Karlsruhe Institute of Technology

Toward Multilingual Neural Machine Translation with Universal Encoder and Decoder

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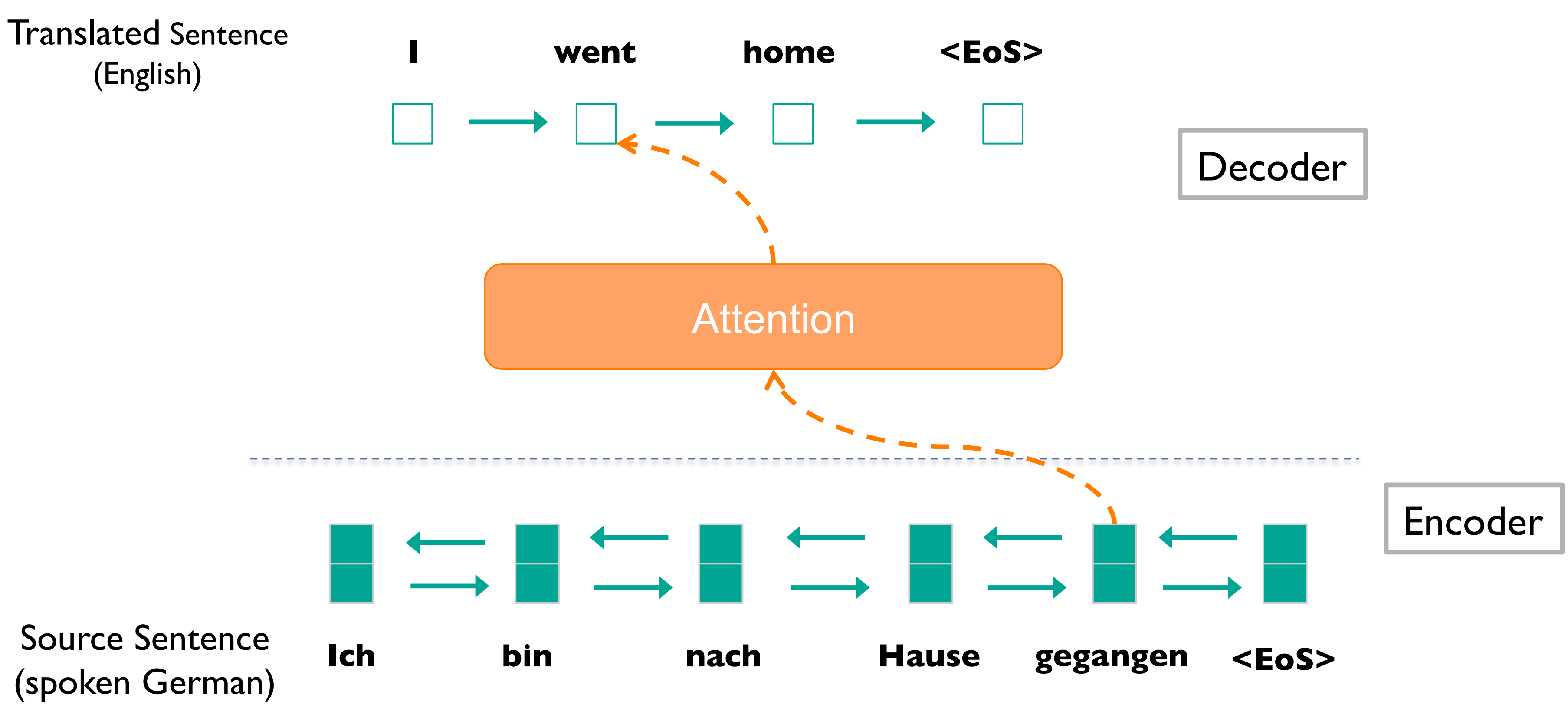
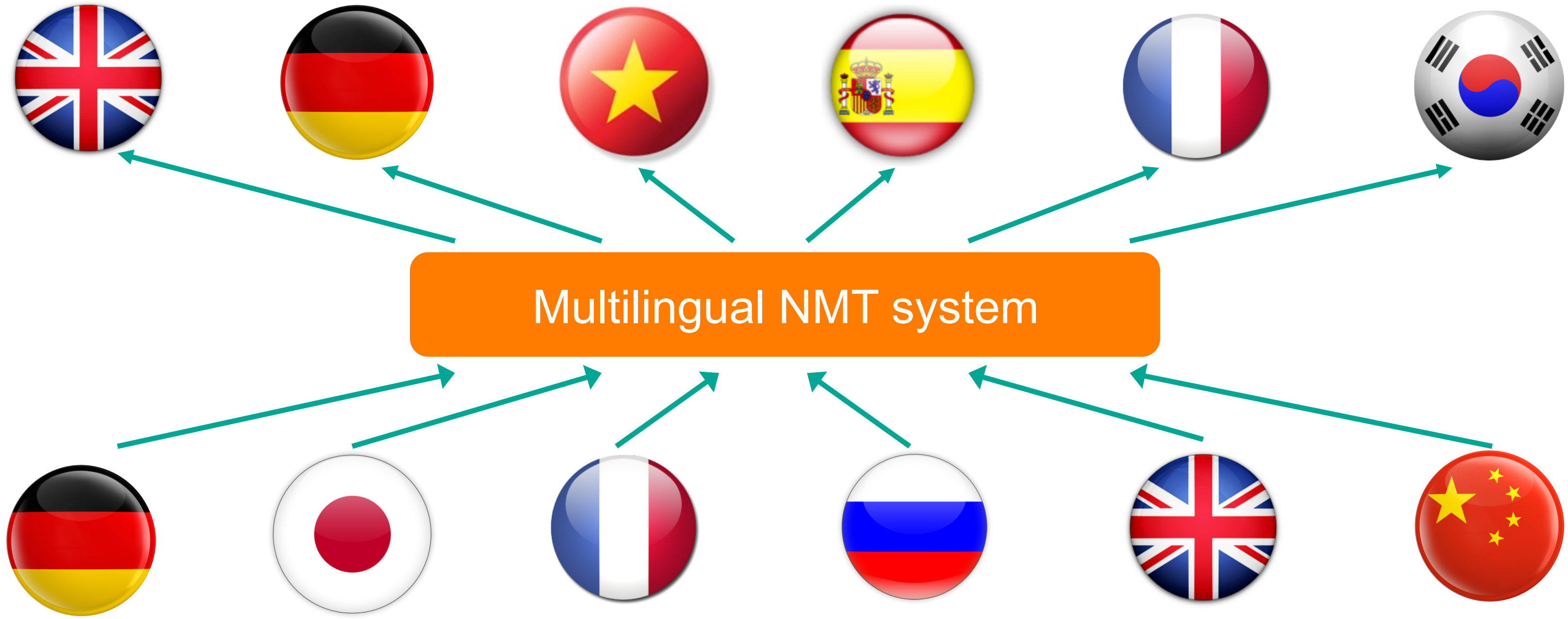
Outline

