Knowledge Integration Into Language Models: A Random Forest Approach

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Dissertation Defense

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Outline

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What Is A Language Model?

- How likely will a sentence be uttered by a human?
- Complete the sentence:

Wouldn't it be . . .

- . . . great?
- . . . awesome?
- . . . lovely?
- . . . loverly!

Lots of choc'lates for me to eat,
Lots of coal makin' lots of 'eat.
Warm face, warm 'ands, warm feet,
Aow, wouldn't it be loverly?

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State of the Art

- *N*-gram language models remain the *de facto* standard
  - Ignore the fact that we are modeling human language
- But we know so much more about language!
  - give, gave, given (morphology)
  - love (verb), lover (noun), lovely (adjective) (part-of-speech)
  - this:is::these:are (agreement)
  - ...
- Even machines "know" something
  - Morphological analyzers
  - Part-Of-Speech (POS) taggers
  - Parsers
  - ...
- Putting language into language modeling (Jelinek and Chelba, 1999)

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Language Models (LMs)

- A probability distribution over all possible word sequences $P(W)$, where $W = w_1 \dots w_N \in V^*$, V is the vocabulary.
- Decompose using the chain rule

$$P(W) = \prod_{i=1}^{N} P(w_i \mid w_1, \dots, w_{i-1}) \approx \prod_{i=1}^{N} P(w_i \mid \Phi(w_1, \dots, w_{i-1})),$$

where $\Phi : V^* \mapsto C$ is an equivalence mapping of histories.

- An important component in speech recognition, machine translation and information retrieval system.

Decision Tree Language Models

- Language modeling as equivalence mapping of histories
- *N*-gram language models
  - Markovian assumption

$$P(w \mid h) \approx P(w \mid \Phi(h)) = P(w \mid w_{i-n+1}^{i-1}),$$

where $h = w_1, \ldots, w_{i-1} = w_1^{i-1}$.

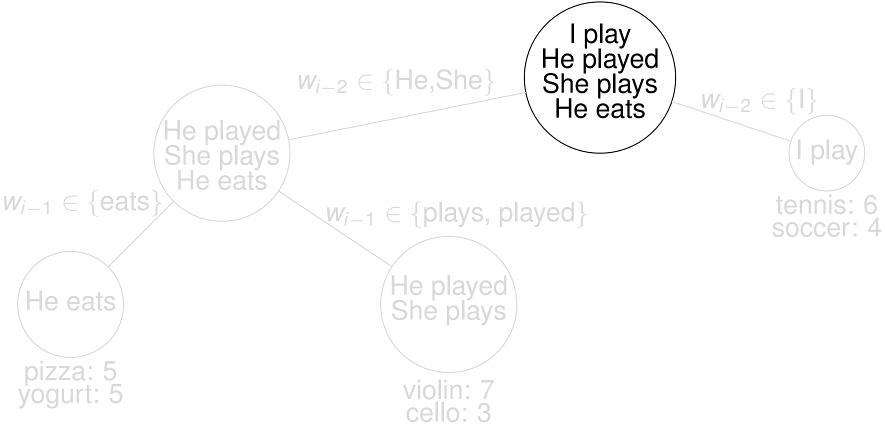
- Decision tree language models (Bahl et al., 1989)
  - Decision tree classifier as equivalence mapping

$$P(w \mid h) \approx P(w \mid \Phi(h)) = P(w \mid \Phi_{DT}(h)).$$

Decision Tree Training

- Growing (Top-down)
  - Start from the root node, which contains all *n*-gram histories in the training text;
  - Recursively split every node to increase the likelihood of the training text by an exchange algorithm (Martin, Liermann and Ney, 1998);
  - Until splitting can no longer increase the likelihood.
- Pruning (Bottom-up)
  - Define the potential of a node as the gain in heldout text likelihood by growing it into a sub-tree
  - Prune away nodes whose potentials fall below a threshold.

