Overview of Statistical Language Models

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Workshop on Data Mining
and its Use and Usability for Linguistic Analysis

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Output

- Probability $[0, 1]$ – all possible outcomes sum to 1
- An unnormalized score, for ranking

Incremental Language Models

Incremental statistical language models provide the probability that a given word will occur next, based on the preceding words:

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- I cooked the fish in a ____

A Few Uses for LMs

Statistical language models ensure fluency in speech recognition (like Siri), machine translation (like Google Translate), on-screen keyboards (smartphones), etc.

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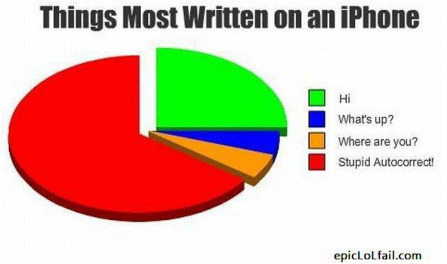
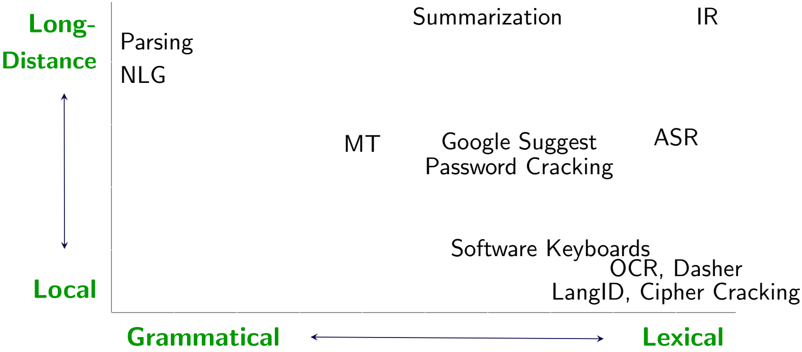
Sometimes they don't work so well...



Actually, There's a Lot of Uses!

- Google suggest
- Machine translation
- Assisting people with motor disabilities. For example, Dasher
- Speech Recognition (ASR)
- Optical character recognition (OCR) and handwriting recognition
- Information retrieval / search engines
- Data compression
- Language identification, as well as genre, dialect, and idiolect identification (authorship identification)
- Software keyboards
- Surface realization in natural language generation
- Password cracking
- Cipher cracking

Differences in LM Uses



LM Usage

Typical LM Queries in ...

- **ASR**: p(recognize speech) vs. p(wreck a nice beach) vs. p(wreck an ice peach), ...
- **Cipher cracking**: p(attack at dawn) vs. p(uebvmkdvkdbsqk)
- **Google Suggest**: p(how to cook french fries) vs. p(how to cook french dictionary)
- **IR**: query(cats and the cradle): doc1(i like cats) vs. doc2(i like dogs)
- **MT & NLG**: lex: p(use the force) vs. p(use the power); ordering: p(ready are you) vs. p(are you ready)
- **OCR**: p(today is your day) vs. p(+qdav ls y0ur d4ij)

A good cipher should obey the principle of diffusion (Shannon, 1949).

Language Modeling is Interesting!

NLP Task	Avg. Entropy
Language Modeling (=Word Prediction)	7.12
English-Chinese Translation	5.17
English-French Translation	3.92
QA (Open Domain)	3.87
Syntactic Parsing	1.18
QA (Multi-class Classification)	1.08
Text Classification (20 News)	0.70
Sentiment Analysis	0.58
Part-of-Speech Tagging	0.42
Named Entity Recognition	0.31

From Li & Hovy (2015)

n-gram Language Models

The simplest statistical language models, *n*-gram LMs, base their prediction on the previous word or two (*Markov assumption*)

$$P(w_i | w_1 \ldots w_{i-1}) \approx P(w_i | w_{i-n+1} \ldots w_{i-1})$$

History Sux!

