal
- machine translation: condition on text in another language
- text completion: condition on the first few words of a sentence
- optical character recognition: condition on an image of text
- image captioning: condition on an image
- grammar checking: condition on surrounding words

DISCLAIMER: Notation is not universally consistent!

In each lecture: notation will be consistent. Variables named.

If you find something confusing or inconsistent, PLEASE ASK! Someone else also found it confusing or inconsistent.

Across lectures: notation will be similar, but not identical.

Expect notation to be **internally consistent** in an individual lecture, paper, or exam question, not globally consistent.

In general: there is no universally agreed upon notation for any of this stuff. Different fields and even subfields have different conventions, but even they tend to vary.

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tl;dr: Notation is a kind of language, and there are many different dialects. I might code switch between dialects without noticing.

Language modeling as probabilistic prediction

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Revision questions:

- What is the sample space?
- What might be some useful random variables?
- What constraints must P satisfy?

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Use the chain rule:

$$
\begin{aligned}
P(w_1 \ldots w_{|w|}) = & P(W_1 = w_1) \times \\
& P(W_2 = w_2 \mid W_1 = w_1) \times \\
& \ldots \\
& P(W_{|w|} = w_{|w|} \mid W_1 = w_1, \ldots, W_{k-1} = w_{|w|-1}) \\
& P(W_{|w|+1} = \langle \text{STOP} \rangle \mid W_1 = w_1, \ldots, W_k = w_{|w|})
\end{aligned}
$$

Note: $\langle \text{STOP} \rangle$ is a symbol not in V.

Written more concisely

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\begin{aligned}
P(w_1 \dots w_{|w|}) =& P(w_1)\times \\
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& \dots \\
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=& \prod_{i=1}^{|w|+1} P(w_i | w_1, \dots, w_{|w|-1})
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Defines a *joint distribution* over an *infinite* sample space in terms of *conditional distributions*, each over a *finite* sample space (but with potentially infinite history!)

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n-gram models make all terms finite with a Markov assumption

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Given $w_{i-n+1}, \ldots, w_{i-1}$, P is a probability distribution, hence:

Probabilities must be non-negative $\quad P : V \to \mathbb{R}_+$

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Any function satisfying these constraints is a probability distribution! How would you define one?

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Simple idea: since the number of $P(w_i \mid w_{i-n+1}, \ldots, w_{i-1})$ terms is finite, let each one be a parameter (i.e. a real number) in a table indexed by $w_{i-n+1}, \ldots, w_i$.

n-gram probabilities can be estimated by counting

Estimate conditional probabilities from n-gram counts in the training data $\mathcal{D}$:

$$P(w_2 \mid w_1) = \frac{\mathrm{Count}_{\mathcal{D}}(w_1 w_2)}{\mathrm{Count}_{\mathcal{D}}(w_1)} \quad P(w_3 \mid w_1, w_2) = \frac{\mathrm{Count}_{\mathcal{D}}(w_1 w_2 w_3)}{\mathrm{Count}_{\mathcal{D}}(w_1 w_2)}$$

Why does this work?

Counting n-grams maximizes likelihood

Suppose we have a bigram model. Let θ be the parameters of this model, indexed by bigrams, so that $P(w_2 \mid w_1) = \theta_{w_1 w_2}$.

The *likelihood* of the training data $\mathcal{D}$, as a function of the model parameters (bigram probabilities) is then:

$$P(\mathcal{D} \mid \theta) = \prod_{w_1 w_2 \in V^2} \theta_{w_1 w_2}^{\mathrm{Count}_{\mathcal{D}}(w_1 w_2)}$$

The *maximum likelihood* estimate chooses $\hat{\theta}$ such that

$$\hat{\theta} = \arg\max_{\theta} P(\mathcal{D} \mid \theta)$$

Counting n-grams maximizes likelihood

Suppose the word *white* appears ten times, followed seven times by *house* and three times by *whale*. Maximum likelihood sets $P(house \mid white) = \frac{7}{10}$.

Estimating *n*-gram probabilities accurately is hard

- The higher *n* gets, the better the model, if you have enough data.
- But most higher-order *n*-grams will never be observed—are these *sampling zeros* or *structural zeros*?
- Requires smoothing and/ or backoff to estimate probabilities of unseen *n*-grams.
- Good models need to be trained on billions of words.
- This entails lots of memory and clever data structures.

