

Sahar Ghannay, Yannick Estève and Nathalie Camelin
LIUM- Le Mans University, France

Introduction

Error detection

- Supervised machine learning task
- Detection of anomalies in automatic transcriptions:
 - from linguistic or semantic levels
 - from acoustic level

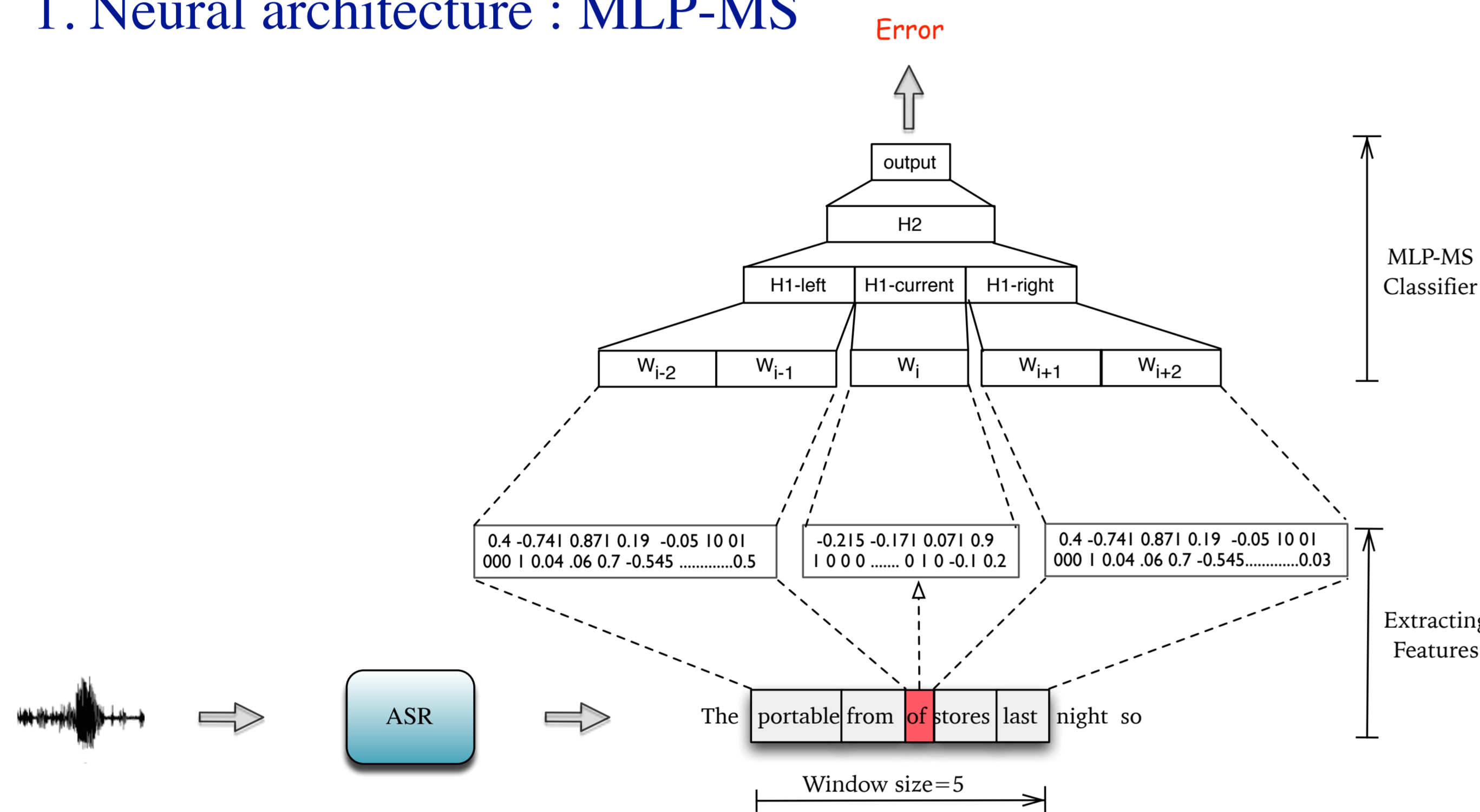
Main goal

- Modeling automatic speech recognition (ASR) errors at the sentence level through:
 - Continuous sentence representations (*embeddings*) specific to ASR error detection task
 - Probabilistic contextual model

In addition, we will compare our approaches to bidirectional long short-term memory (BLSTM) architecture previously published.

