Beyond Parallel Corpora

Philipp Koehn

29 October 2020

data and machine learning

Supervised and Unsupervised

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  - training examples with labels
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- Self-training
  - make predictions on unlabeled training data
  - use predicted labeled as supervised translation data

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- Multi-Task training
  - train on a related task first
  - e.g., part-of-speeh tagging

- Share some or all of the components

using monolingual data

Using Monolingual Data

- Language model
  - trained on large amounts of target language data
  - better fluency of output

- Key to success of statistical machine translation

- Neural machine translation
  - integrate neural language model into model
  - create artificial data with backtranslation

Adding a Language Model

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- Recall state progression in the decoder
  - decoder state s_i
  - embedding of previous output word Ey_{i-1}
  - input context c_i

$$s_i = f(s_{i-1},\ Ey_{i-1}, c_i)$$

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- Pre-train language model

- Leave its parameters fixed during translation model training

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- Use this scaled language model state for decoder state

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Back Translation

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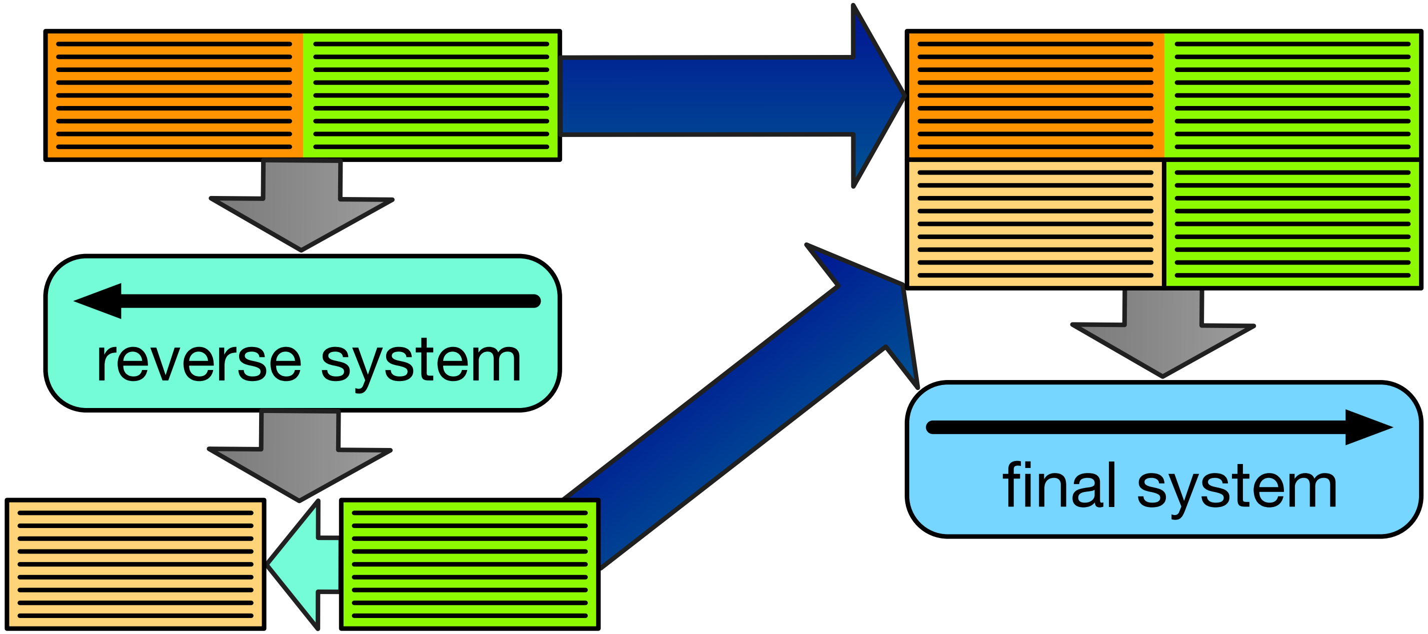
- Let's synthesize that half



Back Translation

- Steps

  1. train a system in reverse language translation
  2. use this system to translate translate target side monolingual data
     → synthetic parallel corpus
  3. combine generated synthetic parallel data with real parallel data to build the final system

- Roughly equal amounts of synthetic and real data

- Useful method of domain adaptation

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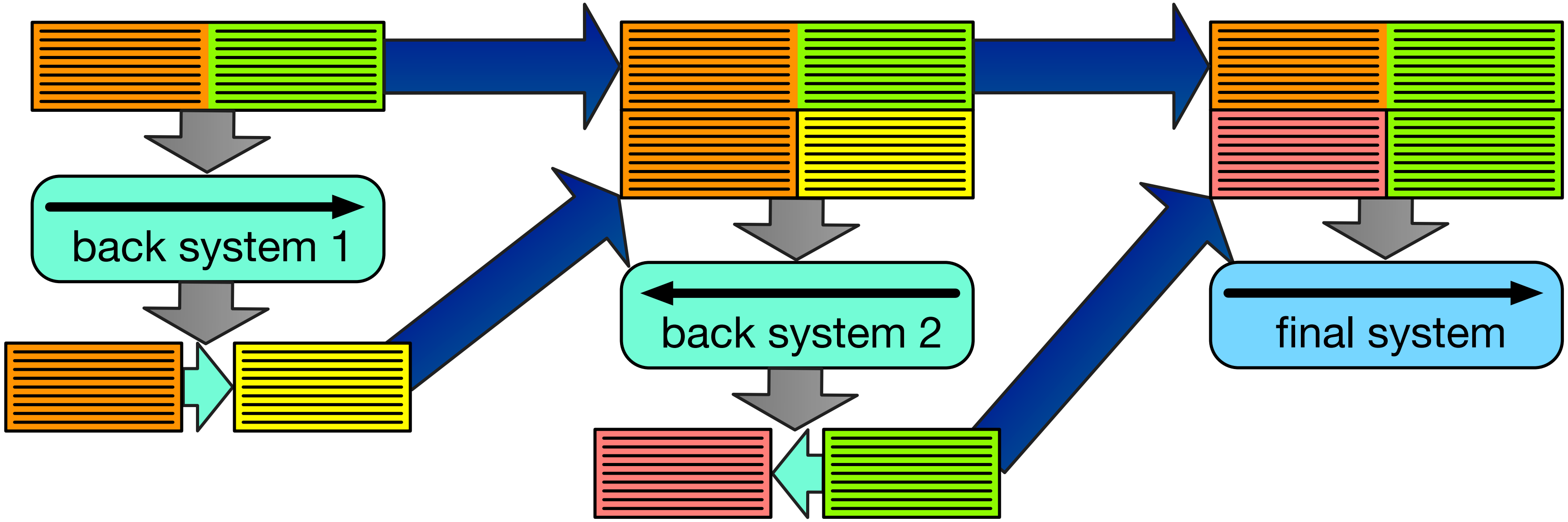

