Multilingual NLP

6. Cross-Lingual Transfer

(+ Multilingual Evaluation)

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Image: Alexander Mikhalchyk

After this lecture, you'll...

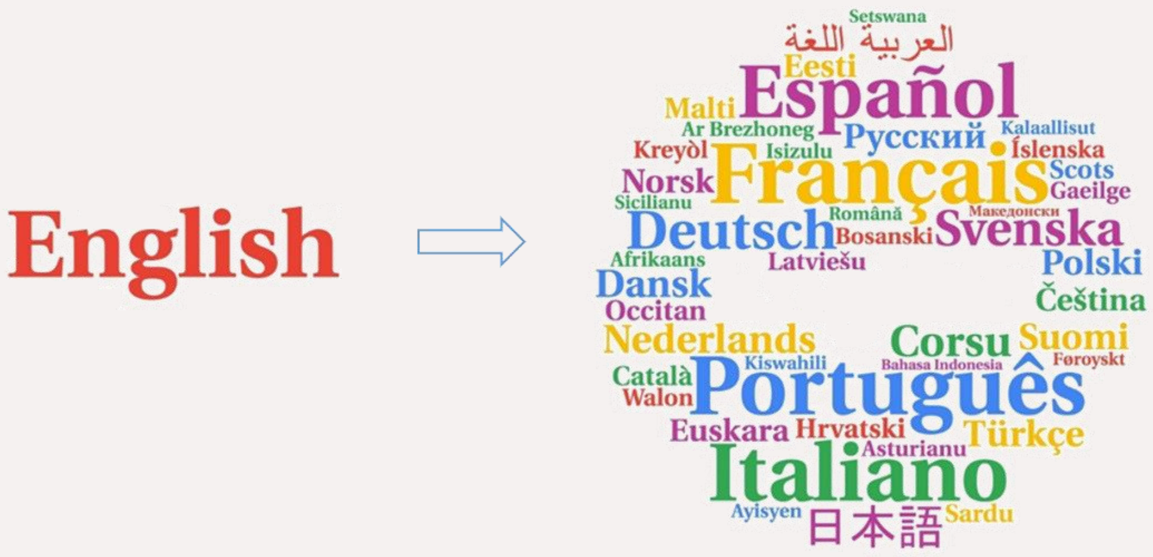
- Know what cross-lingual transfer for NLP tasks is
- Learn about Massively Multilingual LMs and CL transfer with them
- Distinguish between zero-shot and few-shot CL transfer
- Know of promiment multilingual evaluation benchmarks

Content

- **Cross-Lingual Transfer**
- CL Transfer with Massively Multilingual Transformers (MMTs)
- Zero- and Few-Shot Transfer with MMTs
- Multilingual Evaluation

Why Multilingual NLP?

- **Cross-Lingual transfer**: transfer supervised models for concrete NLP tasks
  - Models trained on labeled data in high-resource <u>source</u> language…
  - …make predictions on texts in low-resource <u>target</u> languages with little or no labeled data



Cross-Lingual Transfer: Practical Necessity

- Only a handful of NLP tasks have annotated data in many languages
  - Part-of-speech tagging (Universal Dependencies, UD)
  - Syntactic parsing (UD)
  - Named Entity Recognition (e.g., WikiANN)

- Higher-level semantic tasks often have only English training data
  - Generally more difficult tasks, e.g.:
    - Natural Language Inference (NLI)
    - Semantic Text Similarity (STS)
    - Question Answering (QA)
    - Causal Commonsense Reasoning
    - …

Cross-Lingual Transfer: Practical Necessity

- Natural Language Inference
  - Given a premise and hypothesis, predict whether hypothesis is entailed by the premise, contradicts it, or neither

    Premise: „A man reads the paper in a bar with green lighting."
    Hypothesis: „The man is inside"
    Label: entailment

