# Beyond Parallel Corpora

Philipp Koehn

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# data and machine learning

# Supervised and Unsupervised

- We framed machine translation as a supervised machine learning task
  - training examples with labels
  - here: input sentences with translation
  - structured prediction: output has to be constructed in several steps

- Unsupervised learning
  - training examples without labels
  - here: just sentences in the input language
  - we will also look at using just sentences output language

- Semi-supervised learning
  - some labeled training data
  - some unlabeled training data (usually more)

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

# Transfer Learning

- Learning from data similar to our task

- Other language pairs
  - first, train a model on different language pair
  - then, train on the targeted language pair
  - or: train jointly on both

- 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



- Train a separate language model

- Add as conditioning context to the decoder

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

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

- Add hidden state of neural language model $s_i^{\mathsf{LM}}$

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

- Pre-train language model

- Leave its parameters fixed during translation model training

# Refinements



- Balance impact of language model vs. translation model

- Learn a scaling factor (gate) $\text{gate}_i^{\text{LM}} = f(s_i^{\text{LM}})$

- Use it to scale values of language model state

$$\bar{s}_i^{\text{LM}} = \text{gate}_i^{\text{LM}} \times s_i^{\text{LM}}$$

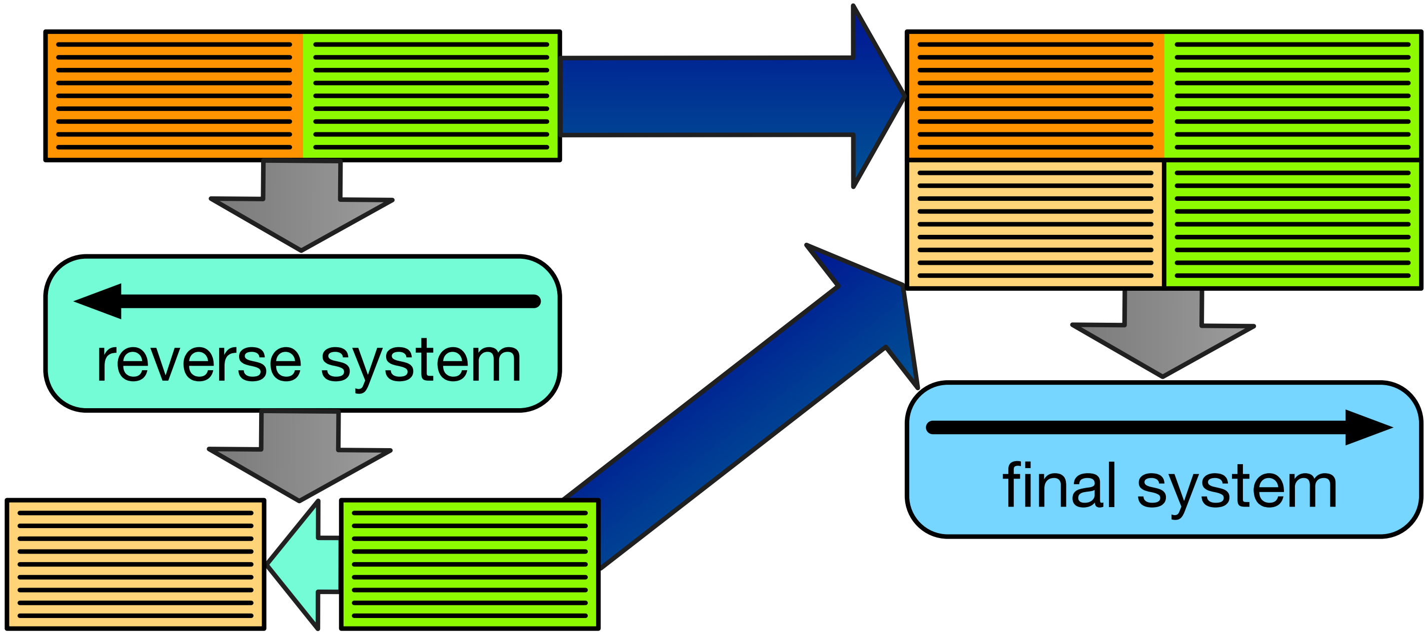
- Use this scaled language model state for decoder state

$$s_i = f(s_{i-1},\ Ey_{i-1}, c_i, \bar{s}_i^{\text{LM}})$$

# Back Translation



- Monolingual data is parallel data that misses its other half
- Let's synthesize that half