- Introduction
- Multilingual Neural Machine Translation
  - Related works
  - Our proposed approach
- Experimental results
- Conclusion & Future Work

Attention Neural Machine Translation



Multilingual NMT: Prospective Benefits



- Automatic Language Transfer:
  - Can be applied to under-resource scenarios

- Number of parameters grows linearly with the number of languages

Multilingual NMT: Challenges

- Attention is language-specific

  $\Rightarrow$ An encoder-attention-decoder triple for each language pair

- Multilingual (and Multimodal) models [Luong 2016]
  - Without attention: attention is modality-(and language-)specific

- One-to-Many NMT [Dong 2015]
  - Single encoder, several pairs of attention-decoder for each target language

Multilingual NMT: Challenges

- Attention is language-specific

  ⇒ An encoder-attention-decoder triple for each language pair
- Want a shared attention or decoder NMT?

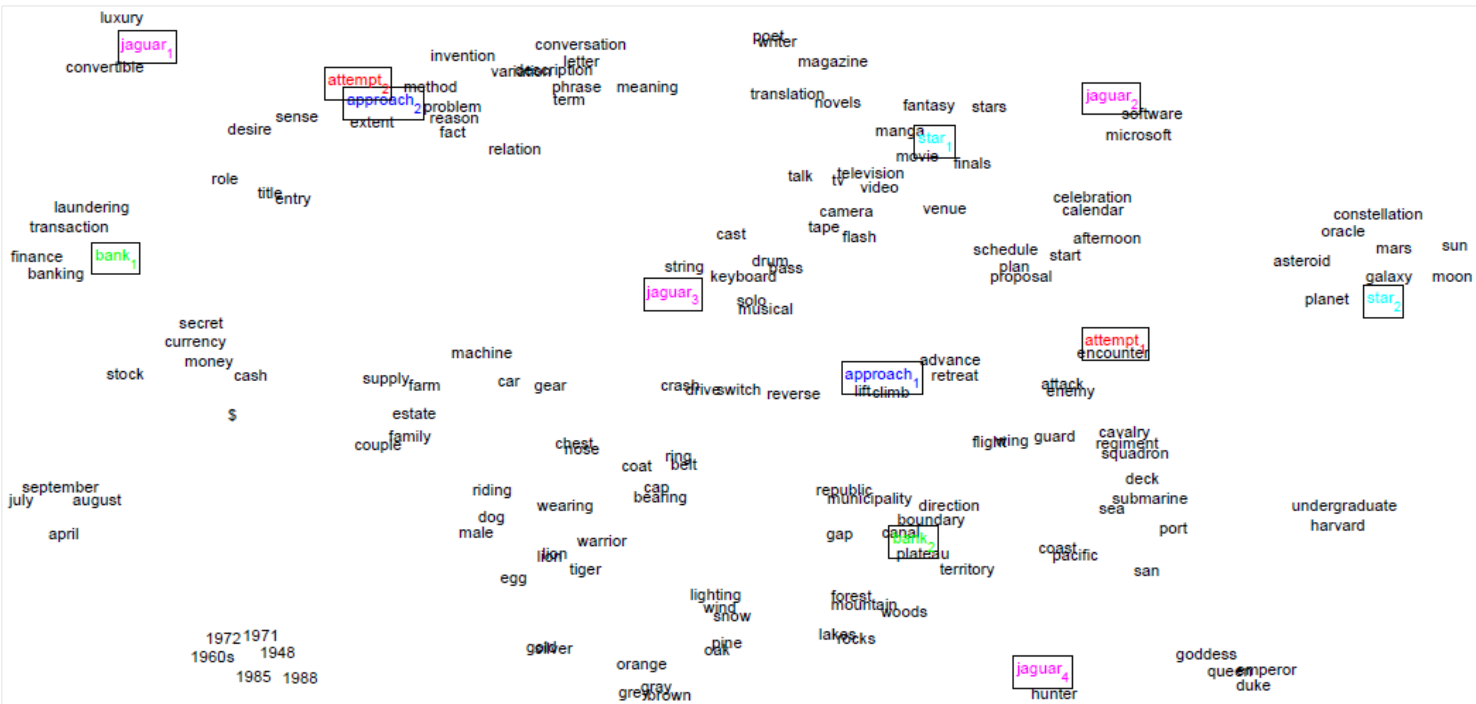
  ⇒ We must modify the architecture

- Many-to-One NMT [Zoph&Knight 2016]