Iterative Back Translation

- Example

German–English	Back	Final
no back-translation	-	29.6
*10k iterations	10.6	29.6 (+0.0)
*100k iterations	21.0	31.1 (+1.5)
convergence	23.7	32.5 (+2.9)
re-back-translation	27.9	33.6 (+4.0)

* = limited training of back-translation system

Round Trip Training

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  - train system
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- Dual learning: train models in both directions together
  - translation models $F \rightarrow E$ and $E \rightarrow F$
  - take sentence **f**
  - translate into sentence **e'**
  - translate that back into sentence **f'**
  - training objective: **f** should match **f'**

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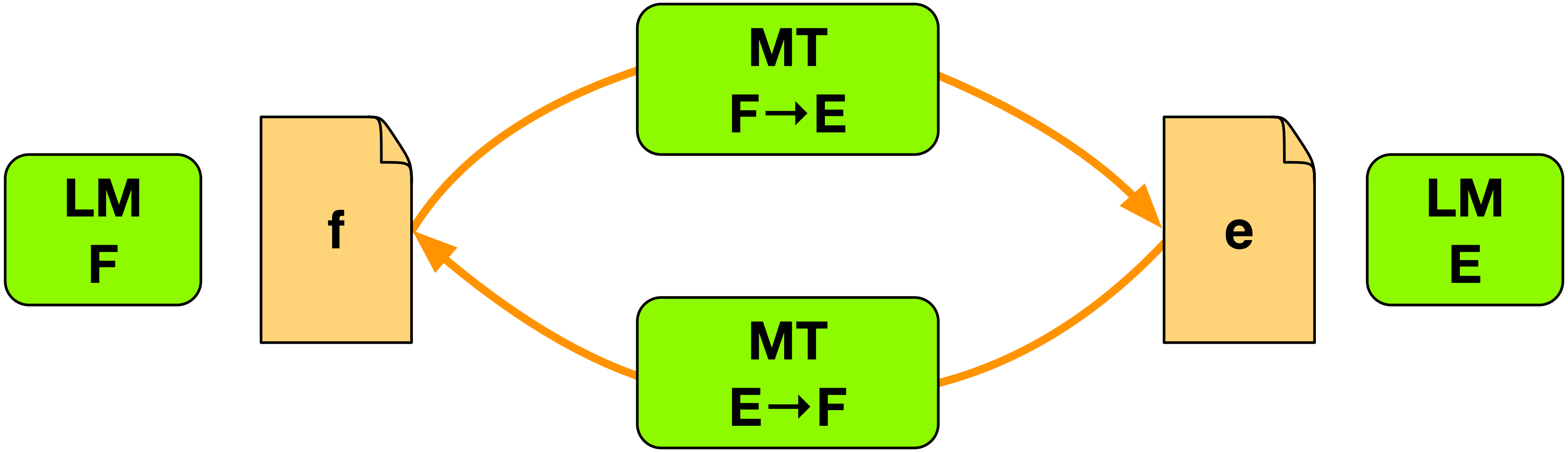
- Setup could be fooled by just copying (**e'** = **f**)

  ⇒ score **e'** with a language for language E
  add language model score as cost to training objective

Round Trip Training



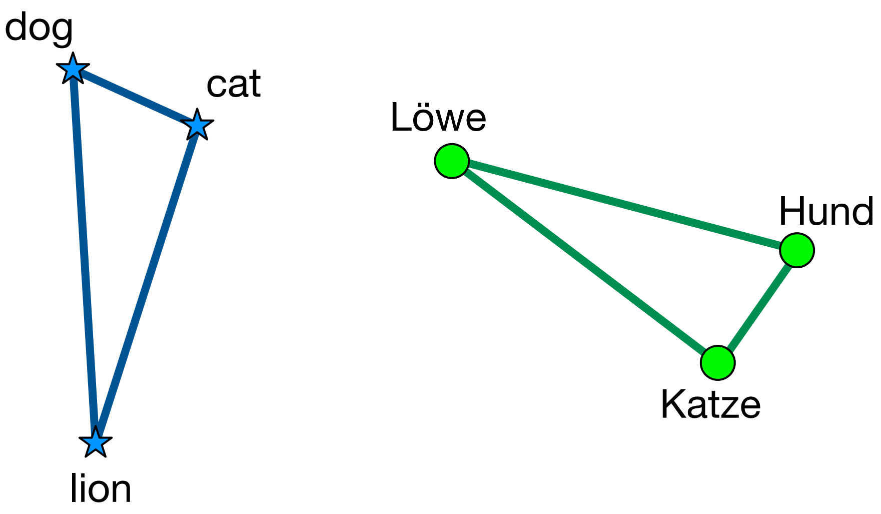
Variants

- Copy Target
  - if no good neural machine translation system to start with
  - just copy target language text to the source