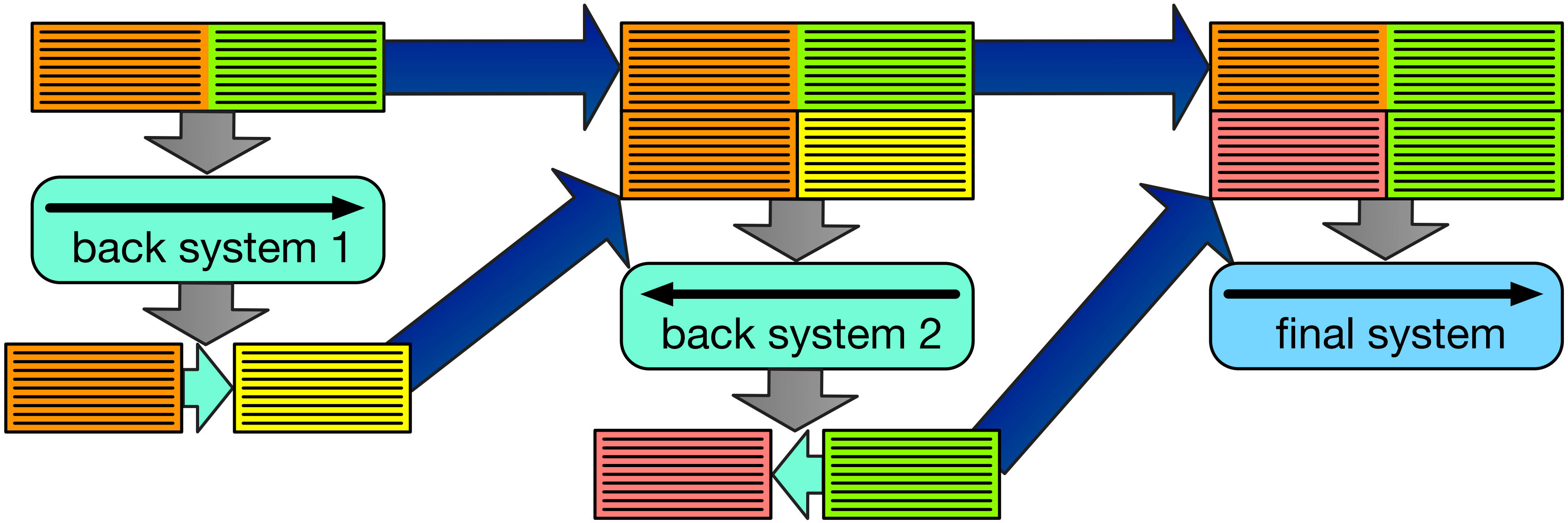
# Back Translation

- Steps
  1. train a system in reverse language translation
  2. use this system to translate target side monolingual data
     $\rightarrow$ 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 for domain adaptation

# Iterative Back Translation



- Quality of backtranslation system matters
- Build a better backtranslation system ... with backtranslation