ASR error detection

1. Neural architecture : MLP-MS



2. List of features

- Posterior probabilities**
- Lexical features:** word length, existence of 3-grams in the ML
- Syntactic features:** POS tag, dependency label, word governor
- Prosodic features:** number and average duration of phonemes, duration of previous and next pause, average f0 of the word, etc.
- Word:** linguistic and acoustic embeddings

Experiments

1. Experimental data

Automatic transcriptions of Etape Corpus

	Name	#words ref	#words hyp	WER
Train		349K	316K	25.3
Dev		54K	50K	24.6
Test		58K	53K	21.9

2. Baseline results

Sys1: all features described above excepting the prosodic ones

Sys2: all features

Corpus	System	Label Error			Global
		P	R	F	CER
Dev	Sys1	0.71	0.58	0.64	9.53
	Sys2	0.71	0.60	0.65	9.38
Test	Sys1	0.70	0.59	0.64	7.94
	Sys2	0.70	0.61	0.65	7.75

- prosodic features improve all the results

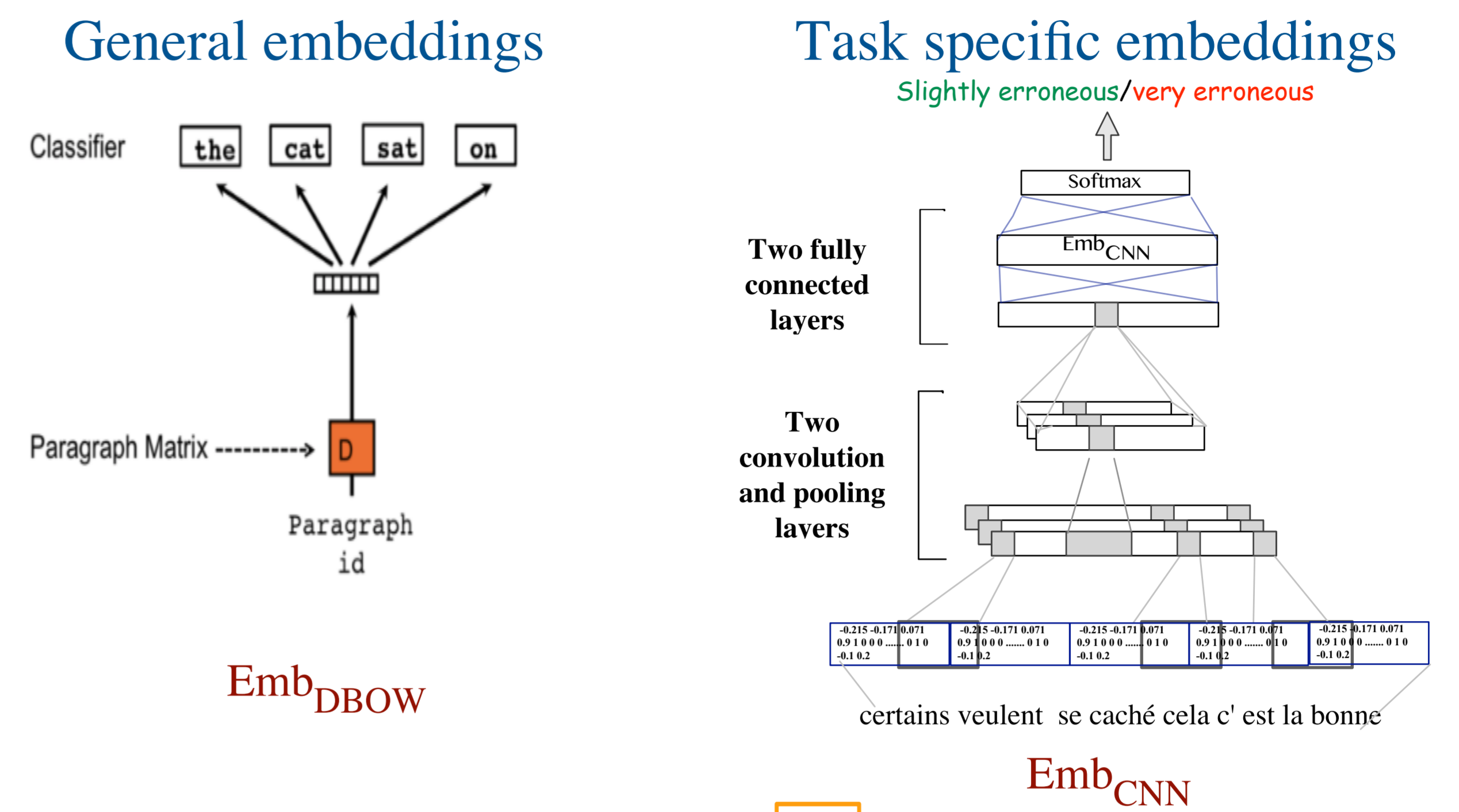
Average ASR error span analysis of Sys2 outputs:

