



Learning Out-of-Vocabulary Words in Automatic Speech Recognition

Long Qin

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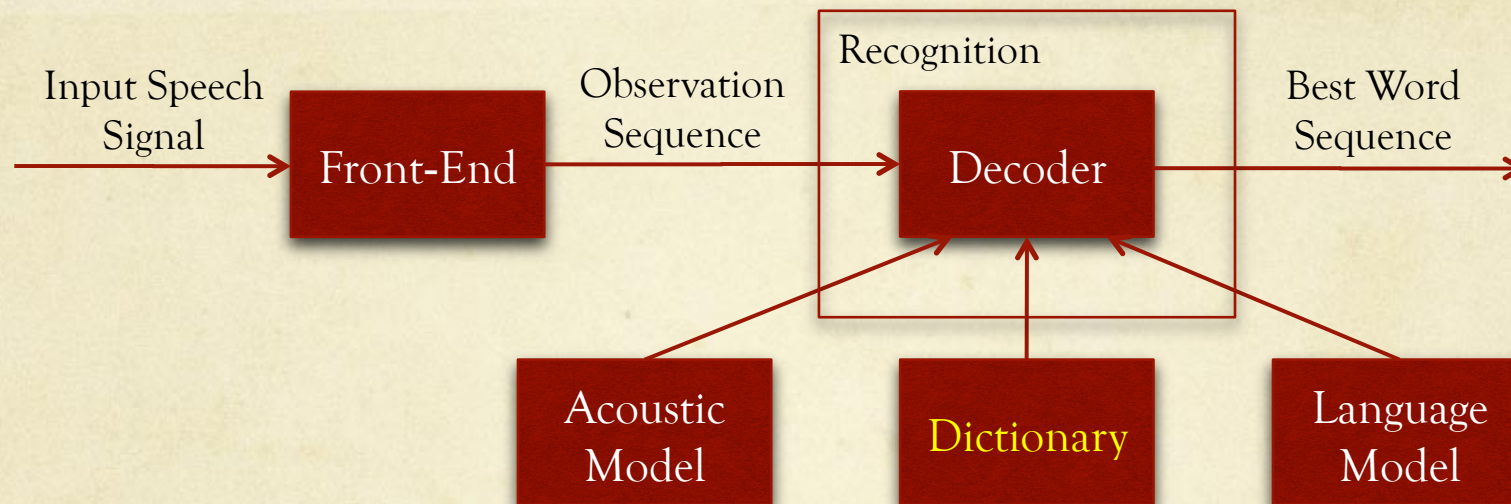
Outline

1. The Out-of-Vocabulary (OOV) word problem
2. The OOV word learning framework
 - a) System overview
 - b) OOV word detection
 - c) OOV word clustering
 - d) OOV word recovery
3. Conclusion and future work

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Automatic speech recognition (ASR)



IV (in-vocabulary) words

OOV (out-of-vocabulary) words:
words not in this list

a	AH
a(2)	EY
abandon	AH B AE N D AH N
⋮	⋮
zurich	Z UH R IH K

The OOV word problem

REF:	associated	inns	known	as	AIRCOA
HYP:	associated	inns	and	is	a tele

- ASR systems **mis-recognize** OOV word as IV word(s)
- OOV words **degrade** the recognition accuracy of surrounding IV words
- OOV words are **content words**, such as **names or locations**, which are crucial to the success of many speech recognition applications
- ASR systems which can **detect and recover** OOV words are of great interest

Related work

- OOV word detection
 - Find the mismatch between the phone and word recognition result
 - Consider OOV word detection as a binary classification task
 - Apply a hybrid lexicon and language model during decoding
- OOV word recovery
 - Apply phoneme-to-grapheme conversion or finite state transducer
 - Use an information retrieval and key word spotting system
 - Estimate rough language model scores from semantic similar IV words
- Convert OOV word into IV word
 - Recognize the same OOV word as IV word when it appears in the future
 - An ASR system can learn new words and operate on an open vocabulary

[Hayamizu et al., 1993; Klakow et al., 1999; Sun et al., 2003; Bisani & Ney, 2005; Hannemann et al., 2010; Parada et al., 2010; Lecorve et al., 2011]

Thesis Statement

OOV words can be automatically **detected, clustered and recovered** in an integrated learning framework. Given the ability to add **new words**, a speech recognition system can operate with an **open vocabulary**.

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OOV word detection

- OOV word detection is to **find the appearance** of OOV word in an utterance

... associated inns known as **AIRCOA** ...



OOV word detection result

... associated inns known as **EH R K OW AH** ...

From the detection
results of all testing
speech

Detected OOV Words

O_1 MAO RAO F

O_2 **EH R K OW AH**

... ...

O_N K EH N DAH L

OOV word clustering

- OOV word clustering is to find the multiple instances of an OOV word from the OOV word detection result

Detected OOV Words

O_1 MAO RAO F

O_2 EH R K OW AH

O_3 BAO RAH S

O_4 BAH RAO F

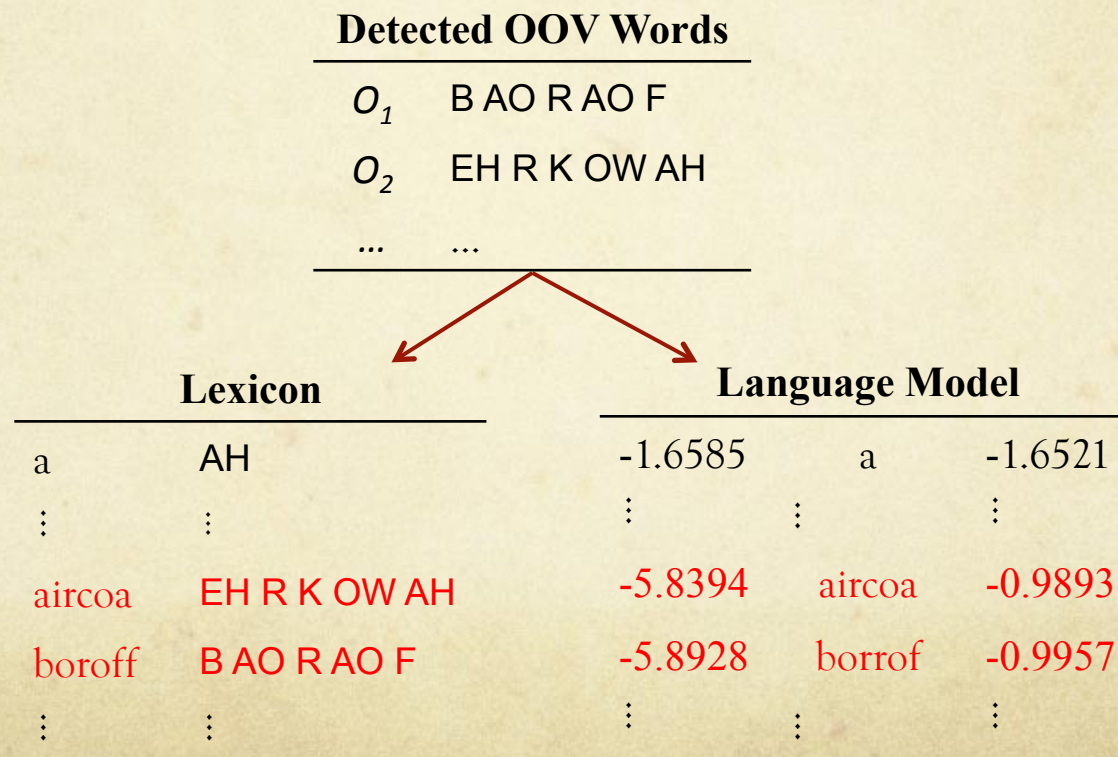
...

