Advanced Methods in Text Analytics Multilingual NLP







Most Spoken Languages (1)



- What are the most spoken languages in the world?
 - According to <u>Ethnologue</u>, 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)



- What if we break this into *native vs non-native* speakers?
 - Again, according to <a>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)



- What about language distribution as used on the world wide web?
 - According to <u>W3 Technology Surveys</u>...

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)



- **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



Aku duwe sepuluh apel, aku mangan telu, mbuwang loro lan menehi loro liyane kanggo pets. Pira apel sing isih ana?







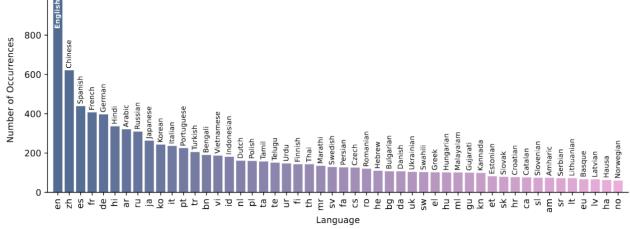
I am still working to learn more languages, so I can't do that just yet. Please refer to the Gemini Help Center for a current list of supported languages. Is there anything else you'd like my help with?

- Google Gemini could not speak Javanese when released (Dec. 2023)
 - But <u>68 million</u> people speak this language in Indonesia
 - That's the <u>same number</u> of people that speak Italian
- Javanese is now supported, but why this limitation originally?

Why Multilingual NLP? (2)



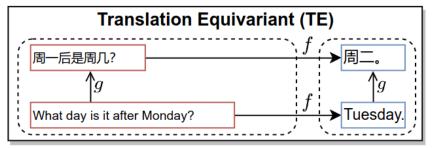
- State-of-the-art (SOTA) NLP methods: data hungry statistical methods
 - Modern language models typically trained on a massive corpus crawled from the web, where English is by far the most common
- So, performance in English much better than less available languages
 - The Bitter Lesson in Multilingual Benchmarks (Wu et al., April 2025)
 - English far more common even in 2000+ recent multilingual benchmarks
 - Multilingual benchmark --> actual effort to get non-English data
 - Multilingual performance on NLP tasks weakly correlated with human evaluations

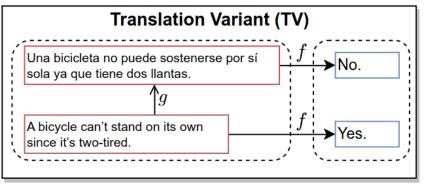


Just Translate to English?



- As machine translation improves, fair question: just translate to English?
 - I.e. translate task to English, feed it to model, translate output back
- Translation is not good enough in many cases
 - E.g. if output is independent of input language, LLMs may solve problems via translation (<u>Zhang et al. 2023</u>)
 - Not if language changes answer
 - Example in image: language independent task (top) vs language dependent task (pun detection, bottom)
- Similarly, <u>Wu et al. (2025)</u> found:





- Strong correlation with human eval. in STEM tasks (language independent)
- Translation not enough, models worse in translation-based benchmarks

Multilingual NLP



- 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



1. Cross-Lingual Transfer

2. Multilingual Transformers

But First...

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Cross-Lingual Transfer

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What is Cross-Lingual Transfer?



- 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 (<u>Brown et al. 2020</u>) and LlaMA-2 (<u>Touvron et al. 2023</u>) trained on data that is heavily skewed toward English
 - Supervised datasets for downstream fine-tuning mostly available in English
- Cross-lingual transfer: model applies knowledge obtained in some source language to a setting 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
- Task for intuition of cross lingual transfer: using an ATM to get cash
 - Some aspects language independent, e.g. button placement, order of actions (first insert card, etc.)
 - Other aspects language dependent, e.g. reading options on screen
 - Another example: driving a car (steering vs reading street signs)

Cross-Lingual Transfer in LMs (1)



- General approach:
 - Pre-train/fine-tune LM on task T in English (source language, lots of data)
 - Then fine-tune/do inference on *T* in Javanese (*target language*, less data)
- Why would you do that?
 - Some aspects of the task may be language independent
 - Training on language with more data may be useful to get language independent aspects of tasks
 - How can we measure if task is indeed transferable?
- Measure performance on the task!
 - Baselines important, e.g. monolingual setting
- 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

