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The INESC-ID IWSLT07 SMT System

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Outline

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- INESC-ID@IWSLT
- Baseline
- Corpora
- System architecture
- Experiments
- Conclusions and future work

INESC@IWSLT

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- First Participation
  - A strong motivation to build “our own” MT system
  - To submerge in MT
- Task
  - translation of spontaneous conversations in the travel domain from Italian to English

Corpora

- Training corpora
  - Italian/English: 19 845 sentence pairs
- Development corpora
  - Dev1: IWSLT05 Written: 506 * 7
  - Dev2: IWSLT06 Speech (read): 489 sentence pairs
  - Dev3: IWSLT07 Speech (spont): 996 sentence pairs
- Test corpora
  - Italian/English Clean: 724 sentence pairs
  - Italian/English ASR: 724 sentence pairs

Baseline

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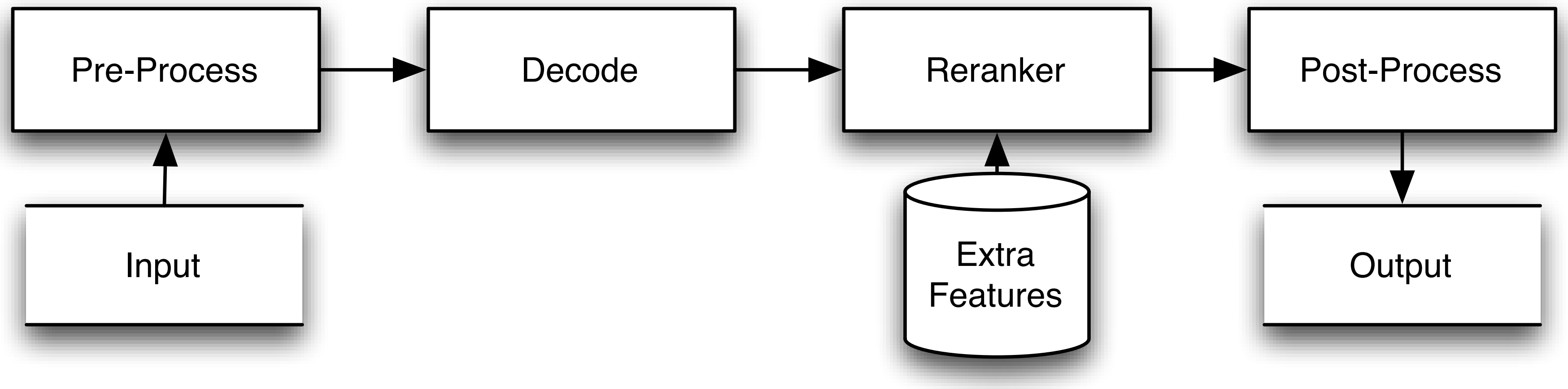
- Standard phrase-based architecture (GIZA++, Moses, SRLIM)
  - Phrase features:
    - Direct and inverse phrase probability
    - Direct and inverse IBM1 model
    - Phrase and word penalties
  - 5-gram LM
  - Minimum error training (BLEU)
  - First pass

	Dev1	Dev2	Dev3
Baseline	56.60	37.19	16.78

System architecture



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Experiments

1. Corpora fattening
2. Pre-processing
3. Phrase based first pass decoding
4. Filtered Phrase Table
5. Reranker
6. Post-processing

1. Corpora Fattening

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      - Terms were collected from phrase books

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+data LM	16.82
+data Phrase	16.10
+data Phrase and LM	16.98

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3. Phrase Based first pass decoding

- Use TreeTagger from Institute for Computational Linguistics of the University of Stuttgart (POS + lemma annotation) in 2 experiments:
  - POS distortion model
  - Lemmas for alignment

3. Phrase Based first pass decoding

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Configuration	BLUE
Baseline + fat corpus - Pre-processing	16.98
POS distortion model	12.24

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Lemma + Fat corpus - Pre-processing	16.41
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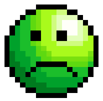

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5. Reranker

- Features according to a log-linear model in order to maximise BLEU
- 1000-best hypotheses

5. Reranker

- Sentence features:
  - first pass score
  - ratio between target and source sentence length
  - some question features
  - 3,4 and 5-grams target words LMs
  - 3,4 and 5-grams target POS LMs
  - Direct and inverse IBM1 model
  - POS similarities

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- POS similarities
  - assume that the number of certain tags should be similar in each pair Italian/English
    - ex: NOM (it) and NNS + NN (en)
  - the Euclidean distance was used to calculate the feature score

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- POS similarities
  - assume that the number of certain tags should be similar in each pair Italian/English
    - ex: NOM (it) and NNS + NN (en)
  - the Euclidean distance was used to calculate the feature score
- POS unlikely sequences
  - assume that certain sequences of tags are very unlikely
    - ex: DT DT (en)
  - sentences with these sequences should be penalised

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Baseline	17.45
+ length ratio	17.45
+ question features	17. 51
+ word n-gram LMs	17.45
+ POS n-gram LMs	17.38
+IBM1 Dictionary	17.45
+POS similarity	17.57
All Features	17.66

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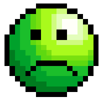

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- Removing leading and trailing commas
  - ex: , please ? good morning .
- Add/remove question marks or periods according with sentences types
  - ex: where ... --> where ...?
- Make changes in specific words
  - ex: good-bye --> goodbye

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Reranked	17.55	21.58

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Test set results

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- Primary System:
  - pre-processing + first pass + re-ranker + post-processing
- Secondary System:
  - pre-processing + first pass + post-processing

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- Secondary System:
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Condition	Primary system	Secondary system
IE clean	26.57	26.35
IE ASR	24.16	24.35

Summary

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- We introduced the INESC-ID MT system being developed at L2F (Spoken Language Systems Lab) from INESC-ID, Lisboa.

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- We participated in the Track of translating spontaneous conversation in the travel domain from Italian to English

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- We introduced the INESC-ID MT system being developed at L2F (Spoken Language Systems Lab) from INESC-ID, Lisboa.
- We participated in the Track of translating spontaneous conversation in the travel domain from Italian to English
- We used a re-rank step where the 1000 n-best hypotheses were analysed. Several features where used at this step, including POS-based features.

Conclusions and Future Work

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- Future Work
  - Understand what went wrong with the re-ranker
  - Perform a more systematic study of the POS-based features
  - Explore the domain adaptation

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