The UEDIN Systems for the IWSLT 2012 Evaluation

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Overview

- UEDIN participated in ASR (English),
  MT (English-French, German-English), SLT (English-French)
- This presentation focuses on experiments carried out for the SLT and MT tasks

Spoken Language Translation

Problem

- ASR output has recognition errors and no punctuation

Approach: Punctuation insertion as machine translation

- Best-performing SLT system of [Wuebker et al., 2011] used this approach (PPMT before translation)
- Advantage: can reuse best MT system for translation into French
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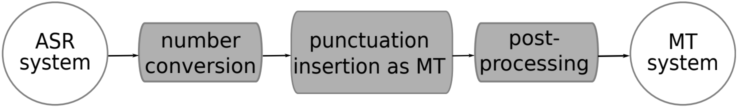
SLT pipeline

1. Preprocessing of ASR output: number conversion
2. Punctuation insertion by translation from English w/o punctuation to English with punctuation
3. Postprocessing: fix sentence initial/final punctuation, single quotation marks
4. Translation from English to French



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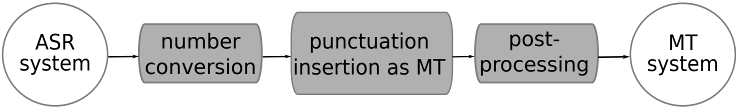

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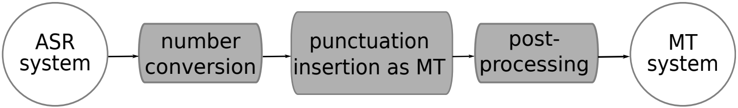

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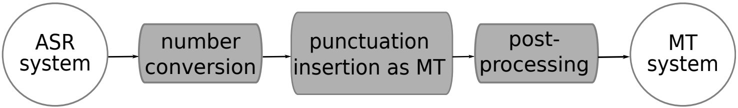

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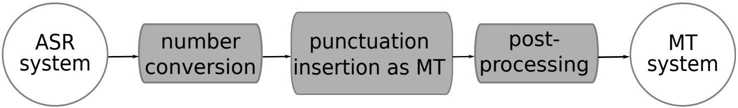

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Training data for punctuation insertion system

- 141K parallel sentences from the TED corpus
- **Source** side: ASR transcripts of TED talks (w/o punctuation, cased)
- **Target** side: source side of MT data (w/ punctuation, cased)
- Source and target TED talks mapped according to talkids, then sentence-aligned
- Differences between ASR transcripts and MT source: (punctuation,) representation of numbers, spellings
  - Doctor $\rightarrow$ Dr.
  - MP three $\rightarrow$ MP3
- Implicit conversion of spellings

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Number conversion

- Explicit conversion as preprocessing step
- Year numbers: mostly consistent in MT data
  - *nineteen thirty two* → *1932*
  - *two thousand and nine* → *2009*
  - *nineteen nineties* → *1990s*
- Other numbers: not always constistent in MT data, but conversion still helps
  - *ten thousand* → *10 thousand* or *10,000* (more frequent)
  - *one hundred seventy four* → *174*
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Punctuation insertion system

- Phrasebased Moses, monotone decoding
- Avoid excessive punctuation insertion
    - Only using cased instead of truecased data improved performance
- Tuning sets (target: MT input)
    - dev2010 transcripts, dev2010+test2010 transcripts, dev2010+test2010 ASR outputs (all number-converted)
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test2010 ASR transcript	70.79
+ number conversion	71.37
+ punctuation insertion	84.80
+ postprocessing	85.17
test2010 ASR out + SLT pipeline	*61.82*

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Tune: dev2010 ASR transcript	
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test2010 ASR out UEDIN	61.82	22.89	33.98
test2011 ASR out system0	**67.40**	27.37	40.44
test2011 ASR out system1	65.73	**27.47**	40.44
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- Limited amount of TED talks data, larger amounts of out-of-domain data
- Need to make best use of both kinds of data

English-French, German-English

- Compare approaches to data filtering and PT adaptation (previous work)
- Adaptation to TED talks by adding sparse lexicalised features
- Explore different tuning setups on in-domain and mixed-domain systems

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Machine Translation

Baseline systems in-domain, mixed domain

- Phrase-based/hierarchical Moses
- 5gram LMs with modified Kneser-Ney smoothing
- German-English:
  compound splitting [Koehn and Knight, 2003] and syntactic preordering on source side [Collins et al., 2005]

Data

- Parallel in-domain data: 140K/130K TED talks
- Parallel out-of-domain data:
  Europarl, News Commentary, MultiUN, (10^9)
- Additional LM data: Gigaword, Newscrawl
  (fr: 1.3G words, en: 6.4G words)
- Dev set: dev2010, Devtest set: test2010, Test set: test2011

Machine Translation

Baseline systems

System	de-en (test2010)
IN-PB (CS)	28.26
IN-PB (PRE)	28.04
IN-PB (CS + PRE)	**28.54**

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System	en-fr	de-en
IN hierarchical	28.94	27.88
IN phrasebased	**29.58**	**28.54**
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Bilingual cross-entropy difference [Axelrod et al., 2011]