O_N KEH N DAH L

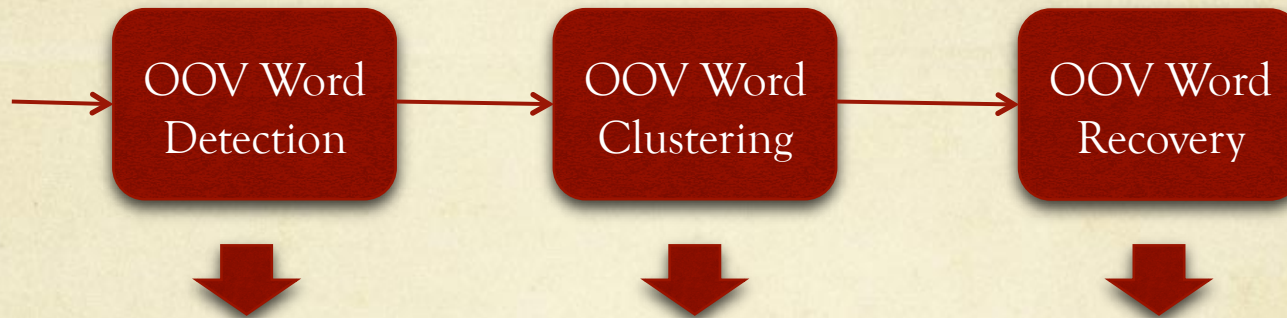
Same OOV word

OOV word recovery

- OOV word recovery is to recover the **written form and language model (LM) scores** of detected OOV words, then integrate them into the **lexicon and LM**



The OOV word learning framework



Detected OOV Words	
O_1	MAO RAO F
O_2	EH R K OW AH
O_3	BAO RAH S
O_4	BAH RAO F
...	...
O_N	KEH N DAH L

Detected OOV Words	
O_1	BAO RAO F
O_2	EH R K OW AH
...	...
O_M	KEH N DAH L

Lexicon	
a	AH
⋮	⋮
aircoa	EH R K OW AH
boroff	BAO RAO F
⋮	⋮

Language Model		
-1.6585	a	-1.6521
⋮	⋮	⋮
-5.8394	aircoa	-0.9893
-5.8928	borrof	-0.9957
⋮	⋮	⋮