# 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

# 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)

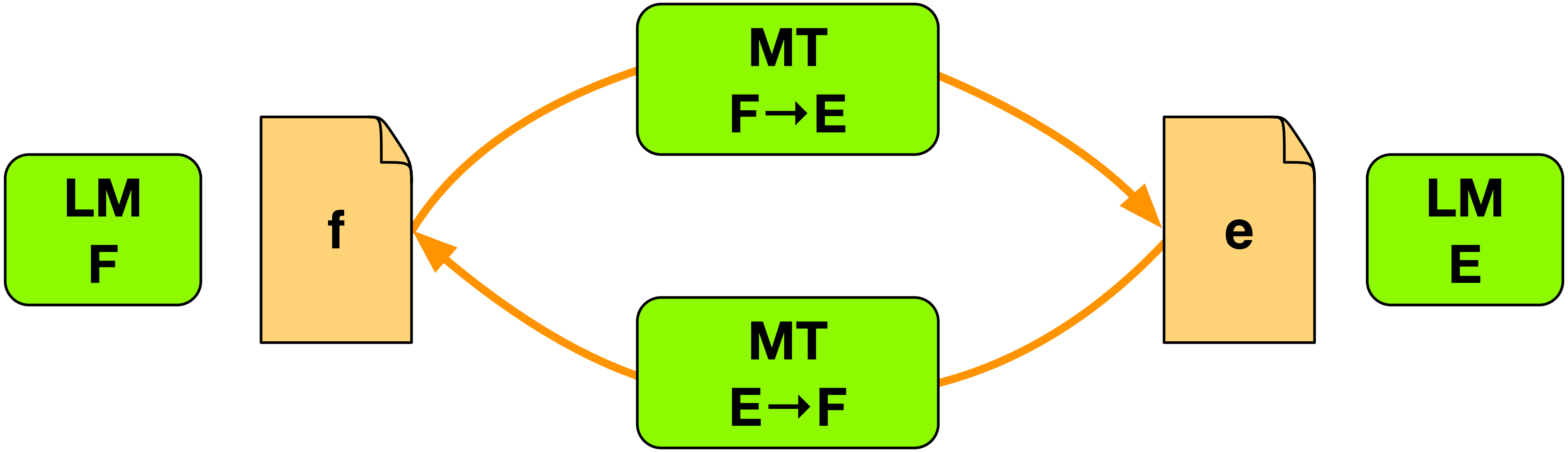
# Round Trip Training



- We could iterate through steps of
  - train system
  - create synthetic corpus
- 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'**
- Setup could be fooled by just copying (**e'** = **f**)

