Continuous word representation and prosodic features for ASR error detection

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Introduction

MGB 2015 challenge results for ASR task on BBC data

	Best Sys	CRIM/ LIUM	Sys1	Sys2	Sys3	LIUM	Sys4	Sys5	Sys6	Sys7	Sys8	Sys9
Overall WER(%)	**23.7**	26.6	27.5	27.8	28.8	30.4	30.9	31.2	35.5	38.0	38.7	40.8

Introduction

MGB 2015 challenge result

Detailed performance of the best system

Show	Best system
Daily Politics	10.4
Magnetic North	11.6
Dragons'Den	11.5
Eggheads	14.1
Athletics London	14.7
Point of View	13.5
Syd Barrett	21.3
Top Gear	21.8
Blue Peter	24.6
Legend of the Dragon	21.7
The North West 200	27.7
Holby City	32.1
The Wall	33.7
One Life Special Mum	35.3
Goodness Gracious ME	37.2
Oliver Twist	**41.4**
Overall WER(%)	***23.7***

Introduction

ASR errors have impact on downstream applications:

- Information retrieval
- Speech to speech translation
- Spoken language understanding
- Enhancement of training corpus of acoustic model from unlabeled data
- etc.

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⇨ ASR error detection can help

Introduction

✓ Related work

- Approaches based on Conditional Random Field (CRF)
  - OOV detection [C. Parada *et al.* 2010]
    - Contextual information
  - Errors detection [F. Béchet & B. Favre 2013]
    - ASR based, lexical and syntactic informations
  - Errors detection at word/utterance level [Stoyanchev *et al.* 2012]
    - Syntactic and prosodic features
- Approach based on neural network
  - Errors detection [T. Yik-Cheung *et al.* 2014]
    - Complementary ASR systems

Introduction

✓ Contributions

✤ Neural approach

- Word embeddings combination
- Prosodic features
- Confidence measures produced by the neural system

Word embeddings

Mapping words to high-dimensional vectors (e.g. 200 dimensions)

$$R : Words = \{W_1, ..., W_n\} \rightarrow Vectors = \{R(W_1), ..., R(W_n)\} \subset R^d$$

Distance between vectors indicates the relation between words

$$R(W_1) \approx R(W_n) \rightarrow W_1 \approx W_n$$

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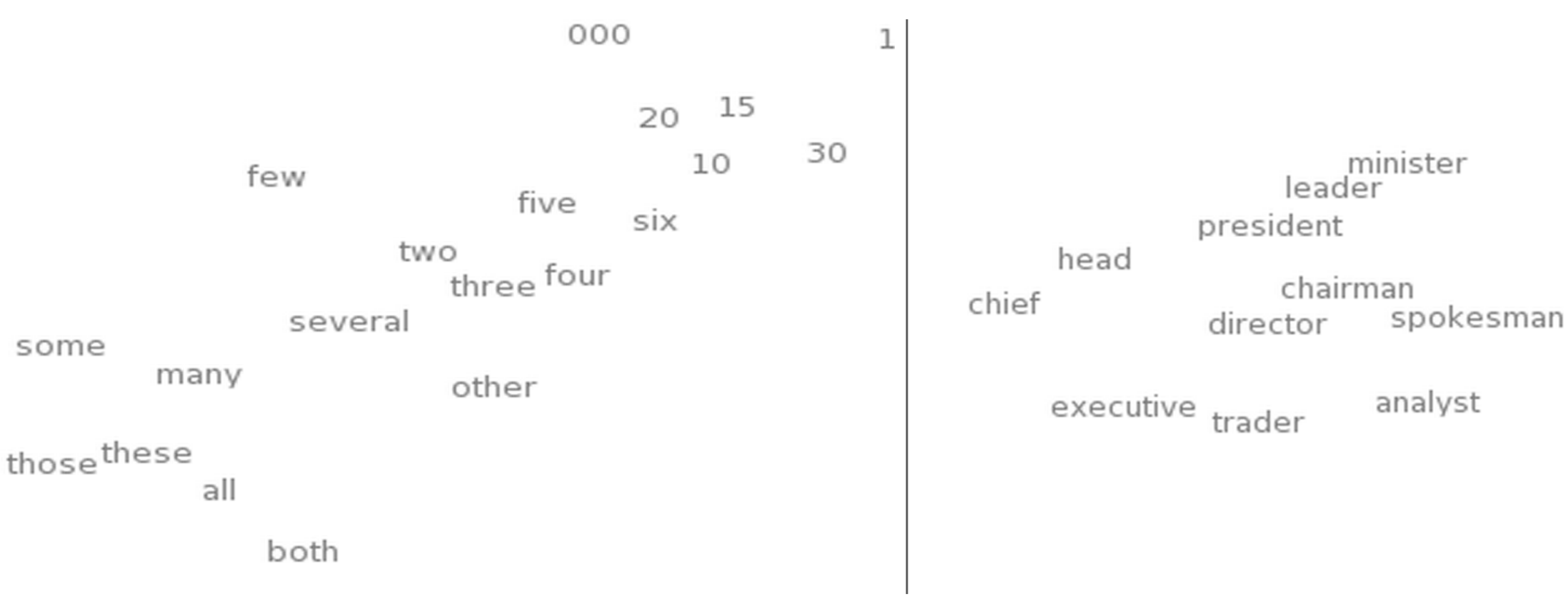


2D t-SNE visualizations of word embeddings. Left: Number Region; Right: Jobs Region [J.Turian *et al* . 2010]