  - Many encoders, need addition layers to combine their outputs before feeding to the attention.

- Multilingual (Many-to-Many) NMT [Firat 2016 papers]
  - Multi-way: Multiple encoders and decoders
  - With shared attention (they must change their architecture)

Multilingual NMT: Our motivations

- NMT should learn common semantic space of all languages
  - "work", "working" and "worked",
  - "car" and "automobile"
  - "player"-English, "joueur"-French, "Spieler"-German



[From Socher 2012]

Multilingual NMT: Our approach

- NMT should learn common semantic space of all languages

- Our multilingual NMT system should:
  - Learn language-independent source and target sentence representations
  - Have a shared language-dependent word embeddings

=> A simple preprocessing step: Language-specific Coding

Multilingual NMT: Our approach

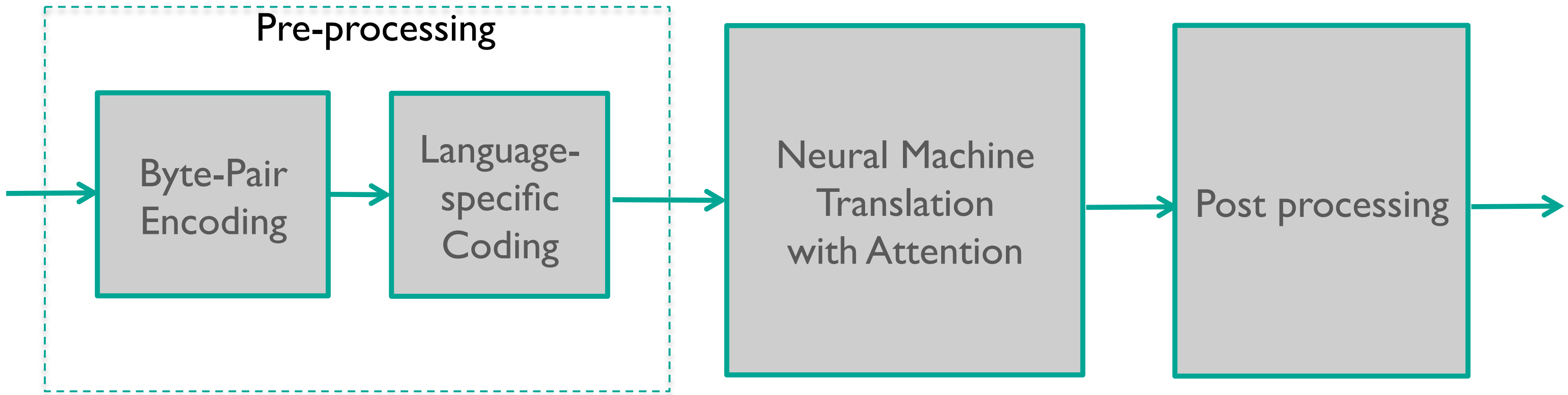
- **Language-specific Coding**
  - Append a language code to the words belonging to that language:
  - (*excuse me* | *excusez moi*) (En-Fr)