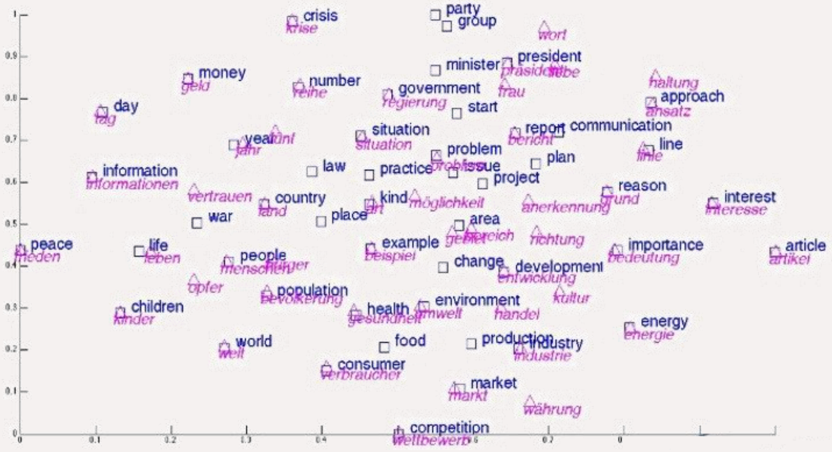
- Causal Commonense Reasoning
  - Given a premise find its most plausible cause among several choices

    Premise: „The politician won the election"
    Choice 1: „No one voted for him"
    Choice 2: „He ran negative campaign ads against the opponent"
    Label: Choice 2

- Such language understanding datasets very expensive to build
  - Thus most often exist only in English
  - Q: Can't we automatically translate them with MT?

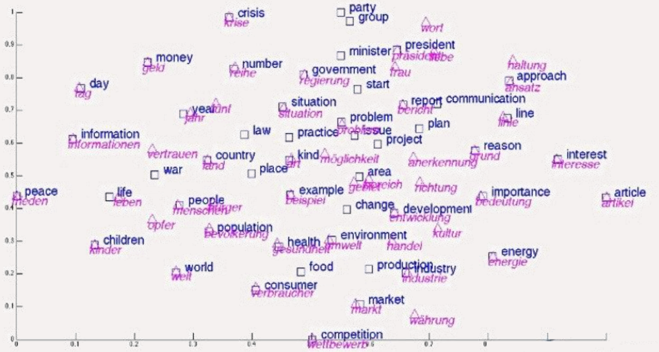
Cross-Lingual Transfer

- **Multilingual representation spaces** necessary for cross-lingual transfer
  - Words/sentences/texts that have the **same/similar meaning**, get same/similar representations…
    - …whether from the same language or different languages
- Cross-lingual word embeddings
- Multilingual LMs



CL Transfer via CLWEs

- **Multilingual representation spaces** necessary for cross-lingual transfer
- Embeddings of words from source and target language semantically „aligned"
- **Training**
  - Texts in source language L_S
  - Input vectors from shared bilingual space
- **Inference**
  - Texts in target language L_T
  - Input vectors **also** from shared bilingual space, which the trained model „understands"

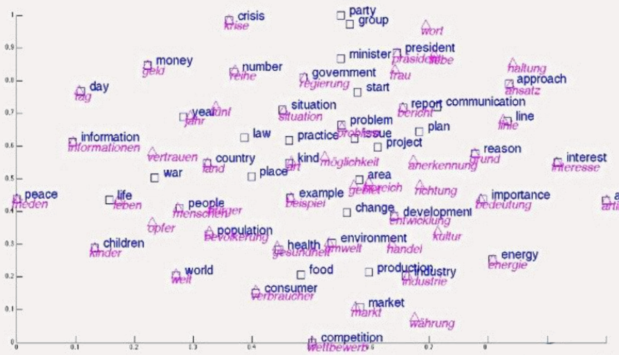


Task-specific model
(e.g., a CNN + classifier)

prediction

CL Transfer via CLWEs

- CL transfer with CLWEs has some clear limitations
- CLWEs: out-of-context representations of words
  - I.e., static word embeddings
  - Static word embeddings conflate senses for words with multiple meanings
- Transfer with CLWEs would be <u>perfect</u> **if**:
  - CLWE space was perfect (ideal alignment)
  - There was a 1-to-1 correspondence between the words of L_S and L_T
  - Representations of phrases and sentences aggregated from word embeddings <u>the same way for both languages</u>



