# What do Multilingual Neural Machine Translation Models Learn about Typology?

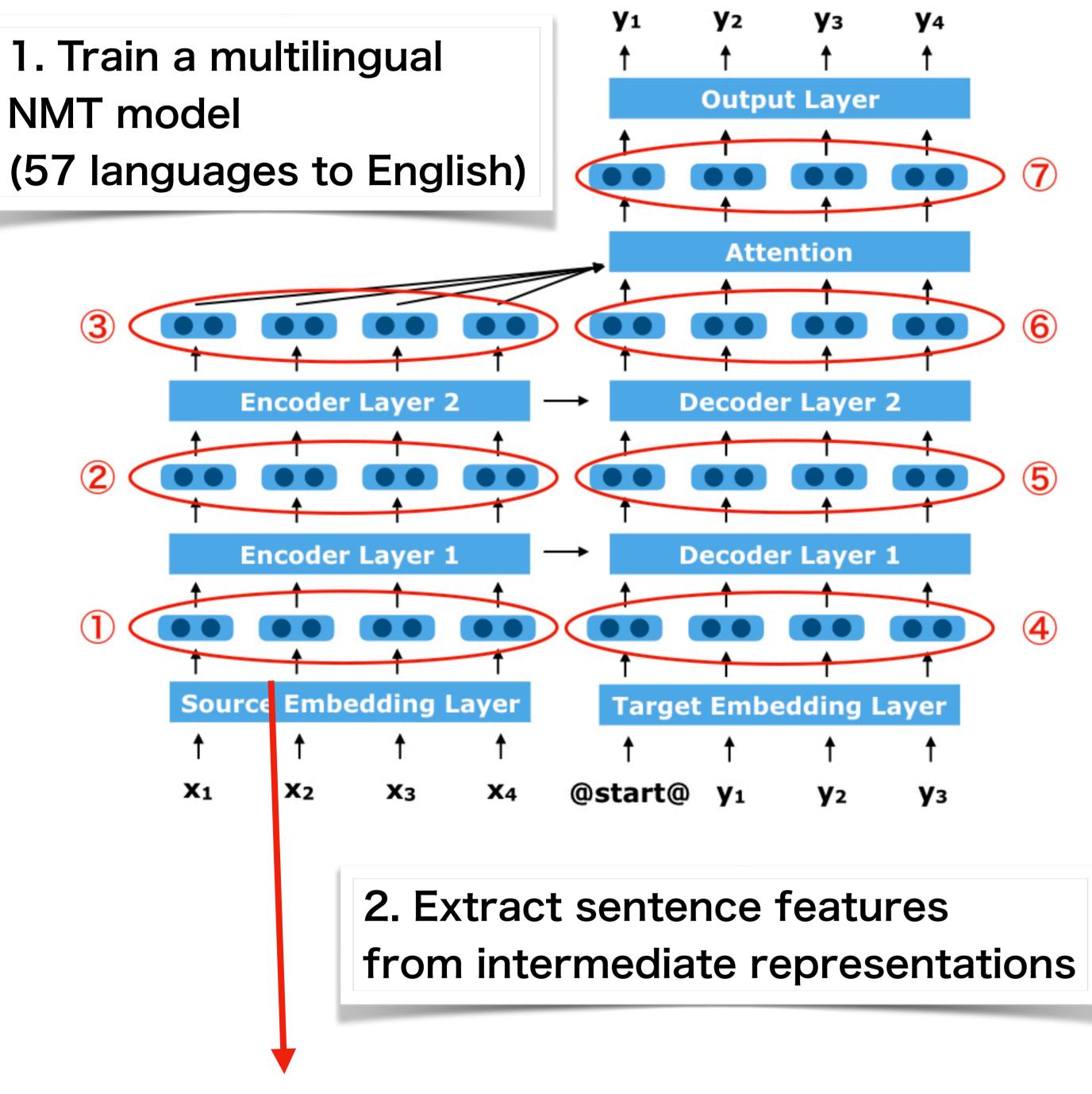