OOV word detection



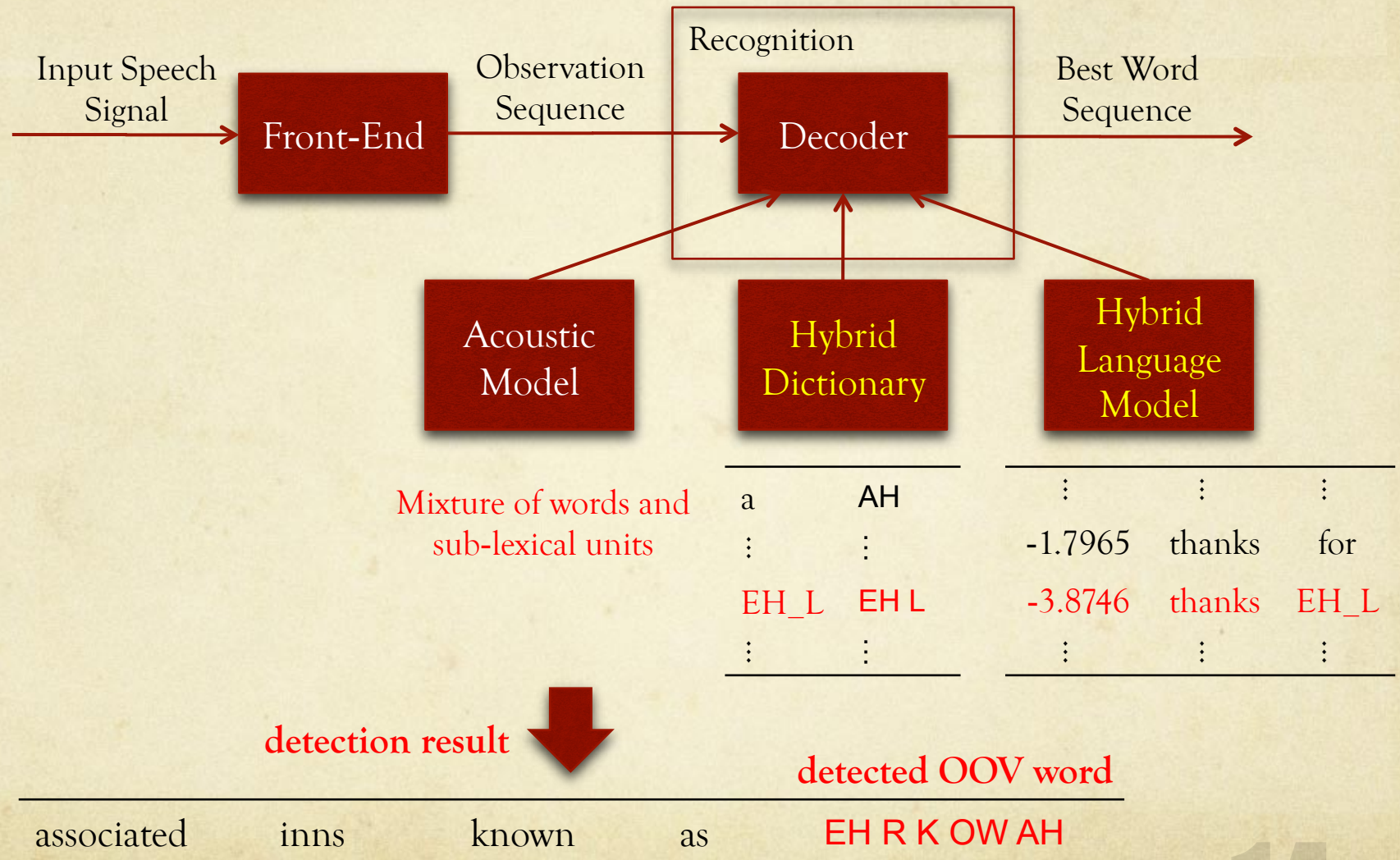
OOV Word
Detection



Detected OOV Words

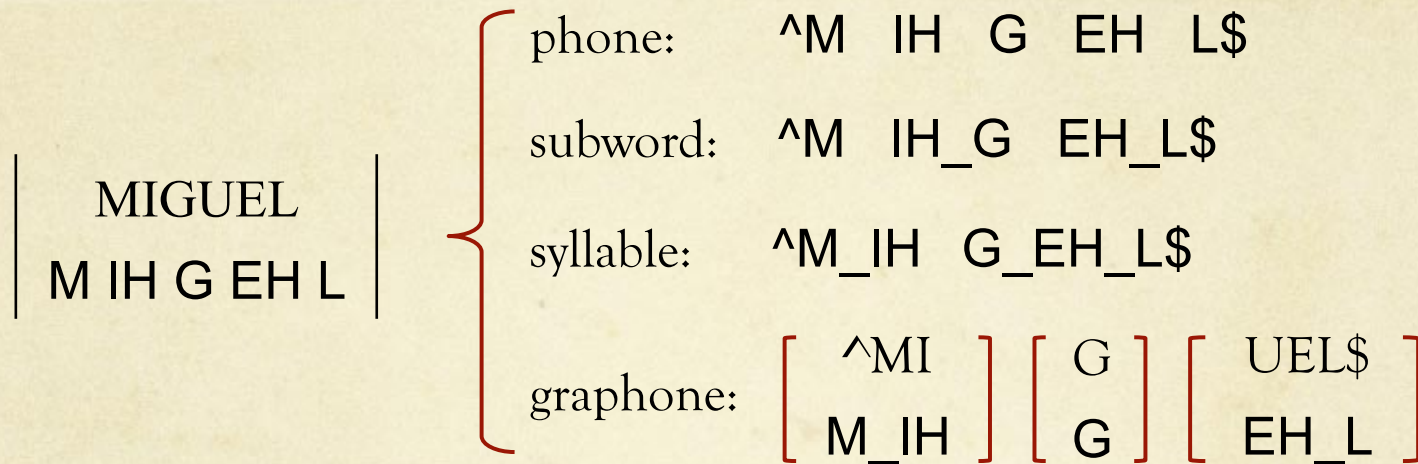
O_1	MAO RAO F
O_2	EH R K OWAH
O_3	BAO RAH S
O_4	BAH RAO F
...	...
O_N	KEH N DAH L

The hybrid system



Sub-lexical units

- Build hybrid systems using different types of sub-lexical units



	Pros	Cons
Subword	simple and robust	lack linguistic restrictions
Syllable	maintain phonetic restrictions	produce long rare units
Grapheme	model both letters and phones	large number of units

Combining multiple systems' outputs

Syllable Hybrid System:	partner	of	EH R K OW AH	hotel
Subword Hybrid System:	partner	of	EH R OW AH	hotel
Graphone Hybrid System:	partner	of	Iowa	hotel

*Convert OOV tokens to *OOV**

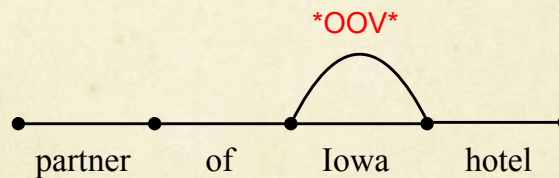


Syllable Hybrid System:	partner	of	*OOV*	hotel
Subword Hybrid System:	partner	of	*OOV*	hotel
Graphone Hybrid System:	partner	of	Iowa	hotel

Combination



Word Transition
Network



Rescoring



Best Result: partner of *OOV* hotel

Combining multiple types of sub-lexical units

- Utilize multiple types of units in one system, so that different units can complement each other

... PRESIDENT **MIGUEL** DE LA MADRID'S SERIOUSNESS ...
... BOARD OF SAN **MIGUEL** CORPORATION ...



For each appearance of **MIGUEL**, we stochastically select one type of units

... PRESIDENT **^M_IH G_EH_L\$** DE LA MADRID'S SERIOUSNESS ...
... BOARD OF SAN **^MI:M_IH G:G UEL\$:EH_L** CORPORATION ...

One OOV word can be modeled by multiple types of sub-lexical units!

Datasets

	WSJ	BN	SWB
Vocabulary Size	20k	20k	10k
Dev OOV	319 (2.1%)	204 (2.0%)	204 (1.7%)
Eval OOV	200 (2.2%)	255 (2.0%)	209 (1.7%)
Test OOV	260 (2.1%) 136	381 (2.8%) 91	383 (1.8%) 253

- Dev data is used to tune parameters in training
- Eval data is used to learn OOV words
- Test data is used to evaluate how many recovered OOV words can be recognized

OOV word detection experiments

- Evaluation metrics:

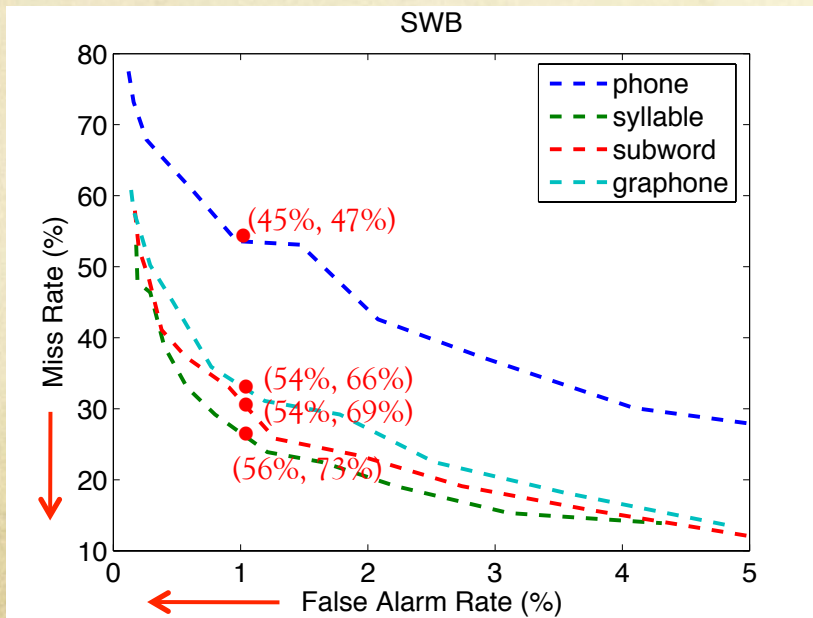
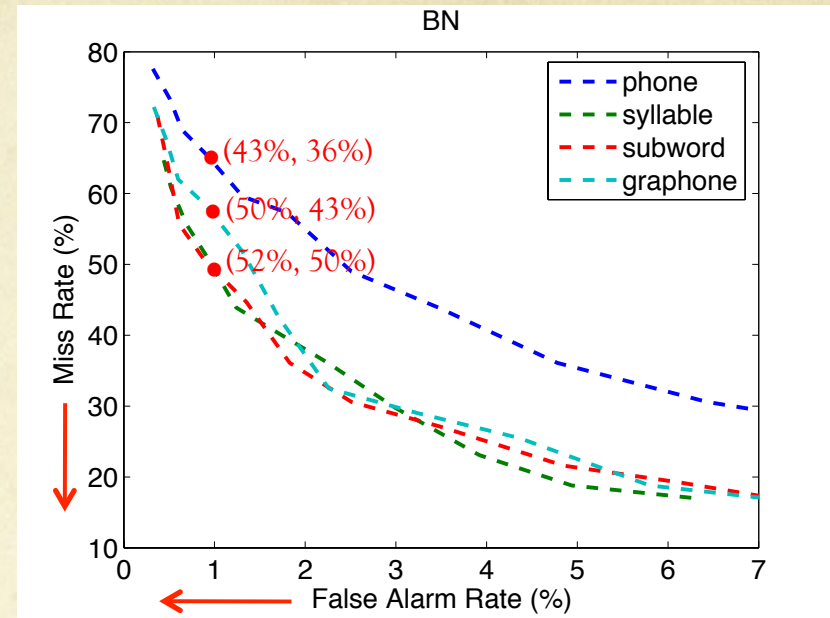
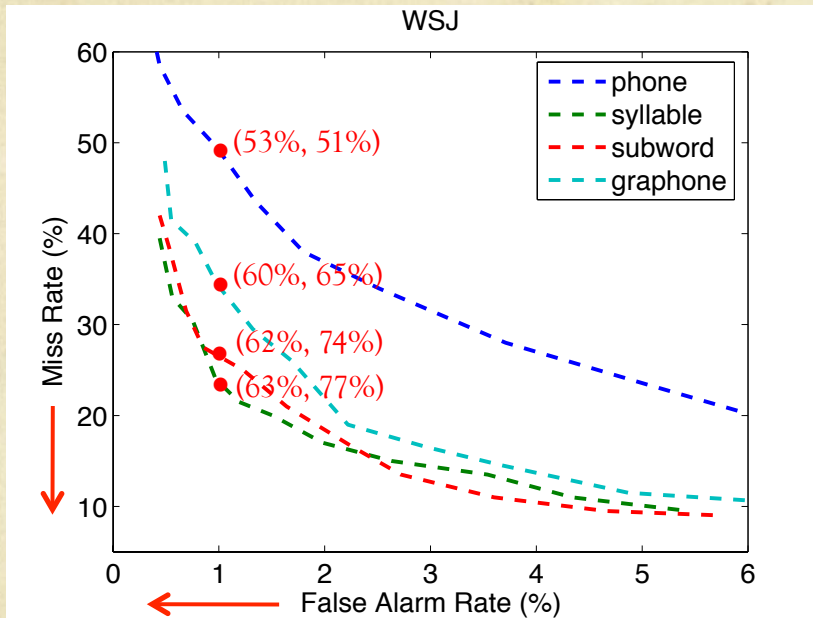
$$\text{Miss Rate (MR)} = \frac{\# \text{OOVs in reference} - \# \text{IVs detected}}{\# \text{OOVs in reference}} * 100\%$$

