Language Modeling with N-grams

Chapter 3 (3.1-3.4)

Review

- Text Normalization
 - Why?
 - How computationally?
 - Example tasks?

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Rule-based vs. Probabilistic

- "But it must be recognized that the notion of "probability of a sentence" is an entirely useless one, under any known interpretation of this term." Noam Chomsky (1969)
- "Anytime a linguist leaves the group the recognition rate goes up." Fred Jelinek (1988, alleged)

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Intuition

- Predict the next word...
 - ... I noticed three guys standing on the ???
- There are many sources of knowledge that can be used to inform this task, including arbitrary world knowledge.
- But it turns out that you can do pretty well by simply looking at the preceding words and keeping track of some fairly simple counts.

Word Prediction

- We can formalize this task using what are called N-gram models.
- N-grams are token sequences of length N.
- This example contains what 2-grams (aka bigrams)?
 - I notice three guys standing on the
- Given knowledge of counts of N-grams such as these, we can guess likely next words in a sequence.

N-Gram Models

- More formally, we can use knowledge of the counts of N-grams to assess the conditional probability of candidate words as the next word in a sequence.
- Or, we can use them to assess the probability of an entire sequence of words.
 - Pretty much the same thing as we'll see...

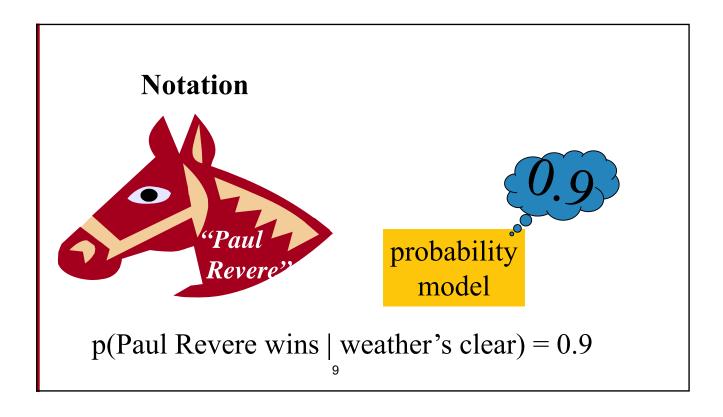
Probability

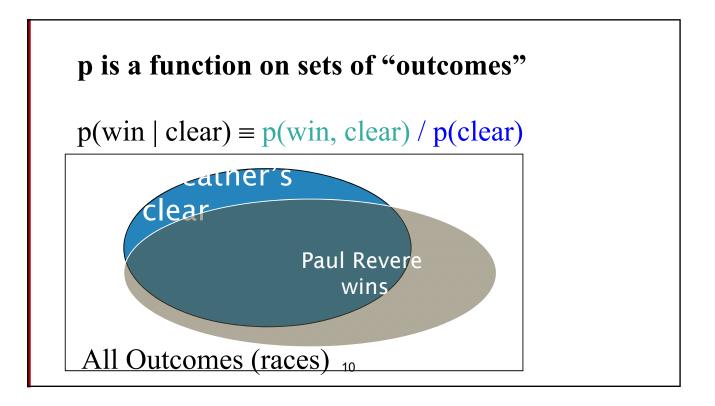
Quick Review

Different Kinds of Statistics

- descriptive: mean Pitt QPA (or median)
- confirmatory: statistically significant?
- predictive: wanna bet?
 - N-grams

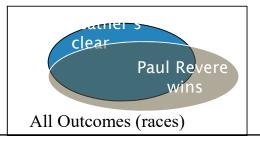
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p is a function on sets of "outcomes"

$$p(win | clear) = p(win, clear) / p(clear)$$
syntactic sugar
logical conjunction predicate selecting
of predicates races where
weather's clear



p measures total probability of a set of outcomes

Required Properties of p (axioms)

- $p(\emptyset) = 0$ p(all outcomes) = 1
- $p(X) \le p(Y)$ for any $X \subseteq Y$
- $p(X) + p(Y) = p(X \cup Y)$ provided $X \cap Y = \emptyset$ e.g., $p(win \& clear) + p(win \& \neg clear) = p(win)$

Commas denote conjunction

p(Paul Revere wins | weather's clear, ground is dry, jockey getting over sprain, Epitaph also in race, Epitaph was recently bought by Gonzalez, race is on May 17, ...)