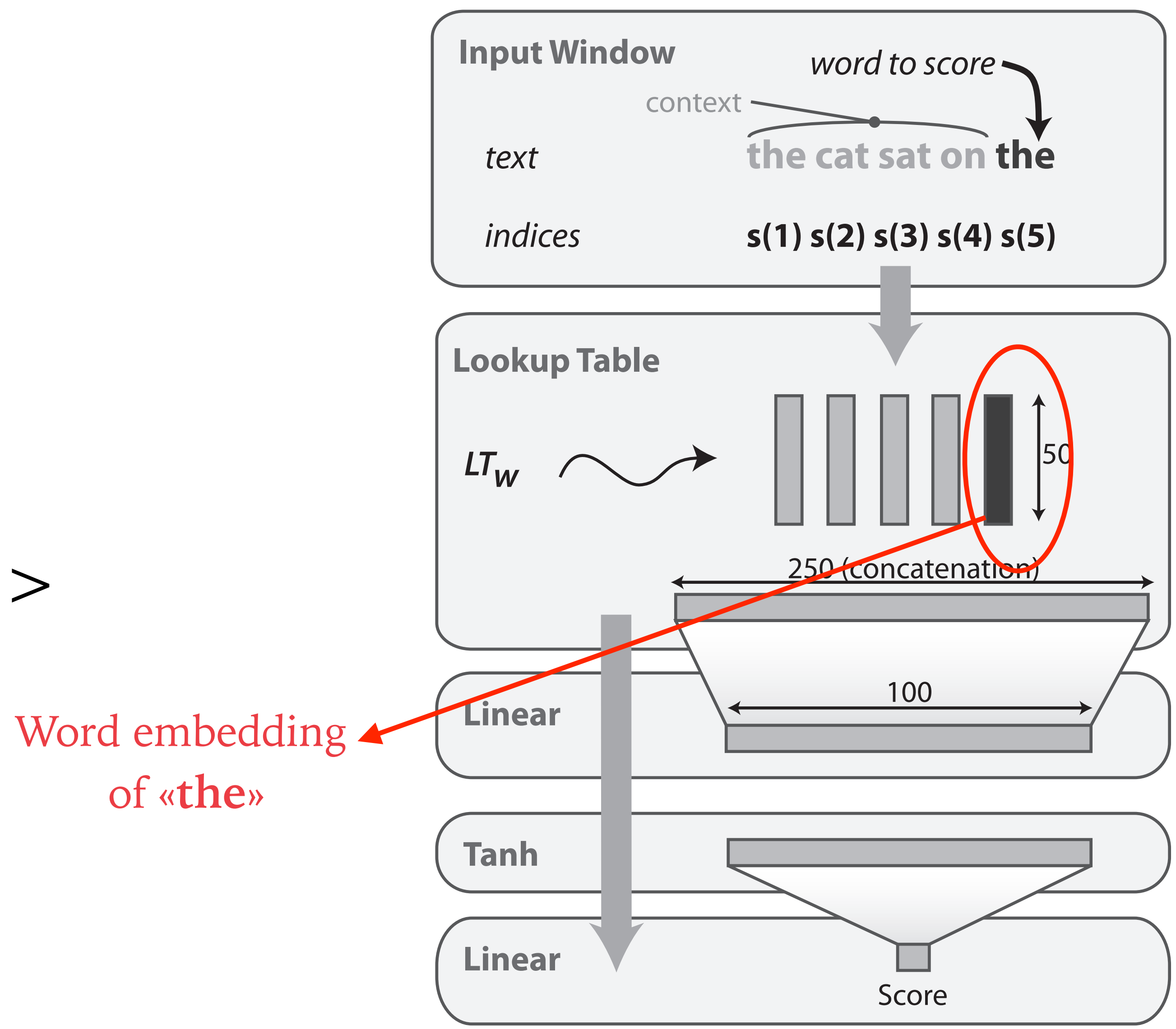
FRANCE	JESUS	XBOX
AUSTRIA	GOD	AMIGA
BELGIUM	SATI	PLAYSTATION
GERMANY	CHRIST	MSX
ITALY	SATAN	IPOD
GREECE	KALI	SEGA
SWEDEN	INDRA	PSNUMBER
NORWAY	VISHNU	HD
EUROPE	ANANDA	DREAMCAST
HUNGARY	PARVATI	GEFORCE
SWITZERLAND	GRACE	CAPCOM

What words have embeddings closest to a given word? [R.Collobert *et al* . 2011]

Word embeddings approaches(1/3)

1. Tur: Collobert and Weston embeddings revised by Joseph Turian [J.Turian *et al.* 2010]

- Existence n-gram
- Training criterion: score (n-gram) > score (corrupted n-gram) + some margin

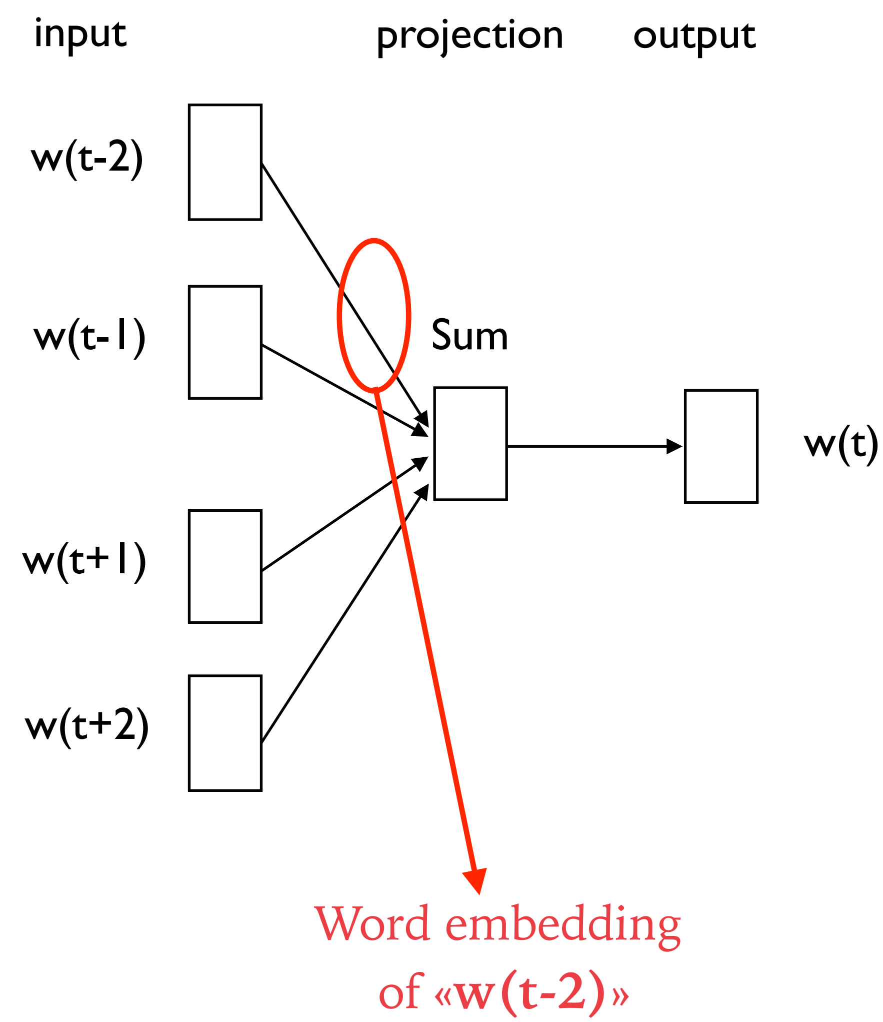


Neural architecture to compute 50 dimensional word embeddings

Word embeddings approaches(2/3)

