Toward Using Word/Fragment Hybrid Systems

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April 17, 2009

Outline

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- Fragments have the potential to provide a good trade off between coverage and accuracy

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Fragments → IH_N

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  - Fragment representation of OOV is obtained by greedy search

Hybrid Language Model in detail

- Step 3: Build LM on the Hybrid word/fragment set
    - Treat fragments as individual terms
    - At this step, Hybrid LM is built and we have a LM including both words and fragments

Outline

1. Introduction

2. Hybrid Systems for OOV Detection
   - Fragment Posteriors Using Consensus
   - Additional Features
   - Evaluation
   - Experimental Setup for OOV detection
   - Results Using Various Features
   - Hybrid vs. JHU Workshop07
   - Looking At False Alarms

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  - **ASR:** TODAY TWO YOUNG GIANT PANDAS FROM CHINA ARRIVED ON A SPECIALLY R_EH_T R_OW F_IH_T IH_D FEDEX JET
  - **REF:** TODAY TWO YOUNG GIANT PANDAS FROM CHINA ARRIVED ON A SPECIALLY RETROFITTED FEDEX JET

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- Having posterior probabilities for each hypothesis, we would be able to look not only at the existence of a fragment but also how likely that existence is.
- For any region in the confusion network we can compute an OOV score to be :

$$OOV_{score} = \sum_{f \in \{t_j\}} p(f|t_j)$$

Additional Scores

- we also explored the use of additional features that contain complimentary information such as those used in the JHU workshop. They include:

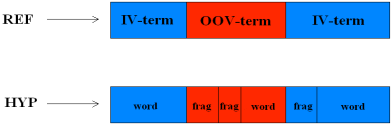
$$Word - Entropy = -\sum_{w \in \{t_j\}} p(w|t_j) \log p(w|t_j) \quad (1)$$

$$Frag - Entropy = -\sum_{f \in \{t_j\}} p(f|t_j) \log p(f|t_j) \quad (2)$$

$$LM - Score = p_{lm}(hyp_{t_j}|hyp_{t_{j-1}}) \quad (3)$$

where w is a word inside region t_j and hyp_{t_j} refers to the one-best hypothesis in the current region and $hyp_{t_{j-1}}$ refers to the one-best hypothesis in the previous region. p_{lm} is the probability of seeing hyp_j given hyp_{j-1} obtained from the hybrid language model.

Evaluating OOV detection



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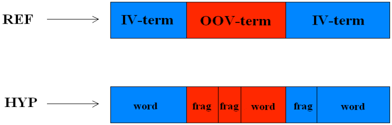

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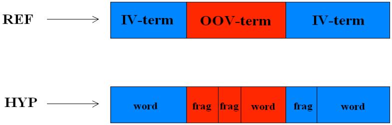

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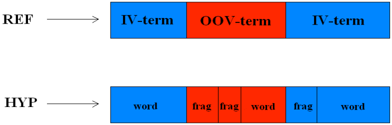

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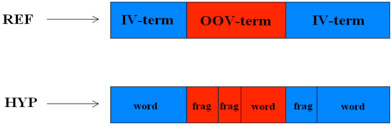

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- *Maximum Entropy*(MaxEnt) classifier is used to combine different scores.
- *False alarm* probabilities and *miss* probabilities on the set are shown in standard detection error trade-off(DET) curves

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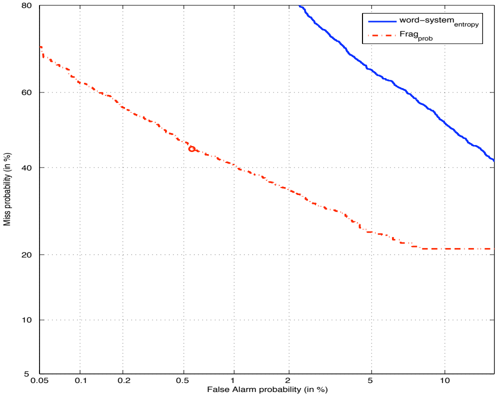
- Test set: RT04 BROADCAST NEWS with 4.5 hours of speech(45k words) and OOV rate of 2.8%

Results using various features

- Our base line is same as WS07 base line which uses Word Entropy of a word system for OOV detection



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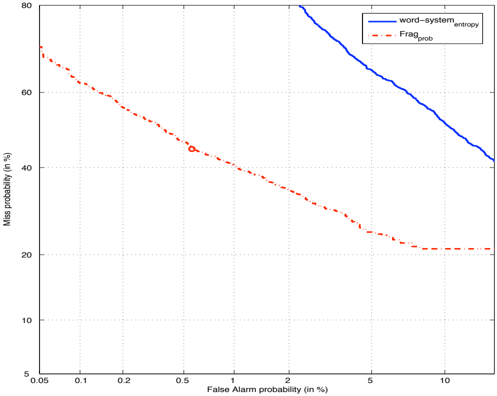
- Comparison of base line with consensus network fragment probability



