The INESC-ID IWSLT07 SMT System

João Graça
Diamantino Caseiro
Luísa Coheur
Outline

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

- 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

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<td>Baseline</td>
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System architecture

Pre-Process → Decode → Reranker → Post-Process

Input → Extra Features → Output

Pipeline:
1. Pre-Processing
2. Decoding
3. Reranking
4. Post-Processing

Sections:
- System architecture
- Pre-Processing
- Decoding
- Reranking
- Post-Processing

Results:
- BLEU scores for different systems and features
- Comparison with baseline systems
- Analysis of system performance

Tasks:
- Spoken language translation
- Machine translation
- Language recognition

Baseline:
- Statistical machine translation
- Optimization methods

Final Remarks:
- Future work
- Evaluation metrics
- Challenges and improvements

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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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- Collect data in the travel domain, namely:
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    - Why?
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      - Terms were collected from phrase books
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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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- Remove
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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
5. Reranker
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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 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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- Features results
  - Some features don’t give good results by its own, but are responsible for bleu increasing when combined with other features
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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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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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- We participated in the Track of translating spontaneous conversation in the travel domain from Italian to English.
Summary

- 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 were used at this step, including POS-based features.
Conclusions and Future Work
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  - Bigger gains came from pre and pos-processing of the data!!!!
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**Conclusions**
- The re-ranker gain is not significant
- Bigger gains came from pre and pos- processing of the data!!!!

**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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