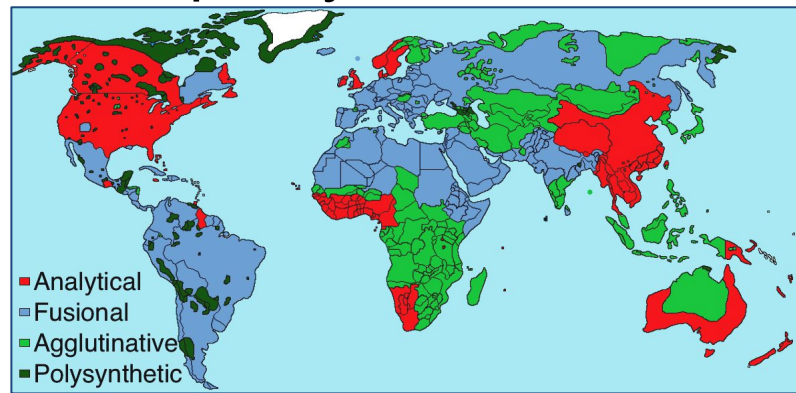


Hybrid Word-Character Neural Machine Translation

Pamela Toman, Sigtryggur Kjartansson
Department of Computer Science, Stanford University

Motivation & Background

- Words are **not** the primary level of meaning in all languages.
- Because traditional NMT is word-level, non-analytic languages tend to have lower-quality translations.
- Want a universalist architecture that performs well for all language pairs.

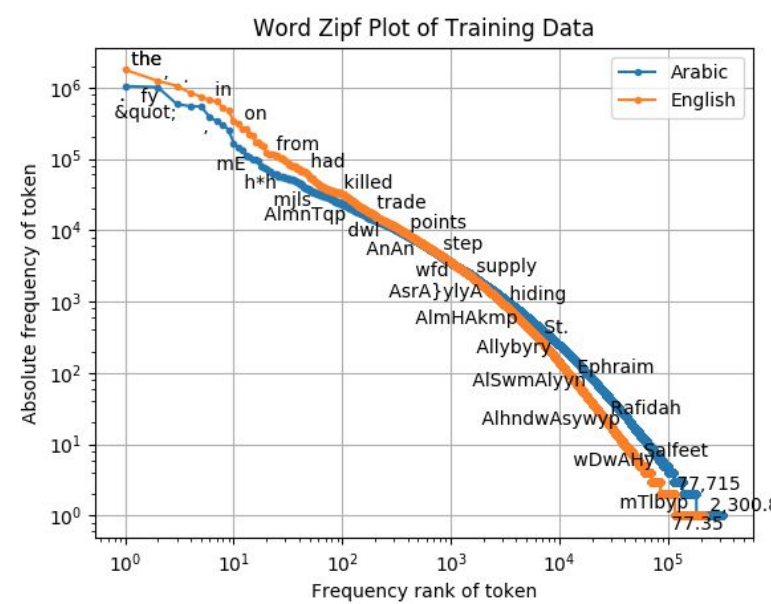


Focusing on **Arabic**: 5th largest language by number of speakers, understudied, and has a variety of clitics, affixes, spelling ambiguities, and the root-and-pattern morphology of Semitic languages.

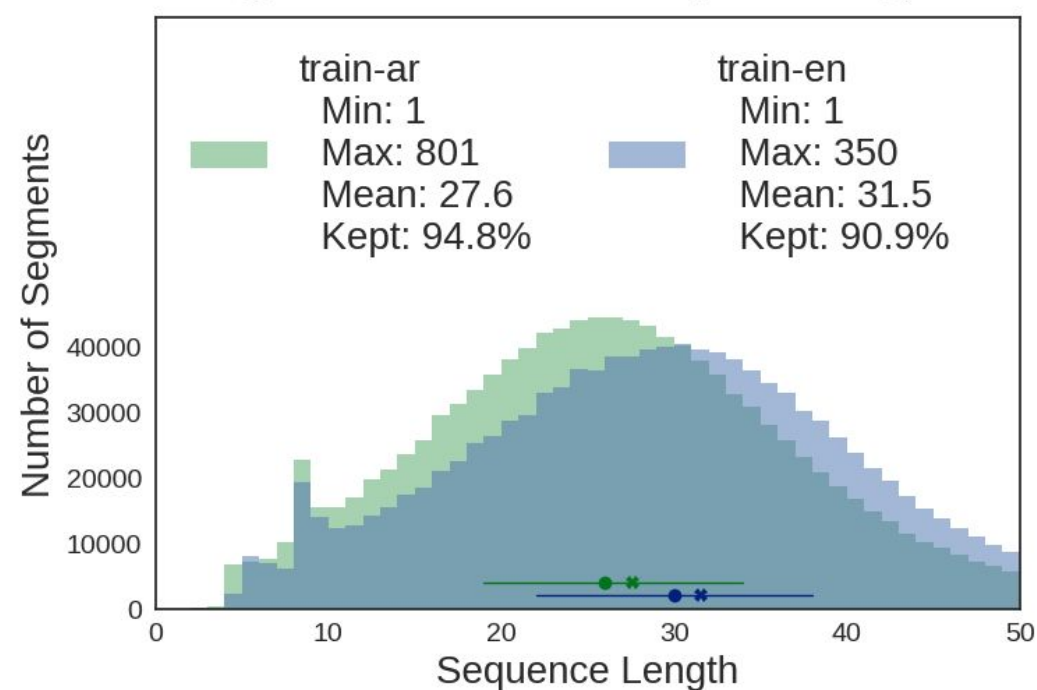
Arabic Morphology	Arabic Example	English Example	Arabic Morphology	Arabic Example	English Example
and summoned him	وَأَسْتَدْعِيهِ	and summoned him	for the purpose of refinement	لِلتَّكْرِيرِ	for the purpose of refinement
trilateral root	دعأ	trilateral root	trilateral root	كر	trilateral root
to call for	دعأ	to call for	to refine	كر	to refine
pattern	أست	requestive verb (Form X)	pattern	كـر	verbal noun (Form II)
prefix	و	and	prefix	لـ	for the purpose of
postfix	هـ	him (accusative)	prefix	لـ	the (abbreviated)