- Select out-of-domain sentences that are similar to in-domain and dissimilar from out-of-domain data
- Select 10%, 20%, 50% of OUT data (incl. LM data)

In-domain PT + fill-up OUT
[Bisazza et al., 2011], [Haddow and Koehn, 2012]

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System	test2010 en-fr	de-en
IN+OUT	31.67	28.39
IN		
+ 10% OUT	32.30	**29.29**
+ 20% OUT	**32.45**	29.11
+ 50% OUT	32.32	28.68
best + gigaword + newscrawl	32.93	31.06
IN + fill-up OUT	**32.19**	**29.59**
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Sparse feature tuning

Adapt to style and vocabulary of TED talks

- Add sparse word pair and phrase pair features to in-domain system, tune with online MIRA
- Word pairs: indicators of aligned words in source and target
- Phrase pairs: depend on phrase segmentation of decoder
- Bias translation model towards in-domain style and vocabulary

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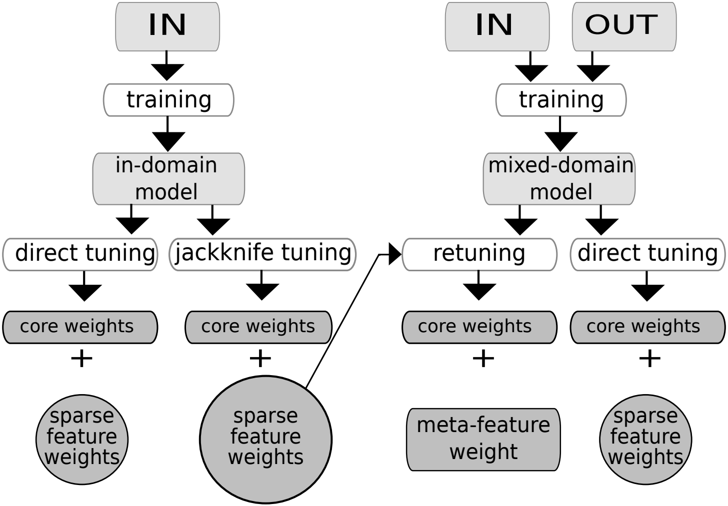

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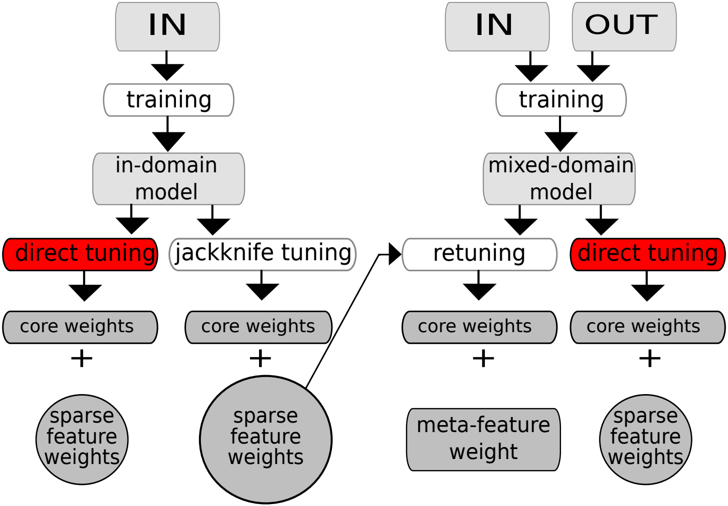

Direct tuning with MIRA

- Tune on development set
- Online MIRA: Select hope/fear translations from a 30best list
- Sentence-level BLEU scores
- Separate learning rate for core features to reduce fluctuation and keep MIRA training more stable
- Learning rate set to 0.1 for core features (1.0 for sparse features)

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Direct tuning with MIRA

Sparse feature sets

Source sentence:
[a language] [is a] [flash of] [the human spirit] [.]

Hypothesis translation:
[une langue] [est une] [flash de] [l' esprit humain] [.]

Word pair features	**Phrase pair features**
wp_a$\sim$une=2	pp_a,language$\sim$une,langue=1
wp_language$\sim$langue=1	pp_is,a$\sim$est,une=1
wp_is$\sim$est=1	pp_flash,of$\sim$flash,de=1
wp_flash$\sim$ flash=1	...
wp_of$\sim$de=1	
...	

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wp_is∼est=1	pp_flash,of∼flash,de=1
wp_flash∼ flash=1	...
wp_of∼de=1	
...	