$$\text{False Alarm Rate (FAR)} = \frac{\# \text{OOVs reported} - \# \text{OOVs detected}}{\# \text{IVs in reference}} * 100\%$$

- OOV cost

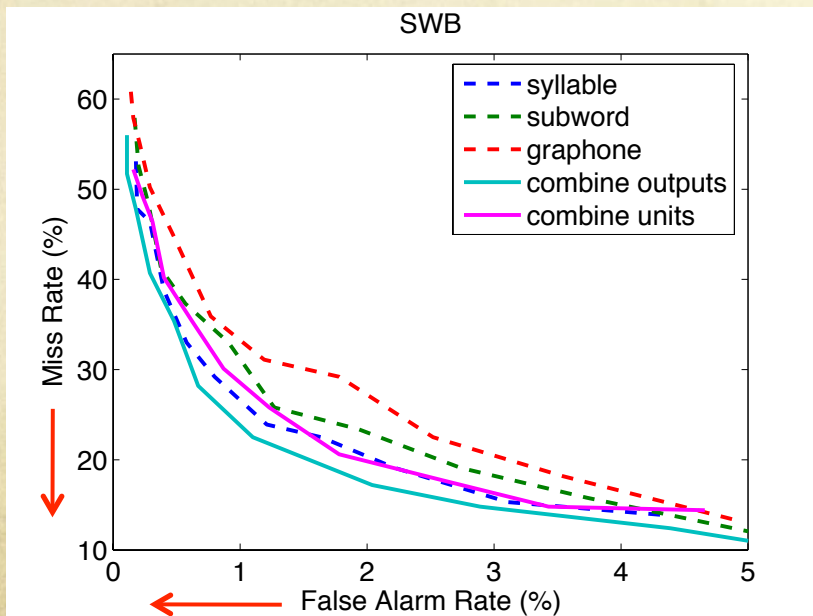
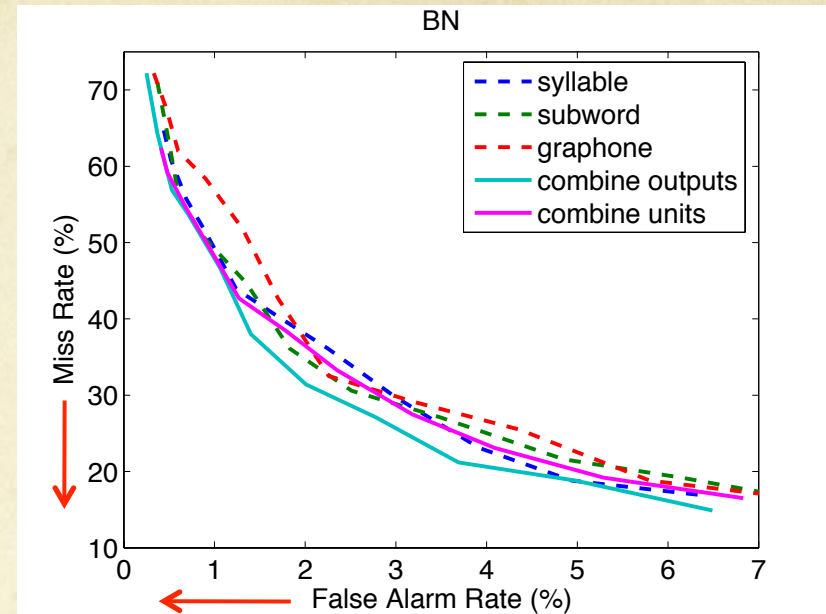
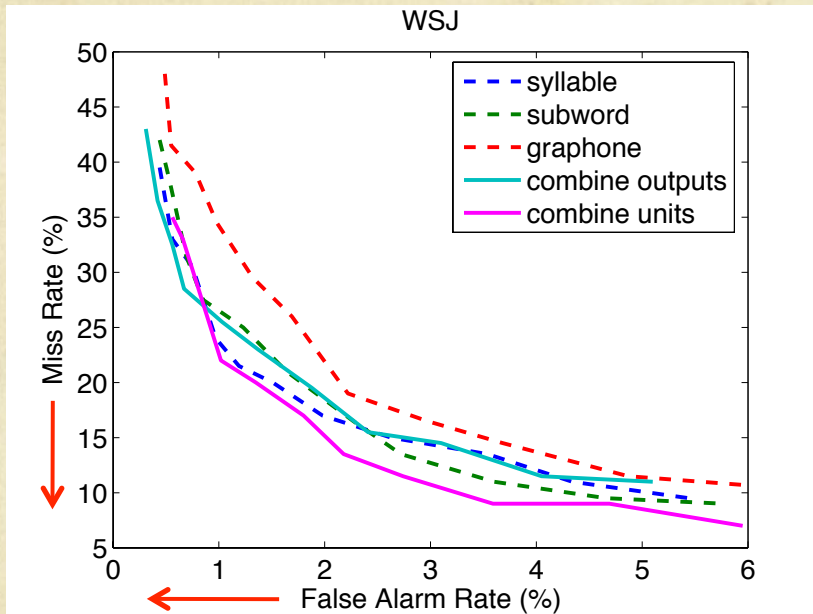
- Control how likely to decode OOV word
- Adjusted from 0 to 2.5 with a step size of 0.25
- Draw MR-FAR curve to select operation point for specific application

The OOV word detection results



- Complex sub-lexical units perform better than simple phone units
- Perform better in the WSJ and SWB tasks than in the BN task
- On average, detect up to 70% OOV words with up to 60% precision (Precision, Recall)

The system combination results



- Two combined systems perform differently across different tasks
- Better combined system performs better than individual systems