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- [redacted] cats and ____
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- [redacted] a shopping ____
- [redacted] the ____
- [redacted] in the ____

n-gram LMs

- In spite of their many, many shortcomings, *n*-gram LMs are still widely used
  1. They train quickly
  2. They require no manual annotation
  3. They are incremental

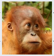
Uniform Distribution (Zero-gram)

Zero-gram Model

- In a zero-gram model, all words from the vocabulary (V) are equally likely:

$$
\begin{aligned}
p(w_i) &= \frac{1}{|V|} \\
&= |V|^{-1}
\end{aligned}
$$

- For example, if we were to open a dictionary and randomly point to a word, then "*orangutan*" would have the same probability as "*the*":

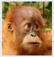
p() $= \mathrm{p}(\lambda P \in D_{\langle e,t \rangle} . \iota x [P(x) \wedge C(x)])$

Unigram Model

- In a unigram model, using maximum likelihood estimation, probabilities are based on word counts:

$$p(w_i) \quad = \quad \frac{\text{count}(w_i)}{\text{count}(w)}$$

- For example, if we were to open a novel and randomly point to a word, then "*orangutan*" would have much less probability than "*the*":

p() $\quad \ll \quad \mathrm{p}(\lambda P \in D_{\langle e,t \rangle}.\iota x[P(x) \wedge C(x)])$

Bigram Model

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  "*I gave a banana to a furry orange* ______"
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$$w_0 \to w_1 \to w_2 \to w_3 \to w_4 \to w_k$$

n-gram LMs

Trigram and other *n*-gram LMs use a longer *contiguous* history

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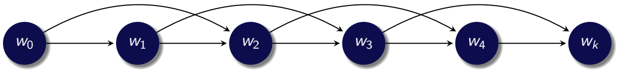

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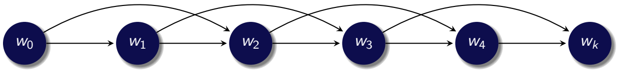

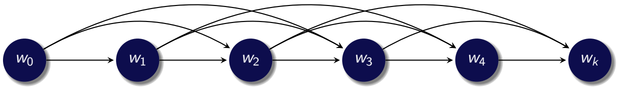

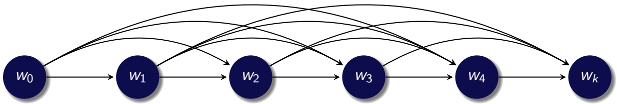

Using n-gram LMs

Using Multiple n-gram Models

Backoff – Use the highest-order n-gram model that has enough occurrences in the training set

Interpolation – Use all n-gram models, weighting them differently

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Smoothing *n*-grams

- *Smoothing* allows us to deal with unseen histories
- Usually steals some probability mass from seen events and gives some to unseen events
- See: `http://statmt.org/book/slides/07-language-models.pdf`

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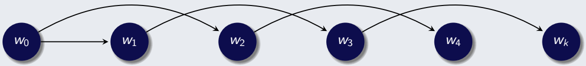

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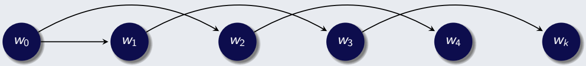


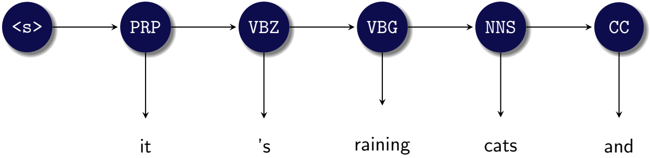
\+ They capture basic word order variation, and are still (more) useful with large corpora (Goodman, 2001, § 4)

± There's many possible combinations of histories to use

− They unnecessarily fragment the training data instead of generalizing it (Rosenfeld, 1994, pg. 16).

Class LMs

- Class-based LMs abstract beyond specific words, so that, eg. '*Thursday*' and '*Friday*' are grouped together to function similarly
- \+ They're useful for small- and medium-sized corpora (up to a billion tokens), and easy to use. Words can be automatically clustered.
- ± They have advantages and disadvantages for morphologically-rich & freer word order languages
- − They're poor at handling fixed phrases and multi-word expressions:



Topic LMs

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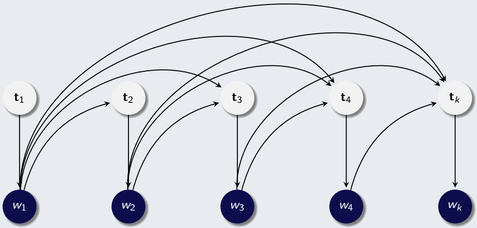