2. Word2vec [T.Micolov *et al.* 2013]

- ✤ Continuous bag of words (CBOW)
  - ✦ predicting the current word based on its context



CBOW architecture

Word embeddings approaches(3/3)

3. Glove: global vector for word representation [J.Pennington *et al.* 2014]

- ✤ Analysis of co-occurrences of words in a window
  - ✦ building a co-occurrence matrix
  - ✦ estimating continuous representations of the words

Word embeddings combination (1/3)

1. Simple concatenation (**GTW**)

   - concatenation of 100 dimensional word embeddings: glove, tur and w2v
   - word = vector of 300 dimensions

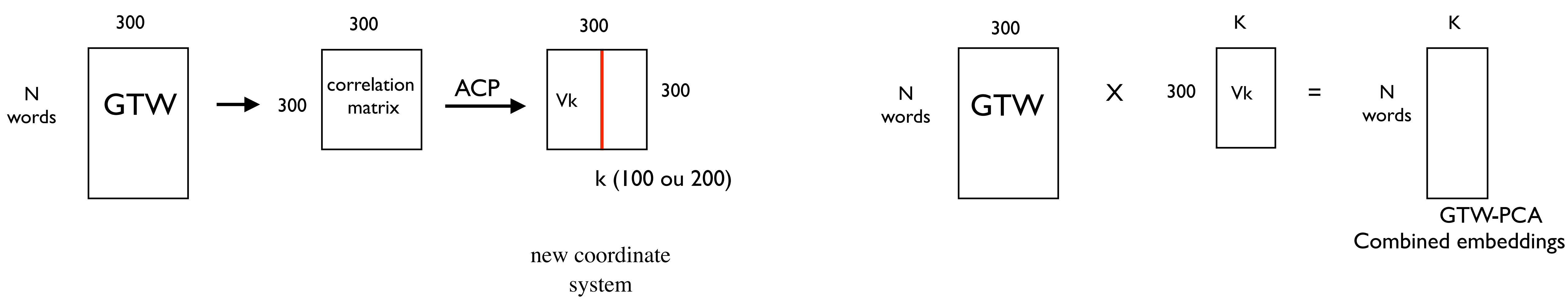
glove	tur	w2v

300 D

Word embeddings combination (2/3)

2. Principal Component Analysis (**PCA**)

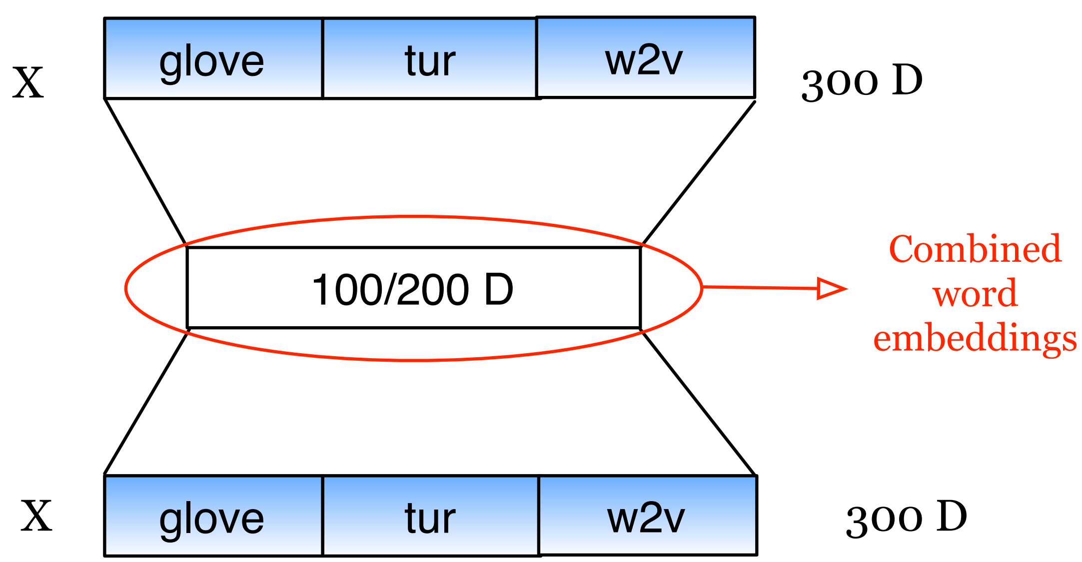
   - ✤ Convert correlated variables into uncorrelated variables called principal components.