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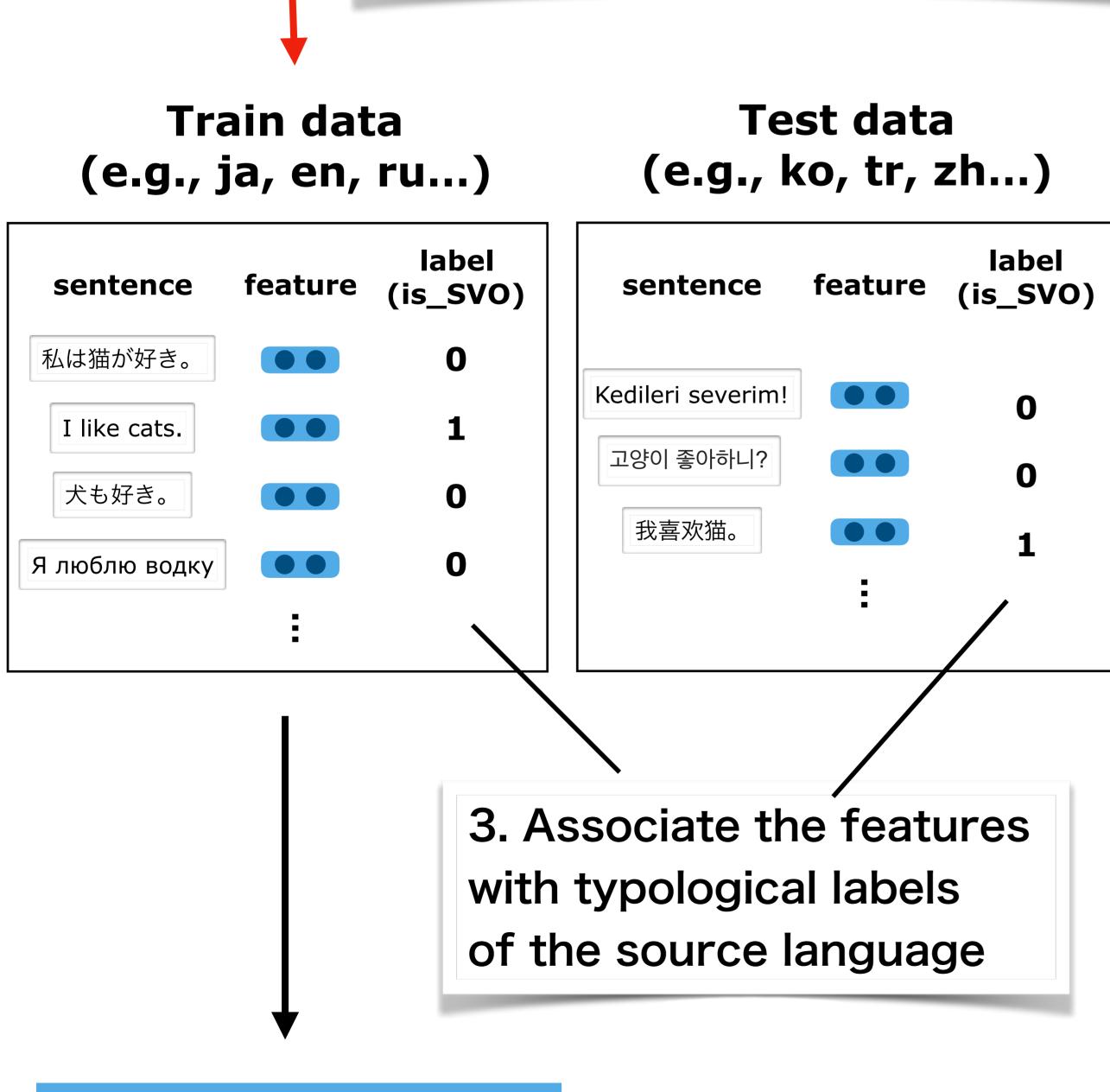