- Forward Translation
  - synthesize training data in same direction as training
  - self-training (inferior but sometimes successful)

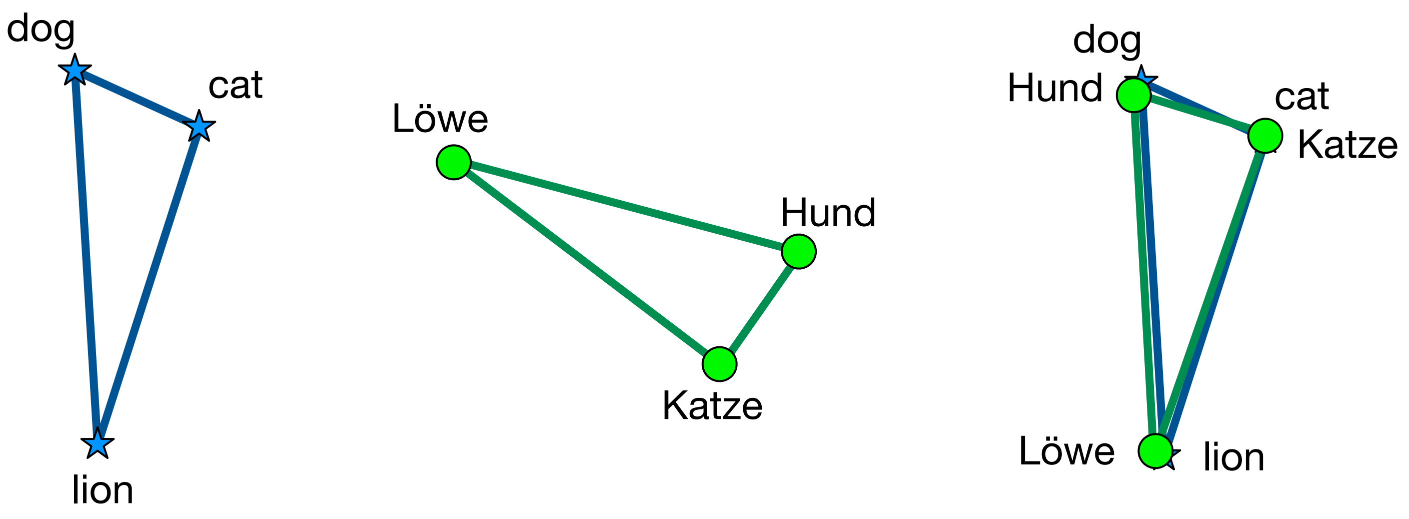
unsupervised machine translation

Monolingual Embedding Spaces



- Embedding spaces for different languages have similar shape
- Intuition: relationship between *dog*, *cat*, and *lion*, independent of language
- How can we rotate the triangle to match up?

Matching Embedding Spaces



- Seed lexicon of identically spelled words, numbers, names
- Adversarial training method: discriminator predicts [Conneau et al., 2018]
- Match matrices with word similarity scores: Vecmap [Artetxe et al., 2018]

Inferred Translation Model

- Translation model
  - induced word translations (nearest neighbors of mapped embeddings)

  → statistical phrase translation table (probability $\simeq$ similarity)

- Language model
  - target side monolingual data

  → estimate statistical n-gram language model

⇒ Statistical phrase-based machine translation system

Synthetic Training Data

- Create synthetic parallel corpus
  - monolingual text in source language
  - translate with inferred system: translations in target language

- Recall: EM algorithm
  - predict data: generate translation for monolingual corpus
  - predict model: estimate model from synthetic data
  - iterate this process, alternate between language directions

- Increasingly use neural machine translation model to synthesize data

multiple language pairs

Multiple Language Pairs

- There are more than two languages in the world
- We may want to build systems for many language pairs
- Typical: train separate models for each
- Joint training

Multiple Input Languages

- Example
  - German–English
  - French–English
- Concatenate training data
- Joint model benefits from exposure to more English data
- Shown beneficial in low resource conditions
- Do input languages have to be related? (maybe not)

Multiple Output Languages

- Example
  - French–English
  - French–Spanish
- Concatenate training data
- Given a French input sentence, how specify output language?