Decision Tree Language Models: Training



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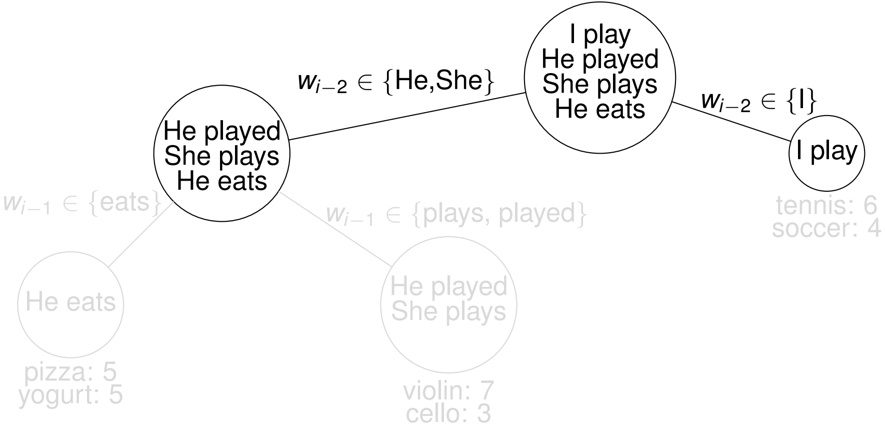

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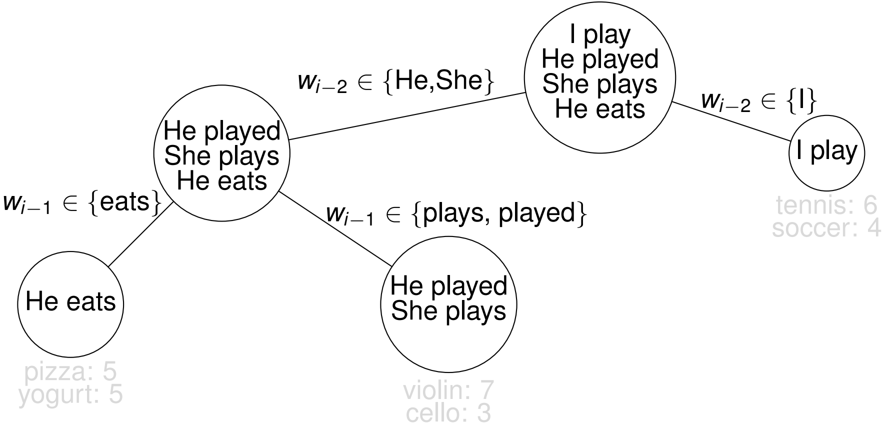

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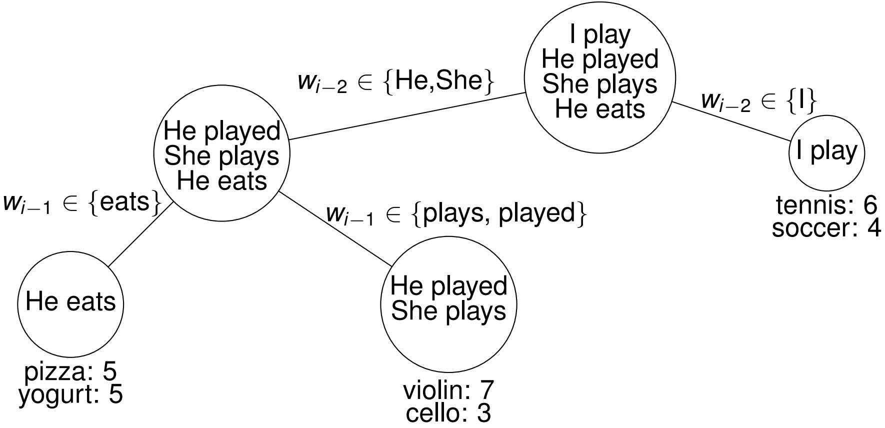

