Maximum Entropy Techniques for min-WER Score Combination with Sausages

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Summary Overview

- Goal: To improve lattice rescoring by including novel information sources with discriminatively trained weights
- Approach: Conditional probability model of the hypothesized word on a sausage edge being the true transcription
  - Exponential model conditioned on the context via a set of features
  - Maximum entropy **(ME)** estimation of the exponential model weights
- Bottom line: Not quite working yet, preliminary setup has so far not given a significant win (<0.1% abs)
- Future Work:
  - Discriminative framework for including side information in rescoring confusion networks, e.g. prosodic features --to be investigated further and many things in the pipeline to try

Talk Plan

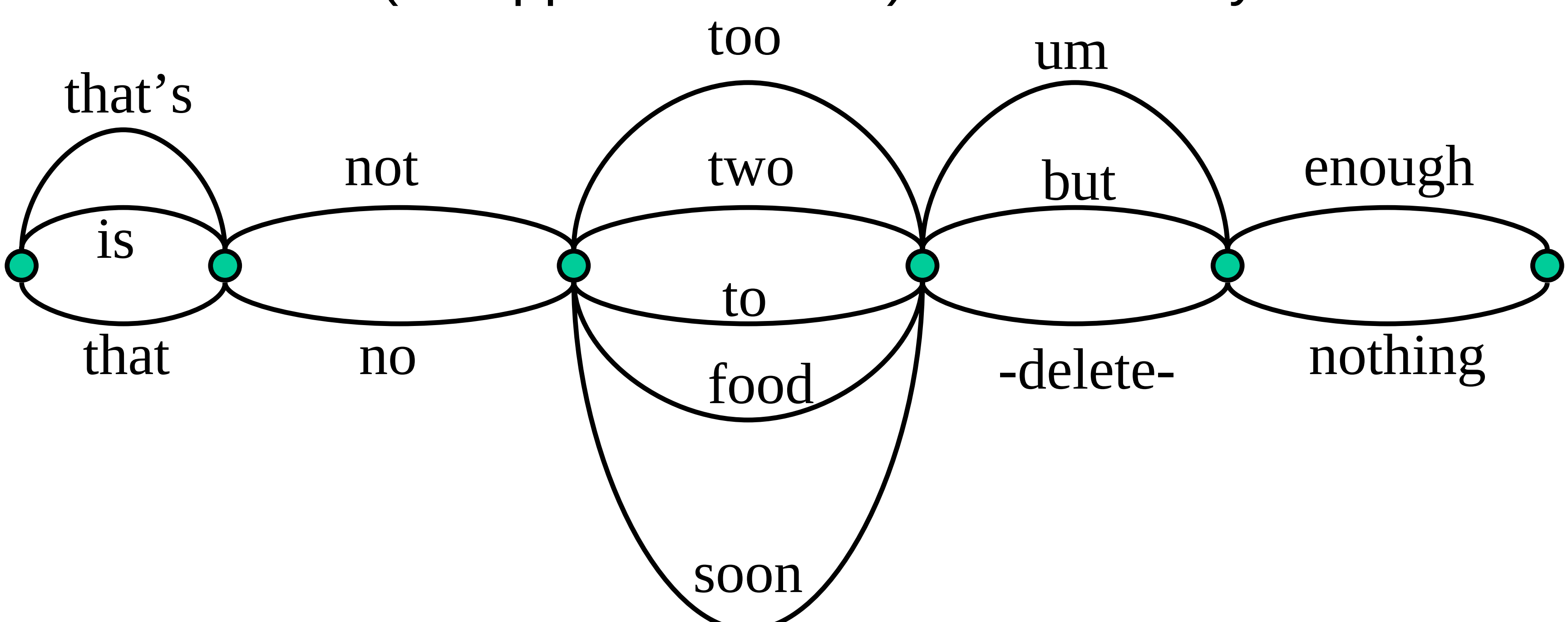
- Rationale
  - Lattices and confusion networks
- Brief synopsis of prior work on discriminative score combination
- Approach
  - Min WER by ME estimation of conditional exponential model over confusion networks
- Experiments
- Preliminary Results