Dataset

- Modern Standard Arabic news articles.
- We follow Almahairi et al. 2016¹:
 - Train: 1,087,343 sentence pairs
 - Dev: 915 sent. pairs
 - Test: 946 sent. pairs



Histogram of Words per Segment



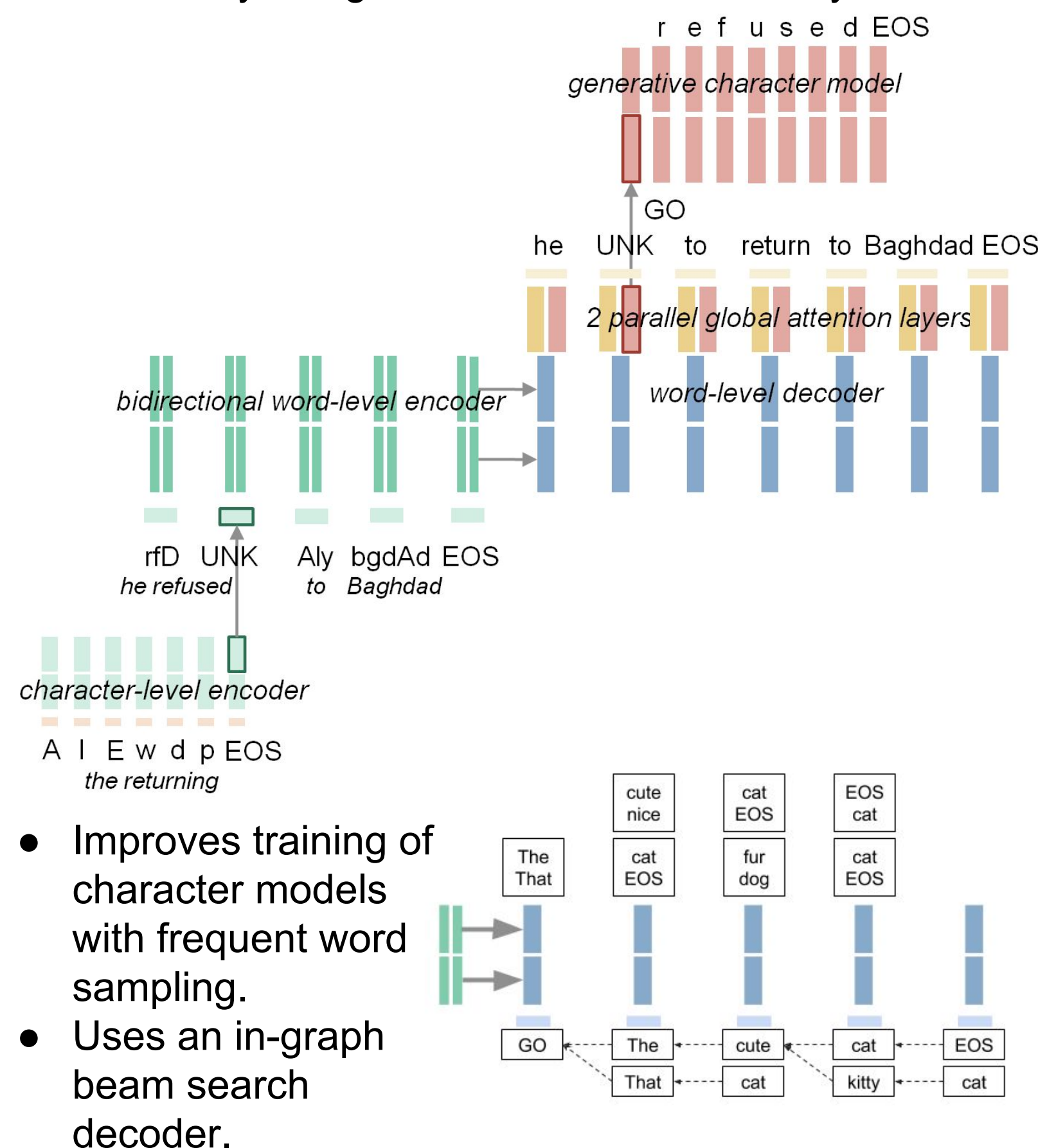
Types	AR	EN
Types	322k	216k
Tokens	27.0m	30.3m