You can use an n-gram LM to predict the next word

If we have a sequence of words $w_1 \dots w_k$, then we can use the language model to predict the next word w_{k+1}:

$$\hat{w}_{k+1} = \operatorname*{argmax}_{w_{k+1}} P(w_{k+1} | w_1 \dots w_k)$$

This is useful for applications that process input in real time (word-by-word).

Conditional language models

How would you model translation with *n*-grams?

Så varför minskar inte vi våra utsläpp?

How would you model translation with n-grams?

Så varför minskar inte vi våra utsläpp?

So

How would you model translation with n-grams?

Så varför minskar inte vi våra utsläpp?

So why

How would you model translation with n-grams?

Så varför minskar inte vi våra utsläpp?

So why are

How would you model translation with n-grams?

Så varför minskar inte vi våra utsläpp?

So why are we

How would you model translation with n-grams?

Så varför minskar inte vi våra utsläpp?

So why are we not

How would you model translation with n-grams?

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Let x be the Swedish sentence, y be English.

$x = x_1 \dots x_{|x|}$

$y = y_1 \dots y_{|y|}$

How can we define $P(y \mid x)$?

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Note: probabilistic machine translation models originated with French-English translation, and in older papers you will often see f (for French) instead of x, and e (for English) instead of y. In ML, x and y typically denote input and output, respectively, and are more common in current literature.

How would you model translation with n-grams?

Så varför minskar inte vi våra utsläpp ? So why are we not reducing our emissions ?

What if we model translation as one long sequence?

$P(yx) = P(x_1 ... x_{|x|} y_1 ... y_{|y|})$

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Problem: the English sentence will usually be longer than n!

How would you model translation with n-grams?

Så So varför why minskar are inte we vi not våra reducing utsläpp our ? emissions ?

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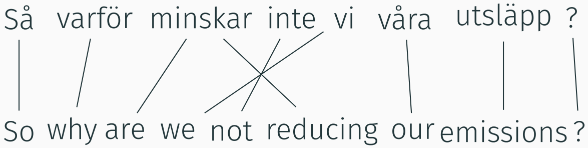
Problem 1: The sentences are not usually the same length!

Problem 2: English and Swedish word orders are different!

Could we use word alignments to model translation?



Key idea: we want to model bigram *translation probabilities*, like $P(\textit{So} \mid \textit{Så})$, $P(\textit{why} \mid \textit{varför})$, $P(\textit{are} \mid \textit{våra})$, and so on...

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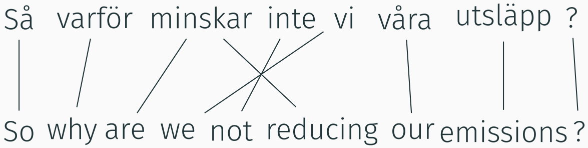

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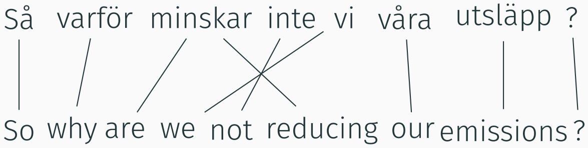

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But this changes our model! If x is Swedish and y is English, we must now also model z, the alignment.

We get $P(y \mid x) = \sum_z P(y, z \mid x)$ from the laws of probability.

Modeling English conditioned on Swedish with bigrams

Decompose $P(y, z \mid x)$ using the chain rule:

$$
\begin{aligned}
P(y, z \mid x) =& P(y \mid x, z) P(z \mid x) \\
=& P(|y|, |z| \mid x) \\
& \prod_{i=1}^{|y|} P(y_i \mid y_1, \ldots, y_{i-1}, x, z) \prod_{i=1}^{|z|} P(z_i \mid z_1, \ldots, z_{i-1}, x)
\end{aligned}
$$

Note: the chain rule is *always true* under the laws of probability. But as the modeler, you get to choose the order of the variables (since any order is valid).

The first term chooses the length of y and z. We need to make some independence assumptions to simplify the other two terms into something we can work with.