  ⇒ (*EN_excuse EN_me* | *FR_excusez FR_moi*)
  - (*entschuldigen Sie* | *excusez moi*) (De-Fr)

  ⇒ (*DE_entschuldigen DE_Sie* | *FR_excusez FR_moi*)

Multilingual NMT: Our approach

- Able to feature attention mechanism for multilingual NMT
- Everything (encoder, attention, decoder) is shared (universal)
- Do not need to change the NMT architecture
  - Language-specific coding is a preprocessing step
  - Can use any NMT framework with any translation unit



Experiments

- Training, validation and testing data
  - TED talks from WIT3
  - WMT'16 parallel and monolingual data
- Framework: Nematus [Sennrich 2016]
  - Sub-word with BPE on joint corpus
  - Vocabularies' size: 40K, sentence-length cut-off at 50
  - One 1024-cell GRU layer, one 1000D embeddings for encoder and decoder
  - Adadelta, mini-batch size: 80. grad norm: 0.1
  - Dropout at every layer

- Experiments on different scenarios:
  - Under-resource (simulated): En-De TED
  - Large-scale, real task: IWSLT'16: En-De WMT tuning on TED

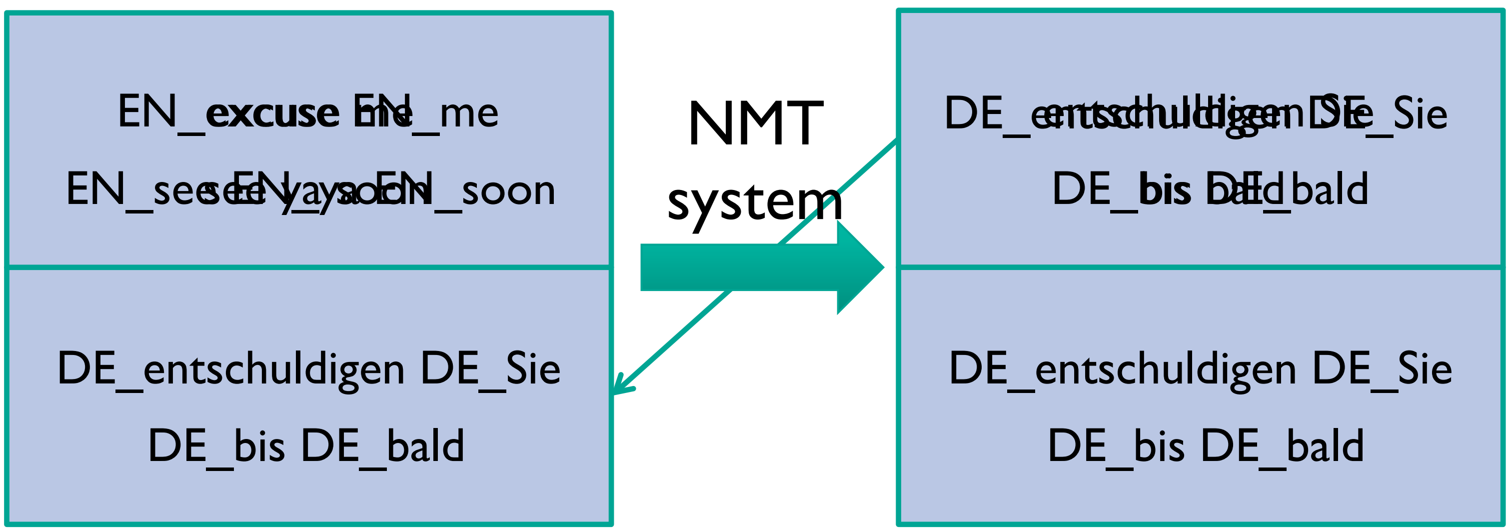
Experiments: Under-resource scenario

- Goal:
  - Translating En to De
  - Using multilingual corpora:
    - En-De: TED 196K
    - Fr-De: TED 165K
  - Two kinds of configurations: Mix-source & Multi-source

