

# Using Word Posterior in Lattice Translation

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# Motivation - Common approaches

- Serial approach:
  - + simple and fast - propagates errors from ASR
- Semi-coupled approach:
  - n-best: + simple - redundancy, time-consuming
  - *lattice*: + full searched space - time-consuming
  - *confusion network*: + simplified lattice, efficient - loss of grammar
- Integrated approach:
  - + theoretically promising - bad performance on non-simple corpora

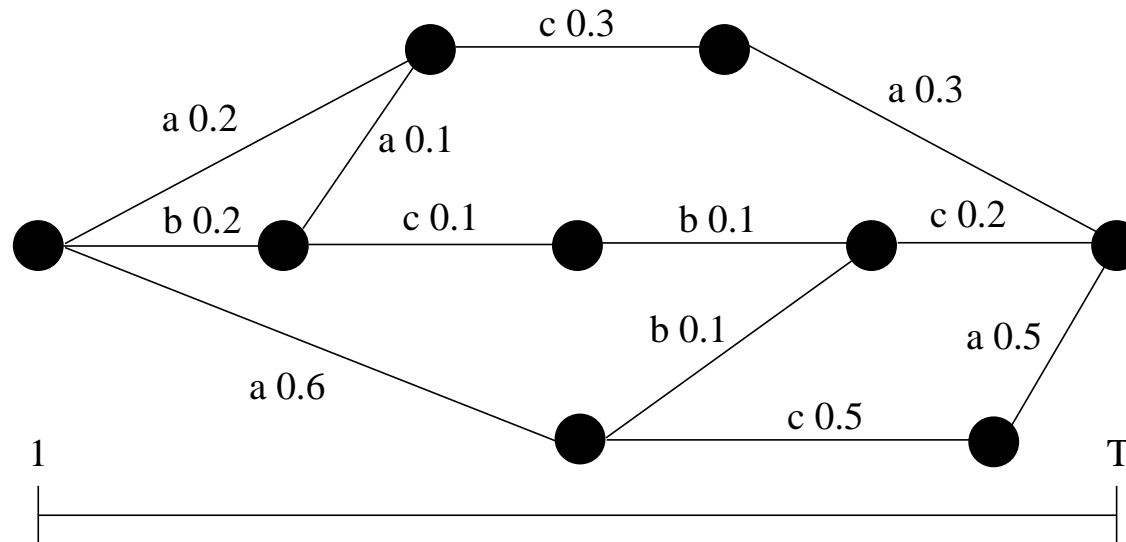
# Word Posterior Probabilities

- Motivation
  - One should maximize word posterior probabilities to minimize WER (Mangu00)
  - Confusion networks (Bertoldi05):
    - \* word posterior probabilities
    - \* lattice simplification
- Our approach
  - Word posterior probabilities over a lattice
  - Take advantage of techniques in confidence measures (Sanchis04)

# Word Posterior Probabilities: Forward-Backward

- being  $w$  the hypothesized word,  $s$  the start node and  $e$  the end node:

$$P([w, s, e] | \vec{x}_1^T) = \frac{1}{P(\vec{x}_1^T)} \sum_{\substack{f_1^J \in G : \\ \exists [w', s', e'] : \\ w' = w, s' = s, e' = e}} P(f_1^J, \vec{x}_1^T) \quad (1)$$

