

Natural Language Processing  
Phrase-based Machine Translation, etc.



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Borrows slides Kevin Knight and Dan Klein



## Feature gains

- The core numeric features should get you a decent baseline MT system
- Expect and be pleased by getting small incremental gains from features you devise
- 0.25 BLEU from a feature is good
- 0.5 BLEU from a feature is fantastic

## Phrase-Based Translation Overview

**Input:** lo haré|rápidamente|. tries different segmentations,

**Translations:** I'll do it | quickly | . *translates phrase by phrase,*  
quickly | I'll do it | . *and considers reorderings.*

The decoder...

translates phrase by phrase,

and considers reorderings.



## Phrase-Based Translation

[illegible]

Table 1: #11# the seven - member crew includes astronauts from france and russia .

Scoring: Try to use phrase pairs that have been frequently observed.  
Try to output a sentence with frequent English word sequences.



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### Local syntax in phrase-based systems

[Och et al., 1999; Och and Ney, 2004]

Phrases capture multi-word expressions, help select correct function words, and enable local reorderings.

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### Phrase-based models at test time

Google translate's actual output, 2010  
Oct 2013 output: Rescue workers in collapsed buildings in search of survivors.

Long test phrases are often unseen in training.  
Short phrases yield poor translations.  
Need a more effective model to account for non-local dependencies.

### Syntax-based MT: Translation as parsing

[Galley et al.; NAACL 2004]

Syntax-based MT: Translation as parsing

### Natural Language Processing

Language Models

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## Language Models

- Traditional grammars (e.g., regular, context free) give a hard ("categorical") model of the sentences in a language
- For NLP, and other applied work, a probabilistic model of a language is *much* more useful
  - It says what people usually say (next)
  - It enables more fine-grained prediction and inference
- Called a **Language Model** ... strange but standard



## Uses of language models

- Speech recognition
  - "I saw a van" is a more likely sentence than "eyes awe of an"
- OCR & Handwriting recognition
  - More probable sentences are more likely correct readings
- Machine translation
  - More likely sentences are probably better translations
- (Fluent Text) Generation
  - More likely sentences are probably better NL generations
- Context sensitive spelling correction
  - "Their are problems wit this sentence."
- Predictive text input systems
  - Please turn your cell phone of\_
  - Google query completion suggestions



## Uses of language models

- Text classification
  - A topic is a language ("the language of finance")
- Gender/style detection
- Information retrieval: Language models for IR
  - Treat either or both the query or each document as a "language"
  - One of the most pursued research approaches recently (at UMass/CMU)
- Certain aspects of grammar checking
  - E.g., preposition choice
- Text compression
  - Way better than gzip/bzip2 for human language text



## Probabilistic Language Models

- Idea is to build models which assign scores to sentences
  - $P(\text{I saw a van}) \gg P(\text{eyes awe of an})$
  - Not really grammaticality
    - $P(\text{artichokes intimidate zippers}) \approx 0$
- Formally, a **probability distribution over sentences of a language** ... sums to 1 over whole language
- One option: empirical distribution over corpus sentences?
  - Problem: doesn't generalize (at all)
  - Whereas languages are infinite



## Probabilistic Language Models

Three major components of generalization

- Decomposition**: sentences generated in small steps
- Discounting**: save some probability mass for the possibility of unseen events
- Backoff**: contexts that words are generated from to equivalence classes of contexts which generalize better

After that, there are a lot of details

- But the details are *very* important in getting good performance in many NLP systems




## Decomposition: N-Gram Language Models

- No loss of generality to break sentence probability down with the chain rule
 
$$P(w_1 w_2 \dots w_n) = \prod_i P(w_i | w_1 w_2 \dots w_{i-1})$$
- Too many histories!
  - $P(??? | \text{No loss of generality to break sentence}) ?$
  - $P(??? | \text{the water is so transparent that}) ?$


- N-gram solution: assume each word depends only on a short linear history (a **Markov assumption**) = equivalence classing

$$P(w_1 w_2 \dots w_n) = \prod_i P(w_i | w_{i-k} \dots w_{i-1})$$

$$= \prod_i P(w_i | w_{i-1}) \text{ for bigram}$$



## Character-level




- Claude Shannon (1951): the entropy of English
  - <http://www.math.ucsd.edu/~crypto/java/ENTROPY/>

$$H(X) = E_P \log \frac{1}{P(X)}$$


$$= - \sum_{x \in \mathcal{X}} P(x) \log P(x)$$

- Cross entropy

$$H(S|M) = \frac{-\log_2 P_M(S)}{|S|} = \frac{-\sum_{i=1 \dots N} \log_2 P_M(w_i | w_{1 \dots i-1})}{N}$$


e.g., 

$$\sum_j \log_2 P_M(w_j | w_{j-1})$$




## Word level

... denied the \_\_\_\_\_



## Character-level

The Palestinian security chief in Gaza **denied the** report  
 Judge Kathleen Kennedy-Powell **denied the** motion to strike  
 Pineau-Valencienne has **denied the** charges  
 The FDA **denied the** group's request  
 the show's writer and co-star, **denied the** characters had real-life  
 The district attorney's office had **denied the** KCBS-TV report  
 Coleman **denied the** charge  
 Defense attorney Al Kitching **denied the** allegations  
 Local officials have consistently **denied the** existence of armed  
 Kraft has categorically **denied the** remarks  
 Goddard has **denied the** charges  
 congressional employees **denied the** legal protections  
 who **denied the** accusation of the woman




## Discounting/Smoothing

- We often want to make estimates from sparse statistics:
 

allegations	reports	claims	request	attack	man	outcome	...
3	2	1	1	0	0	0	0
7 total							
- Smoothing flattens spiky distributions so they generalize better
 


allegations	reports	claims	request	attack	man	outcome	...
2.5	1.5	0.5	0.5	0.5	0.5	0.5	0.5
7 total							

Very important all over NLP, but easy to do badly!  
 Illustration with trigrams (h = previous word, could be anything).



## Discounting/Backoff/Interpolation

- $P(w|h)$  is just a multinomial
  - but we need to estimate it well
  - We want to know how often a word follow some history  $h$
  - There's some true distribution  $P(w|h)$
  - We saw some small sample of  $N$  words from  $P(w|h)$
  - We want to reconstruct a useful approximation of  $P(w|h)$
  - Counts of events we didn't see are always too low
  - Counts of events we did see are *in aggregate* too high
- Discounting: providing mass for what we haven't seen
- Backoff: Increasing  $N$  by decreasing the amount of history  $h$
- Interpolation between backed-off distributions: how to allocate that mass amongst unseen events



## Evaluation

- What we want to know is:
  - Will our language model prefer natural sentences?
    - Does it assign *higher probability* to "real" or "frequently observed" sentences than "rarely observed" sentences?
- We train parameters of our model on a **training set**.
- To evaluate how well our model works, we look at the model's performance on some **different data**
- This is what happens in the real world; we want to know how our model performs on data we haven't seen
- So a **test set**. A dataset which is different from our training set
  - Preferably totally unseen/unused!
- So we can do this, we do model development with a separate development test (**devtest**) set



## Language models

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- Language models are a cool technology
- You can have them for not only a language like “English” but for particular languages/topics
  - Papers about language modeling
  - “Spam emails”
  - Seventeenth century novels
- Because they flexibly model higher order context, they can be very powerful models
  - And work very well

Look at the videos and J&M chapter 4!