Task-specific model
(e.g., a CNN + classifier)

prediction

Content

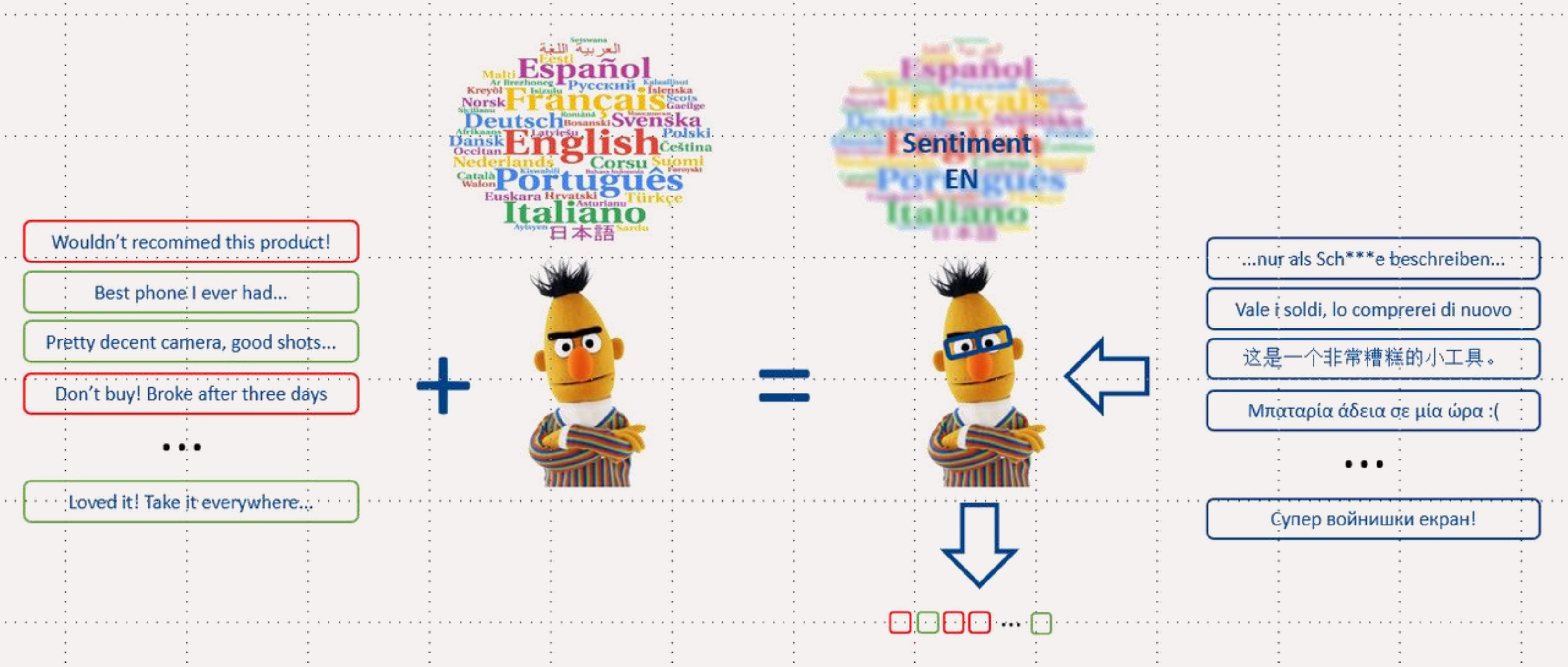
- Cross-Lingual Transfer
- **CL Transfer with Massively Multilingual Transformers**
- Zero- and Few-Shot Transfer with MMTs
- Multilingual Evaluation

Massively Multilingual Transformers

- With pretrained Transformer-based LMs (i.e., BERT & co.)
  - We obtain more than static word embeddings
  - Contextualized representations of tokens – meaning in context
- If we could make the same Transformer (same parameters) learn how to contextualize tokens in multiple languages…
  - We could support CL transfer „out of the box"
  - Fixing for limitations of transfer with CLWEs
- **Multilingual BERT**
  - BERT's Transformer pretrained on multilingual corpora
  - Concatenation of monolingual corpora in 104 languages
  - Without any cross-lingual supervision?!
    - No word alignments, no parallel sentences