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

# Round Trip Training



# 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*

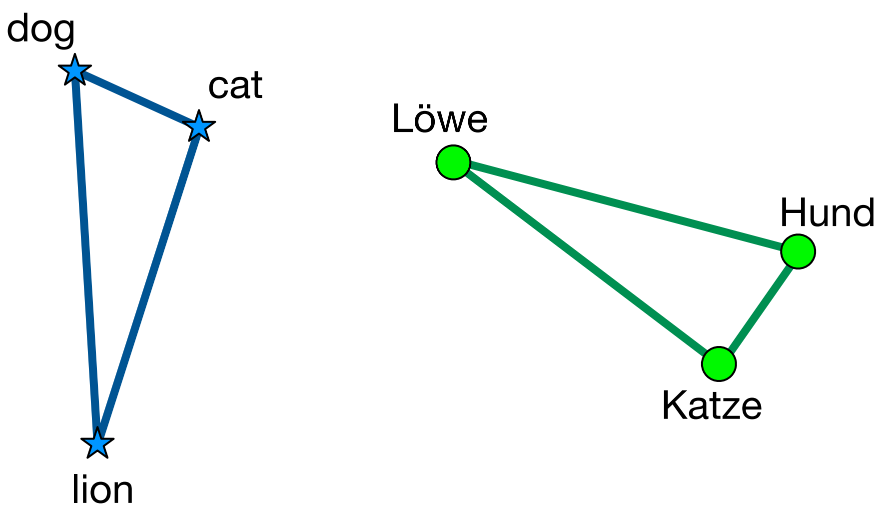
⇓

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

# unsupervised machine translation

# Monolingual Embedding Spaces

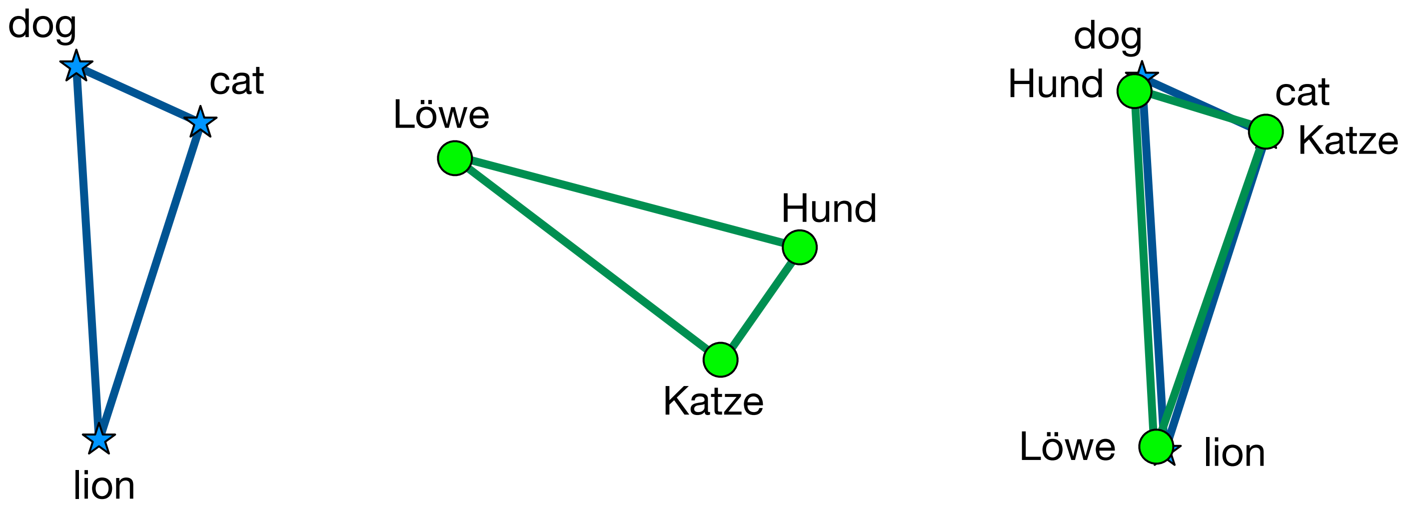





- Embedding spaces for different languages have similar shape
- Intuition: relationship between *dog*, *cat*, and *lion*, independent of language
- How can we rotate the triangle to match up?

# Matching Embedding Spaces






- Seed lexicon of identically spelled words, numbers, names
- Adversarial training: discriminator predicts language [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)
  
  $\rightarrow$ statistical phrase translation table (probability $\simeq$ similarity)

- Language model
  - target side monolingual data
  
  $\rightarrow$ estimate statistical n-gram language model

$\Rightarrow$ 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?

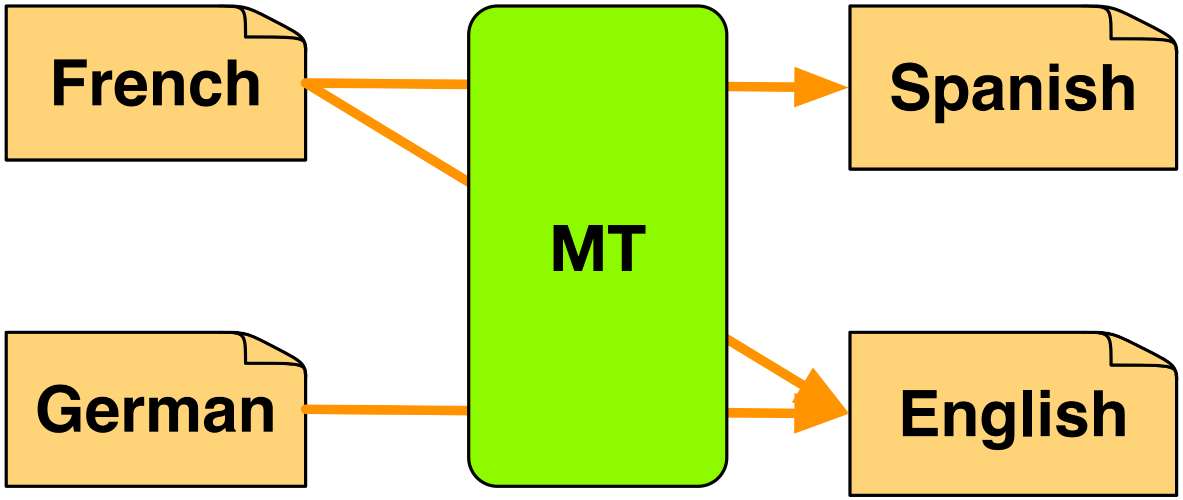
- Indicate output language with special tag

