Advanced Methods in Text Analytics

Multilingual NLP

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Most Spoken Languages (1)

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- What are the most spoken languages in the world?
  - According to Ethnologue, this is the distribution for *native* speakers

Languages with at least 50 million first-language speakers[7]

	Language	Native speakers (in millions)	Language family	Branch
1	Mandarin Chinese	941	Sino-Tibetan	Sinitic
2	Spanish	486	Indo-European	Romance
3	English	380	Indo-European	Germanic
4	Hindi	345	Indo-European	Indo-Aryan
5	Bengali	237	Indo-European	Indo-Aryan
6	Portuguese	236	Indo-European	Romance
7	Russian	148	Indo-European	Balto-Slavic
8	Japanese	123	Japonic	Japanese
9	Yue Chinese	86	Sino-Tibetan	Sinitic
10	Vietnamese	85	Austroasiatic	Vietic

Image source

- The top 10 languages cover 3 billion people (37.5% of the world)

Most Spoken Languages (2)

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- What if we break this into *native vs non-native* speakers?
  - Again, according to Ethnologue...

Most spoken languages, *Ethnologue*, 2023[4]

	Language	Family	Branch	First-language (L1) speakers	Second-language (L2) speakers	Total speakers (L1+L2)
1	English (excl. creole languages)	Indo-European	Germanic	380 million	1.077 billion[5]	1.456 billion
2	Mandarin Chinese (incl. Standard Chinese, but excl. other varieties)	Sino-Tibetan	Sinitic	939 million	199 million[6]	1.138 billion
3	Hindi (excl. Urdu)	Indo-European	Indo-Aryan	345 million	266 million[7]	610 million
4	Spanish (excl. creole languages)	Indo-European	Romance	485 million	74 million[8]	559 million
5	French (excl. creole languages)	Indo-European	Romance	81 million	229 million[9]	310 million

Image source

- The top 5 languages cover 4 billion people (50% of the world)

Most Spoken Languages (3)

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- What about language distribution as used on the *world wide web*?
  - According to W3 Technology Surveys...

Rank	Language	16 May 2023	07 May 2024
1	English	55.5%	50.5%
2	Spanish	5.0%	5.7%
3	Russian	4.9%	4.2%
4	German	4.3%	5.2%
5	French	4.4%	4.3%
6	Japanese	3.7%	4.7%
7	Portuguese	2.4%	3.5%
8	Turkish	2.3%	1.9%
9	Italian	1.9%	2.5%
10	Persian	1.8%	1.4%

- English alone covers 50% of the content online (top 10 languages 84%)
  - **Massive difference in language distribution in the world vs online**

Why Multilingual NLP? (1)

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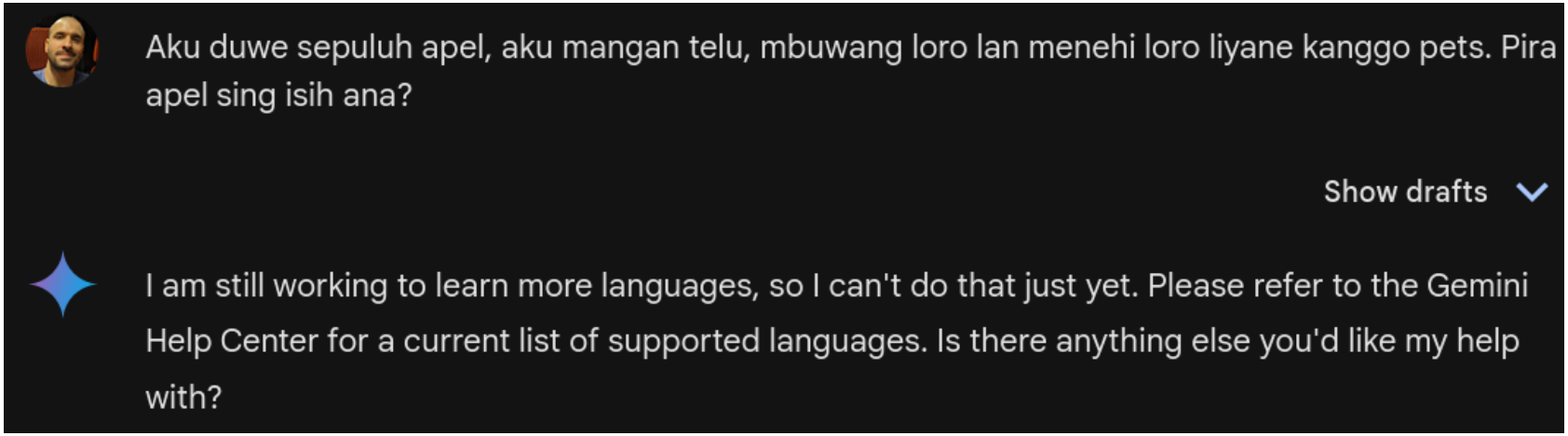
- **NLP:** roughly, automatically processing *human language* with computers
  - There are over *7100 human languages* in the world (source)
  - **Ideally**, all of these languages have **equal access to information**



- Google Gemini (released Dec. 2023) does not speak *Javanese*
  - But 68 million people speak this language in Indonesia
  - That's the same number of people that speak Italian
- Why this limitation then?