Cross-Lingual Transfer in LMs (2)

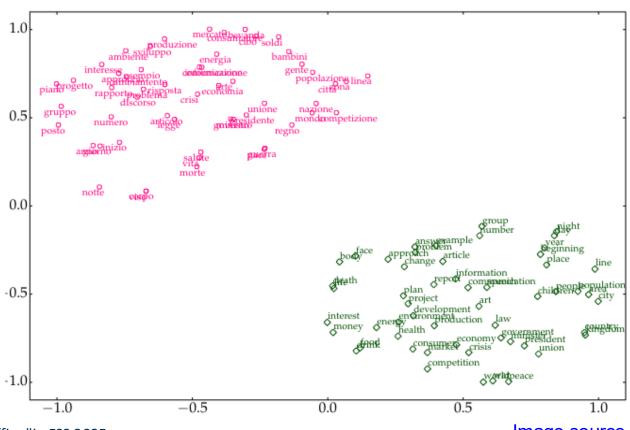


- More common setting:
 - First pre-train LM on English & Javanese (already support more languages)
 - Then fine-tune on some specific task, e.g. sentiment analysis, using data in English (safe to assume lots of data for the task in English)
 - Then do inference on same task using data in Javanese (where 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
 - E.g. why support more languages during pre-training already?
 - We discuss such details in the next section
- How to study/enable cross-lingual transfer?
 - Normally, by looking into 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 (<u>Mikolov et al.</u>
 2013) in two different languages: English and Italian
 - The embedding space may look as shown below (clustered by language)



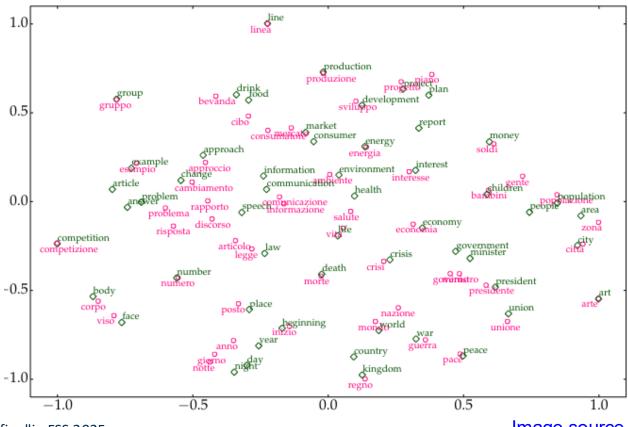
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Image source

Embedding Space Alignment (2)



- We may 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



Cross-Lingual Word Embeddings (1)



- Example: the bilingual skip-gram model by <u>Luong et al. 2015</u>
 - 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)

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- Given source language s and target language t, such a method requires:
 - Corpora C_s , C_t , vocabularies V_s , V_t and parameters \mathbf{W}_1^s , \mathbf{W}_2^s , \mathbf{W}_1^t , \mathbf{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)



- 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_s to align corresponding words in W_i^s and W_i^t ?
 - E.g. minimize distance between vectors of aligned words in $(s_i^s, s_i^t) \in D_s$
- What did the authors do?
 - Set $\mathbf{w}_i^s = \mathbf{w}_j^t$ for aligned words in every example from D_s , where \mathbf{w}_i^s , \mathbf{w}_j^t are i-th and j-th row of \mathbf{W}_i^s and \mathbf{W}_i^t , resp.
 - I.e. we require new set D_w of aligned word pairs (w_i^s, w_i^t)

Evaluating CLWE



- Intrinsic evaluation:
 - Bilingual lexicon induction (BLI)
 - Cross-lingual word similarity (XL-SIM)
- **BLI:** given $(w_i^s, w_i^t) \in D_{w_i}$ take \mathbf{w}_i^s as query and rank all rows from \mathbf{W}^t based on similarity to \mathbf{w}_i^s , then check rank r_i of correct answer \mathbf{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 $(w_i^s, w_i^t) \in D_w$, 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



- 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



Multilingual Transformers

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Multilingual BERT



- 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

Training Multilingual LMs



- 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: <u>about 6.8M articles</u>
 - Number of articles in Vietnamese: <u>about 1.3M articles</u>
 - 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)