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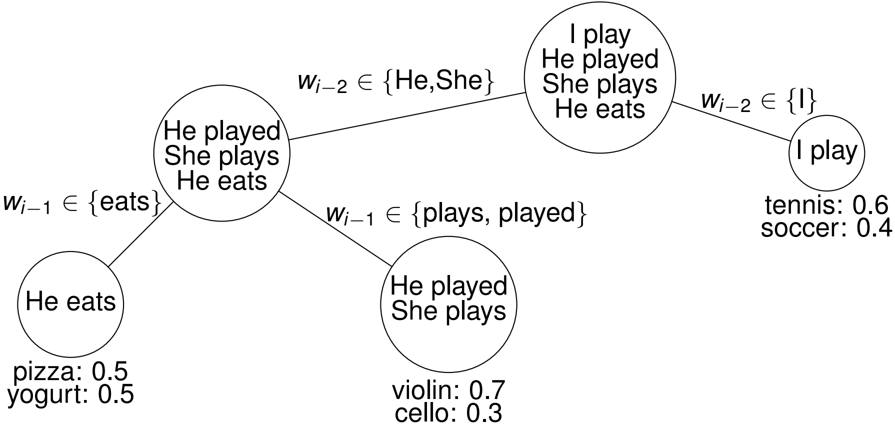

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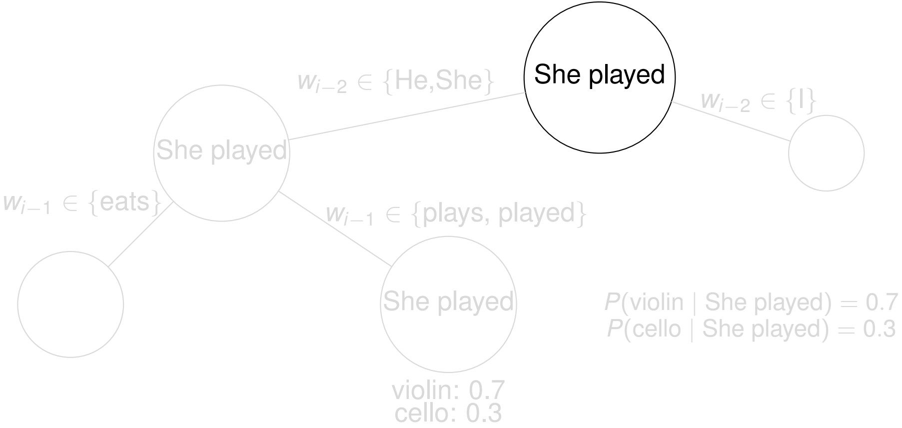

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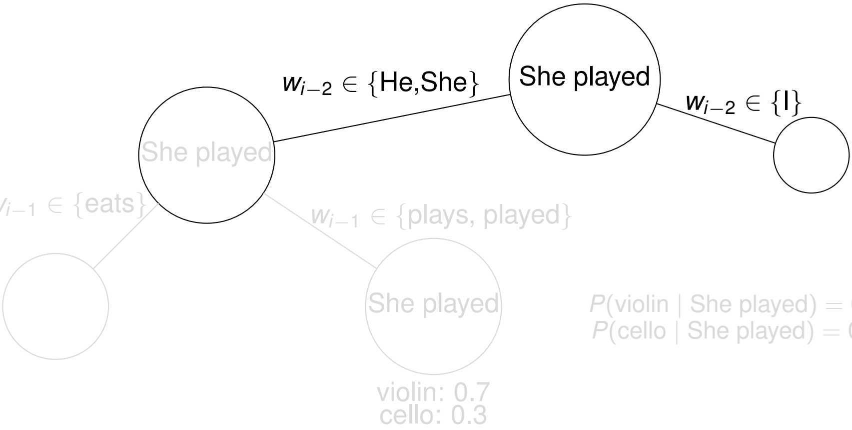