Why Multilingual NLP? (2)

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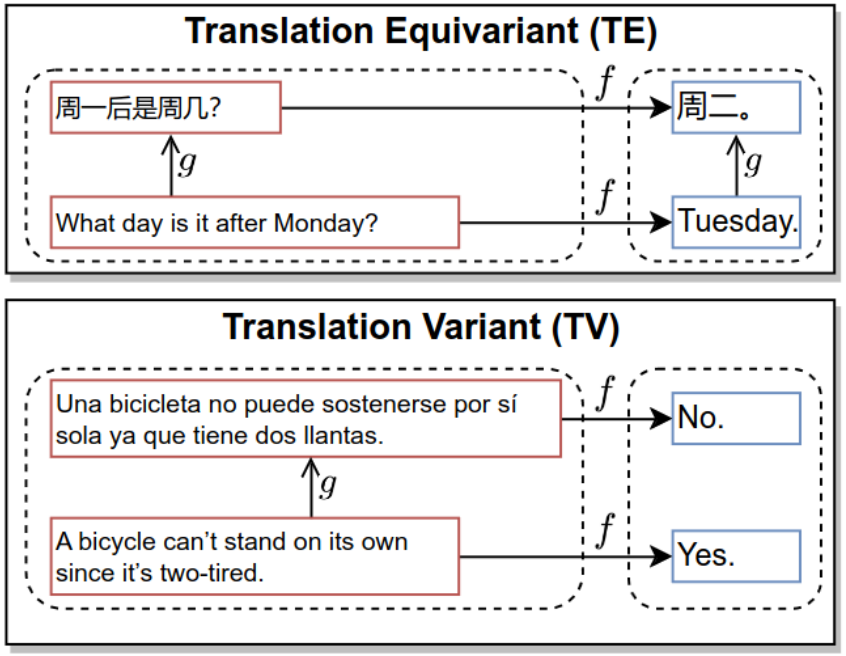
- **State-of-the-art** (SOTA) **NLP** methods are **statistical methods**
  - In other words, lots of data required to achieve SOTA performance
  - E.g. large language models (LLMs) typically trained on a massive corpus crawled from the web
- **So, performance in English much better than in less available languages**
  - **Translation not always a solution**
  - E.g. if output is independent of input language, LLMs can solve problems via translation (Zhang et al. 2023)
  - But not if input language changes answer
  - Example in bottom: pun detection



Why Multilingual NLP? (3)

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- **Multilingual natural language processing (mNLP):** NLP systems that can process *multiple* natural languages
  - But how many languages?
  - Ideally, the more the better!
  - But, the more languages, the more challenges
- **In this lecture:**
  - Cross-lingual transfer (fundamental goal of mNLP)
  - Multilingual transformers

Outline

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1. Cross-Lingual Transfer

2. Multilingual Transformers

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Cross-Lingual Transfer

What is Cross-Lingual Transfer? (1)

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- Due to their statistical nature, SOTA NLP models perform much better in English than in languages less available online (Zhang et al. 2023)
  - E.g. GPT-3 (Brown et al. 2020) and LlaMA-2 (Touvron et al. 2023) trained on data that is heavily skewed toward English
  - Supervised datasets for downstream fine-tuning mostly available in English
- **Cross-lingual transfer:** use knowledge a model obtained in some *source language* in an application in a different *target language*
  - **Source language *s*** usually a high resource language, e.g. English
  - **Target language *t*** usually a low-resource language, e.g. Quechua
  - Essentially, **transfer learning across languages**
- General example:
  - Pre-train or fine-tune LM on data in English (*source* language), then fine-tune LM or do inference with it using data in Portuguese (*target language*)
- Why would you do that? More data -> stronger "source model"
  - **Is what the "source model" has learned transferable to other languages?**

What is Cross-Lingual Transfer? (2)

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- More common setting:
  - **First pre-train** LM on English and Javanese, e.g. a CLM or MLM.
  - **Then fine-tune** on some specific task, e.g. sentiment analysis, using data in English (safe to assume lots of data for the task in English)
  - **Then do inference** on same task using data in Javanese (where there is little data in this language for fine-tuning your LM for the task)
- Easier said than done, more details to handle in most cases
- Success is cross-lingual transfer suggests:
  - There are **aspects of the task** that are **shared across languages**
  - Trained models learned these shared/transferable aspects of the task
- This success could enable **democratization of SOTA NLP methods!**
  - Thus, cross-lingual transfer is a **fundamental goal** of mNLP
- How to get there? Normally, by relying on **shared cross-lingual features**
  - I.e. features that are similar across more than one language
  - Easy way to visualize this: cross-lingual word embeddings (**CLWE**)