Rationale

- Lattice rescoring is an important part of information combination in ASR
- Rescoring by confusion networks allows minimization of WER directly
- Confusion network oracle error rates leave room for significant improvements
- Ideally, the scores need to be combined in a discriminative manner
- We develop a framework for rescoring of confusion networks based on a discriminatively estimated conditional model

Lattices to Sausages

- Lattice rescoring plays an important role in information combination in ASR
- Confusion networks are compacted lattices with nodes merged into ordered equivalence classes
- Word-level rather than sentence-level posteriors
- Minimize (an upper bound on) WER directly



RT03-dev sausages

- How much room is left in RT03-devset confusion networks?

Max Depth in confusion network	WER
top	25.8%
2	23.9%
3	23.0%
4	22.4%
5	22.0%

Some recent prior work

- Sentence Error Rate minimization
  - Yu, Waibel, ICASSP 2004
- Word Error Rate minimization
  - Mangu, Padmanabhan, ICASSP 2001
- Discriminative Model Combination
  - Beyerlein, ASRU 1997

Prior Work

- Sentence Error Rate Minimization by Conditional Exponential Models (Yu,Waibel, ICASSP 2004)
- Conditional exponential model of score combination estimated by ME
- Set of feature functions:

$$f_1(obs, hyp) = \log p_{AM}(obs \mid hyp)$$
$$f_2(obs, hyp) = \log p_{LM}(hyp)$$
$$f_3(obs, hyp) = [\# words(hyp)]$$
$$\ldots$$

- Similar to usual score combination, with a normalization term

$$\log P(hyp \mid obs) = \sum_i \lambda_i f_i(obs, hyp) - \log Z(obs)$$

- MMIE-like normalization computation

$$Z(obs) \approx \sum_{hyp(N-best)} \exp\left(\sum_i \lambda_i f_i(obs, hyp)) \right)$$

Prior Work

- WER minimization via **error correction** over confusion networks (Mangu, Padmanabhan, ICASSP 2001)
- Transformation-based learning to train rules to distinguish hypotheses in a confusion network using additional information
  - *choose the 2nd candidate ('-') if 1st candidate is a short word with posterior < 0.46*
- 0.5% absolute improvement on WS97

Conditional Exponential Models of Word Error

- Probability that $w^i_{e,}$ the word on edge *e* of alignment is correct:

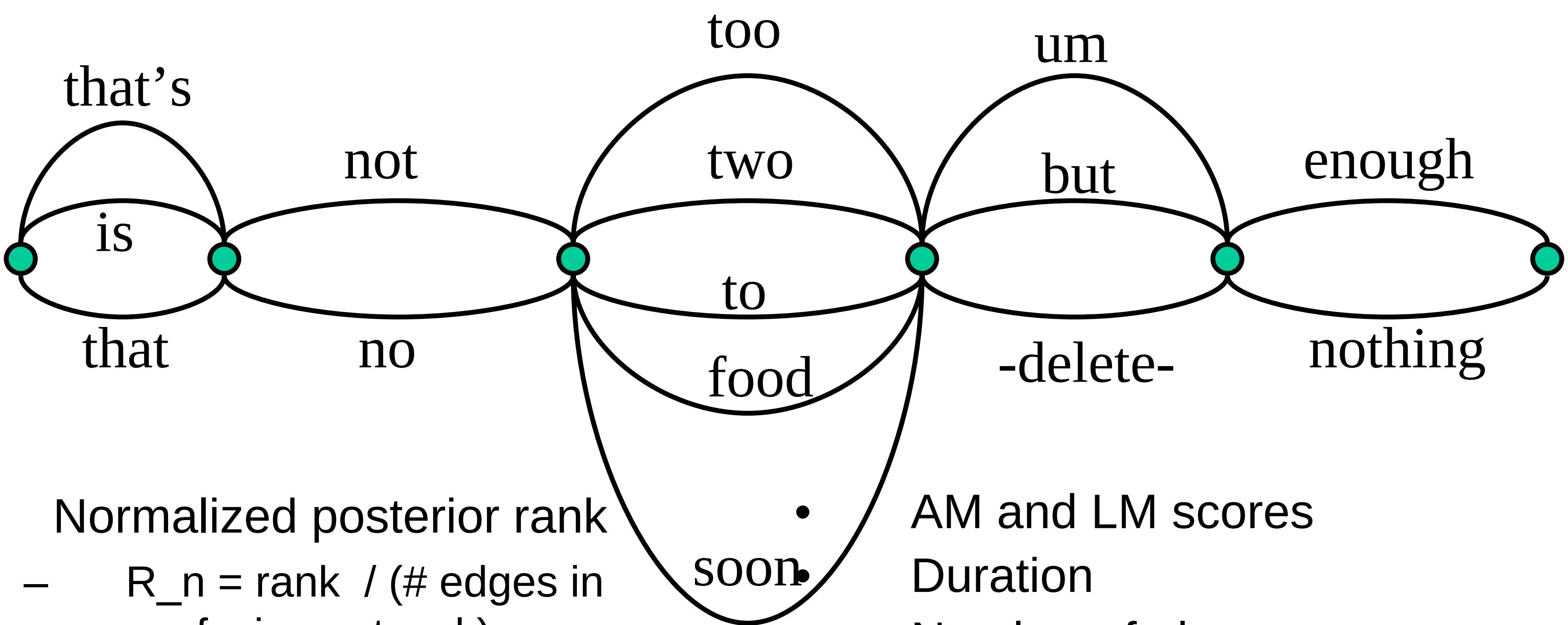
$$\log P(w_e^i = w_{ref}^i \mid context) = \sum_i \lambda_i f_i(context, w_e^i) - \log Z(context)$$

