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.

Translations: I'll do it quickly .

quickly I'll do it .

The decoder...

tries different segmentations,

translates phrase by phrase,

and considers reorderings.

Phrase-Based Translation 汶 中包括 来自 法国 和 俄罗斯 的 宇航 员 including the 7 people by some and the russian the the astronauts it 7 people included by france and the the russian international astronautical of rapporteur . this 7 out including the from the french and the russian the fifth these 7 among including from the french and of the russian of members space including from the of france and to of the that 7 persons russian aerospace members 7 include from the of france and russian astronauts . the 7 numbers include from france and russian of astronauts who those from france 7 populations include and russian astronauts 7 deportees included come from france and russia in astronautical personnel 7 philtrum including those from france and russia member a space including representatives from france and the russia astronaut include came from france and russia by cosmonauts include representatives from french and russia cosmonauts include and russia 's came from france cosmonauts. includes coming from french and russia 's cosmonaut french and russian 's astronavigation member. and russia astronauts french

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.

and russia 's

and russia

, and russia

russia

russia 's

, and

special rapporteur

rapporteur

rapporteur.

Phrase-Based Translation 俄罗斯 员 这 中包括 来自 法国 和 的 字航 7 people the including by some and the russian the the astronauts 7 people included by france and the the russian international astronautical of rapporteur . thin 7 cat including the from the french and the russian the fifth these 7 among including from the french and of the russian of members space including from the of france of the and to russian members tnat 7 persons aerospace 7 include from the of france and russian astronauts . the 7 numbers in lude from france and russian of astronauts who those from france 7 populations include and russian astronauts 7 deportees included come from france and russia in astronautical personnel 7 philtrum in luding those from france and russia member a space including representatives from france and the russia astronaut include came from france and russia by cosmonauts french menuce representatives from and russia cosmonauts and russia 's include came from france cosmonauts. includes coming from french and russia 's cosmonaut french and russian 's astronavigation member. and russia astronauts french and russia 's special rapporteur , and russia rapporteur and russia rapporteur. , and russia russia 's

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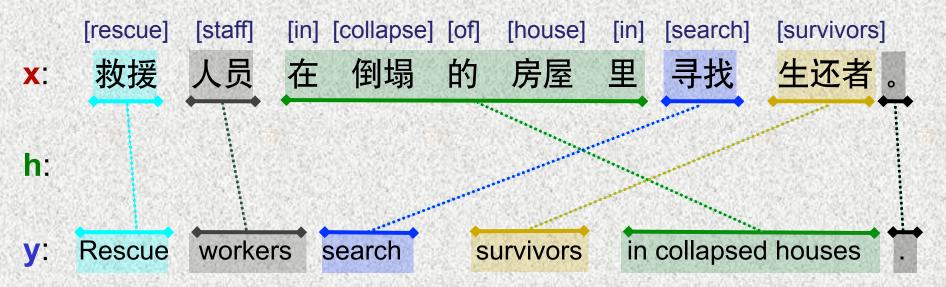
Scoring: Try to use phrase pairs that have been frequently observed.

Try to output a sentence with frequent English word sequences.



Local syntax in phrase-based systems

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

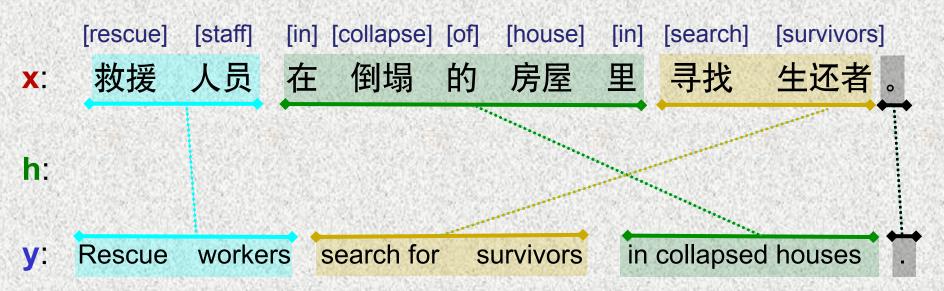


Phrases capture multi-word expressions, help select correct function words, and enable local reorderings.