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wp_flash∼ flash=1	...
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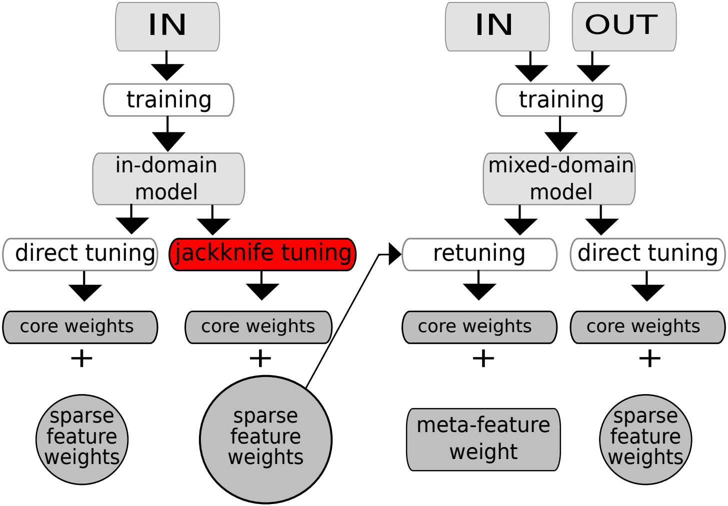
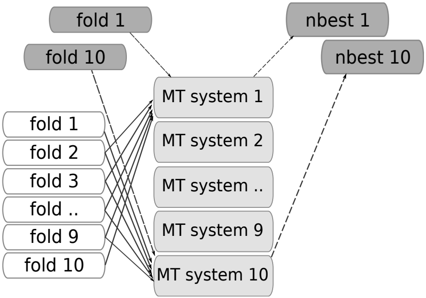


Jackknife tuning with MIRA

- To avoid overfitting to tuning set, train lexicalised features on all in-domain training data
- Train 10 systems on in-domain data, leaving out one fold at a time
- Then translate each fold with respective system
- Iterative parameter mixing by running MIRA on all 10 systems in parallel



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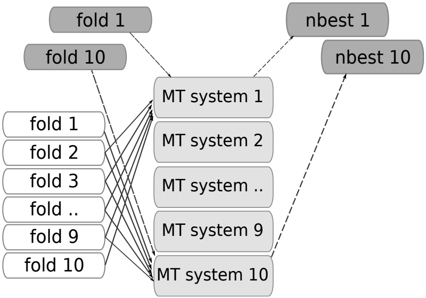

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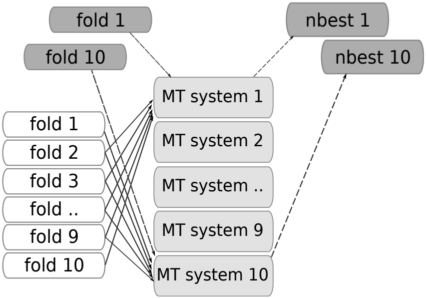

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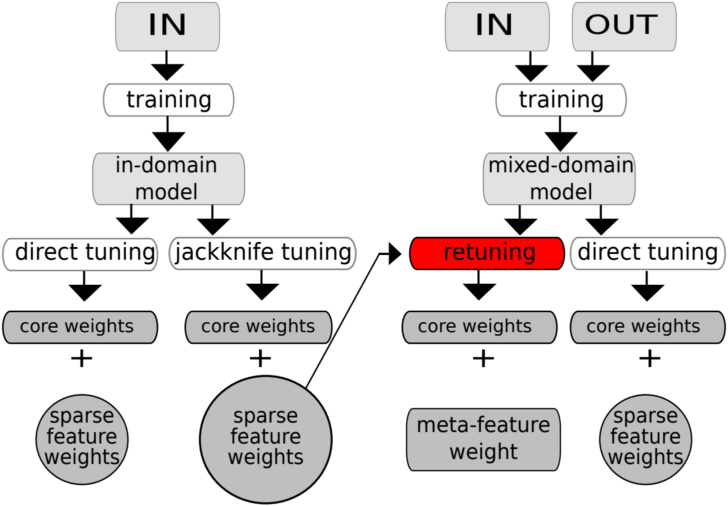

Retuning with MIRA

Motivation

- Tuning sparse features for large translation models is time/memory-consuming
- Avoid overhead of jackknife tuning on larger data sets
- Port tuned features from in-domain to mixed-domain models

Feature integration

- Rescale jackknife-tuned features to integrate into mixed-domain model
- Combine into aggregated meta-feature with a single weight
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Results with sparse features

System	test2010 en-fr	test2010 de-en
IN, MERT	29.58	28.54
IN, MIRA	30.28	28.31
+ word pairs	**30.36**	**28.45**
+ phrase pairs	**30.62**	**28.40**
+ word pairs (JK)	**30.80**	**28.78**
+ phrase pairs (JK)	**30.77**	**28.61**

Table: *Direct tuning and jackknife tuning on in-domain data*

- en-fr: +0.34/+0.52 BLEU with direct/jackknife tuning
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System	en-fr test2010	en-fr test2011	de-en test2010	de-en test2011
IN + %OUT, MIRA	33.22	40.02	28.90	34.03
+ word pairs	**33.59**	39.95	28.93	33.88
+ phrase pairs	33.44	40.02	**29.13**	33.99
IN + %OUT, MERT	32.32	39.36	29.13	33.29
+ retune(word pair JK)	**32.90**	40.31	**29.58**	33.31
+ retune(phrase pairs JK)	32.69	39.32	29.38	33.23
Submission system (grey) + gigaword + newscrawl	33.98	40.44	31.28	36.03

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Thank you!

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