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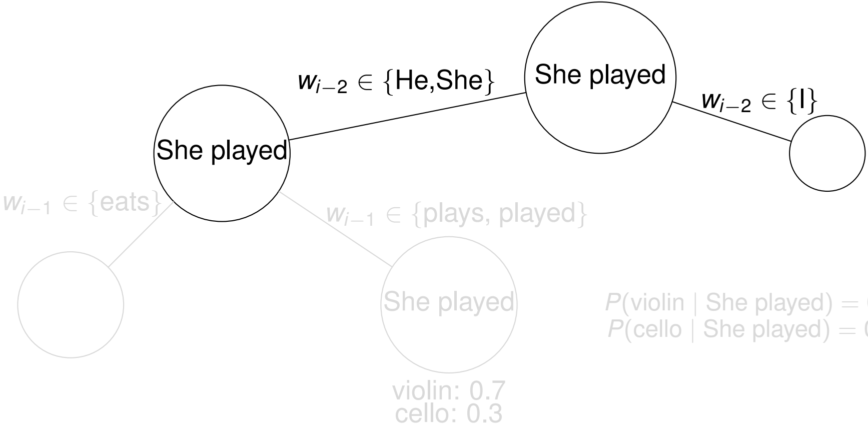

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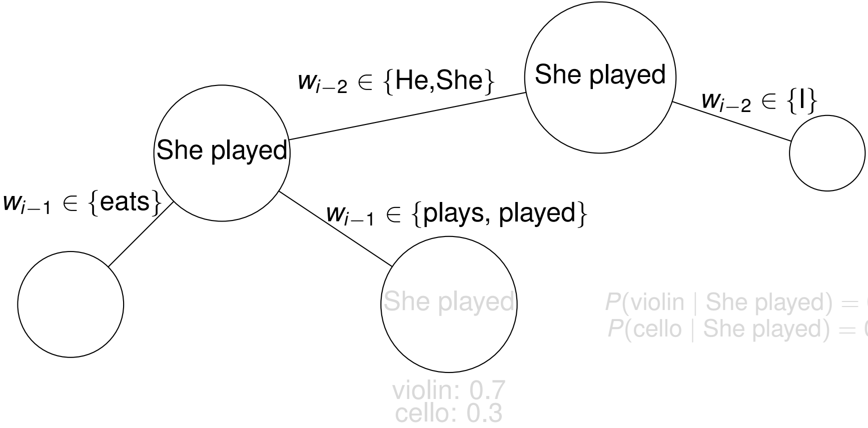

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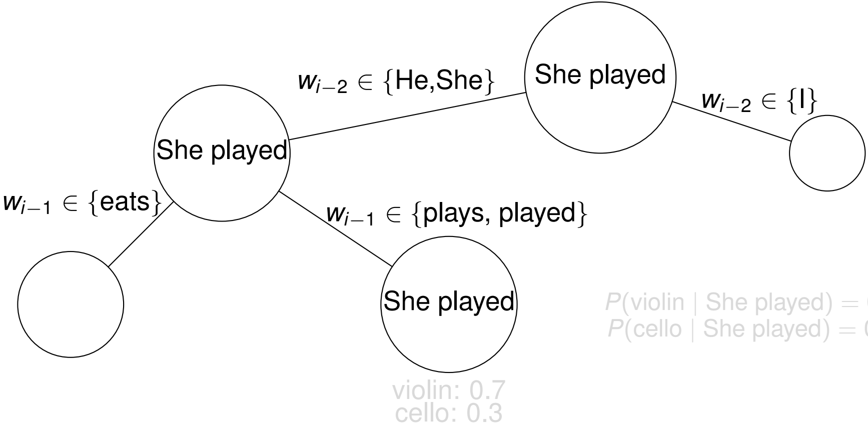

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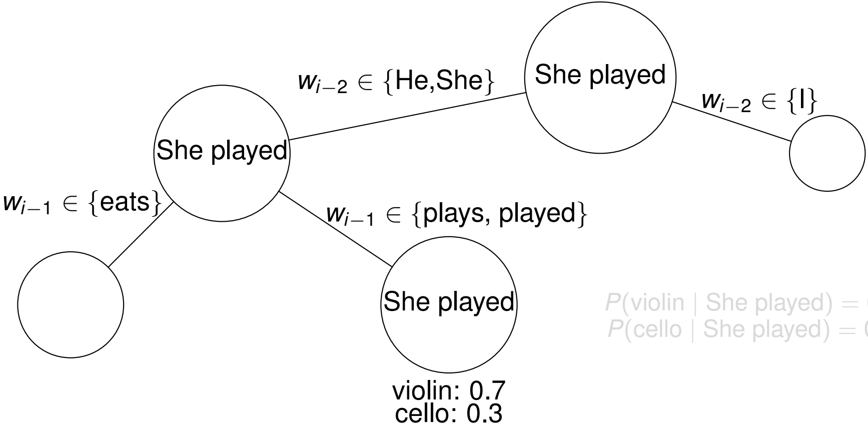