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  - French–English
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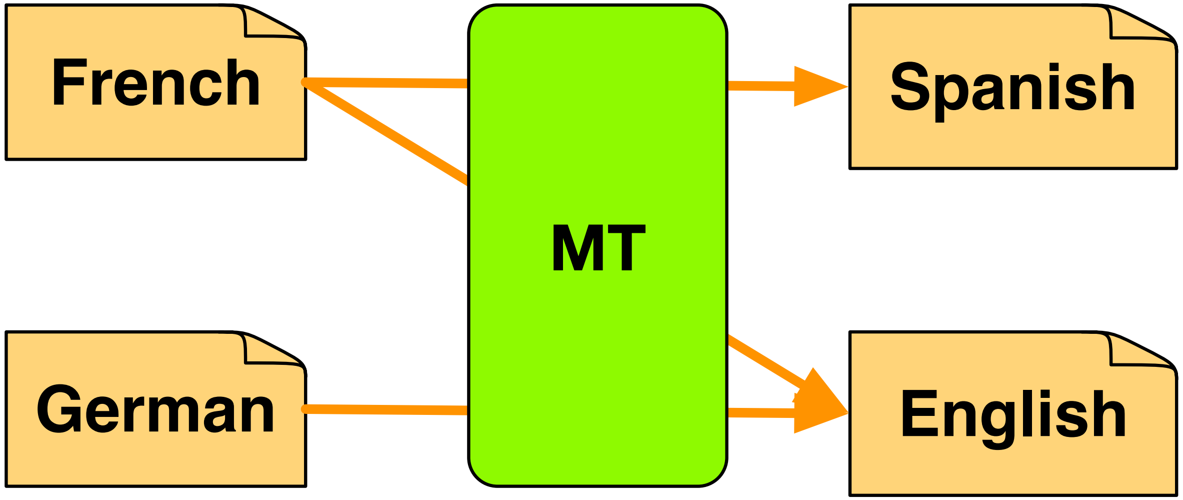
- Concatenate training data
- Given a French input sentence, how specify output language?
- Indicate output language with special tag

[ENGLISH] *N'y a-t-il pas ici deux poids, deux mesures?*
⇒ *Is this not a case of double standards?*

[SPANISH] *N'y a-t-il pas ici deux poids, deux mesures?*
⇒ *¿No puede verse con toda claridad que estamos utilizando un doble rasero?*

Zero Shot Translation

- Example
  - German–English
  - French–English
  - French–Spanish
- We want to translate
  - German–Spanish



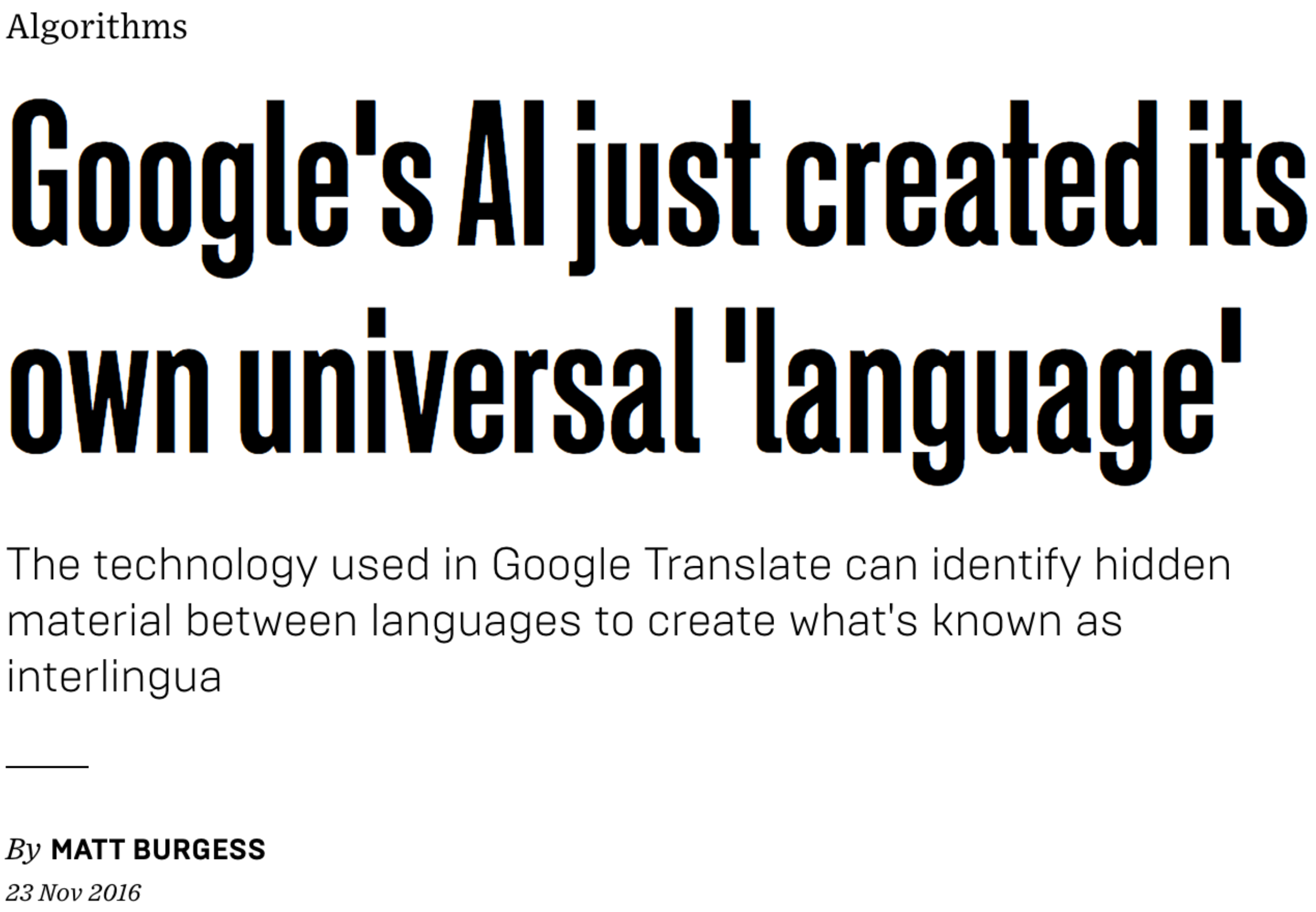
Zero Shot

- Train on
  - German–English
  - French–English
  - French–Spanish

- Specify translation

[SPANISH] *Messen wir hier nicht mit zweierlei Maß?*
⇒ *¿No puede verse con toda claridad que estamos utilizando un doble rasero?*