Embedding Space Alignment (1)

- Say we **train static word embeddings** with skip-gram (Mikolov et al. 2013) **in two different languages**: English and Italian
  - The embedding space may look as shown below (clustered by language)

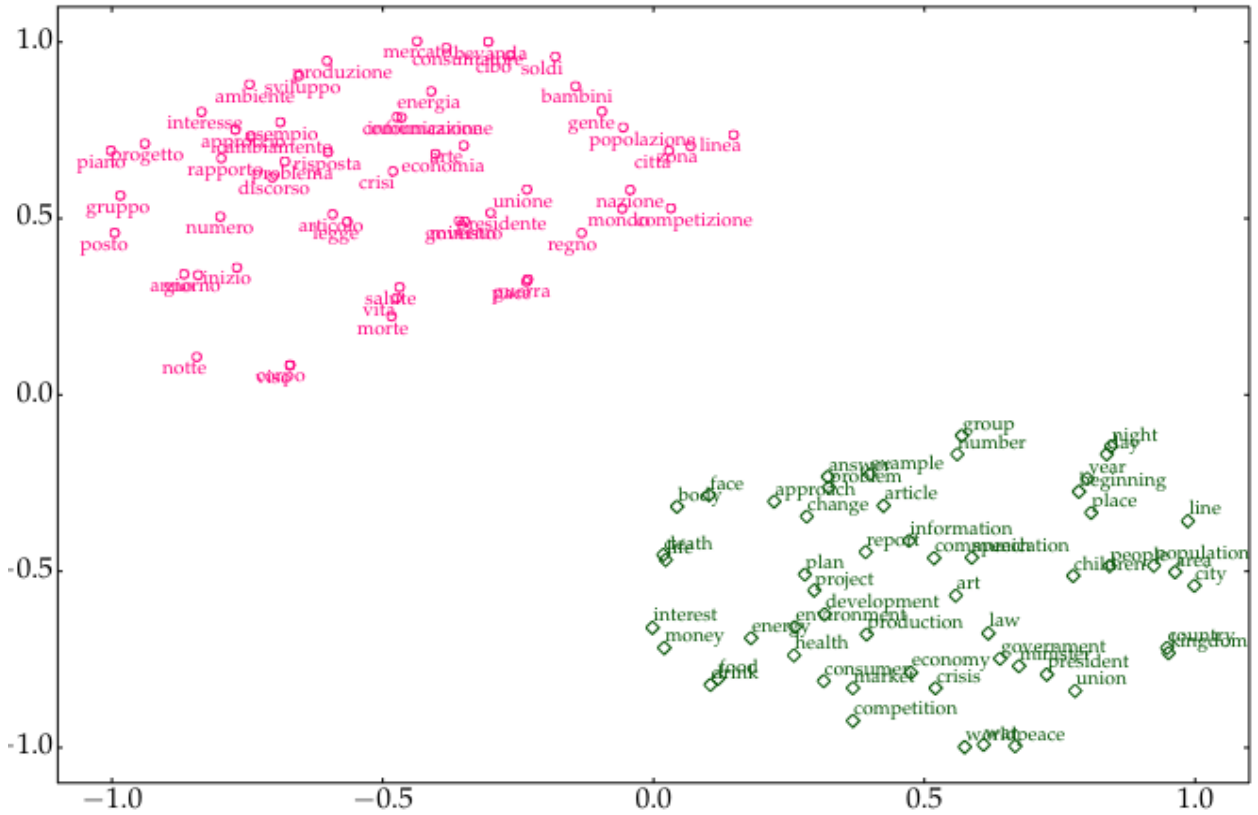

Image source

Embedding Space Alignment (2)

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- We want **shared features across languages**, i.e. a bilingual embedding space clustered (often referred to as *aligned*) by meaning
  - This requires an **alignment signal**, e.g. word-to-word translations