Experiments: Mix-source Multilingual NMT

Language-specific coded **English**

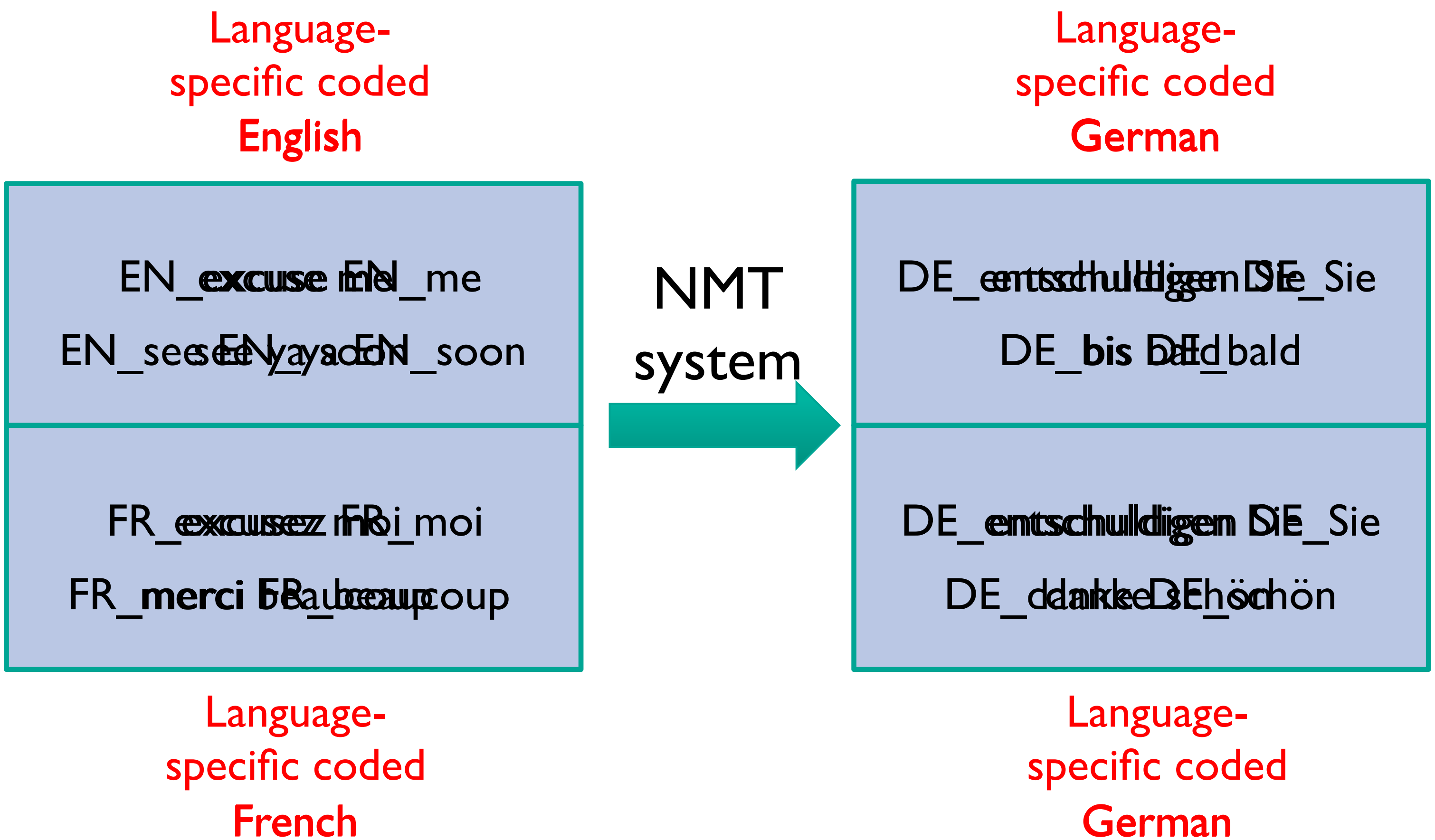
Language-specific coded **German**



Language-specific Coding

Mix-source

Experiments: Multi-source Multilingual NMT



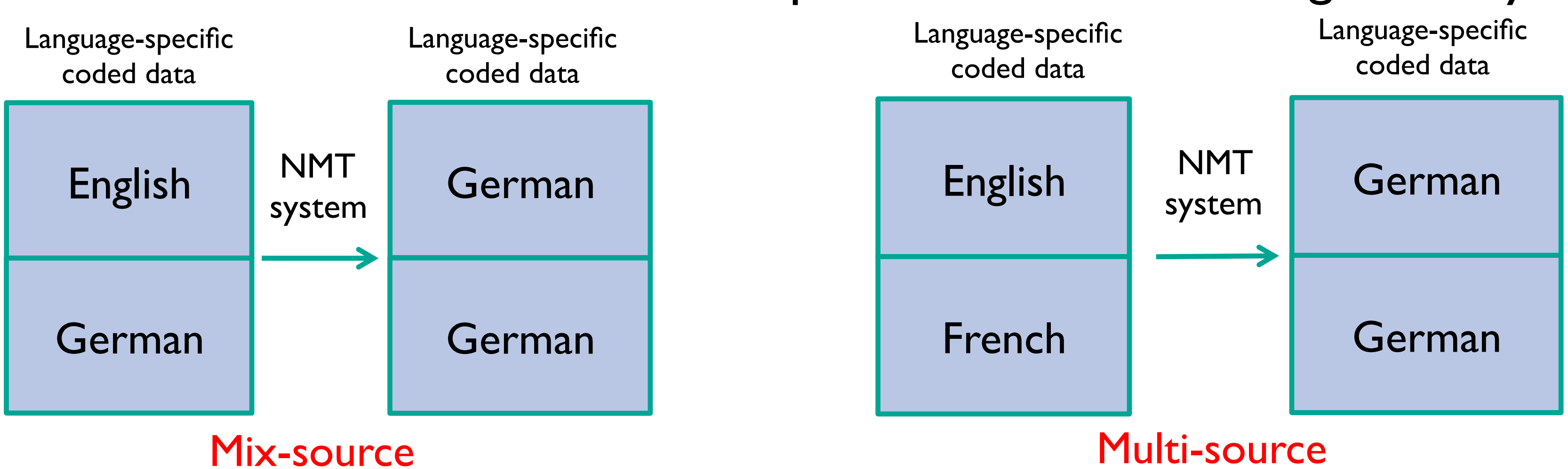
Language-specific Coding

Multi-source

Experiments: Under-resource scenario

System	tst2013		tst2014	
	BLEU	ΔBLEU	BLEU	ΔBLEU
Baseline (En => De)	24.35	-	20.62	-
Mix-source (En,De => De,De)	26.99	+2.64	22.71	+2.09
Multi-source (En,Fr => De,De)	26.64	+2.21	22.21	+1.59

- Both *Mix-source* and *Multi-source* improve the translation significantly



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Baseline 2 (En => De) x2	24.58	+0.23	20.55	-0.07

- Both *Mix-source* and *Multi-source* improve the translation significantly
- ~~Because we have larger data (double the baseline)?~~
  - Baseline 2: Double the corpus