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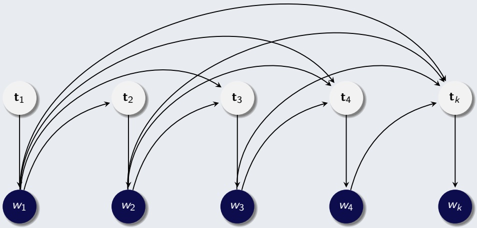
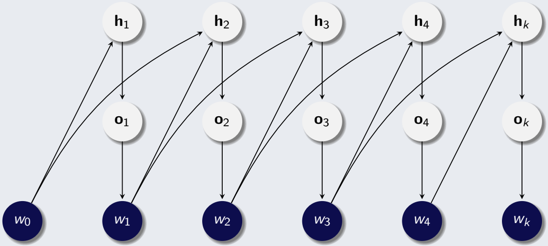


\+ Useful for domain adaptation. Widely used in information retrieval

− They're slow and don't scale up well. They don't capture local grammatical info, so they're combined with other LMs

Neural Net LMs

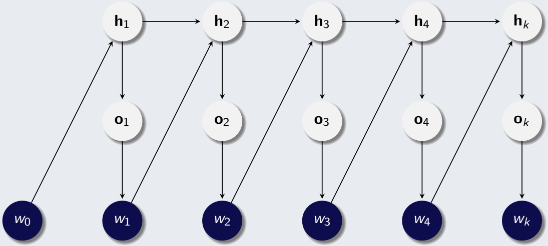
- Like topic-based LMs, neural net LMs reduce high-dimensional discrete probability distributions to low-dimensional continuous distributions
- Original idea inspired by biological neurons, but architecture has diverged from biology
- Has (multiple) hidden layers, to allow multiple levels of generalization



Recurrent Neural Net LMs

Elman Networks

- Like previous feedforward layout, but also has the previous hidden state feed into current hidden state
- In principle can capture longer dependencies



RNNLM's Continued

When training Elman networks the cycle gets unwrapped (called BPTT)

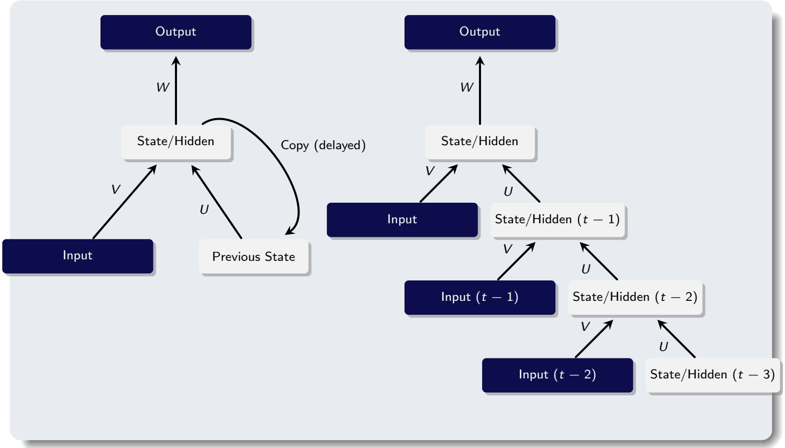


Image derived from Bodén (2002)

Comparison

Language Model	Incremental	Lexical	Distance	Speed
n-gram	Y	Y	Short	Fast
Class	Y	N	Medium	Fast
Cache	Y	Y	Long	Fast
Skip	Y	Y	Medium	Fast
PCFG	N	N	Long	Slow
Topic	Y	N	Long	Slow
FF-NN	Y	Y	Medium	Slow
RNN	Y	Y	Medium	Slow

Fine print goes here. No purchase necessary. Void where prohibited. Medium distance here is longer than a typical *n*-gram history length (eg. 5-gram), but isn't the full sentence history. Elman network-based LMs aren't trained using the full sentence history due to BPTT, and a word's effect decays over time. While advances have been made in improving softmax normalization, models that use it are still orders of magnitude slower at training than a typical generative model. Induced PCFG (eg. Baker (1979), Lari & Young (1990,1991), Hänig et al (2008), Hänig (2010)) are costly to train from unannotated texts.

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