Massively Multilingual Transformers

- **Cross-lingual transfer with MMTs** is conceptually trivial
  1. Place a task-specific head on top of the Transformer body
  2. Perform standard fine-tuning using task-specific training data in L_S
  3. Use the Transformer and classifier to make predictions for data in L_T



Massively Multilingual Transformers

- **Cross-lingual transfer with MMTs** is conceptually trivial
- But a lot of open questions about what's encoded in such an MMT
  - Q: Size of pretraining corpora for each language?
  - Q: How does tokenization work in a massively multilingual setup?
  - Q: How/why are representations of different languages semantically aligned if there is no explicit cross-lingual supervision?
  - Q: Are all pretraining languages „equal" in the representation space of mBERT?
  - Q: Is CL transfer equally good for any L_S and L_T from pretraining languages?
  - Q: What about languages not seen in pretraining?

MMTs: Corpora and Tokenization

- mBERT trained on 104 largest Wikipedias
  - Obviously, the corpus of each language is not of the same size
  - English Wikipedia: 6.6M articles; Chuvash Wikipedia: 50K articles
    - Articles also much longer for English and other major languages
- Multilingual tokenization
  - mBERT (like monolingual BERT) uses WordPiece tokenization
    - Vocabulary size: 110K tokens
  - Languages without whitespaces:
    - Characters separated with a special character (CJK Unicode block)
  - Problem: WordPiece merges dominated by large languages
    - Large languagess have many more whole-word tokens than small languages

MMTs: Corpora and Tokenization

- Problem: WordPiece merges dominated by large languages
  - Large languagess have many more whole-word tokens than small languages

```
from transformers import BertTokenizer, BertModel
tokenizer = BertTokenizer.from_pretrained('bert-base-multilingual-uncased')

encoded_input = tokenizer("wonderful", return_tensors='pt')
tokenizer.convert_ids_to_tokens(encoded_input["input_ids"][0])
```

- „wonderful" (EN) → `['[CLS]', 'wonderful', '[SEP]']`
- „prekrasno" (HR) → `['[CLS]', 'pre', '##kra', '##sno', '[SEP]']`

MMTs: Corpora and Tokenization

- Problem: WordPiece merges dominated by large languages
  - Large languagess have many more whole-word tokens than small languages
  - „wonderful" (EN) → `['[CLS]', 'wonderful', '[SEP]']`
  - „prekrasno" (HR) → `['[CLS]', 'pre', '##kra', '##sno', '[SEP]']`
- Several shortcomings:
  1. Token sequences longer for smaller languages and Transformer has fixed input size → we can encode shorter texts in smaller languages
  2. We need Transformer's body parameters to correctly contextualize subword tokens that belong to the same word-level token
     - Learn that `'pre'`, `'##kra'`, and `'##sno'` should attend over one another
     - But smaller languages have less data to learn from!
  3. Shorter tokens more likely to appear across multiple languages
     - wonderful will appear predominantly in English text, what about `##kra`?
     - Shared tokens will commonly have different „meaning" in different langs

CL Transfer with mBERT

Pires, T., Schlinger, E., & Garrette, D. (2019, July). How Multilingual is Multilingual BERT? In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (pp. 4996-5001).

→ „mBERT surprisingly good at zero-shot CL model transfer"

Wu, S., & Dredze, M. (2019, November). Beto, Bentz, Becas: The Surprising Cross-Lingual Effectiveness of BERT. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP) (pp. 833-844).

→ „Suprising cross-lingual effectiveness of BERT"

CL Transfer with mBERT

- Q: But where does the cross-lingual transfer ability of mBERT come from?
  - No explicit alignment across languages of any time in pretraining

Dufter, P., & Schütze, H. (2020). Identifying Necessary Elements for BERT's Multilinguality. In Proceedings of EMNLP 2021.

- The capacity of the model (12-layer Transformer; 110M parameters) is too small to precisely and accurately „learns" every of 104 languages
- MLM training on massively multilingual corpora forces the Transformer to use its parameters efficiently -- i.e., share them across languages
  - This exploits commonalities between languages and results in (some) alignment
- Shared embeddings also help
  - Positional embeddings*: Q: when could shared PEs hurt?
  - Token embeddings, for tokens with same meaning across languages
    - E.g., digits or names („1", „Joe", ...)