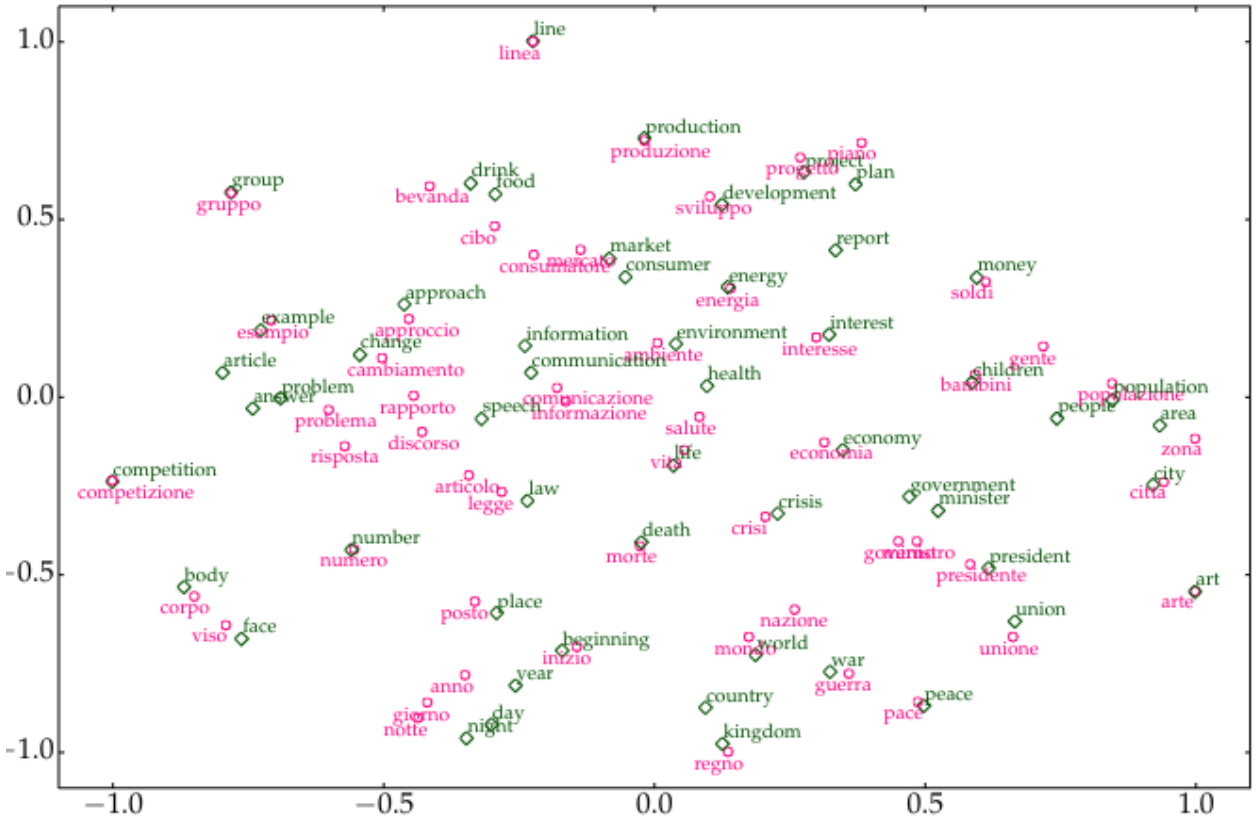

Image source

Cross-Lingual Word Embeddings (1)

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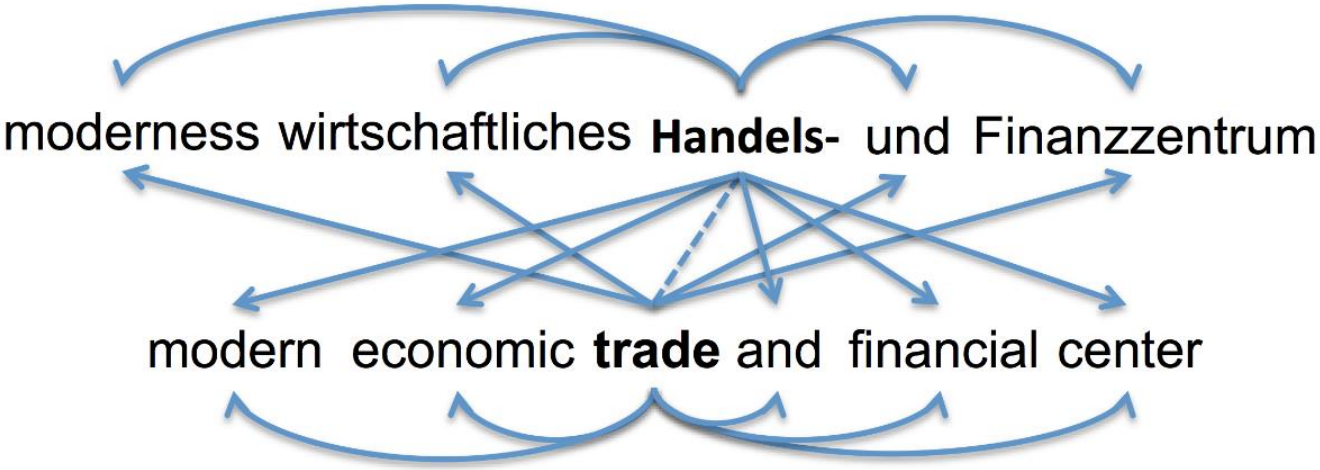
- **Example:** the bilingual skip-gram model by Luong et al. 2015
  - Recall **skip-gram:** given center word, predict neighboring words
- **Bilingual skip-gram:** in addition to *monolingual* objective (curved arrows), predict surrounding words in target language (straight arrows)