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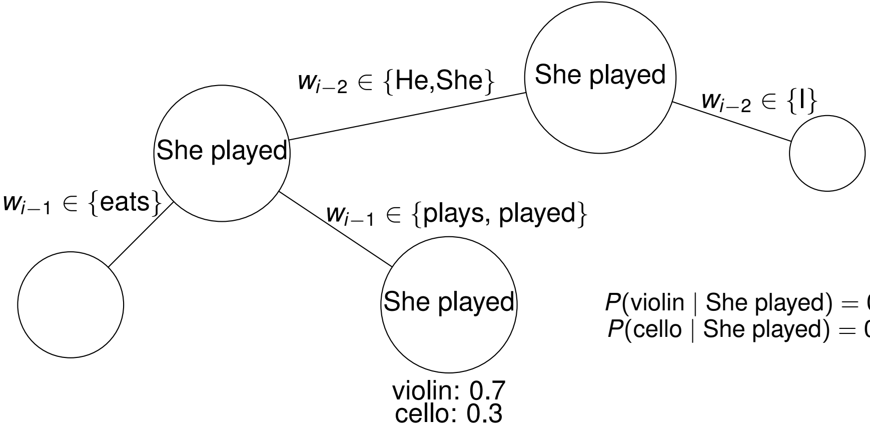

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Decision Tree Language Models

- Failed to improve upon *n*-gram language models (Potamianos and Jelinek,1998)
  - Without efficient search algorithm, greedy tree building can't find a good tree
  - Failed to control the variance
- Random forest (Breiman, 2001)
  - A collection of randomized decision trees
  - Reach final decision by voting to reduce variance
  - Good results in many classification tasks

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Random Forest Language Models (RFLMs)

- A collection of randomized decision tree language models or an i.i.d. sample of decision trees (Xu and Jelinek, 2004)
- Probability via averaging

$$P(w \mid h) = \frac{1}{M} \sum_{j=1}^{M} P(w \mid \Phi_{DT_j}(h))$$

- Superior to *n*-gram language model in terms of perplexity and word error rate on small size corpora (Xu and Mangu, 2005)

Training Randomization

- Random initialization of the exchange algorithm
  - Combat local maximum problem caused by greediness of the exchange algorithm (Martin, Liermann and Ney, 1998)
- Random selection of questions
  - Set membership of a word in a history position j

$$q_S^j(w_1^{i-1}) = \begin{cases} 1 & \text{, if } w_j \in S; \\ 0 & \text{, otherwise.} \end{cases}$$

    where $1 \leq j \leq i-1$ and $S \subset V$.
  - Randomly choose a subset of history positions to investigate
- Random sampling of the training data

Smoothing RFLM

- Kneser-Ney-style smoothing

$$
\begin{aligned}
P(w_i \mid w_{i-n+1}^{i-1}) &= \frac{\max(C(w_i, \Phi(w_{i-n+1}^{i-1})) - D, 0)}{C(\Phi(w_{i-n+1}^{i-1}))} \\
&+ \lambda(\Phi(w_{i-n+1}^{i-1})) P_{KN}(w_i \mid w_{i-n+2}^{i-1})
\end{aligned}
$$

- Can be improved by modified Kneser-Ney smoothing (Chen and Goodman, 1999)
    - Used in all experiments henceforth.