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_ _ _ _ _ _ _ _ _

Step 1. Draw length of English, conditioned on Swedish.

Full model: $P(|y| \mid x)$

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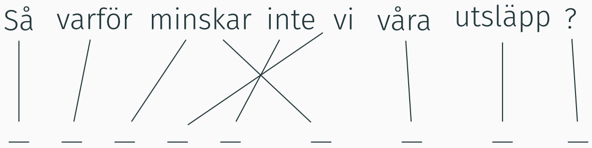

Step 1. Draw length of English, conditioned on Swedish.

Step 2. For each English position, draw a Swedish word uniformly at random. Let $|z| = |y|$ and let z_i be position of aligned Swedish word for y_i.

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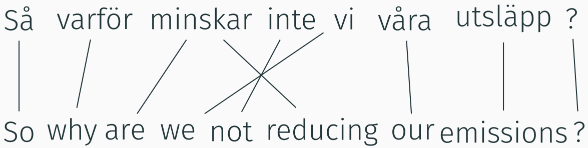

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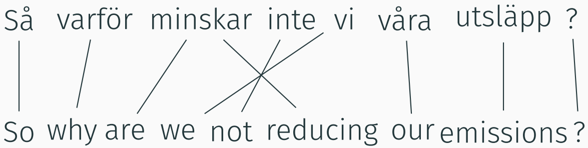

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Is this model familiar?

Modeling English conditioned on Swedish with bigrams

Input states: {Så, varför, minskar, inte, vi, våra, utsläpp, ?}

Input: So why are we not reducing our emissions

Alternative view: each training example contains a set of states (Swedish words), and a sequence of English words that we tag with those states.

Modeling English conditioned on Swedish with bigrams

Input states: {Så, varför, minskar, inte, vi, våra, utsläpp, ?}

Tags:	Så	varför	minskar	vi	inte	minskar	våra	utsläpp
Input:	So	why	are	we	not	reducing	our	emissions

Alternative view: each training example contains a set of states (Swedish words), and a sequence of English words that we tag with those states.

This is just a (zero-order) *hidden Markov model*. You can also use higher order Markov models!

$$P(|y| \mid x) \prod_{i=1}^{|y|} \underbrace{P(z_i \mid |x|)}_{\text{transition probability}} \underbrace{P(y_i \mid x_{z_i})}_{\text{emission probability}}$$

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Maximum likelihood says:

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In words: use *expected counts* for unobserved events.

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Problem: to compute expected counts, we need to know θ!

Expectation maximization requires iteration

Expectation maximization iteratively improves an estimate of θ:

1. Make an initial guess (random or uniform), called $\hat{\theta}_0$.
2. At iteration i, let $\hat{\theta}_i = \arg\max_\theta P(\mathcal{D} \mid \theta_{i-1})$.

Likelihood is provably non-decreasing for each new estimate of θ.

Decoding with (conditional) language models

Question. What is the most probable string, according to a language model $P(w)$, or a conditional language model $P(y \mid x)$?

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The language model and translation model can be trained separately!

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Greedy/ beam search don't find optimal y according to $P(y \mid x)$!

n-gram models exemplify many key concepts in ML for NLP

Why care about *n*-grams? Aren't they obsolete?

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1. Many of these ideas turn up again in neural models.
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    - Neural models still use *beam search*.
    - Latent variables are common in *unsupervised learning*.
    - Alignment directly inspired neural *attention*.
    - Neural models exploit same signals, though more powerful.

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4. Understanding the tradeoffs of working with *Markov assumptions* will help you appreciate the fact that neural models usually make them go away!

Summary

- Language models assign probabilities to discrete sequences.
- Useful for natural language generation in many applications.
- *n*-gram models use a *Markov assumption* to model an infinite sample space with a finite set of parameters.
- Machine translation is just *conditional language modeling*.
- To effectively model translation with *n*-grams, we need additional *latent variables* to model *word alignment*.
- One way to estimate the parameters of latent variable models is with a generalization of maximum likelihood estimation, called *expectation maximization*.

Next Week

- Feedforward NN
- Recurrent NN
- How to format the input and output data
- Assignment will be out next week.