### **Abstract**

How do multilingual models handle the multilingualism? In this work, we probed multilingual neural machine translation (NMT) models by typological feature classification task.

## **Experimental Procedure**





**Probing Classifier** 

4. Train and test

a probing classifier

### **Dataset**

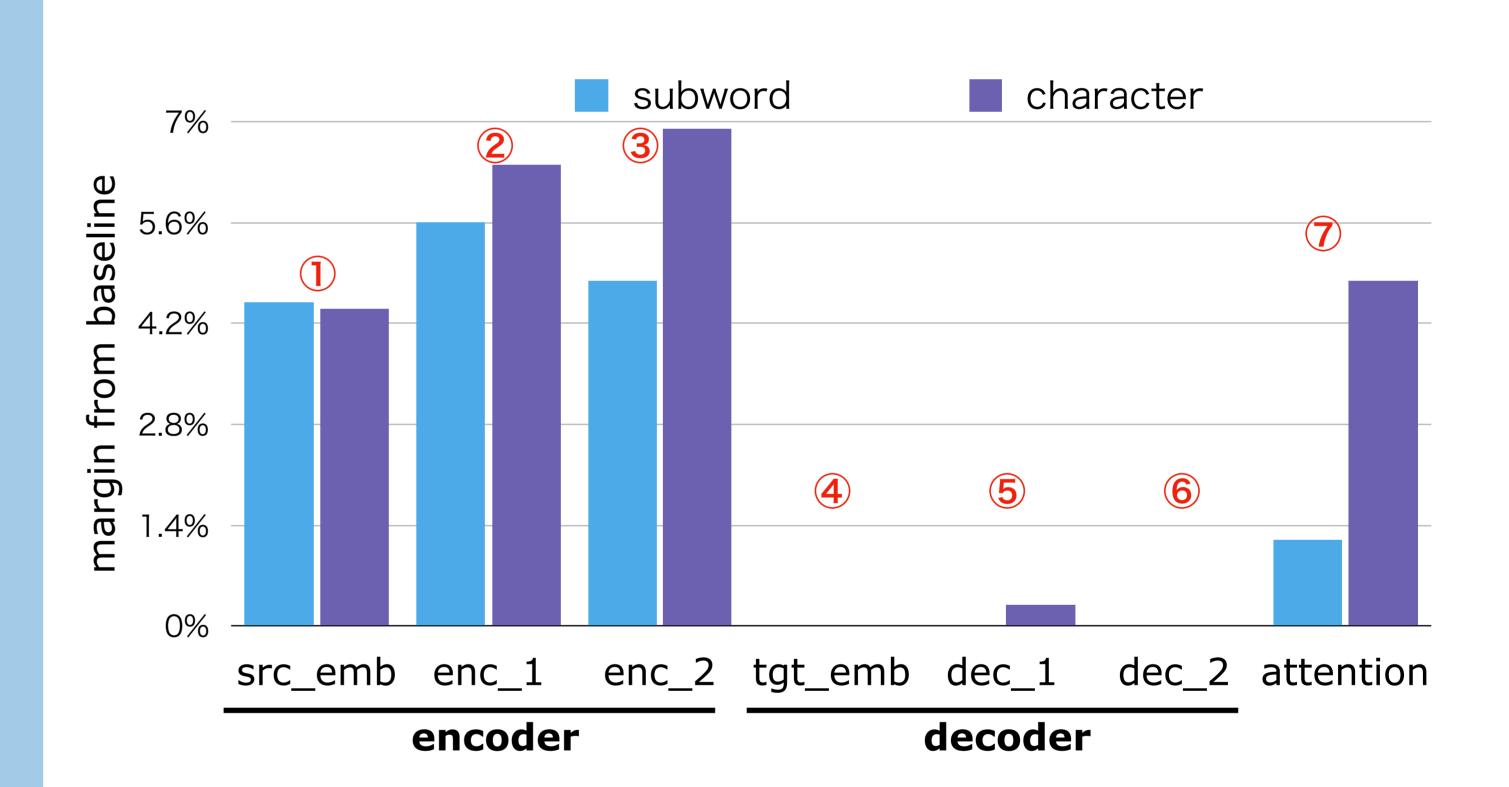
Bible Corpus: Translation of the Bible

- contains sentences with the same meaning in multiple languages
- Train: 23,555 sentences for each language (Dev: 455, Test 455)

URIEL database: The database for typology

- Used 103 syntactic features
- For missing data, predicted values are used (by kNN regressions based on phylogenetic or geographical neighbours).

## Result



- The encoder is aware of the source language, while the decoder is not. However, the attention module again introduce source-dependent representation. This is undesirable if we expect the multilingual NMT to used shared meaning representation (interlingua).
- Character-level models are better at capturing typology, probably because of its morphological competence.

**Top 5 improvements** 

Feature	Subword	Character	Gain
S ADJECTIVE_AFTER_NOUN	73.33	85.09	11.76
S_ADJECTIVE_BEFORE_NOUN	77.63	87.76	10.13
S_INDEFINITE_WORD	61.81	70.76	8.94
S_ADJECTIVE_WITHOUT_NOUN	65.67	73.85	8.17
$S_{-}TEND_{-}DEPMARK$	70.12	78.13	8.00
S_SVO	85.97	81.47	-4.49
S_SUBORDINATOR_WORD_BEFORE_CLAUSE	92.30	86.75	-5.54
$S\_SOV$	87.75	81.65	-6.10
S_OBJECT_AFTER_VERB	96.44	89.99	-6.45
S_NEGATIVE_WORD_BEFORE_OBJECT	83.79	76.80	-6.98