[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 |

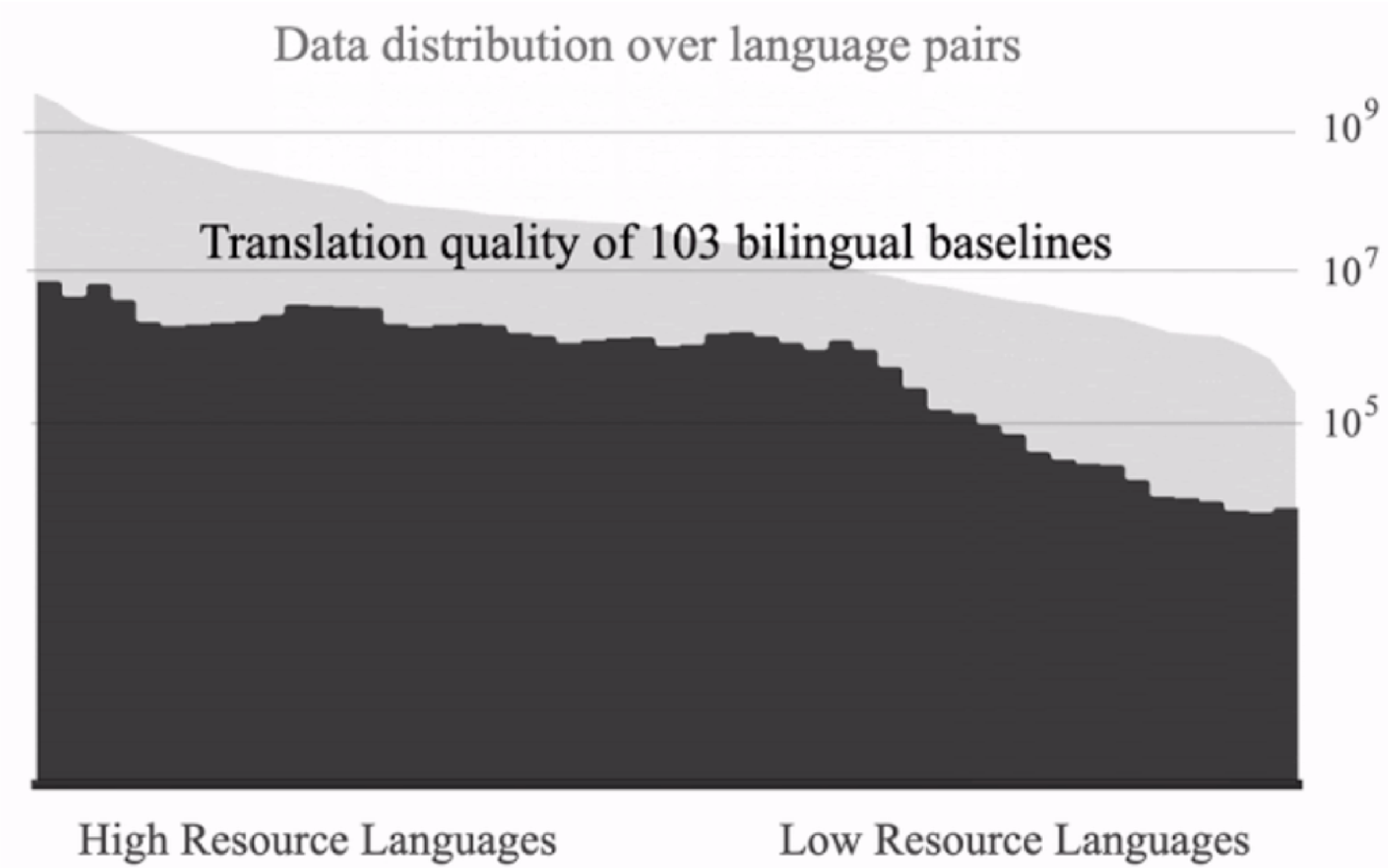
- Bridged: pivot translation Portuguese → English → Spanish
- Model 1 and 2: Zero shot training
- Model 2 + incremental training: use of some training data in language pair