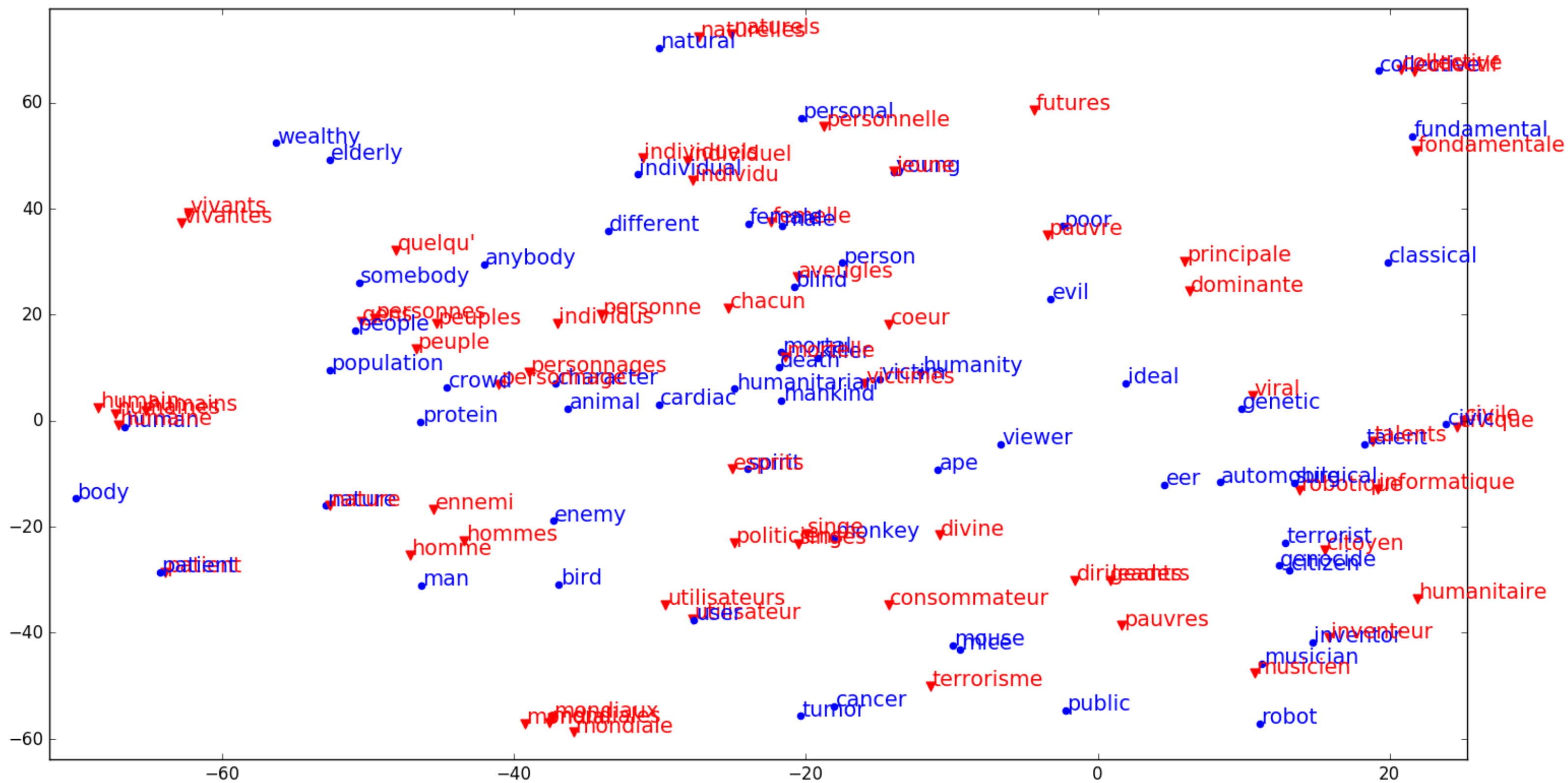
Experiments: Under-resource scenario

System	tst2013		tst2014	
	BLEU	ΔBLEU	BLEU	ΔBLEU
Baseline (En => De)	24.35	-	20.62	-
Mix-source (En,De => De,De)	26.99	+2.64	22.71	+2.09
Multi-source (En,Fr => De,De)	26.64	+2.21	22.21	+1.59
Mix-source 2 (En,De => De,De)	27.18	+2.83	23.74	+3.12

- *Multi-source* performs worse than *Mix-source*. Why?
  - ~~Smaller training data?~~
    - **Mix-source: 392K, Multi-source: 361K**
    - Mix-source 2: De part of En-Fr: 361K < Mix-source:392K
  - Having more data in other languages confuses NMT?
    - Need more analyses (more source languages, more language types)

Experiments: Multi-source Visualization

- Take the source word embeddings (1000 dims) to visualize
- Using t-SNE [Maaten 2008] to project to 2-dim points



En&Fr Word Embeddings topic “human”