OOV word recovery



OOV Word
Detection

OOV Word
Clustering

Detected OOV Words	
O_1	MAO RAO F
O_2	EH R K OWAH
O_3	BAO RAH S
O_4	BAH RAO F
...	...
O_N	KEH N DAH L

Detected OOV Words	
O_1	BAO RAO F
O_2	EH R K OWAH
...	...
O_M	KEH N DAH L

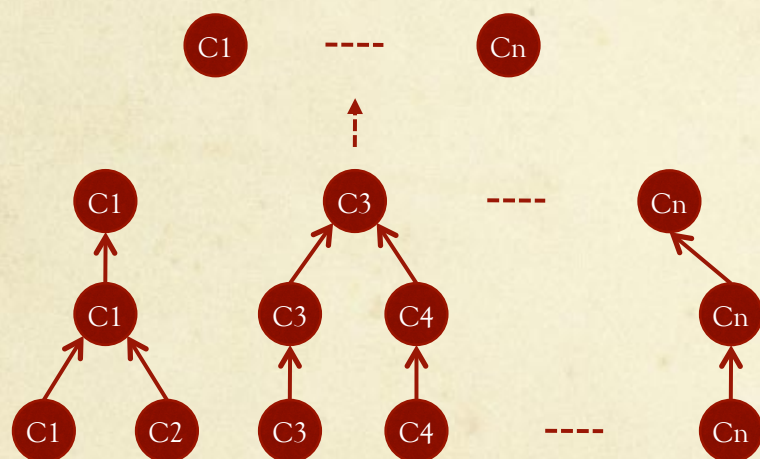
Detect up to 70%
OOV words

Recurrent OOV words

- OOV words can **appear more than once** in a conversation or over a period of time
 - Find **multiple instances** of an OOV word in the detection result
- Multiple instances of an OOV word are valuable for estimating
 - Pronunciation
 - Part-of-Speech (POS) tag
 - Language model (LM) scores

A bottom-up clustering process

- Finding multiple instances of the same OOV word through bottom-up clustering



$$D(C_i, C_j) = \varpi_1 d_1 + \varpi_2 d_2 + \varpi_3 d_3$$

d_1 : phonetic distance

d_2 : acoustic distance

d_3 : contextual distance

Collecting features from hybrid system output

OOV	Phonetic (Decoded Phones)	Acoustic (Posterior Vectors)	Contextual (Surrounding IV Words)
O_1	S E H L T S	[0.00 ... 0.17]	... from in O_1 major Dietz ...
O_2	K A E D I Y	[0.01 ... 0.24]	... people's party O_2 moved into ...
O_3	W A O L I Y	[0.02 ... 0.01]	... the rule of O_3 ball ...

- Phonetic distance
 - Modified edit distance
- Acoustic distance
 - Dynamic time warping (DTW) distance
- Contextual distance
 - Local contextual distance works like a LM
 - Global contextual distance resembles a topic model

OOV word clustering experiments

- Hybrid system outputs

	WSJ	BN	SWB
F1 (%)	69	55	71

- Number of recurrent OOV words

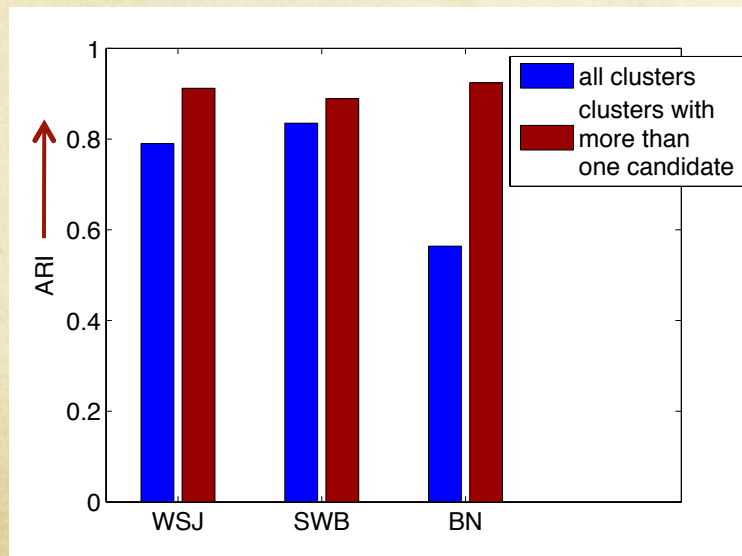
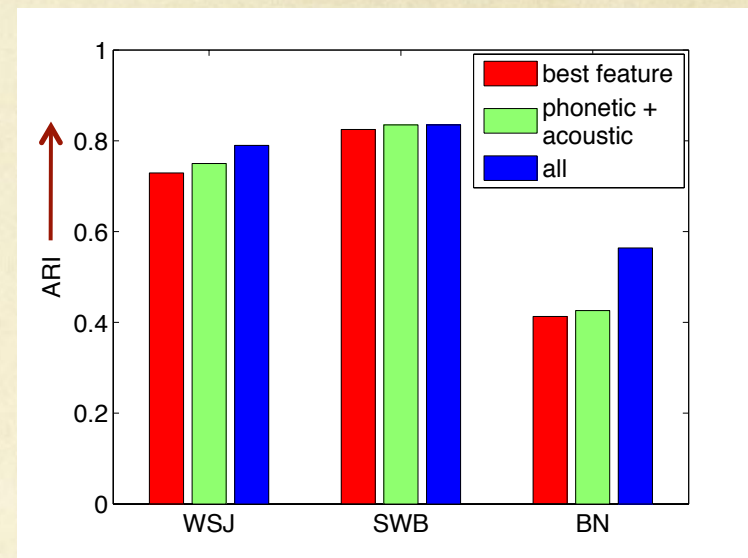
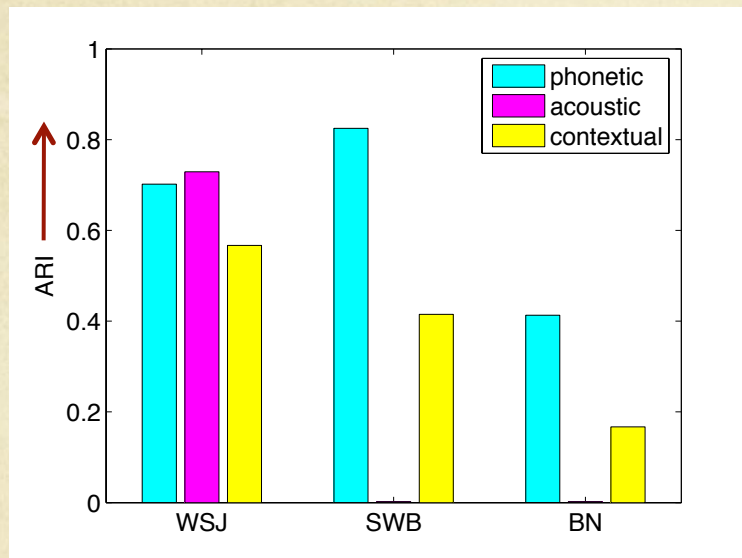
	WSJ	BN	SWB
Count	68 (29%)	109 (31%)	52 (22%)