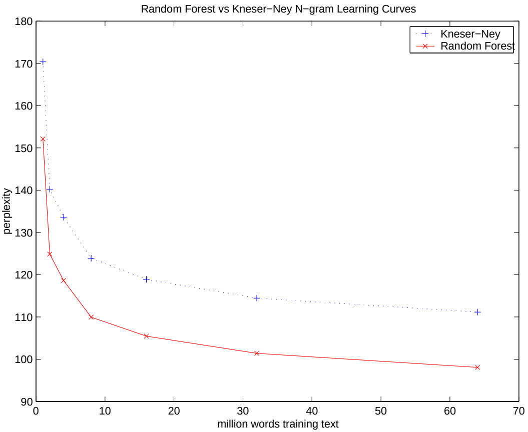
Why *N*-gram LMs Work

- “There is no data like more data.” — Robert L. Mercer
  - Performance of a statistical model depends on the amount of training data
- Simplicity implies scalability
  - *N*-gram LMs outperform complex LMs by using more data

Large-Scale Training and Testing

- Problem: straightforward implementation quickly uses up addressable space.
  - Memory requirement grows as tree grows
- Solution: an efficient disk swapping algorithm exploiting
  - Recursive structure of binary decision tree
    - Compact representation for fast reading and writing
  - Local access property of tree-growing algorithm
    - Node-splitting depends only on the data it contains
- Achieve I/O overhead linear to the size of training *n*-gram types (Su, Jelinek and Khudanpur, 2007).

Learning Curves



Automatic Speech Recognition (ASR)

- System: IBM GALE Mandarin ASR
- Vocabulary: 106K words
- Data: $100M * 7 = 700M$ words for training, 10M for held-out, 20k for testing
- Parameters: 4-grams, 50 trees per forest

Table: Lattice rescoring for IBM GALE Mandarin ASR

Character Error Rate (%)	All	BN	BC
Baseline	18.9	14.2	24.8
RFLM	18.3	13.4	24.4

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1. Introduction
2. Basic Language Models
3. Random Forest Language Models
4. Knowledge Integration with RFLMs
5. Exploiting Prosodic Breaks in LMs
   - Introduction
   - Prosodic Language Models
   - Experimental Results
6. Conclusions

Knowledge Integration

- RFLM as a framework for integrating linguistic knowledge
  - Decision tree can ask any question about the history
- Feature: a function $f(h)$ that maps h to an element of a finite set.

$$f : V^* \mapsto E,$$

  where V is the vocabulary, E is the set of feature values.
- Question: the indicator function $q_S^f(h)$ of the set $f^{-1}(S) = \{h : f(h) \in S \subset E\}$.

$$q_S^f(h) = \begin{cases} 1 & \text{, if } f(h) \in S \subset E; \\ 0 & \text{, otherwise.} \end{cases}$$

Feature Engineering

- Features we have used so far:
  - Word features: if $h_i = w_1 \cdots w_{i-1}$, then

$$\mathrm{WORD}_j(h_i) \doteq w_{i-j},$$

- Features we can potentially use:
  - Any discrete-valued function on the history!
  - E.g., Part-Of-Speech (POS) features: $\mathrm{POS}_j(h_i) \doteq r_{i-j}$, where r_{i-j} is the POS tag of the word w_{i-j}, as provided by an incremental POS tagger.
  - Feature vector representation of a history h

$$F(h) \doteq (f_0(h), f_1(h), \cdots, f_k(h)).$$

Outline

What Is Prosody?

- Suprasegmental properties of spoken language units
- A *wide* range: tone, intonation, stress, break, etc.
- Many applications
  - Disfluency & sentence boundary detection (Stolcke et al, 1998)
  - Topic segmentation (Hirschberg and Nakatani, 1998)
  - Spoken language parsing (Hale et al, 2006)
  - ...
- We are interested in using prosodic breaks for language modeling.

What Is A Prosodic Break Index?

- Number representing subjective strength of one word's association with the next
- On a scale from 0 (the strongest conjoining) to 4 (the most disjoining)
- Example:

Time flies like an arrow.
Time/3 flies/2 like/1 an/0 arrow/4.
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- Prosodic breaks help resolve syntactic ambiguity (Dreyer and Shafran, 2007)
- We think they should help resolve lexical ambiguity, too.