Zero Shot: Hype



Algorithms

Google's AI just created its own universal 'language'

The technology used in Google Translate can identify hidden material between languages to create what's known as interlingua

By **MATT BURGESS**

23 Nov 2016

Zero Shot: Reality

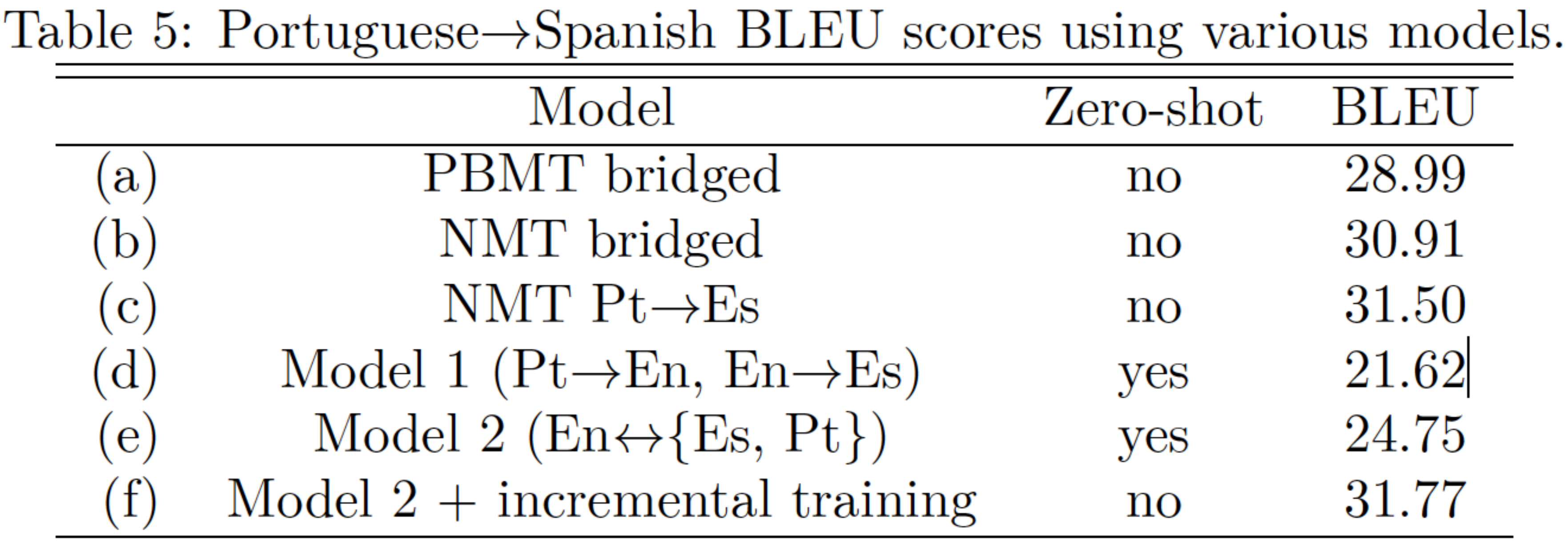


Table 5: Portuguese→Spanish BLEU scores using various models.

	Model	Zero-shot	BLEU
(a)	PBMT bridged	no	28.99
(b)	NMT bridged	no	30.91
(c)	NMT Pt→Es	no	31.50
(d)	Model 1 (Pt→En, En→Es)	yes	21.62
(e)	Model 2 (En↔{Es, Pt})	yes	24.75
(f)	Model 2 + incremental training	no	31.77

- Bridged: pivot translation Portuguese → English → Spanish
- Model 1 and 2: Zero shot training
- Model 2 + incremental training: use of some training data in language pair

Sharing Components

- So far: generic neural machine translation model

- Maybe better: separate systems with shared components
  - encoder shared in models with same input language.
  - decoder shared in models with same output language.
  - attention mechanism shared in all models