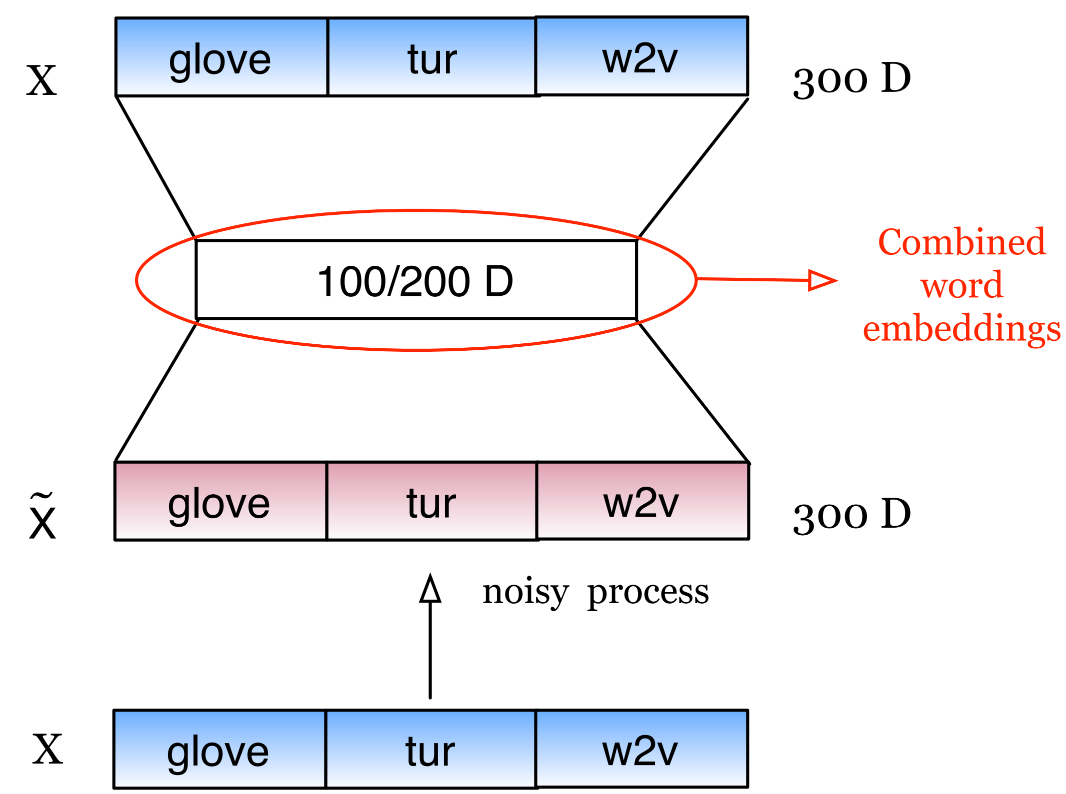
Word embeddings combination (3/3)

3. Auto-encoders

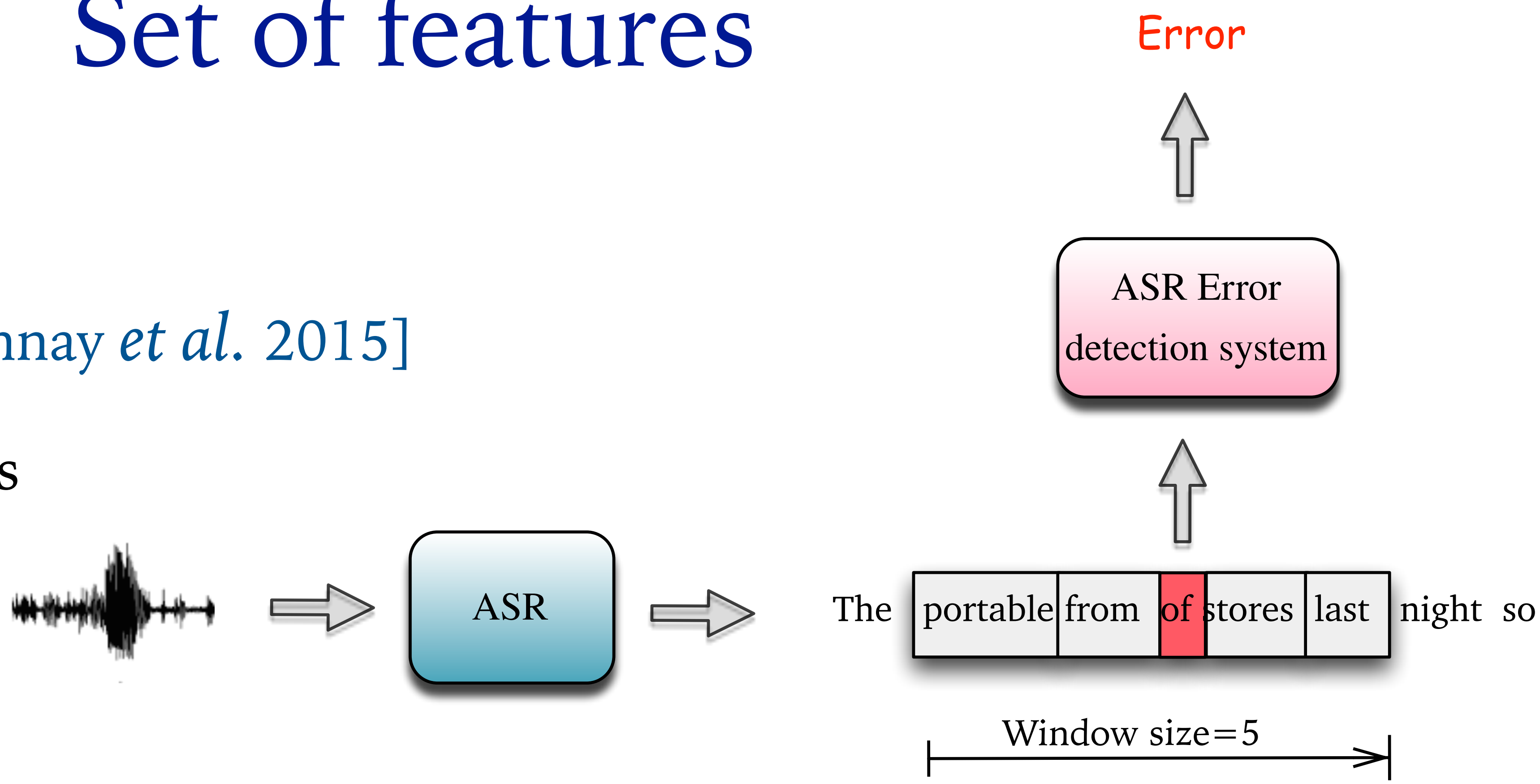
- Ordinary auto-encoder (**GTW-O**)



- Denoising auto-encoder (**GTW-D**)



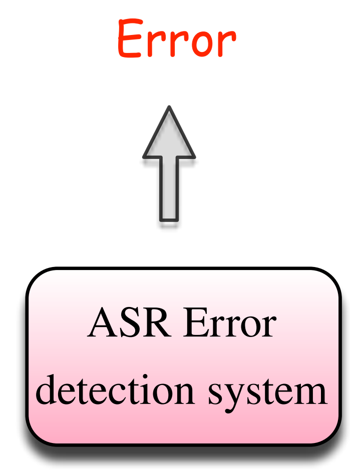
Set of features



Features used in [S.Ghannay *et al.* 2015]