- Given source language *s* and target language *t*, **such a method requires:**
  - Corpora C_s, C_t, vocabularies V_s, V_t and parameters $\boldsymbol{W}_1^s$, $\boldsymbol{W}_2^s$, $\boldsymbol{W}_1^t$, $\boldsymbol{W}_2^t$
  - Dictionary $D_s = \{(s_i^s, s_i^t)\}$ of *sentence translation pairs* where $s_i^s \in V_s$, $s_i^t \in V_t$

Cross-Lingual Word Embeddings (2)

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- Why does this method require *parallel sentences*?
  - I.e. why do we require translation?
  - And why translations of sentences and not just words?
- **Parallel sentences**, i.e. translated sentences, is **alignment signal** to enforce shared features across languages
  - **Task dependent:** for skip-gram objective, which is based on predicting context words given center word, we require **sentences** to **provide suitable context windows during training** (principle of **distributed semantics**)
  - Such parallel sentences commonly found in machine translation datasets
- But **how do we use *D* to align** corresponding words in $\boldsymbol{W}_i^s$ and $\boldsymbol{W}_i^t$?
  - We could add a term to the training objective to force model to minimize distance between corresponding vectors for *aligned words* in $(s_i^s, s_i^t) \in D_s$
- What did the authors do?
  - Set $\boldsymbol{w}_i^s = \boldsymbol{w}_j^t$ for *aligned words* in every example from D_s, where $\boldsymbol{w}_i^s$, $\boldsymbol{w}_j^t$ are i-th and j-th row of $\boldsymbol{W}_i^s$ and $\boldsymbol{W}_i^t$, resp. (additional word alignment needed)

Evaluating CLWE

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- **Intrinsic evaluation:**
  - Bilingual lexicon induction (BLI)
  - Cross-lingual word similarity (XL-SIM)
- **BLI:** given $(w_i^s, w_i^t) \in D$, take $\boldsymbol{w}_i^s$ as query and rank all rows from $\boldsymbol{W}^t$ based on similarity to $\boldsymbol{w}_i^s$, then check rank r_i of correct answer $\boldsymbol{w}_i^t$
  - We compute metrics based on r_i averaged over all w_i
  - E.g. precision@1 (P@1): percentage of k pairs where $r_i = 1$
  - Mean reciprocal rank (MRR): average of $1/r_i$ across k pairs
- **XL-SIM:** given $(w_i^s, w_i^t) \in D$, compare similarities of corresponding vectors with semantic similarity *scores* given by human annotators
  - Subjective task, requires averaged scores across multiple annotators
- **Extrinsic evaluation:** use CLWE on **downstream cross-lingual tasks**
  - Zou et al. 2013 used CLWE as features in phrase-based **machine translation**
  - **Entity linking:** match *mention* in one language to *entity* in another language

Beyond CLWE

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- **Static representations** of words seldom used today
  - Instead, NLP relies almost exclusively on **contextualized representations**
  - Typically, these representations are provided by transformer-based language models (LMs)
  - Even if multilingual, static representations are still limited
- Nevertheless, the **following concepts** are **still relevant in mNLP**:
  - **Cross-lingual transfer**
  - **Alignment of representation space**
- In the next section:
  - Cross-lingual transfer using transformer-based models

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Multilingual Transformers

Multilingual BERT

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- What could cross-lingual transfer look like with transformer-based LMs?
  - Any ideas?
- Pires et al. 2019 developed multilingual BERT to explore this question
  - They framed **cross-lingual transfer with BERT** as follows
    1. Pre-Train BERT on corpus of concatenation of text (Wikipedia) in multiple different languages (let's call it **mBERT**)
    2. Fine-tune mBERT on some task using language *s* (seen in pre-training)
    3. Evaluate mBERT on same task using different language *t* (seen in pre-training)
  - They called this ***zero-shot cross-lingual transfer***
  - Note: **no cross-lingual supervision**, e.g. parallel sentences
- **If successful**, it would mean the **model learns the task beyond its representation in some language**
  - "Learns the task", some aspects of it at least
  - **Example task:** using an ATM. Some aspects of it are beyond language, e.g. button placement, order of actions (first insert card, etc.)