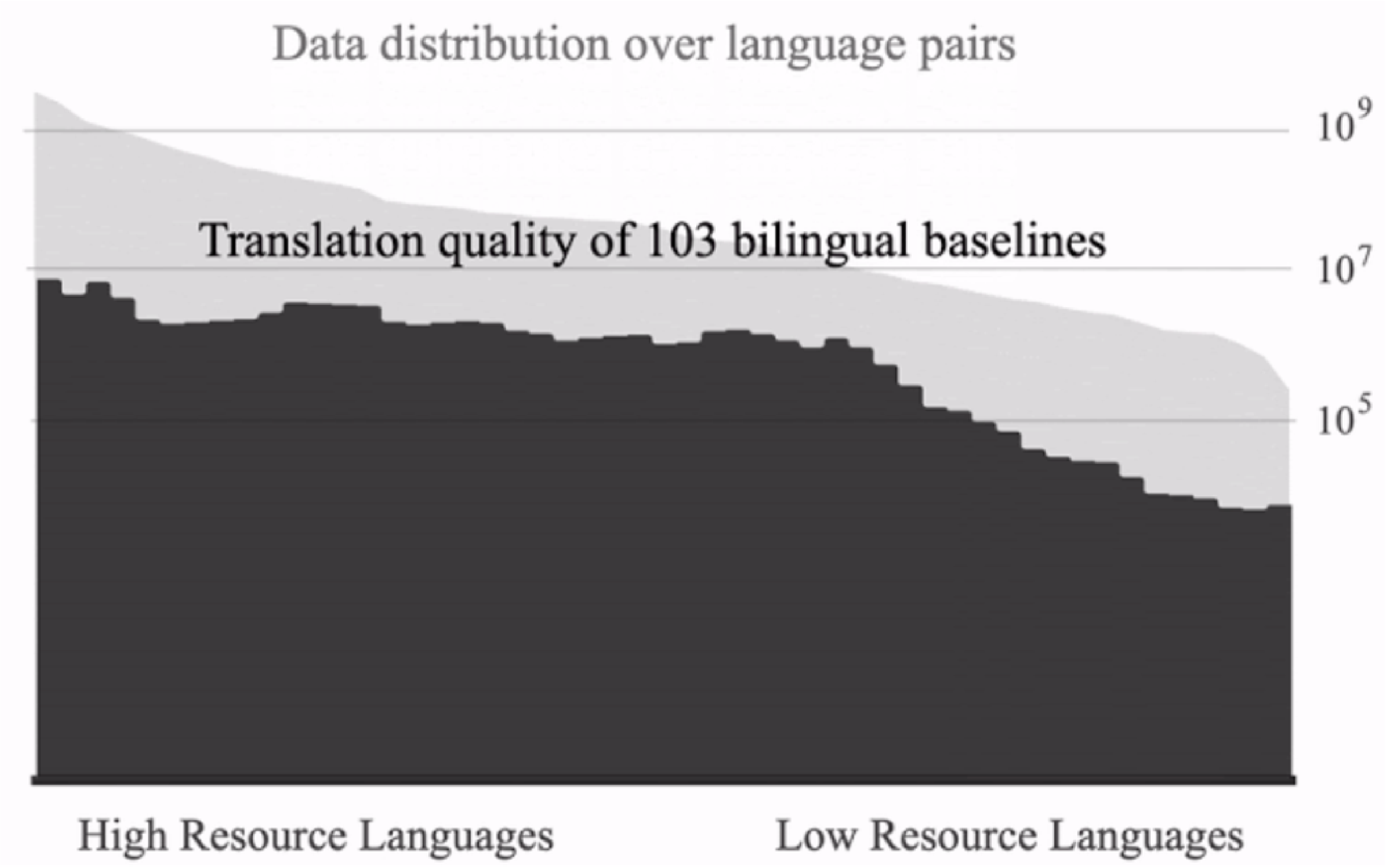
- Sharing = same parameters, updates from any language pair training

- No need to mark output language

Massively Multilingual Training

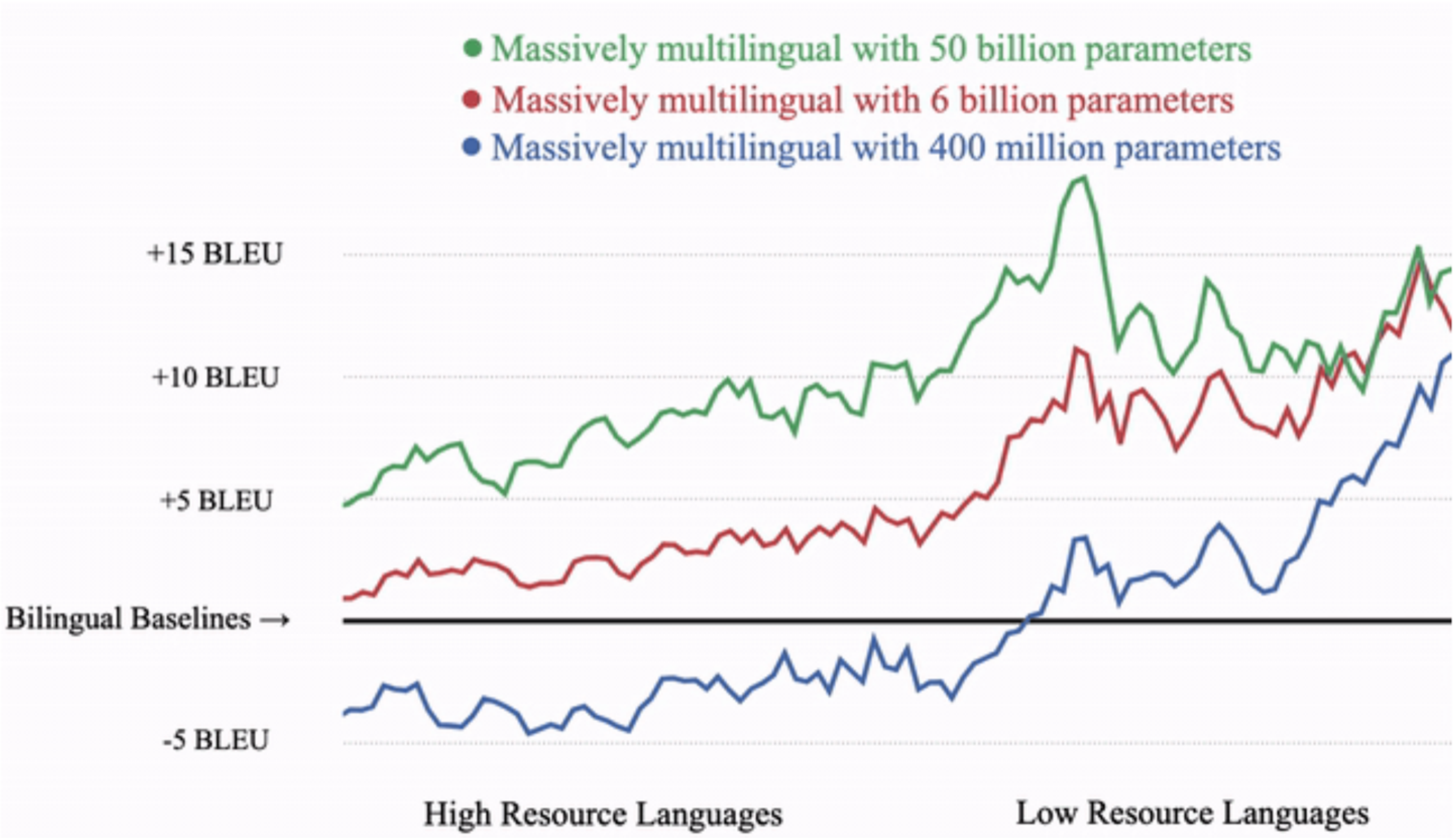
- Scaling up multilingual machine translation for more languages
  - many-to-English
  - English-to-many
  - many-to-many
- Mainly motivated by improving low-resource language pairs
- Move towards larger models