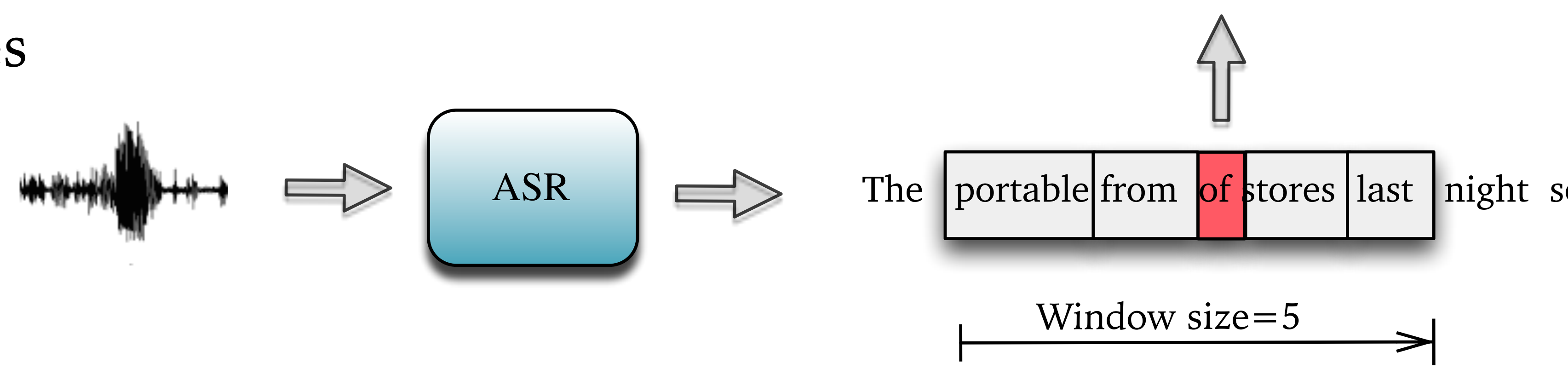
- ✤ Posterior probabilities
- ✤ Lexical features
  - word length
  - existence 3-gram
- ✤ Syntactic features
  - POS tag
  - word governors
  - dependency labels
- ✤ Word → Word embeddings

Set of features



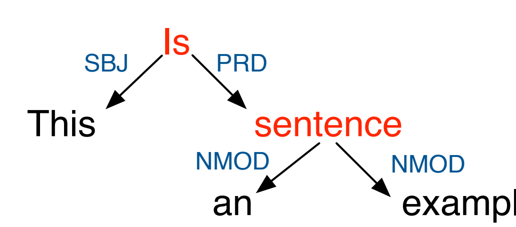
Features used in [S.Ghannay *et al.* 2015]

- Posterior probabilities



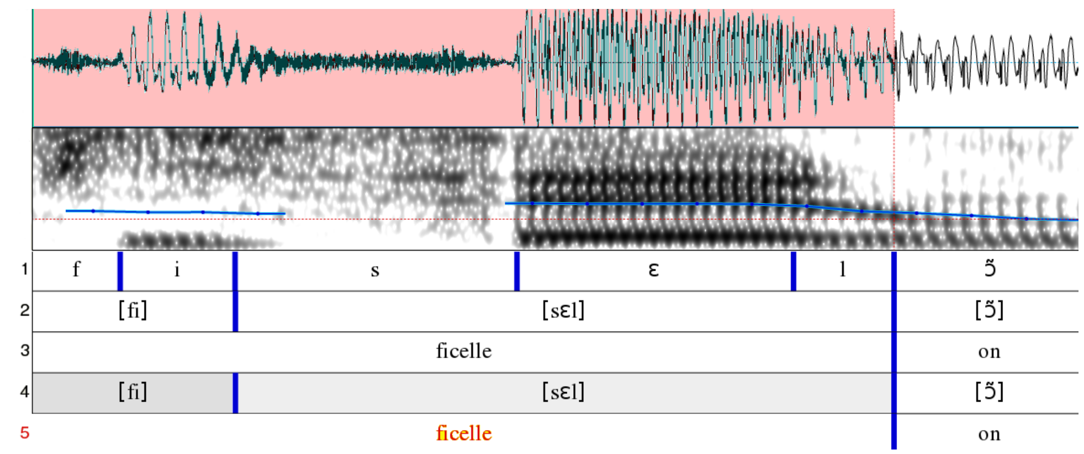
- Lexical features
  - word length
  - existence 3-gram
- Syntactic features
  - POS tag
  - word governors
  - dependency labels

Word	This	is	an	example	sentence
Pos	DT	VBZ	DT	NN	NN
dependency labels	SBJ	ROOT	NMOD	NMOD	PRD
Word governors	is	ROOT	sentence	sentence	is

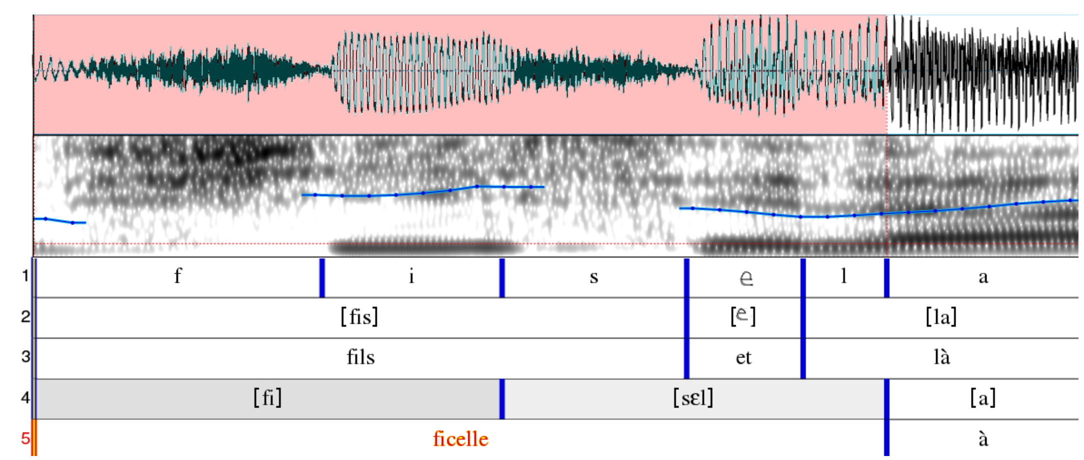


- Word → Word embeddings

Set of features



(a)