- Evaluation metrics: adjusted Rand index (ARI)

$$RI = \frac{TP + TN}{TP + FP + TN + FN}$$

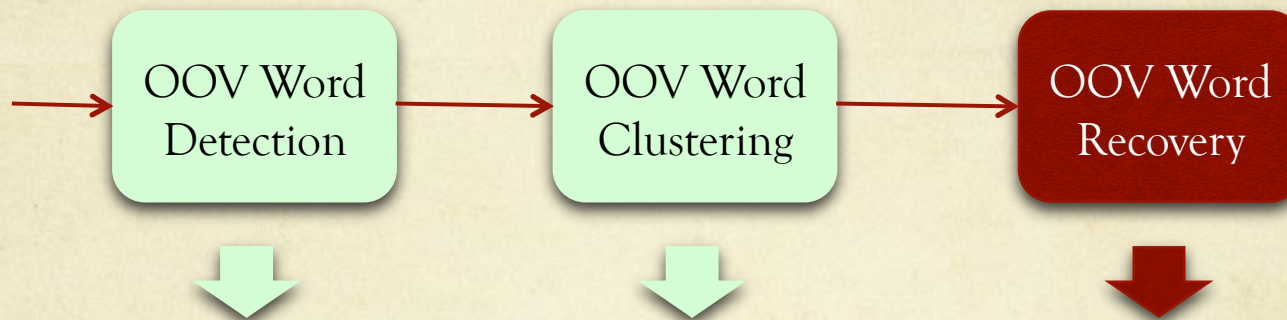
- Adjusted for the chance of a clustering
- Bounded between [-1, 1], 0 for random clustering
- If without clustering, ARI is close to 0

The OOV word clustering results



- Using one feature
 - Phonetic feature is effective in all tasks
 - Acoustic features only works in WSJ
 - Contextual feature produces positive result
- Using more features is better
- ARI is 0.9 on found recurrent OOV words (comparable to 10% or less errors)

The OOV word learning framework



Detected OOV Words	
O_1	MAO RAO F
O_2	EH R K OW AH
O_3	BAO RAH S
O_4	BAH RAO F
...	...
O_N	KEH N DAH L

Detect up to 70%
OOV words

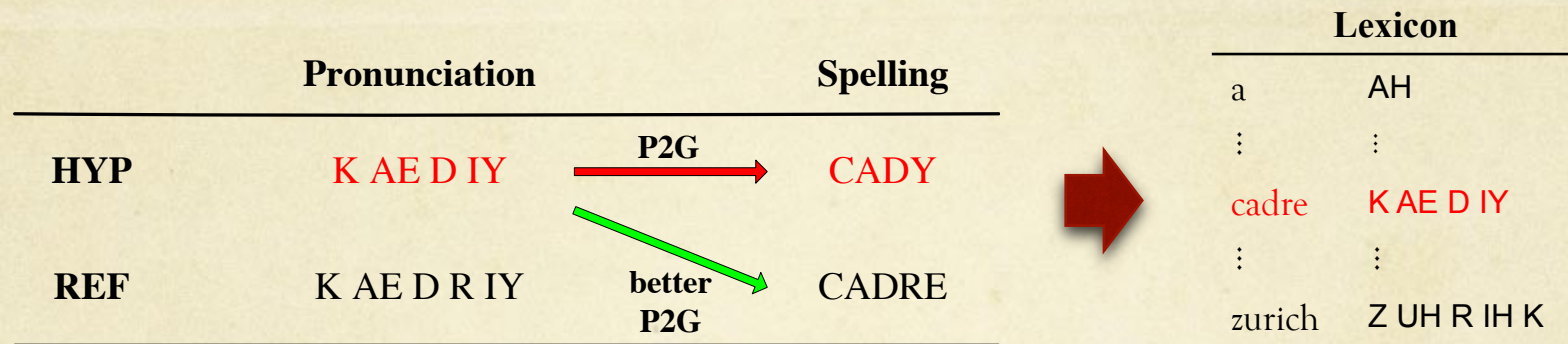
Detected OOV Words	
O_1	BAO RAO F
O_2	EH R K OW AH
...	...
O_M	KEH N DAH L

ARI is up to 0.9

Lexicon	
a	AH
:	:
aircoa	EH R K OW AH
boroff	BAO RAO F
:	:

Language Model		
-1.6585	a	-1.6521
:	:	:
-5.8394	aircoa	-0.9893
-5.8928	borrof	-0.9957
:	:	:

Estimating the written form of an OOV word



- Conventional P2G model is trained from alignments between correct spelling and pronunciation
- Train better P2G model also from alignments between correct spelling and incorrect decoded pronunciation
 - Extract alignments from hybrid decoding result of training speech

Estimating language model scores of an OOV word

- Learn from IV words in the **same syntactic category**
 - Train a **Part-of-speech (POS) class-based LM** from training text data (Stanford POS tagger)
 - Estimate LM scores based on the **POS label of an OOV word**

HYP	partner	of	AIRCOA	hotel	partners
POS	NN	IN	NNP	NN	NNS

$$P(\text{AIRCOA} | \text{partner, of}) = P(\text{AIRCOA} | \text{NNP})P(\text{NNP} | \text{NN, IN})$$

- OOV words may **appear in different context** in future
 - Estimate **possible context** an OOV word may appear
 - Substitute **surrounding IV words** of an OOV word with **other semantic similar IV words** (WordNet)

hotel ↔ inn
↓

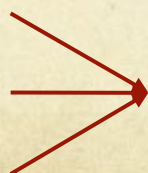
New Context	partner	of	AIRCOA	inn	partners
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Recovering recurrent OOV words

- Estimate better pronunciation

OOV	Pronunciation	
O_1	MAO RAO F	
O_2	BAO RAH S	
O_3	BAH RAO F	
		BAO RAO F → BOROFF

- Estimate better language model scores

OOV	POS		Multiple Context
O_1	NNP		... Philip BOROFF has more from ...
O_2	NNP+POS		... I am Philip BOROFF </s>
O_3	NNP		... this is Philip BOROFF from ..

OOV word recovery experiments

○ Evaluation metrics

$$\text{Phone Accuracy (PA)} = \frac{\# \text{OOVs with correct pronunciation}}{\# \text{OOVs detected}} * 100\%$$

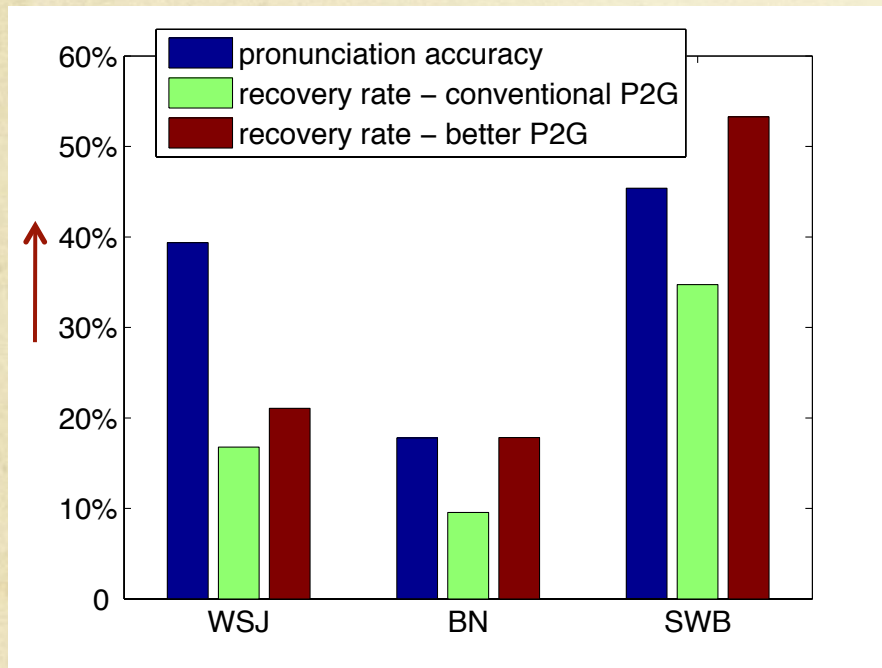
$$\text{Recovery Rate (RR)} = \frac{\# \text{OOVs recovered}}{\# \text{OOVs detected}} * 100\%$$

$$\text{Word Error Rate (WER)} = \frac{\# \text{substitution errors} + \# \text{deletion errors} + \# \text{insertion errors}}{\# \text{words in reference}} * 100\%$$