MMTs beyond mBERT

- XLM: Cross-Lingual Language Modeling

Conneau, A., & Lample, G. (2019). Cross-lingual language model pretraining. Advances in neural information processing systems, 32.

- BPE tokenizer trained on modified corpora obtained by
  - Oversampling sentences from small languages
  - Undersampling sentences from large languages

$$q_i = \frac{p_i^\alpha}{\sum_{j=1}^{N} p_j^\alpha} \qquad p_i = \frac{n_i}{\sum_{k=1}^{N} n_k}$$

modified distribution   original distribution

  - Smoothing factor α set to 0.5
  - More whole-word tokens for small languages, 95K tokens in total

MMTs beyond mBERT

- XLM: Cross-Lingual Language Modeling

Conneau, A., & Lample, G. (2019). Cross-lingual language model pretraining. Advances in neural information processing systems, 32.

- MLM as the main training objective (across all languages)
  - Self-supervised objective
- Additionally leverages parallel data with the new objective named translation language modeling (TLM)
  - Just MLM, but on pairs of parallel sentences
  - Also introduces trainable language embeddings
  - TLM is a supervised objective: requires parallel data

MMTs beyond mBERT

Conneau, A., & Lample, G. (2019). Cross-lingual language model pretraining. Advances in neural information processing systems, 32.