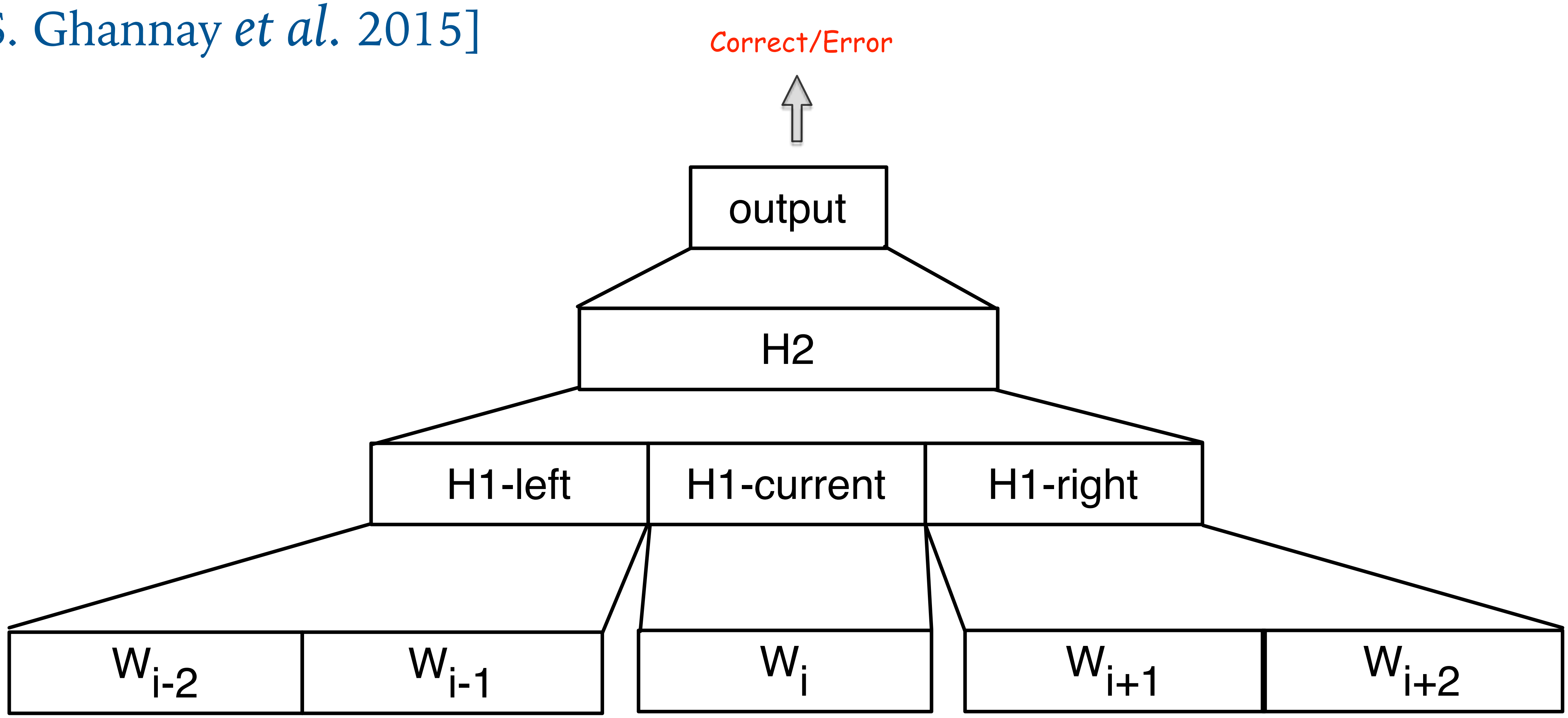
(b)

✤ Classic acoustic-prosodic features

- number of phonemes
- average duration of phonemes
- duration of the previous pause
- average f0 of the word
- f0 delta between the last and the first vowel of the word
- f0 semitone delta between the last and the first vowel of the word

Neural architecture: MLP-Multi-Stream

[S. Ghannay *et al.* 2015]



Experimental data

Training of the neural system:

Automatic transcriptions of the ETAPE Corpus [G.Gravier *et al.* 2012], generated by:

- ASR: CMU Sphinx decoder
  - acoustic models: GMM/HMM

ASR	Name	#words REF	#words HYP	WER
Sphinx GMM	Train	349K	316K	25.9
	Dev	54K	50K	25.2
	Test	58K	53K	22.5

Training data of the word embeddings:

Corpus composed of 2 billions of words:

- Articles of the French newspaper ”Le Monde”,
- French Gigaword corpus,
- Articles provided by Google News,
- Manual transcriptions: 400 hours of French broadcast news.

Evaluation results

- Neural architecture vs. CRF [F. Béchet and B. Favre 2013]
- Evaluation metrics:
  - Error label: F-measure (weighted average of the precision and recall)
  - Overall classification: Classification error rate (CER)
  - Confidence measures: Normalized cross entropy (NCE)

Experimental results

Comparison of different word embeddings (Dev corpus)

Without prosodic features

		Label error	Global
Neural architecture	Embeddings	F-measure	CER
MLP-MS	Glove tur w2v	59.64 57.58 56.69	10.60 10.54 10.49

Experimental results

Comparison of different word embeddings (Dev corpus)

Without prosodic features

		Label error	Global
Neural architecture	Embeddings	F-measure	CER
MLP-MS	Glove tur w2v	59.64 57.58 56.69	10.60 10.54 10.49
	GTW 300	59.71	10.38

Experimental results

Comparison of different word embeddings (Dev corpus)

Without prosodic features

		Label error	Global
Neural architecture	Embeddings	F-measure	CER
MLP-MS	Glove tur w2v	59.64 57.58 56.69	10.60 10.54 10.49
	GTW 300	59.71	10.38
	GTW-PCA100 GTW-PCA200	59.04 57.09	10.39 10.48

Experimental results

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	tur	57.58	10.54
	w2v	56.69	10.49
	GTW 300	59.71	10.38
	GTW-PCA100	59.04	10.39
	GTW-PCA200	57.09	10.48
	GTW-O100	56.43	10.28
	GTW-O200	61.86	**9.86**
	GTW-D100	61.63	10.12
	GTW-D200	**63.42**	9.89

Experimental results

Performance of MLP-MS on Test corpus

Without prosodic features

	Label error	Global
Approach	F-measure	CER
CRF(baseline)	57.52	8.79
GTW-O200	61.83	**8.10**
GTW-D200	**62.25**	8.25