Problem Statement

Goal: Improve Arabic-English Machine Translation.
Benchmark: Almahairi et al. 2016¹ using BLEU metric.
Approach: Neural Machine Translation model that achieves open vocabulary.

Method

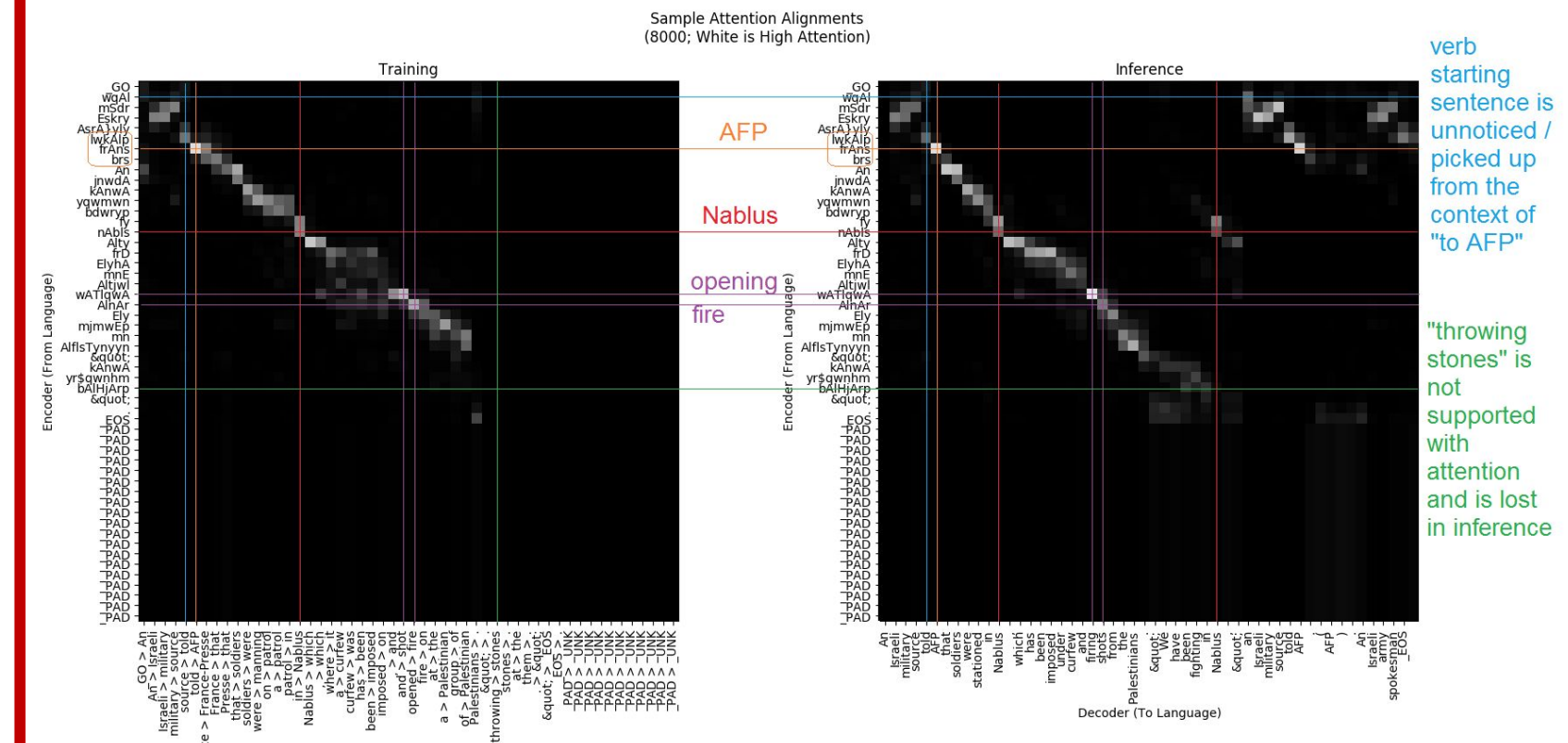
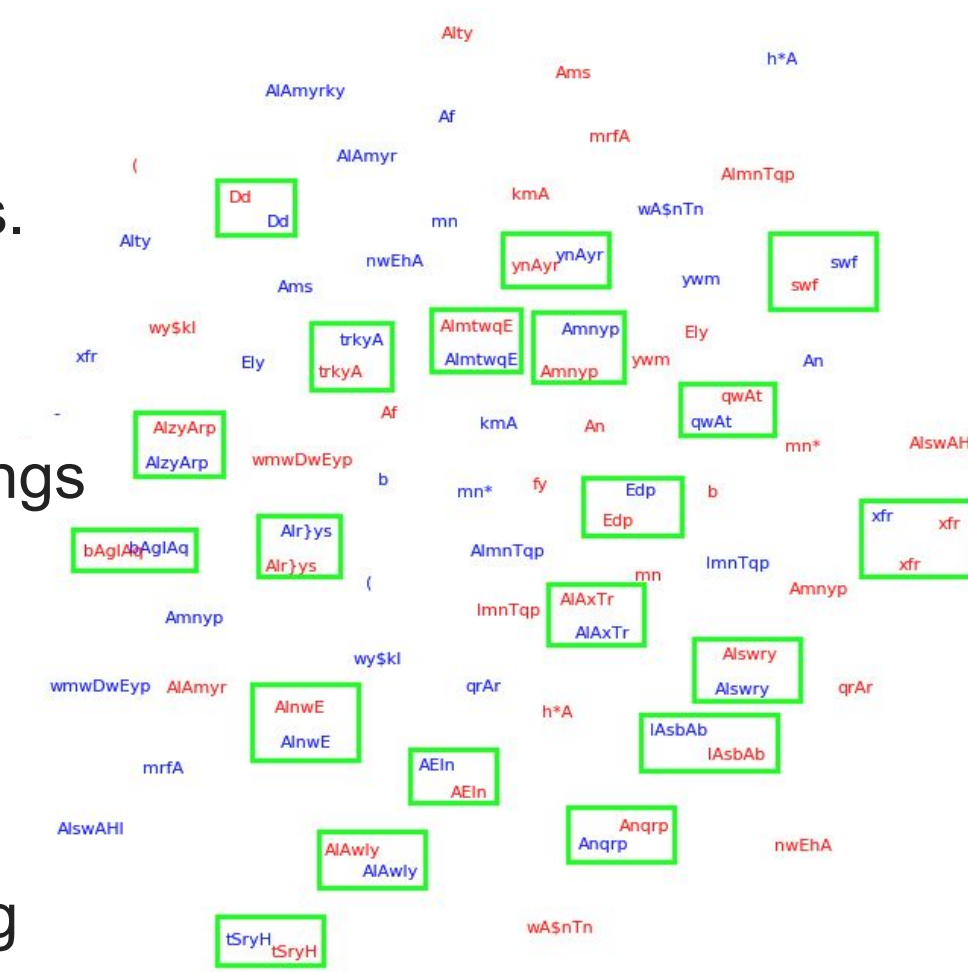
- We unite three models to create a hybrid word-character model, based on Luong and Manning 2016:²
 - Source Character-Level Encoder.
 - Word-Level Sequence-to-Sequence with global bilinear attention.³
 - Target Character-Level Generator.
- Backs off to the character level when word-level representations do not exist, in order to achieve open vocabulary using a small known vocabulary.



Experimental Evaluation & Results

- Achieved BLEU score: 42.10
- Evaluate model by:
 - Train with different hidden states sizes.
 - Train with different vocabulary sizes.
 - Visualize embeddings using t-SNE.
 - Inspect attention alignments.
 - Use alternative frequency sampling techniques.

Similarities Between Unit-Level Word Embeddings and Character-Derived Word Embeddings (Step 18003; Unit-Level Blue, Character-Derived Red)



Conclusion & Future Direction

- Hybrid architecture combines the strength of both word- and character-based models; fast to train and offer high-quality translation; and achieves open vocabulary.
- Want to add a character-level attention mechanism and/or a convolutional layer to facilitate interactions with Arabic's complex morphology.

¹ Almahairi et al., 2016; arXiv:1606.02680
² Luong and Manning, 2016; arXiv:1604.00788
³ Luong, Pham and Manning, 2015; arXiv:1508.04025
Acknowledgements: Ignacio Cases, Microsoft Azure, CS224N staff