- Features to represent sausage context

$$f_1(context, w_e^i) = \log p_{AM}$$
$$f_2(context, w_e^i) = \log p_{LM}$$
$$f_3(context, w_e^i) = \log p_{DBN}$$
$$f_4(context, w_e^i) = [\# words(hyp)]$$
$$\ldots$$

- Weights estimated by ME

Sausage Context Features



- Normalized posterior rank
  - R_n = rank / (# edges in confusion network)
- Posterior
- Landmark Pronunciation Model scores
  - DBN scores
  - Discriminative pronunciation model scores

- AM and LM scores
- Duration
- Number of phones
- Relative confusion network position in the lattice
- Confusability
  - c(w)=log(# w in the training confusion network set)
- Function word membership
- Delete feature

Experiments

- Selection of features
- Confidence smoothing
  - conf_score = p(top edge)/p(runner up edge)
  - rerank edges only if conf_score < threshold
- Two ways of dealing with –delete- edges
  - Leave out sausages with deletes in the active depth
  - Include -delete- edges in the training with binary delete features (f_{delete} = 1[w = -delete-])
- Training edge depth into the confusion network:
  - True edge + top 2,3,4,5

Preliminary Results

- RT03 development set
  - sausages from 2000-best lists, aligned with references
  - divided into ME training (2000 sausages) and testing sets (930 sausages)
- Rescoring with ME trained posteriors
  - Test set performance:

system	sub	del	ins	**WER**
Baseline	16.8	**10.9**	3.5	31.1
Rescored with top2	16.8	**10.9**	3.5	31.1
Conf-rescored with top2	**16.7**	11.0	**3.4**	31.1

Preliminary Results

- RT03 development set
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- Rescoring with ME trained posteriors
  - Test set performance:

system	sub	del	ins	**WER**
Baseline	15.8	13.4	3.8	33.0
conf-rescored with sausage features	15.8	13.4	3.8	33.0
+ landmark (DBN) features	15.8	13.4	3.8	33.0

Summary and Future Work

- Sausage-based discriminative rescoring via ME
- Further work needed in assessing merits
  - as a score combination technique for landmark based pronunciation models as well as other side information
  - so far, results tentative and not conclusive
- Future Work:
  - New features from prosody
    - Stress accent levels
    - Energy and/or F_0 profiles
  - Many more things to try:
    - Interpolation of the exponential model with the original posterior
    - Confidence threshold informed by utterance and/or speaker characteristics (more in Emily's talk)