Experimental results

Corpus	Approach	Label error	Global
		F-measure	CER
Test	*CRF(baseline)*	57.52	8.79
	GTW-O200	62.25	8.10
	GTW-D200	64.42	8.25

- prosodic features

Performance of MLP-MS (Test corpus)

With prosodic features

Corpus	Approach	Label error	Global
		F-measure	CER
Test	*CRF(baseline)+pros*	**59.17**	**8.57**
	GTW-O200+pros	64.73	7.96
	GTW-D200+pros	64.42	8.03

+ prosodic features

Experimental results

Corpus	Approach	Label error	Global
		F-measure	CER
Test	*CRF(baseline)*	57.52	8.79
	GTW-O200	62.25	8.10
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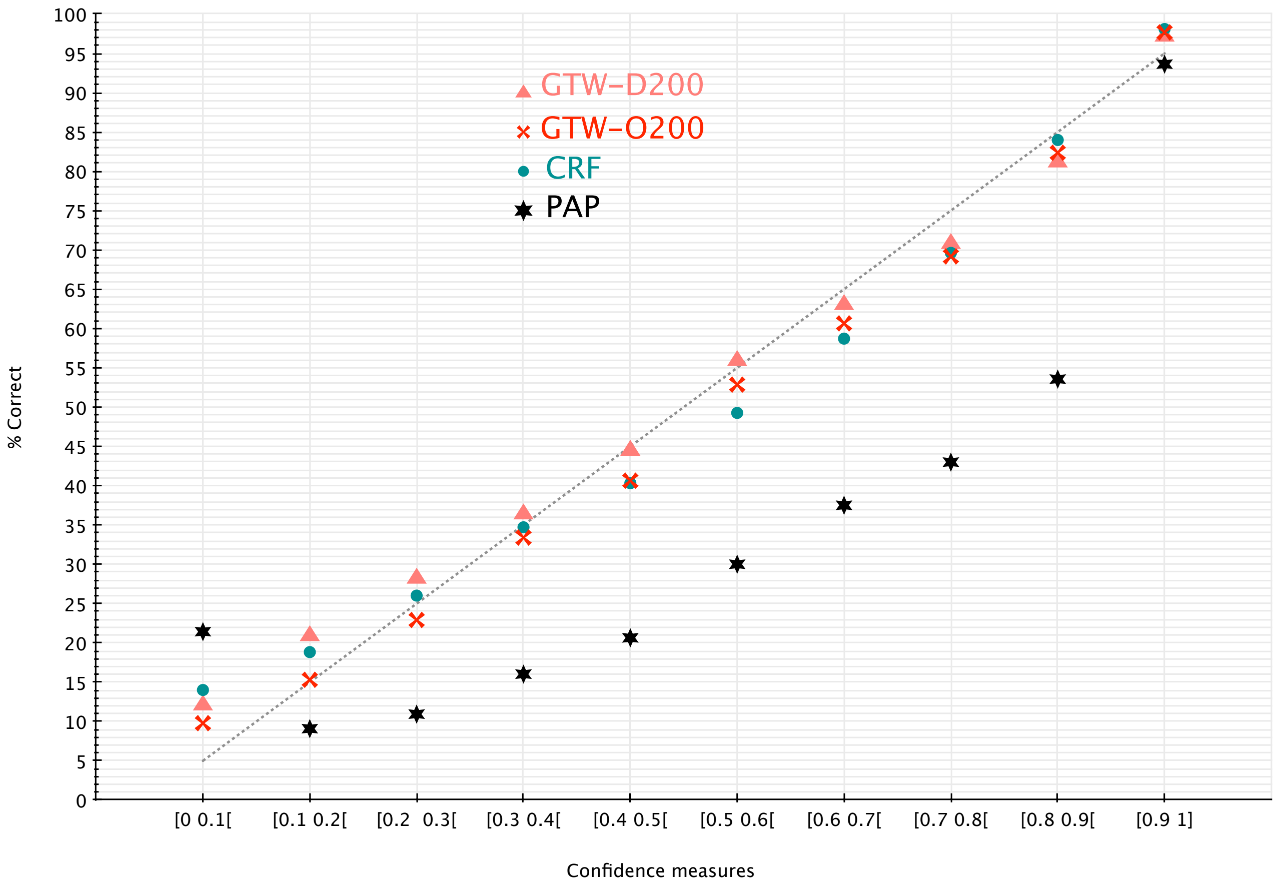
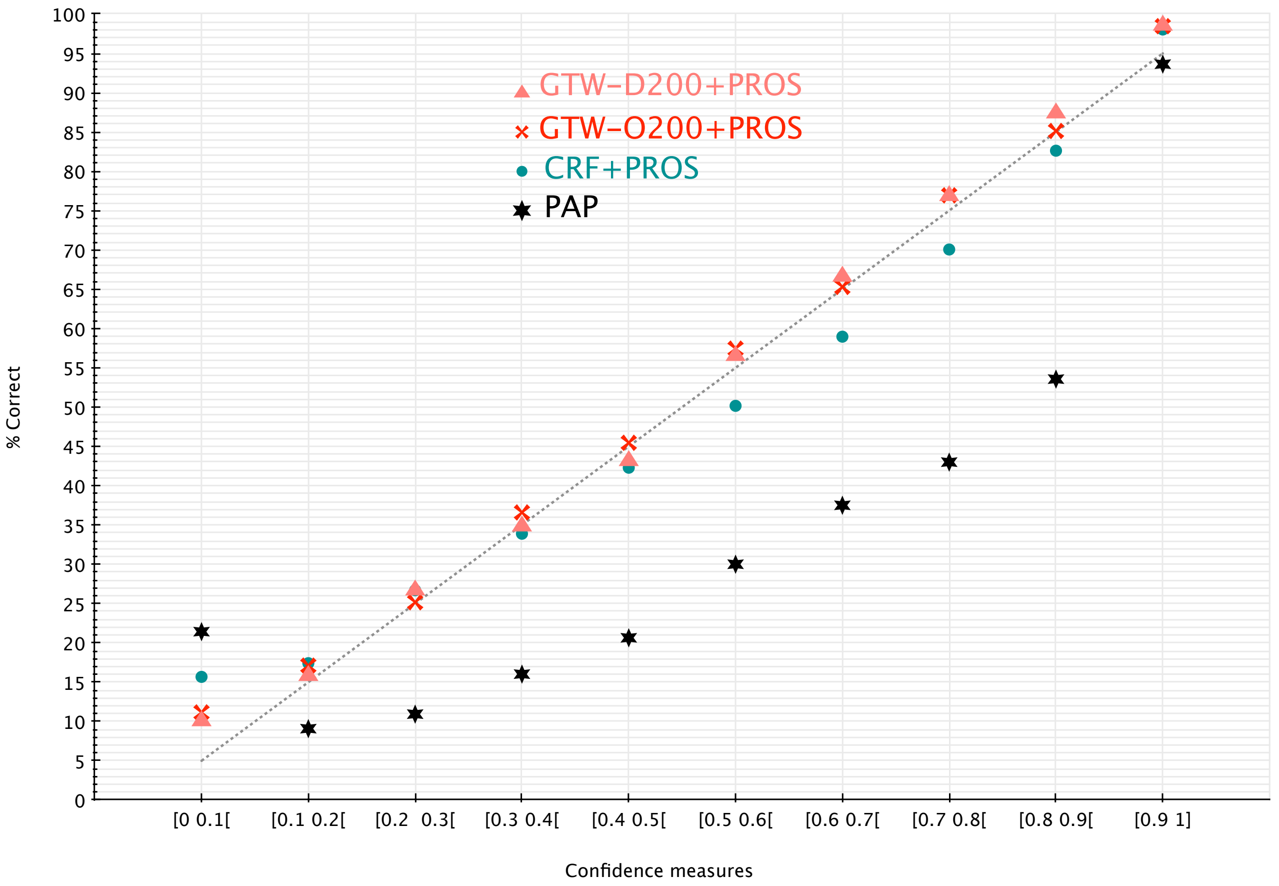
Experimental results