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Simplifying Right Side: Backing Off

p(Paul Revere wins | weather's clear, ground is dry, jockey getting over sprain, Epitaph also in race, Epitaph was recently bought by Gonzalez, race is on May 17, ...)

- not exactly what we want but at least we can get a reasonable estimate of it!
- try to keep the conditions that we suspect will have the most influence on whether Paul Revere wins

Language Modeling

Introduction to N-grams

Probabilistic Language Models

- Goal: assign a probability to a sentence
 - Machine Translation:
 - P(high winds tonite) > P(large winds tonite)

Why?

- Spell Correction
 - The office is about fifteen **minuets** from my house
 - P(about fifteen minutes from) > P(about fifteen minuets from)
- Speech Recognition
 - P(I saw a van) >> P(eyes awe of an)
- + many more applications

Probabilistic Language Modeling

Compute the probability of a sentence or word sequence

$$P(W) = P(W_1, W_2, W_3, W_4, W_5...W_n)$$

· Related task: probability of an upcoming word

$$P(w_n | w_1, w_2...w_{n-1})$$

• A model that computes either is a language model

What kind of probabilities are these?

How to compute P(W)

- How to compute this joint probability:
 - P(its, water, is, so, transparent, that)
- Intuition: let's rely on the Chain Rule of Probability

Reminder: The Chain Rule

Recall the definition of conditional probabilities

$$p(B|A) = P(A,B)/P(A)$$
 Rewriting: $P(A,B) = P(A)P(B|A)$

- Independent p(B|A) = P(B)
- More variables:

$$P(A,B,C,D) = P(A)P(B|A)P(C|A,B)P(D|A,B,C)$$

The Chain Rule in General

$$P(x_1,x_2,x_3,...,x_n) = P(x_1)P(x_2|x_1)P(x_3|x_1,x_2)...P(x_n|x_1,...,x_{n-1})$$

The Chain Rule applied to compute joint probability of words in sentence

$$P(w_1 w_2 \square w_n) = \prod_i P(w_i \mid w_1 w_2 \square w_{i-1})$$

P("its water is so transparent") =

$$P(its) \times P(water|its) \times P(is|its water)$$

× P(so|its water is) × P(transparent|its water is so)

How to estimate these probabilities

Could we just count and divide?

 $P(\text{the } | \text{its water is so transparent that}) = \frac{Count(\text{its water is so transparent that the})}{Count(\text{its water is so transparent that})}$

- No! Too many possible sentences!
- We'll never see enough data for estimating these

Markov Assumption

Simplifying assumption:



 $P(\text{the }|\text{ its water is so transparent that}) \approx P(\text{the }|\text{ that})$

Or maybe

 $P(\text{the }|\text{ its water is so transparent that}) \approx P(\text{the }|\text{ transparent that})$

Markov Assumption

$$P(w_1 w_2 \square w_n) \approx \prod_i P(w_i \mid w_{i-k} \square w_{i-1})$$

 In other words, we approximate each component in the product

$$P(w_i | w_1 w_2 \square w_{i-1}) \approx P(w_i | w_{i-k} \square w_{i-1})$$

$$P(w_i | w_1 w_2 \square w_{i-1}) \approx P(w_i | w_{i-k} \square w_{i-1})$$

Bigram model (k=1, e.g., context of one so model two words)

Simplest case: Unigram model

$$P(w_1 w_2 \square w_n) \approx \prod_i P(w_i)$$

Some automatically generated sentences from a unigram model

fifth, an, of, futures, the, an, incorporated, a, a, the, inflation, most, dollars, quarter, in, is, mass

thrift, did, eighty, said, hard, 'm, july, bullish

that, or, limited, the

Bigram model

Condition on the previous word:

$$P(w_i | w_1 w_2 \square w_{i-1}) \approx P(w_i | w_{i-1})$$

texaco, rose, one, in, this, issue, is, pursuing, growth, in, a, boiler, house, said, mr., gurria, mexico, 's, motion, control, proposal, without, permission, from, five, hundred, fifty, five, yen

outside, new, car, parking, lot, of, the, agreement, reached

this, would, be, a, record, november

N-gram models

- We can extend to trigrams, 4-grams, 5-grams
- In general this is an insufficient model of language
 - because language has long-distance dependencies:

"The computer(s) which I had just put into the machine room on the fifth floor is (are) crashing."

But we can often get away with N-gram models