- What impact does unbalanced data across languages have on tokenization?
 - mBERT used <u>WordPiece</u> (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)



- 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)
 - In short, tokenization crucial for performance across languages
- 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)

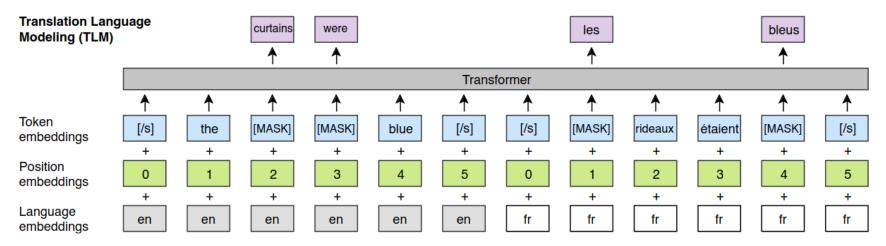


- mBERT was indeed "surprisingly" successful despite unbalanced data
 - I.e. model was quite good at zero-shot cross-lingual transfer
 - This suggests model can do tasks beyond language, but why surprising?
- How can we explain mBERTs success without alignment signal?
 - Recall: **no alignment signal**, e.g. parallel sentence translations
- Several studies have focused on this question and found:
 - <u>K et al. 2020</u>: 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
 - <u>Dufter et al. 2020</u> hypothesized that mBERT is multilingual due to limited parameters, forced to share feature across languages
 - Blevins et al. 2022: language contamination -> no real monolingual models

Generalizing Across Languages (2)



- mBERT was the first of many multilingual transformer-based LMs
- <u>Lample et al. 2019</u> 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



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Generalizing Across Languages (3)



- 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
- <u>Lauscher et al. 2020</u> 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
 - <u>Conneau et al. 2020</u> 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



- 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
- <u>Lauscher et al. 2020</u> 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)



- <u>Muller et al. 2021</u> studied the internal mechanism that allow mBERT do perform 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.)

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Cross-lingual Transfer in mBERT (2)

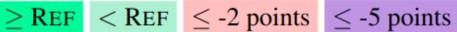


- They found lower layers more important in cross-lingual setting
 - Replacing lower layers with random weights had much more impact cross-lingually
 - Replacing upper layers had little impact in both settings
- This suggests lower layers act as "multilingual encoder", and upper layers as task-specific, 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	g		
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



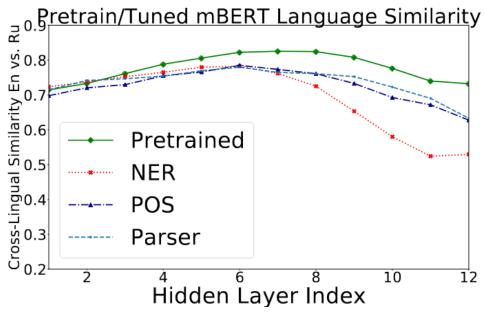




Cross-lingual Transfer in mBERT (3)



- 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 (<u>Chi et al.</u>, <u>Gaschi et al</u>)

Multilingual Evaluation



- 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
 - <u>MaskhaNER</u>: 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 (1)



- Since LLMs, research in mNLP mostly reproduced prior results
 - I.e. no new concepts, no new findings compared to PLM-based research
- 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 <u>over 40 languages</u>
 - Llama-3.1 supports <u>8 languages officially</u> (many more unofficially)
- But cross-lingual signals usually not present during pre-training
 - So, <u>ongoing research</u> to determine whether specific changes to architecture or training regimes are necessary
 - E.g. <u>cross-lingual attention</u> (feed model cross-lingual training examples)
 - Or perhaps simply scaling will get us to the mNLP goal

Multilinguality in LLMs (2)



- Recently, <u>Ahuja et al. 2023</u> studied multilingual performance of LLMs
 - They found significant gap in performance in English vs non-English
 - Especially true in low-resource language with non-latin scripts
 - Machine translating not enough
- Something that is special to LLMs: ICL
 - Zhang et al. (2024) studied impact of ICL demonstrations across languages
 - The found effectiveness of demonstration is also language dependent

Summary



- 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



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



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