Calibrated confidence measure



- prosodic features



+prosodic features

Percentage of correct words based on PAP and confidence measures derived from MLP-MS and CRF

Experimental results

Calibrated confidence measure

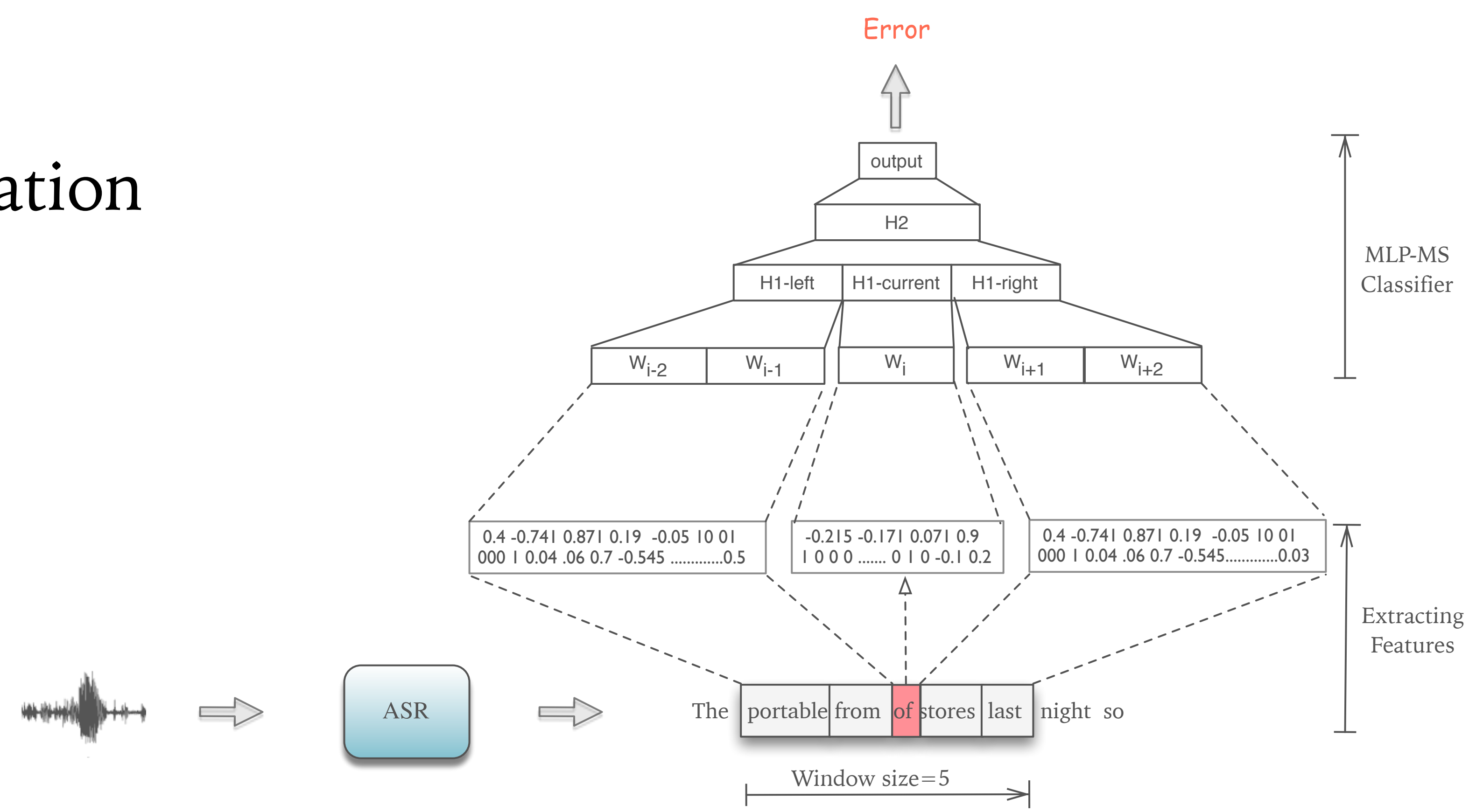
Name	PAP	Softmax proba GTW-D200	Softmax proba GTW-O200	CRF
Without prosodic features				
Dev	-0.064	0.425	0.443	**0.445**
Test	-0.044	0.448	**0.461**	0.457
With prosodic features				
Dev	-0.064	0.461	**0.463**	0.449
Test	-0.044	0.471	**0.477**	0.463

NCE for PAP and the probabilities resulting from MLP-MS and CRF

Conclusions

ASR error detection system

- Word embeddings combination
- Prosodic features



- MLP-MS architecture:
  - ➡ Outperforms CRF approach
  - ➡ Produces well calibrated confidence measures

Thank you