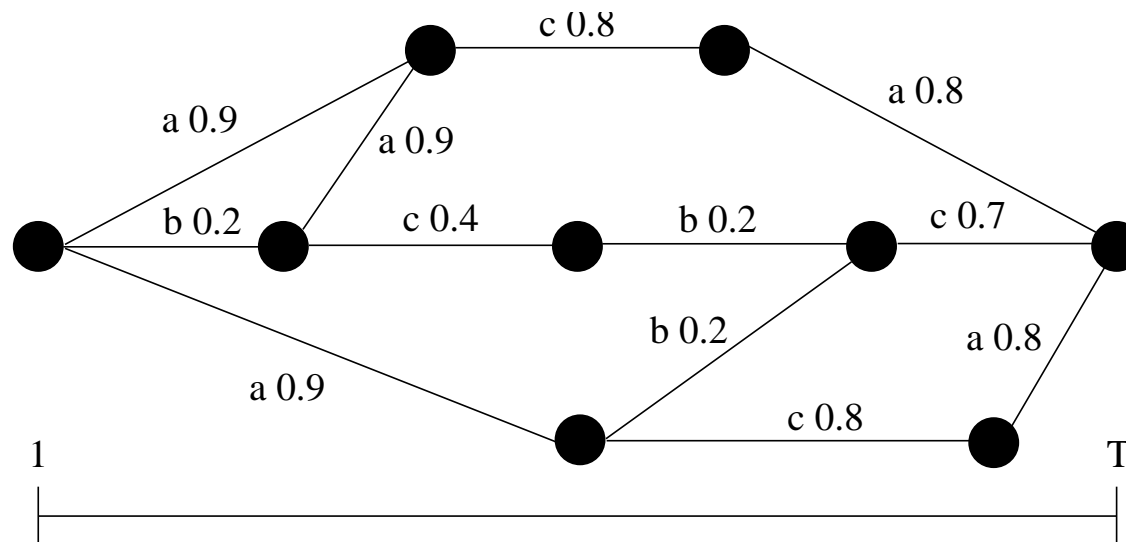


# Word Posterior Probabilities

- maximum of the frame time posterior probability (Wessel01)

$$P_t(w | \vec{x}_1^T) = \sum_{t \in [s', e']} P([w, s', e'] | \vec{x}_1^T) \quad (2)$$

$$P([w, s, e] | \vec{x}_1^T) = \max_{s \leq t \leq e} P_t(w | \vec{x}_1^T) \quad (3)$$



# Translation System

- Log-linear model:
  - Word posterior probabilities
  - GIATI:
    - \* Joint probability model
    - \* N-grams of bilingual pairs
    - \* 5-gram (w/o cutting off)
    - \* integrated lattice search
    - \* monotonous search
  - Output word penalty
  - Output language model (5-gram)

# Translation System

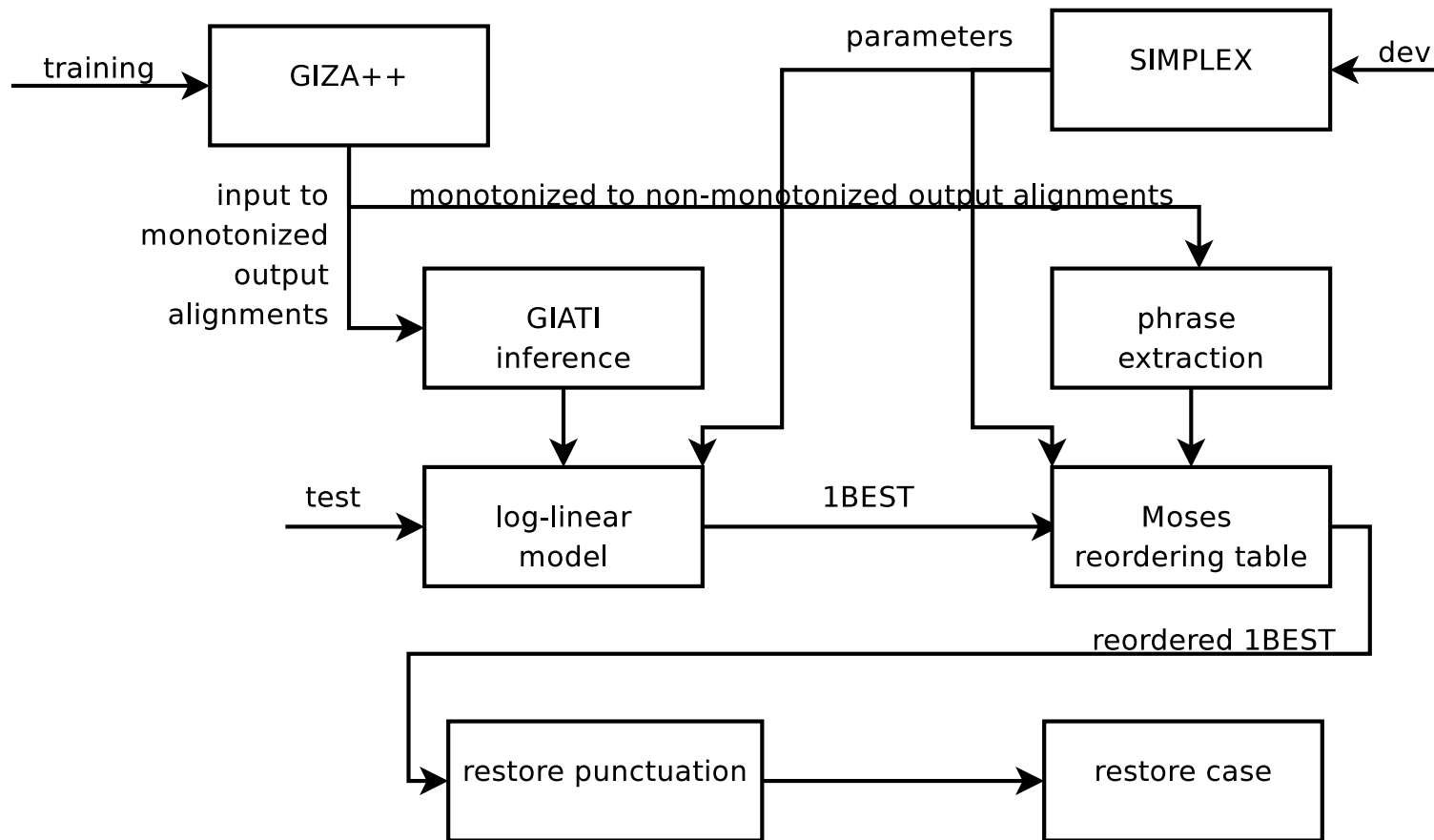
- Reordering:
  - Serial, 1BEST approach
  - Monotonization of the output
  - Translate with mooses from monotonized to regular word order
  - Models: reordering table and output language model
  - Monotonous search