Translation Quality for 103 Languages



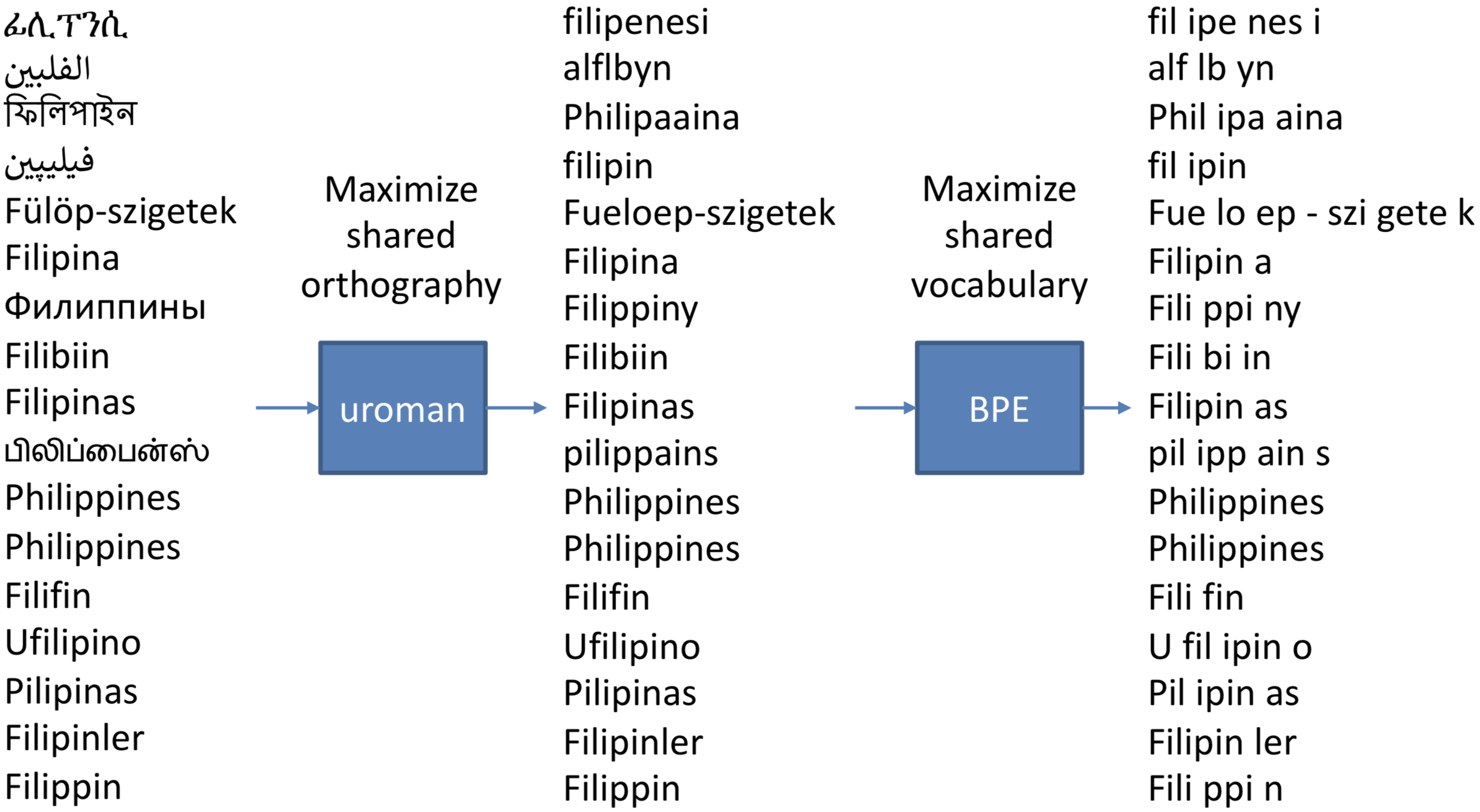
(source: Google)

Gains with Multilingual Training



(source: Google)