○ Compare

- The number of recovered OOV words - **detected OOV words with correct written form**
- The number of recovered OOV words **recognized in the 2nd pass decoding of Eval data**
- The number of recovered OOV words **recognized in the 1st pass decoding of Test data**

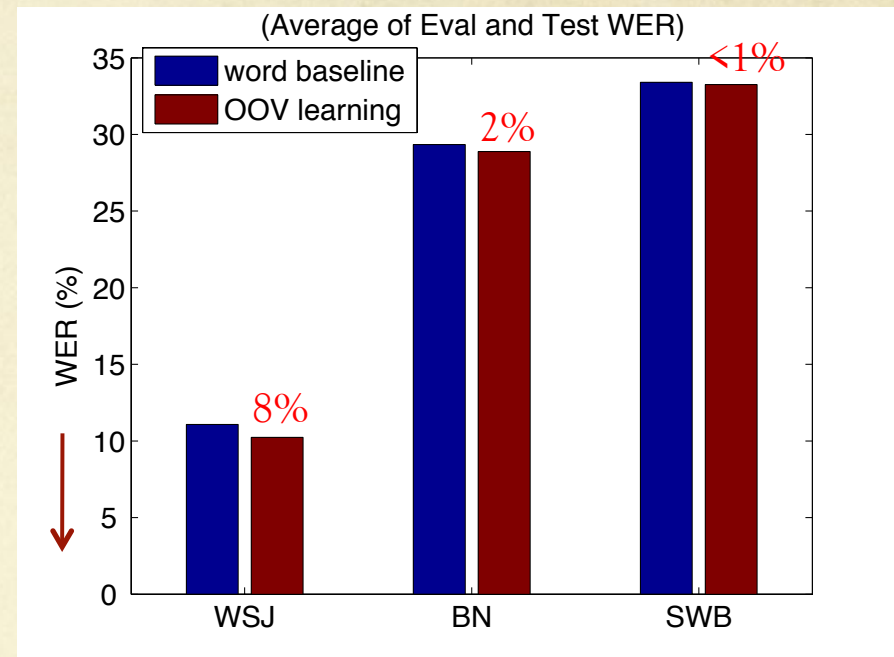
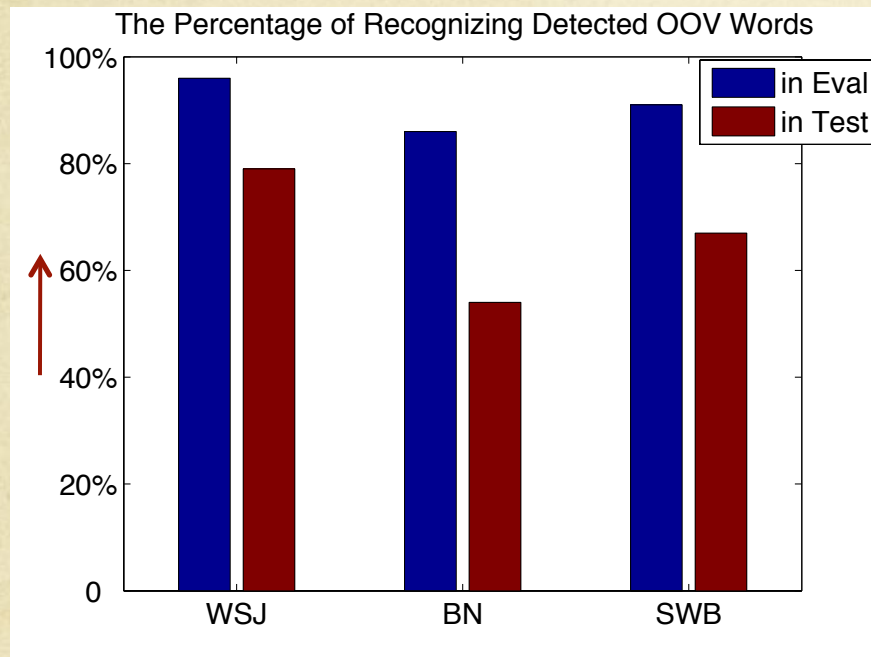
The results of estimating the written form



	WSJ	BN	SWB
No. OOV in Eval	200	255	209
No. recovered OOVs in Eval	90 (45%)	73 (29%)	101 (48%)
No. OOV in Test	136	91	253
No. recovered OOVs in Test	61 (45%)	39 (43%)	119 (47%)

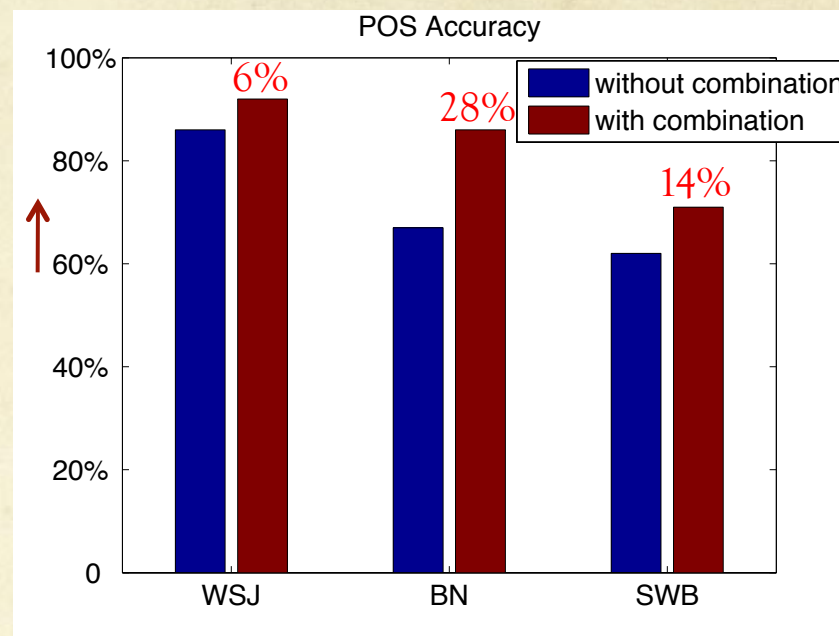
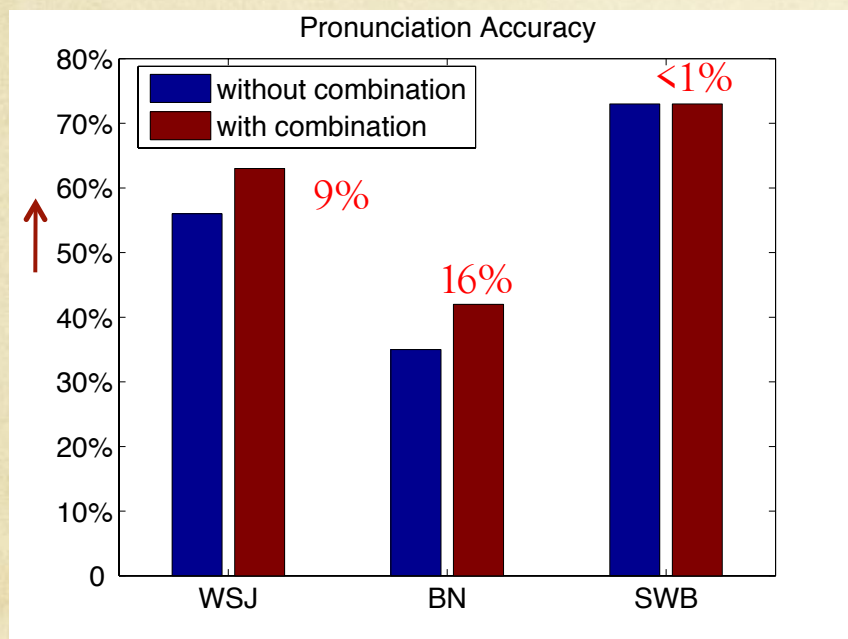
- Significantly higher recovery rate when using the better P2G model
- Eliminate 40% OOV words after integrating recovered OOV words into the lexicon