Training Multilingual LMs

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- Training data was highly unbalanced in mBERT
  - This has important implications on performance
- **Training corpus:** concatenation of Wikipedia in 104 different languages
  - But size of Wikipedia is different in different languages
  - Number of articles in English: about 6.8M articles
  - Number of articles in Vietnamese: about 1.3M articles
  - Number of articles in Javanese: about 73000 articles
- **Impact on performance** is predictable
  - Performance on more common languages is better. Why?
  - Transformer has more data to *learn* from
  - *Learn* = adjust its 100M parameters so it generalizes instead of overfitting
- In addition, **low-resource languages typically require more data given same number of parameters**
  - Why?
  - **Hint:** the model uses a **single shared subword vocabulary** for all languages

Tokenization in Multilingual LMs (1)

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- **What impact does unbalanced data across languages have on tokenization?**
  - mBERT used WordPiece (mentioned in tokenization lecture)
  - **Recall WordPiece:** similar to BPE (covered in detail in tokenization lecture)
    1. Start with vocabulary *V* made of characters
    2. Merge pairs of tokens that increase data likelihood of n-gram LM
    3. Keep merging until you reach desired vocabulary size
  - If we add frequent tokens to vocabulary, a count-based n-gram model can better estimate their probabilities.
  - Similar effects in other forms of tokenization, e.g. BPE, UnigramLM
- In other words, **multilingual vocabulary dominated by "larger" languages, as measured by training data size**
  - Recall example from tokenization lecture: *hello* in English -> 1 token
  - Corresponding word in Hindi: *namaste* -> 3 tokens
- Why does this matter?

Tokenization in Multilingual LMs (2)

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- Impacts of multilingual tokenization already discussed in tokenization lecture
  - **Same message requires more tokens** to be represented **in low-resource languages**
  - Given limited input length in modern LMs, **low-resource languages are limited to shorter input sequences**
- But **why does this mean low-resource languages require more data** given the same number of parameters?
  - Because transformer needs to **learn to contextualize subword tokens that belong to the same word**
  - E.g. learn that *na*, *ma* and *ste* should attend to one another
  - Can be challenging, because **subword tokens more likely to appear in different languages, but with different meanings** (e.g. article *a* in English)
- Note **vicious circle**: low-resource languages train with low amounts of data, which creates problems that can be solved with more data

Generalizing Across Languages (1)

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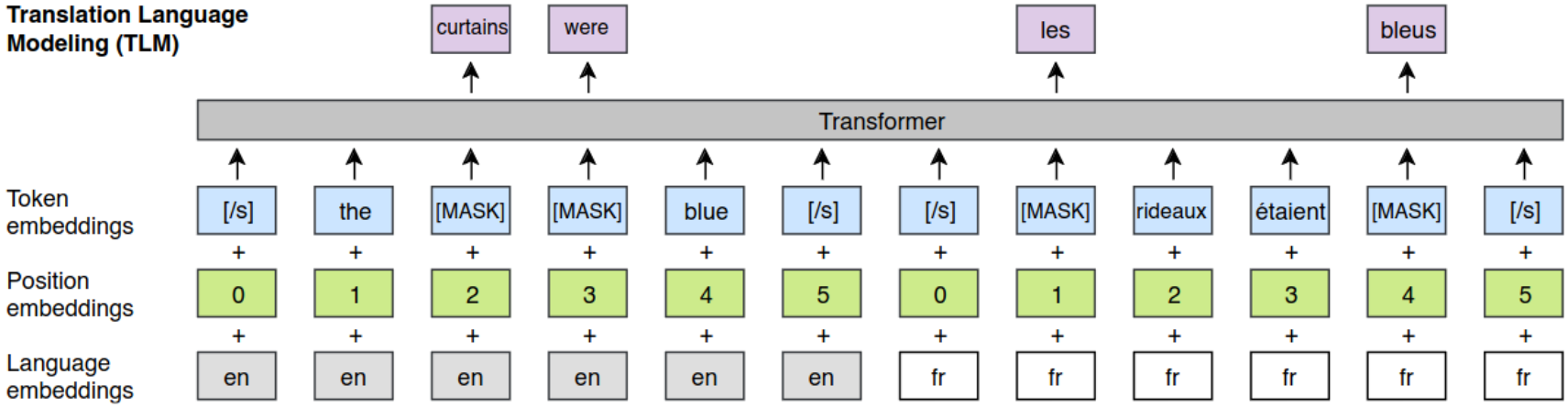
- mBERT was indeed "surprisingly" successful despite unbalanced data
  - I.e. the model was quite good at zero-shot cross-lingual transfer
  - This suggests model can do tasks beyond language
  - Why surprising?
- **How can we explain mBERTs success without alignment signal?**
  - Recall: **no alignment signal**, e.g. parallel sentence translations
- Several studies have focused on this question and found:
  - K et al. 2020: shared vocabulary not needed, model depth needed, languages should be of similar structure
  - Artetxe et al. 2020 show that neither shared vocabulary nor joint training is needed (given pre-trained model in language *s*, they froze all parameters except embedding matrix and fine-tuned on new language *t*)
  - Conneau et al. 2020 showed that independent monolingual BERT models can be aligned post-hoc by tying parameters in top layer
  - Dufter et al. 2020 hypothesized that mBERT is multilingual due to limited parameters, forced to share feature across languages

Generalizing Across Languages (2)