# 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

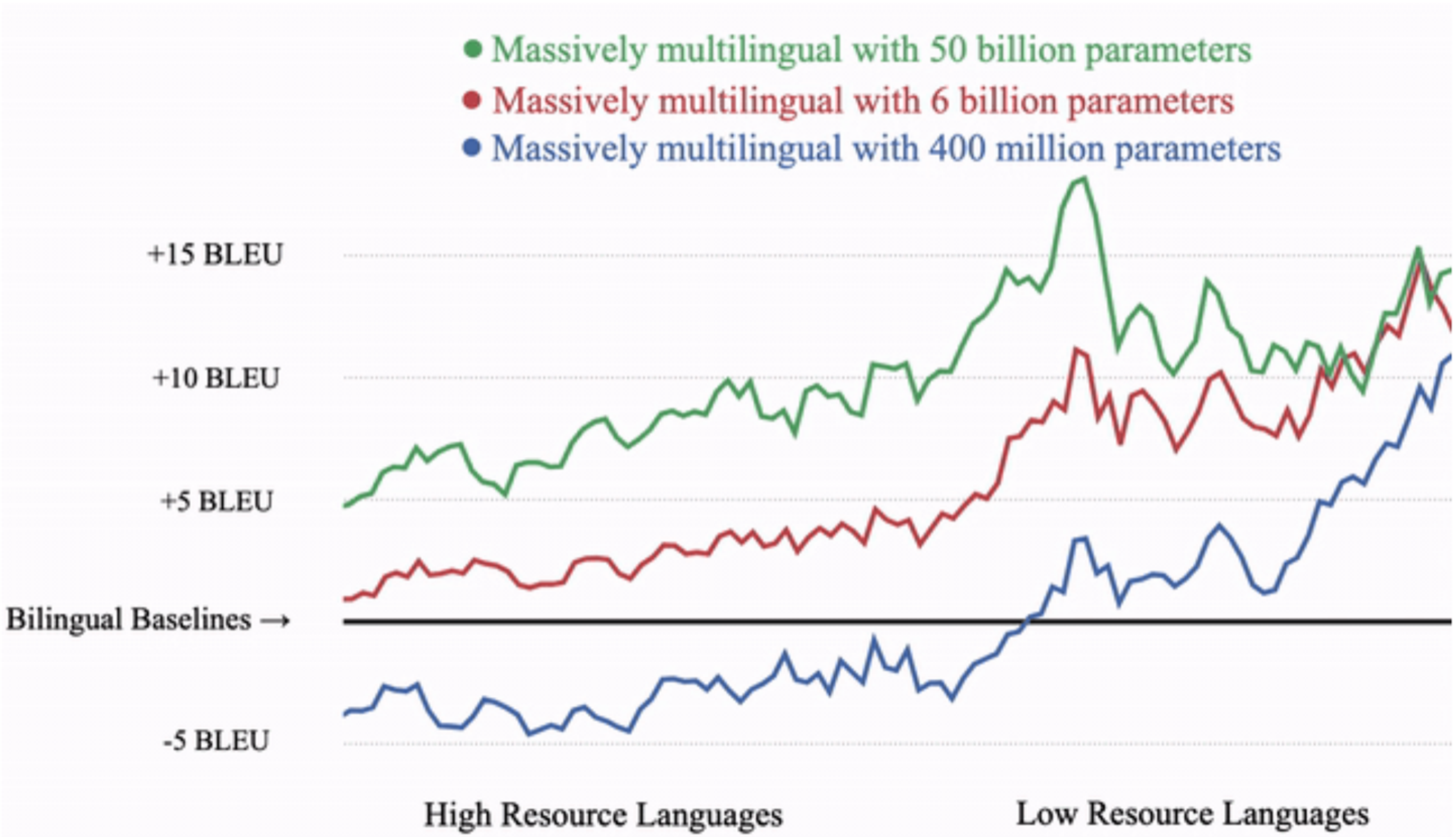





(source: Google)