Local syntax in phrase-based systems

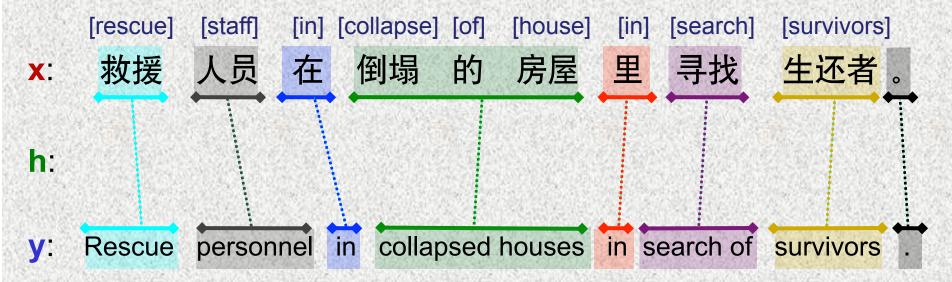
[Och et al., 1999; Och and Ney; 2004]



Phrases capture multi-word expressions, help select correct function words (e.g., now also "for"), and enable local reorderings.



Phrase-based models at test time



Google translate 's actual output, 2010

Oct 2013 output: Rescue workers in collapsed buildings in search of survivors.

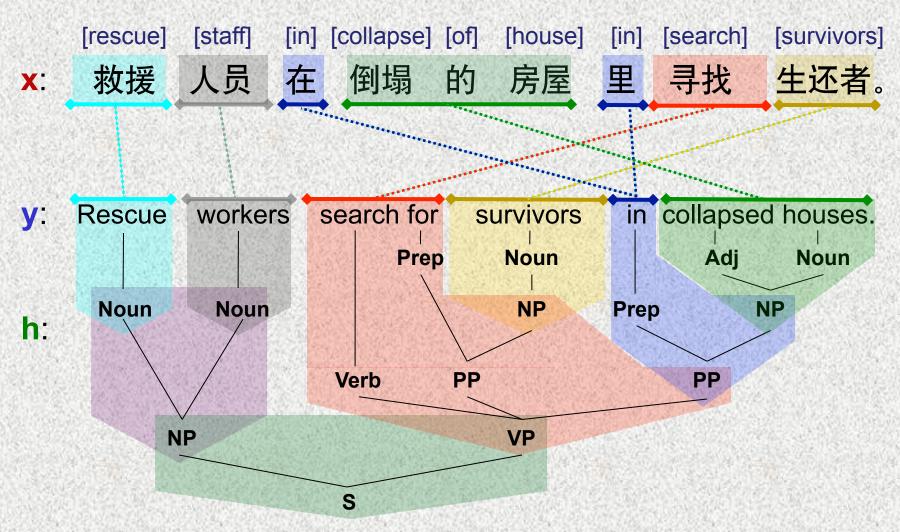
Long test phrases are often unseen in training.

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]



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(I saw a van) >> P(eyes awe of an)
 - Not really grammaticality
 - P(artichokes intimidate zippers) ≈ 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

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

- Too many histories!
 - P(??? | No loss of generality to break sentence) ?
 - P(??? | the water is so transparent that) ?
- N-gram solution: assume each word depends only on a short linear history (a Markov assumption) = equivalence classing

$$P(w_1 w_2 \dots w_n) = \prod_{i} P(w_i \mid w_{i-k} \dots w_{i-1})$$
$$= \prod_{i} P(w_i \mid w_{i-1}) \text{ for bigram}$$



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

... denied the _____



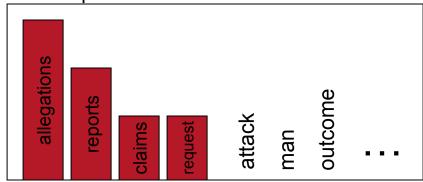
The Palestinian security chief in Gaza denied the report Judge Kathleen Kennedy-Powell denied the motion to strike Pineau-Valencienne has denied the charges The FDA **denied the** group's request the show's writer and co-star, **denied the** characters had real-life The district attorney's office had **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 are denied the legal protections who denied the accusation of the woman

Discounting/Smoothing

We often want to make estimates from sparse statistics:

P(w | denied the)

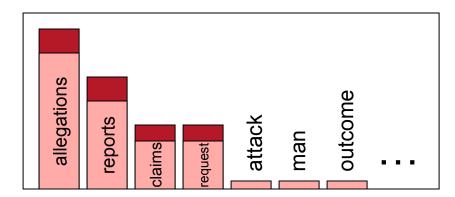
- 3 allegations
- 2 reports
- 1 claims
- 1 request
- 7 total



Smoothing flattens spiky distributions so they generalize better

P(w | denied the)

- 2.5 allegations
- 1.5 reports
- 0.5 claims
- 0.5 request
- 2 other
- 7 total



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



Discounting/Backoff/Interpolation

- $P(w_i|h)$ 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 $P(w \mid h)$
 - We saw some small sample of N words from $P(w \mid h)$
 - 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

- 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!