Corpus		Average span	Standard deviation
Train	Ground truth	3.03	1.72
	Dev	3.24	2.15
Dev	Predictions	2.82	1.28
	Correct predictions	2.66	1.05

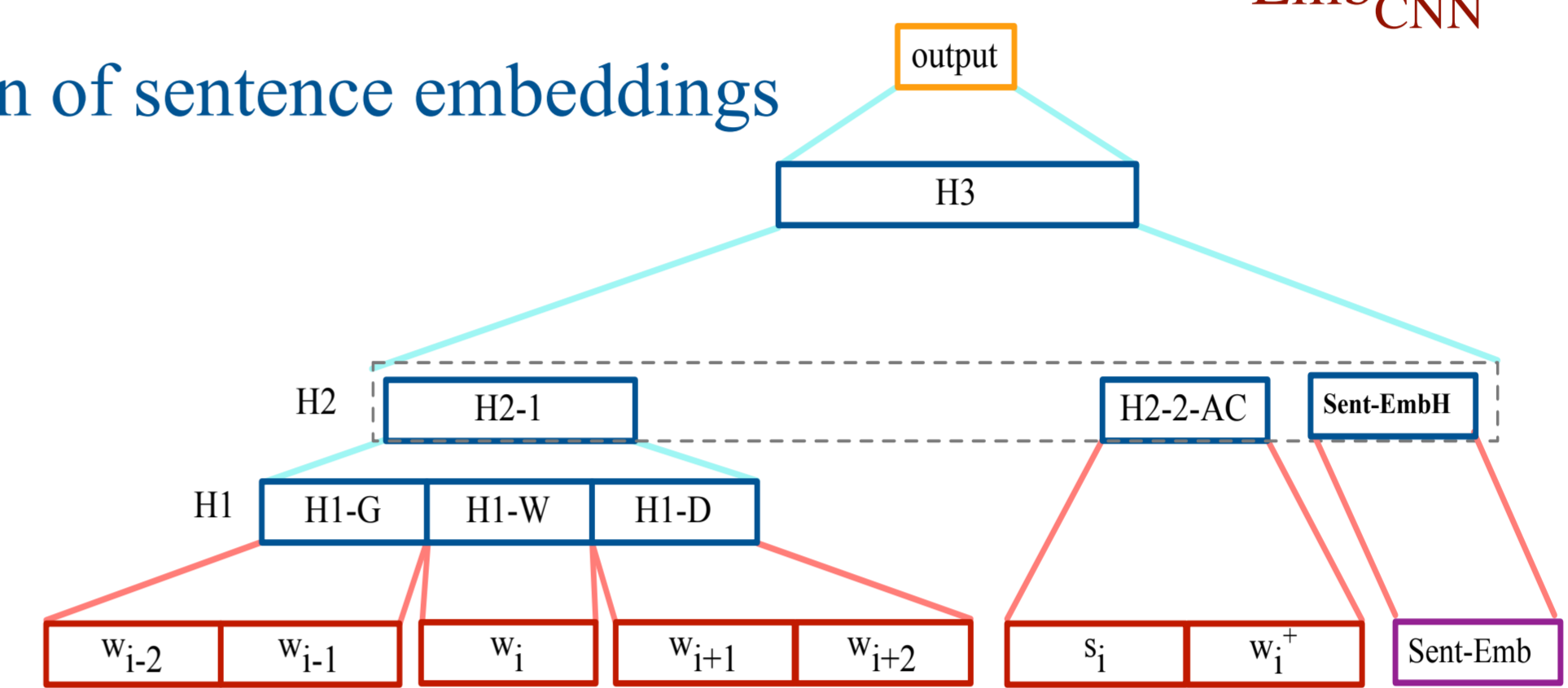
- Average span of Sys2 is too small in comparison to the ground truth