Experiments: Multi-source Visualization

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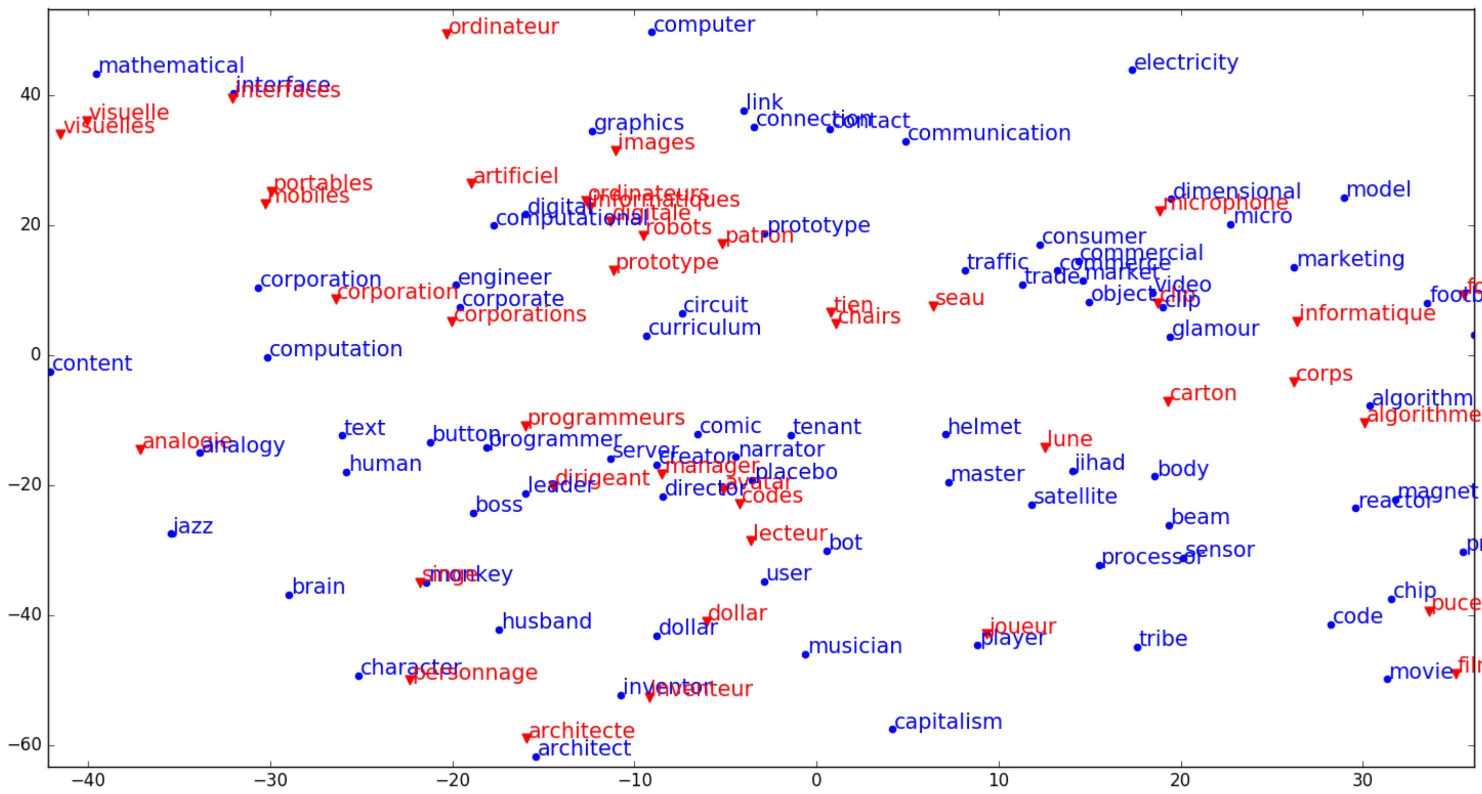
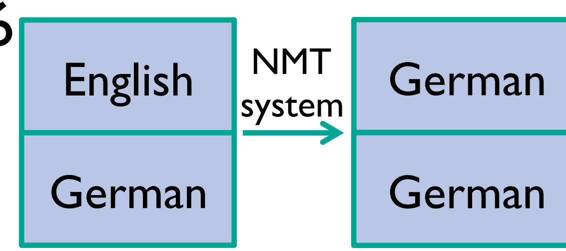


En&Fr Word Embeddings topic "computer"

Experiments: Large-scale, real task

System	tst2013		tst2014	
	BLEU	ΔBLEU	BLEU	ΔBLEU
Baseline (En => De)	25.74	-	22.54	-
1) Sampled Mix-source (En,De => De,De)	27.74	+2.00	24.39	+1.85
2) Mono Mix-source (En,De => De,De)	28.89	+3.15	24.86	+2.32

- Translate En-De for the real task of IWSLT16
  - Baseline: WMT data + BackTranslation
- Train Mix-source configuration on
  - 1) WMT parallel data (En-De) + sampled additional mono data (De-De)
  - 2) WMT parallel data (En-De) + mono part of that parallel data (De-De)
- Adapt on TED En-De (continue training)
  - Also Mix-source on TED



Conclusion & Future work

- Conclusion
  - We proposed a simple but elegant approach for multilingual NMT
    - Allows to use attention seamlessly
    - A preprocessing step, no need to change an NMT architecture
  - Improve significantly in under-resource scenarios
  - Provide natural, effective way to leverage monolingual data in NMT

- Future work
  - More languages and the impact
  - Apply multilingual NMT in zero-resource scenario


Tak
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Thank you
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شكرا
Danke
謝謝
Grazie