The results of estimating language model scores



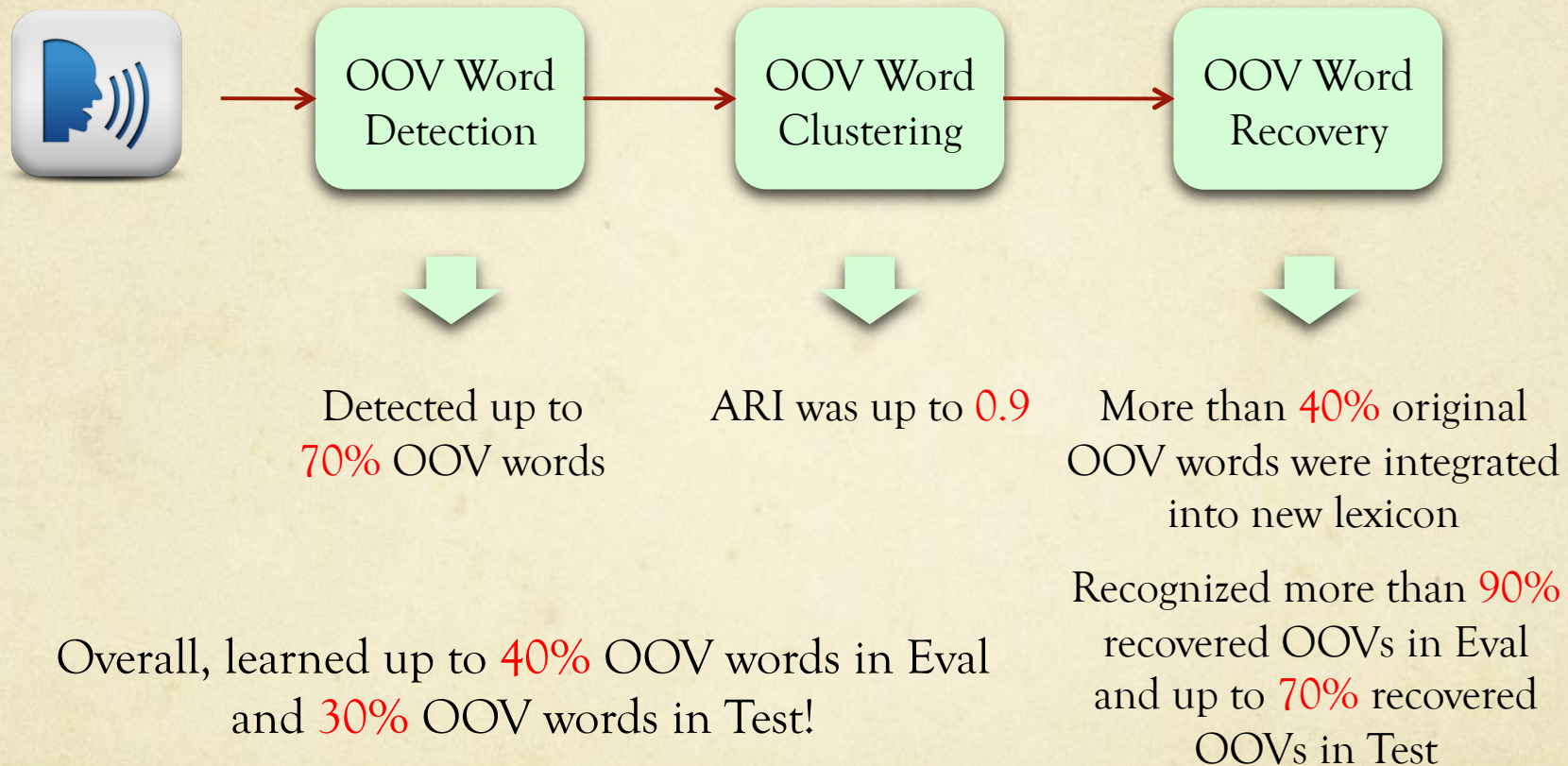
- Recognized more than 90% recovered OOV words in 2nd pass decoding of Eval data and up to 70% in 1st pass decoding of Test data
- Small improvement on WER
 - Higher WER when adding bigrams, trigrams and new context, but recognized more OOV words

The results of recovering recurrent OOV words



- Only calculated on Recurrent OOV words
- No improvement on recognizing more recovered OOV words or WER
 - Only a few recurrent OOV words in the Eval and Test data

The overall performance



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 - a) OOV word detection
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Thesis contributions

- We proposed an OOV word learning framework and showed an ASR system was capable of learning new words.
- Compared different training schemes and types of sub-lexical units for building the hybrid system. Found that flat hybrid system is better than hierarchical hybrid system, and syllable, subword and grapheme units are better than simple phone units. [Qin et al., 2011]
- Applied system combination and OOV word classifier techniques to improve the OOV word detection performance. Combined systems outperformed individual systems built with one type of units. [Qin et al., 2012; Qin and Rudnicky, 2012]
- Identified recurrent OOV words through bottom-up clustering. And showed that multiple instances of an OOV word were valuable for improving the OOV word recovery performance. [Qin and Rudnicky, 2013]
- Trained a better P2G model from the decoding result of training speech. And successfully estimated LM scores for OOV words from syntactic and semantic similar IV words.

Conclusion

- Hybrid system is effective at detecting OOV words. Our system can detect up to 70% OOV words with up to 60% precision.
- Bottom-up clustering finds most recurrent OOV words. Multiple instances of recurrent OOV words improve OOV word learning performance.
- Up to 90% recovered OOV words are recognized after integrating them into the recognizer's lexicon and language model.
- Overall, this OOV word learning framework can successfully learn up to 40% OOV words.

Future work

- OOV word learning curve
 - Human has learning curve to learn new words
 - How to update knowledge about learned new words?
- OOV word learning in a dialog system
 - How to learn OOV words through interactions between user and system?
 - Learn semantic information about a word

Acknowledgments



Q&A

THANKS!