Experiments: Integration of global information

1. Continuous sentence representations



Integration of sentence embeddings



Performance of sentence embeddings

Corpus	Sentence Embed.	Label Error			Global
		P	R	F	CER
Dev	-(Sys2)	0.72	0.60	0.65	9.38
	Emb _{DBOW}	0.73	0.58	0.65	9.36
	Emb _{CNN}	0.72	0.60	0.65	9.26
Test	-(Sys2)	0.70	0.61	0.65	7.75
	Emb _{DBOW}	0.72	0.57	0.64	7.72
	Emb _{CNN}	0.72	0.58	0.64	7.69

- Integration of sentence embeddings improves the results
- Task specific sentence embeddings outperforms generic ones

2. Probabilistic contextual model (PCM)

- Smoothing of the classification results at the sentence level
- Re-scoring of a graph of labels by applying an n-order probabilistic model of error distribution
- Find the sequence label S that maximizes:

$$\bar{S} = \arg \max_e \prod_{i=1}^n c(e_i)^\lambda \times P(e_i | e_{i-2}, e_{i-1}, e_{i+1}, e_{i+2})$$

Sys3: Sys2 features + task specific sentence embeddings (Emb_{CNN})

Corpus	System	Label error			Global
		P	R	F	CER
Dev	Sys2-PCM	0.73	0.56	0.65	9.31
	Sys3-PCM	0.73	0.60	0.65	9.23
Test	Sys2-PCM	0.72	0.59	0.65	7.67
	Sys3-PCM	0.73	0.57	0.64	7.69

- PCM improves Sys2 results: global information is brought
- Sys3 already contains global information: no real gain with PCM

3. BLSTM architecture

- BLSTM composed of two hidden layers (512 hidden units each)
- Includes the Sys2 features

Corpus	System	Label Error			
		P	R	F	CER
Dev	BLSTM	0.70	0.63	0.67	9.28
Test	BLSTM	0.69	0.63	0.66	7.83

- BLSTM vs. Sys2
- Better on Dev
- Not generalized on Test, too few training data?

Conclusions

Effective integration of global information about the sentence into ASR error detection system to improve local decision

- The task specific sentence embeddings Emb_{CNN} perform better than generic embeddings Emb_{DBOW}
- The probabilistic contextual model improves the results when no global information is included in the features