Romanization



Maximize shared orthography

uroman

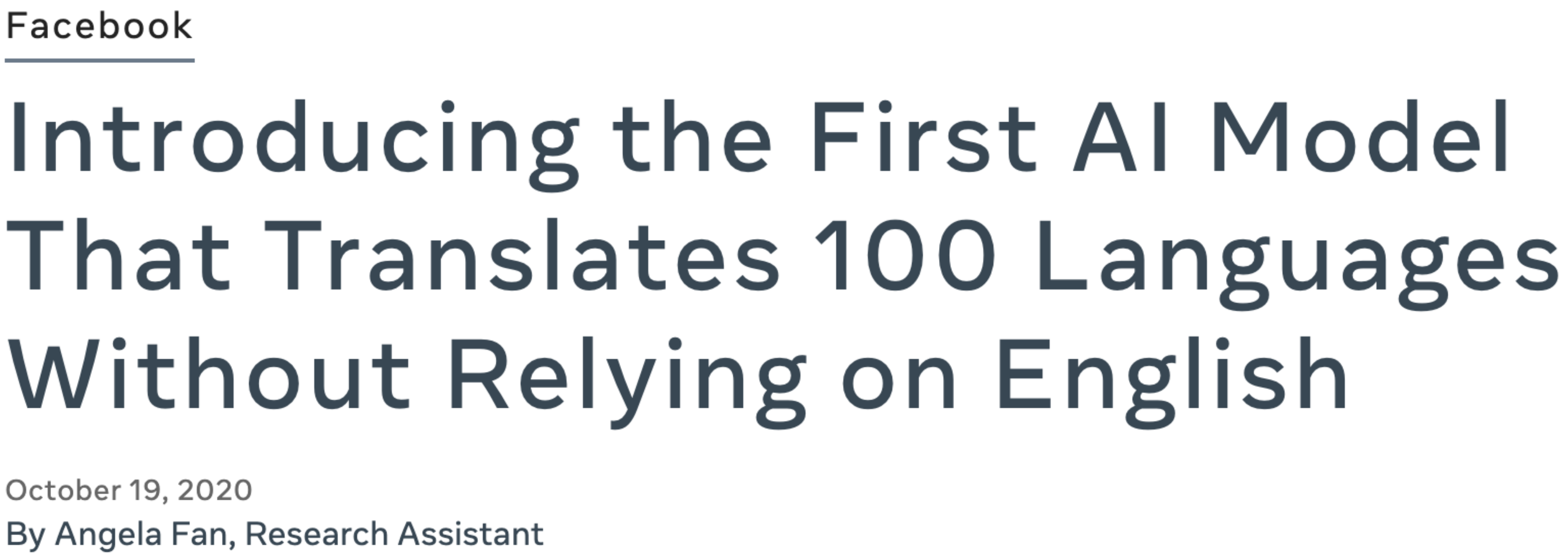
Maximize shared vocabulary

BPE

ፊሊፒንሲ	filipenesi	fil ipe nes i
الفلبين	alflbyn	alf lb yn
ফিলিপাইন	Philipaaina	Phil ipa aina
فیلیپین	filipin	fil ipin
Fülöp-szigetek	Fueloep-szigetek	Fue lo ep - szi gete k
Filipina	Filipina	Filipin a
Филиппины	Filippiny	Fili ppi ny
Filibiin	Filibiin	Fili bi in
Filipinas	Filipinas	Filipin as
பிலிப்பைன்ஸ்	pilippains	pil ipp ain s
Philippines	Philippines	Philippines
Philippines	Philippines	Philippines
Filifin	Filifin	Fili fin
Ufilipino	Ufilipino	U fil ipin o
Pilipinas	Pilipinas	Pil ipin as
Filipinler	Filipinler	Filipin ler
Filippin	Filippin	Fili ppi n

(source: USC/ISI)

Many-to-Many



Facebook

Introducing the First AI Model That Translates 100 Languages Without Relying on English

October 19, 2020

By Angela Fan, Research Assistant

- 7.5 billion sentences for 100 languages
  (mined from web-crawled data)
- Model with 15 billion parameters
- Improvements especially for low resource languages

multi-task training

Related Tasks

- Our translation models: generic sequence-to-sequence models
- Same model used for many other tasks
  - sentiment detection
  - grammar correction
  - semantic inference
  - summarization
  - question answering
  - speech recognition
- For all these tasks, we need to learn basic properties of language
  - word embeddings
  - contextualize word representations in encoder
  - language model aspects of decoder
- Why re-invent the wheel each time?

Training on Related Tasks

- Train model on several tasks
- Maybe shared and task-specific components
- System learns general facts about language
  - informed by many different tasks
  - useful for many different tasks

Pre-Training Word Embeddings

- Let us keep it simple...

- Neural machine translation models use word embeddings
  - encoding of input words
  - encoding of output words

- Word embeddings can be trained on vast amounts of monolingual data

⇒ pre-train word embeddings and initialize model with them

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- Not very successful so far
  - monolingual word embeddings trained on language model objectives
  - for machine translation, different similarity aspects may matter more
  - e.g., *teacher* and *teaching* similar in MT, not in LM

Pre-Training the Encoder and Decoder

- Pre-training other components of the translation model

- Decoder
  - language model, informed by input context
  - pre-train as language model on monolingual data
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- Encoder
  - also structures like a language model
    (however, not optimized to predict following words)
  - pre-train as language model on monolingual data

Monolingual Pre-Training

- Initial training of neural machine translation model on monolingual data
- Replace some input word sequences with <pad> (30% of words)
- Train model MASKED → TEXT on both source and target text
- Reorder sentences (each training example has 3 sentences)

<en> Advanced NLP techniques master class ” how <pad> ” </s>
3rd <pad> : 18 </s>
Results <pad> 40 of 729

⇓

3rd grade : 18 </s>
Advanced NLP techniques master class ” how to with clients ” </s>
Results 1 – 40 of 729

Multi-Task Training

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  - need to encode an input word sequence
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  - sentiment detection: output is sentiment value
  - part-of-speech tagging: output is tag sequence
  - syntactic parsing: output is recursive parse structure (may be linearized)
  - semantic parsing: output is logical form, database query, or AMR
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- Input and output in the same language, may be mostly copied
  - grammar correction, automatic post-editing
  - question answering, semantic inference

Multi-Task Training

- Train a single model for all tasks
- Positive results with joint training of
  - part-of-speech tagging
  - named entity recognition
  - syntactic parsing
  - semantic analysis.
- Tasks may share just some components