- **mBERT** was the **first of many** multilingual transformer-based LMs
- Lample et al. 2019 proposed **XLM** model (stands for cross-lingual LM)
  - **Balanced data for learning tokenizer** (upsampled "small" languages, downsampled "large" languages)
  - Additional objective: **translation language modeling (TLM)**
  - **TLM:** masked language modeling (MLM) but with pairs of parallel sentences (i.e. translations), i.e. alignment signal required
  - Note: **objective no longer self-supervised but supervised**



Generalizing Across Languages (3)

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- Conneau et al. 2020 proposed XLM-R
  - **Just MLM, no more TLM**
  - Much larger training data
  - Much larger vocabulary: 250K
  - **Significantly outperformed mBERT** on cross-lingual tasks
- Lauscher et al. 2020 showed cross-lingual performance largely dependent on type of "size" of language and "distance" to English
  - **Size:** size of pre-training set
  - **Distance:** how structurally similar it is to English
  - They found performance drops a lot with smaller/more distant languages
- **Number of languages also impactful** to cross-lingual performance
  - Conneau et al. 2020 found a trade-off between performance and number of languages for a fixed model size
  - **Curse of multilinguality:** more languages lead to better cross-lingual performance up to a point, after which performance generally degrades

Zero-Shot vs Few-Shot

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- **Most works** described **so far** focused on zero**-shot transfer**
  - **Assumption:** zero-labeled examples in target language
  - Perhaps more a scientific question rather than a realistic setting
  - E.g. "can we do it in a zero-shot setting?"
  - Why?
- In practice, almost always possible to label a small number of examples in any target language
  - This would mean a **few-shot cross lingual** setting
- Lauscher et al. 2020 proposed **sequential few-shot transfer**
  - **First**, **fine-tune** LM on **specific task** using **"large" language**, e.g. English
  - **Then**, **fine-tune** on **same task** using **"small" target language**, e.g. Javanese
  - PROs: They found massive improvements over zero-shot setting
  - CONs: first step expensive, not cross-lingual signal about task due to separate steps
- Besides such quantitative studies, **qualitative research** was also done

Cross-lingual Transfer in mBERT (1)

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- Muller et al. 2021 studied the internal mechanism that allow mBERT do performn cross-lingual transfer.
  - **Recall mBERT:** *pre-trained* on multiple languages, *fine-tuned* on some source language, *performed inference* on another target language
- **First**, they replaced (pre-trained) transformer layers one by one with new, randomly initialized layers, compared performance with mBERT
  - Method for **feature attribution**: what is the impact of this feature on the model prediction?
  - By replacing the layer with random weights and checking difference in performance, we can see how important that layer is for the model
- This was done on **three tasks**:
  - Part-of-Speech (POS) tagging: (assign labels to parts of sentences, e.g. verb)
  - Dependency parsing: predicting dependency between parts of sentence
  - Named Entity Recognition (NER): identify entities in text, e.g. Jane Austen
- Each task evaluated in **two settings**: monolingual, cross-lingual (2 lang.)

Cross-lingual Transfer in mBERT (2)

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- They found **lower layers more important in cross-lingual setting**
  - Replacing lower layers with random weights had much more impact cross-lingually
  - Replacing upper layers had little impact in both settings
- This suggests lower layers act as "multilingual encoder", and upper layers as task-specific, language-agnostic "predictor"
  - Upper layers not important for cross-lingual transfer
  - Lower layers much more Important cross-lingually than monolingually

		RANDOM-INIT *of layers*					
SRC-TRG	REF	Δ 1-2	Δ 3-4	Δ 5-6	Δ 7-8	Δ 9-10	Δ 11-12
		Parsing					
EN - EN	88.98	-0.96	-0.66	-0.93	-0.55	0.04	-0.09
RU - RU	85.15	-0.82	-1.38	-1.51	-0.86	-0.29	0.18
AR - AR	59.54	-0.78	-2.14	-1.20	-0.67	-0.27	0.08
EN - X	53.23	-15.77	-6.51	-3.39	-1.47	0.29	1.00
RU - X	55.41	-7.69	-3.71	-3.13	-1.70	0.92	0.94
AR - X	27.97	-4.91	-3.17	-1.48	-1.68	-0.36	-0.14
		POS					
EN - EN	96.51	-0.30	-0.25	-0.40	-0.00	0.05	0.02
RU - RU	96.90	-0.52	-0.55	-0.40	-0.07	0.02	-0.03
AR - AR	79.28	-0.35	-0.49	-0.36	-0.19	-0.05	-0.00
EN - X	79.37	-8.94	-2.49	-1.66	-0.88	0.20	-0.14
RU - X	79.25	-10.08	-2.83	-1.65	-2.74	0.01	-0.45
AR - X	64.81	-6.73	-3.50	-1.63	-1.56	-0.73	-1.29
		NER					
EN - EN	83.30	-2.66	-2.14	-1.43	-0.63	-0.23	-0.12
RU - RU	88.20	-2.08	-2.13	-1.52	-0.64	-0.33	-0.13
AR - AR	87.97	-2.37	-2.11	-0.96	-0.39	-0.15	0.21
EN - X	64.17	-8.28	-5.09	-3.07	-0.79	-0.47	-0.13
RU - X	62.13	-15.85	-9.36	-5.50	-2.44	-1.16	-0.06
AR - X	65.59	-16.10	-8.42	-3.73	-1.40	-0.25	0.67