# Preprocess and postprocess

- Preprocess:
  - Case and punctuation were removed from training
  - Sentence splitting at sentence boundaries (.?!)
  - Lattice pruning
- Postprocess:
  - Punctuation and case restoration: IWSLT06 method using SRILM
  - Capitalization after punctuation marks

# System architecture



# Corpus statistics

		Italian	English
Train	Sentences	19971	
	Running words	172k	189k
	Vocabulary	10,152	7,165
Dev4	Sentences	489	
	Running words	4,831	6,848
	OOV words	224	208
Dev5a	Sentences	500	
	Running words	5,607	7,491
	OOV words	296	264
Dev5b	Sentences	996	
	Running words	8,487	11,968
	OOV words	591	611
Test	Sentences	724	
	Running words	6,420	9,054
	OOV words	542	439

# Effect of adding features to the baseline model

- Primary run: 16.13 BLEU

	dev4		dev5a		dev5b		test	
	BLEU	NIST	BLEU	NIST	BLEU	NIST	BLEU	NIST
baseline	36.29	7.59	31.96	7.06	12.53	4.02	22.80	5.49
+WP	37.45	7.35	32.55	6.82	14.07	3.77	19.56	5.06
+OL	37.06	7.42	32.55	6.91	12.37	3.82	22.32	5.25
+WP+OL	38.19	7.20	32.67	6.66	13.44	4.20	21.83	5.57
+RM	37.53	7.95	32.74	7.41	13.94	4.30	23.92	5.79
+WP+OL+RM	38.98	7.81	32.86	7.18	14.34	4.37	23.22	5.86

- *WP*, output word insertion penalty
- *OL*, output language model
- *RM*, reordering model

# Effect of adding dev corpus to the training corpus

- Primary run: 16.13 BLEU

	w/o dev		with dev	
	BLEU	NIST	BLEU	NIST
baseline	22.80	5.49	31.29	6.66
+WP	22.09	5.56	12.16	2.97
+OL	22.79	5.52	30.83	6.64
+WP+OL	21.79	5.56	11.89	2.91
+RM	23.46	5.74	<b>32.28</b>	<b>6.95</b>
+WP+OL+RM	23.22	5.86	31.21	6.77

- *WP*, output word insertion penalty
- *OL*, output language model
- *RM*, reordering model

## Results for different input conditions

	dev4		dev5a		dev5b		test	
	BLEU	NIST	BLEU	NIST	BLEU	NIST	BLEU	NIST
1BEST	33.53	6.92	26.97	6.12	13.21	4.19	21.50	5.56
LAT	33.69	6.95	27.24	6.14	13.35	4.16	18.71	5.22
GER	34.11	7.02	27.49	6.18	13.90	4.29	22.64	5.77
CLEAN	38.98	7.81	32.86	7.18	14.34	4.37	23.22	5.86

- *LAT*, lattice with word posterior probabilities
- *GER*, using the sentence from the lattice with less word error rate

# Conclusions

- Word Posterior approach
  - Results not conclusive
  - Small differences between 1BEST and CLEAN scores
  - Some improvements were achieved
  - Needs work on pruning
- Adding devset to training matters

# Future Work

- Comparison with n-best, confidence measures, lattice with acoustic scores
- Add additional state-of-the-art confidence features
- Add translation features
- Features based on multiple lattices
- Lattice reduction



**Thank you for your attention!**

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# References

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