# 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 |
| فيليپين | 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

# Even Bigger: NLLB (2022)



- No Language Left Behind: 200 languages
- Hand-translated test set: Flores-200
- Uses diverse data sources
  - public parallel data
  - translations created by professional translators
  - sentence pairs based on sentence embedding similarity
  - monolingual data for
    - monolingual pre-training
    - back-translation
    - self-training
- Models of different scale (up to 54B parameters), publicly released

# Different Amounts of Data per Language



- High-resource language pairs are undertrained
- Low-resource language pairs are overtrained

⇒ Oversampling low resource language pairs
Data selection probability $p_l$ for language pair $l$ based on corpus sizes $D_k$

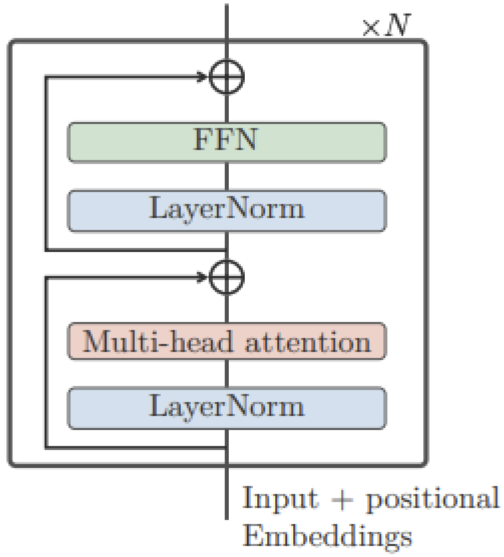
$$p_l = (D_l / \sum_k D_k)^{1/T}$$

- Curriculum training: adding low-resource data only in later training stages

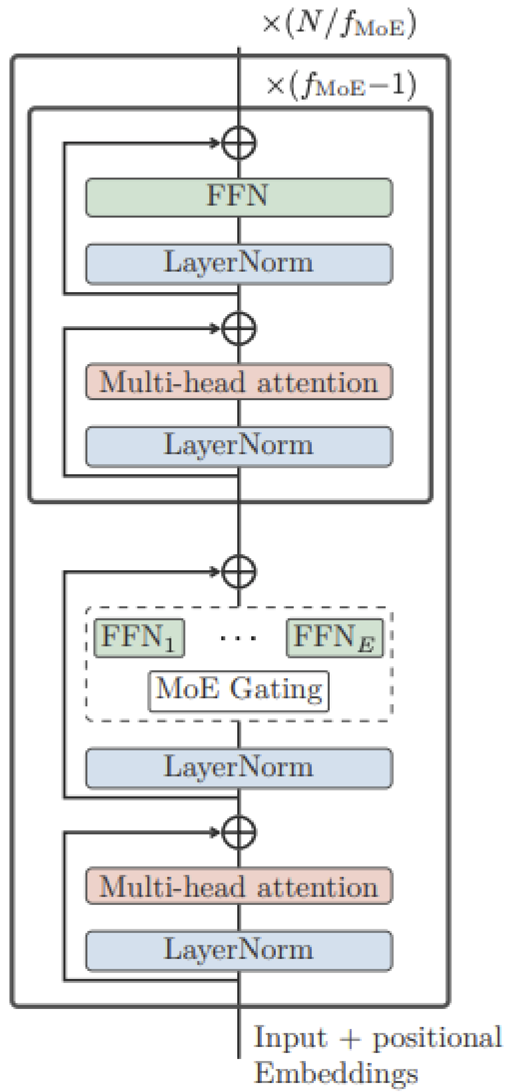
# Mixture of Experts



- Conditional compute
- Gating mechanism decides which FF step to utilize
- Allows scaling to many more parameters without increasing computational cost




(a) Dense Transformer




(b) MoE Transformer