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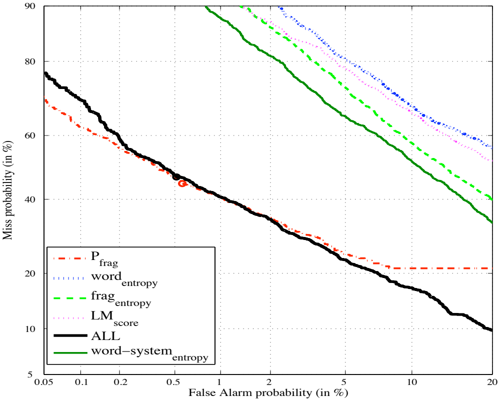

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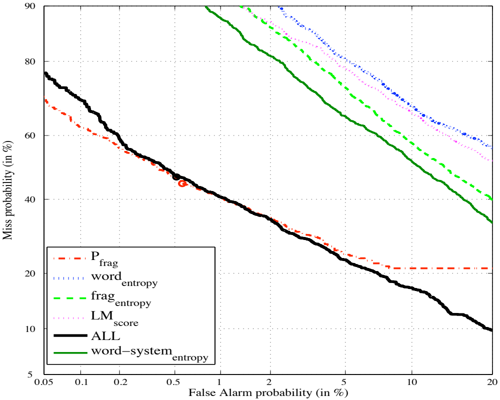
- Using all features we get better performance in regions with higher false alarm



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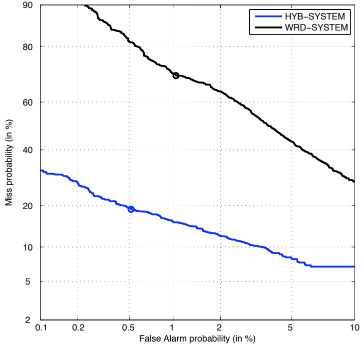
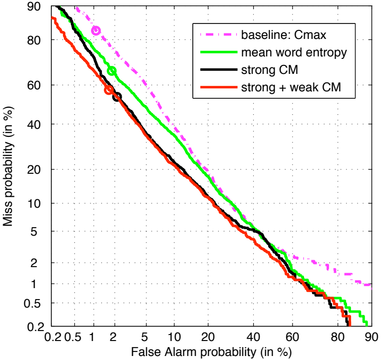
- In order to be consistent with workshop results, we used 8kHz down-sampled speech data

Results


HYB−SYSTEM
WRD−SYSTEM
Miss probability (in %)
False Alarm probability (in %)
90
80
60
40
20
10
5
2
0.1
0.2
0.5
1
2
5
10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Looking at False Alarms

- Despite our attempt to capture OOV regions by modeling them with sub-word units, The ASR system will make errors in both OOV and IV regions
- Some examples:

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  - Vector models to capture confusions between IV terms and fragments.

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- We can define a vector for a given region in the test data's confusion network

$$
\begin{aligned}
\overline{V}(t_j) &= (c_1, c_2, \cdots, c_{|F|}) \\
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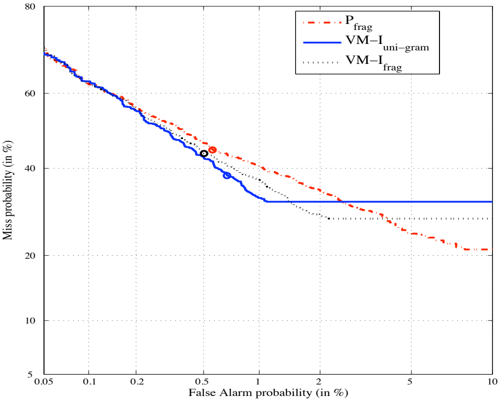
$$\begin{aligned} OOV_{score} &= \sum_{f \in \{t_j\}} p(f|t_j) \\ VM1 &= OOV_{score} - \alpha \\ VM2 &= OOV_{score} \cdot (1 - \alpha) \end{aligned}$$

Vector Model Results



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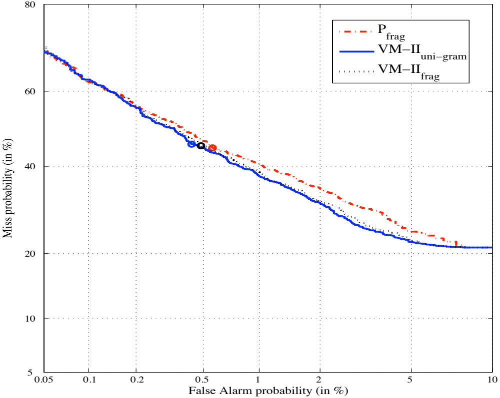

Questions/Comments