≥ REF | < REF | ≤ -2 points | ≤ -5 points

Cross-lingual Transfer in mBERT (3)

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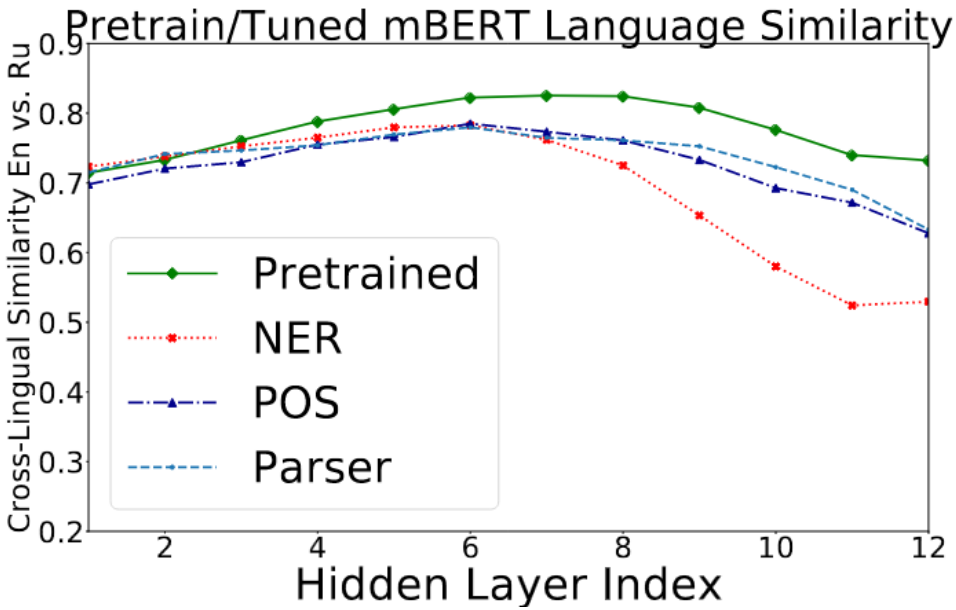
- They also looked at **alignment per layer**
  - **How?** Average contextualized representations of input sentence in one language, compare with averaged representation in another language



- They found **representations more aligned toward center layers**
  - Suggests model initially learns similar representations across languages
  - May be task dependent, similar results found later (Chi et al., Gaschi et al)

Multilingual Evaluation

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- **mNLP:** democratization of NLP methods across languages
  - Still an open challenge, e.g. Gemini does not speak javanese
  - Research still ongoing in this direction
- Many **multilingual tasks** proposed for research, e.g.:
  - Americas NLI: natural language inference (NLI) covering 10 low-resource indigenous languages of the Americas
  - MaskhaNER: named-entity recognition (NER) on 10 low-resource african languages
- Today, **common to evaluate LMs on benchmarks with multiple tasks**
  - XGLUE: 11 tasks, 19 languages
  - X-TREME-R: 10 tasks, 50 languages
  - Etc.

Multilinguality in LLMs

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- **Have LLMs solved mNLP?**
  - In short, **no**.
  - Many languages still not covered
  - Large variance in performance across languages
- Aren't some LLMs multilingual?
  - Yes!
  - Gemini supports over 40 languages
  - Llama-3 supports 30 languages
- But **cross-lingual signals usually not present during pre-training**
  - So, ongoing research to determine whether specific changes to architecture or training regimes are necessary
  - E.g. cross-lingual attention (feed model cross-lingual training examples)
  - Or if simply scaling will get us to the mNLP goal

Summary

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- **Multilingual NLP:** NLP systems that can process multiple natural languages
- **Cross-lingual transfer:** using knowledge acquired in some source language *s* on a task described in another target language *t*
  - Can be accomplished in many ways depending on task, model architecture
- **Representation alignment:** similar words in different languages clustered together in embedding space
- **Multilingual transformers**: typically pre-trained in multiple languages
  - LMs designed for cross-lingual transfer
  - E.g. via zero-shot cross lingual transfer, sequential cross-lingual fine-tuning
- Modern **LLMs are already multilingual**, they are trained in multiple languages
  - But performance across languages varies a lot given task and language
  - **Open challenge**: improve multilingual performance of LLMs

References

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- References linked in corresponding slides
- Multilingual NLP by Prof. Goran Glavaš