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Speech Recognition with Side Information

- Proposal 1: If S is hidden, then

$$W^* = \arg\max_W P(W \mid A) = \arg\max_W P(A \mid W) \sum_S P(W, S).$$

- Proposal 2: If S is observable, then

$$(W, S)^* = \arg\max_{W,S} P(W, S \mid A) \approx \arg\max_{W,S} P(A \mid W) P(W, S).$$

Are Prosodic Breaks Hidden or Observable?

- Strictly speaking, only acoustic features are observable in speech recognition;
- However, unlike hidden structures such as parse trees, prosodic breaks can be predicted from acoustic features with high precision. (Hale et al, 2006)
  - 83.12% for predicting a 3-valued break on annotated Switchboard
- Each case has its pros and cons.
- We are going to investigate these two options for the purpose of language modeling.

Joint Model of Words and Breaks

$$P(W, S) \approx \prod_{i=0}^{m} P(w_i, s_i \mid w_{i-n+1}^{i-1}, s_{i-n+1}^{i-1})$$

- Tuple Model: Let $t_i = (w_i, s_i)$, for all $0 \leq i \leq m$. We have

$$P(w_i, s_i \mid w_{i-n+1}^{i-1}, s_{i-n+1}^{i-1}) = P(t_i \mid t_{i-n+1}^{i-1}).$$

- Decomposed Model

$$\begin{aligned} & P(w_i, s_i \mid w_{i-n+1}^{i-1}, s_{i-n+1}^{i-1}) \\ = \quad & P(w_i \mid w_{i-n+1}^{i-1}, s_{i-n+1}^{i-1}) P(s_i \mid w_{i-n+1}^{i}, s_{i-n+1}^{i-1}) \end{aligned}$$

One Problem

$$P(s_i \mid w_{i-n+1}^{i}, s_{i-n+1}^{i-1}) = ?$$

- How do we smooth things like this? Back-off! Deleted interpolation!
- In what order do we back off or delete? Well...
  - No "natural order" of backing off
  - Previous research either relied on heuristics (Chelba and Jelinek, 2000; Charniak, 2001)
  - Or tried to find the "optimal" path or combination of paths (Bilmes and Kirchhoff, 2003; Duh and Kirchhoff, 2004)
- We have something better... Random Forests!

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Ask the Right Question

- Questions
  - We have asked:

    Is the word w_{i-1} in the set of words $\{a, an, the\}$?
  - We would like to ask:

    Does the prosodic break s_{i-1} take its value in the set of values $\{1, 2, 3\}$?
- Same algorithms for training and testing
- Natural integration with background *n*-gram LM
- Feature selection on-the-fly!

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Experimental Setup

- Vocabulary: 10k
- Data: ToBI-labeled Switchboard (Ostendorf et al., 2001).
  - 666k words for training
  - 51k words for held-out
  - 49k words for testing
- Parameters:
  - history up to 2 words and 2 breaks (“3-grams”)
  - 100 trees per forest

Granularity

- Granularity of prosodic breaks might be too coarse for LM
- Compared 2-, 3- and 12-valued scheme for

$$P(w_i \mid w_{i-1}, w_{i-2}, s_{i-1}, s_{i-2})$$

Table: *Granularity of Prosodic Breaks*

Model	two-level	three-level	cont.-valued
KN.3gm	66.1	66.1	66.1
RF-100	65.5	65.4	56.2

Main Results

Table: *Main Perplexity Results*

Model	Method	KN	RF
$P(W,S)$	tuple 3gm	358	306
	decomp.	274	251
$P(W)$	tuple 3gm	69.3	67.2
$=\sum_S P(W,S)$	decomp.	66.8	64.2
$P(W)$	word 3gm	66.1	62.3

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Conclusions

- Random forest language model as a general framework
  - For integrating knowledge into language models
- Exploiting prosodic breaks in language modeling with random forests (Su and Jelinek, 2008)
  - Finer grained prosodic break indices are needed.
  - Prosodic breaks should be given to language models.

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Publications

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