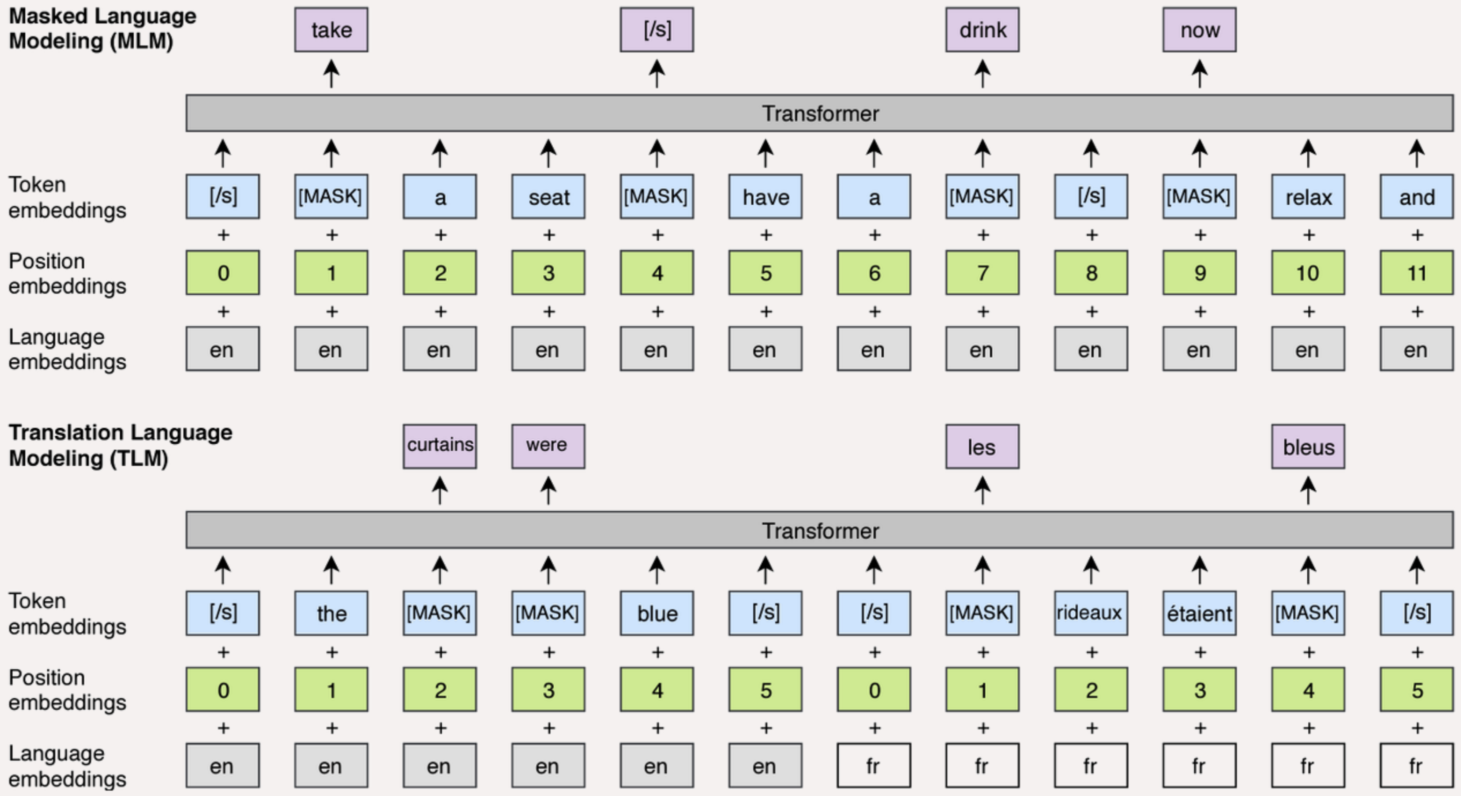


Image from the original paper

MMTs beyond mBERT

- XLM-R: XLM-on-RoBERTa

Conneau, A., Khandelwal, K., Goyal, N., Chaudhary, V., Wenzek, G., Guzmán, F., ... & Stoyanov, V. (2020, July). Unsupervised Cross-lingual Representation Learning at Scale. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (pp. 8440-8451).

- Just MLM-ing, but...
- On much much larger corpora:
    - CC100 – filtered CommonCrawl for 100 languages: 2TB of text!
- Larger vocabulary: 250K tokens

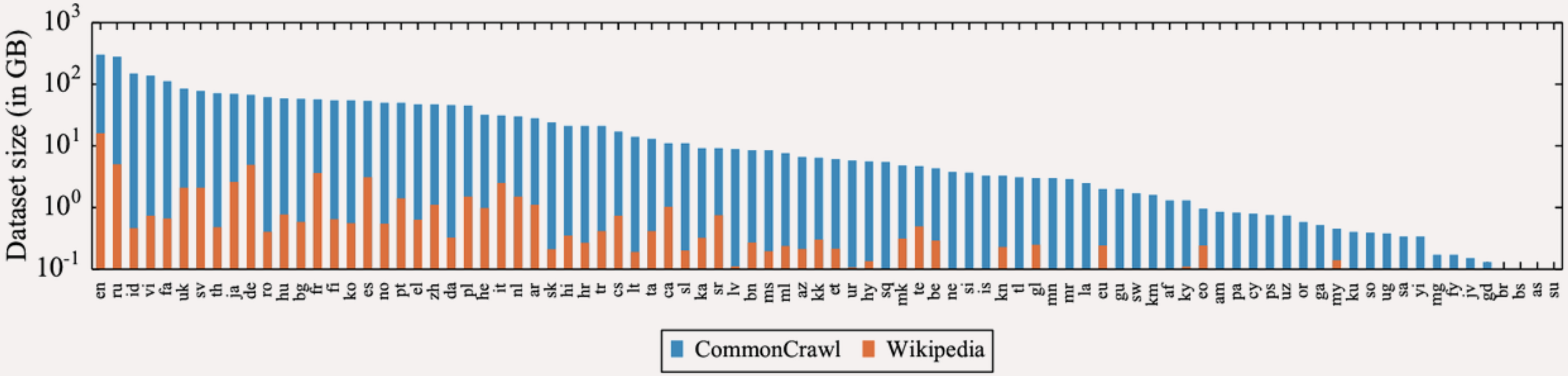


Image from the original paper

CL Transfer with MMTs

- Initial evaluations
  - Source language: EN
  - Target languages: high-resource, closely related to EN
    - E.g., NL, DE, IT, FR, ES

- What about small target languages distant from English?
  - small: small corpus in pretraining
  - distant from English:
    - genealogically, etymologically, typologically (recall Lecture 1 :))
  - Basically, what about the vast majority of world languages?

CL Transfer with MMTs

Lauscher, A., Ravishankar, V., Vulić, I., & Glavaš, G. (2020, November). From Zero to Hero: On the Limitations of Zero-Shot Language Transfer with Multilingual Transformers. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP) (pp. 4483-4499).

Task	Model	EN	ZH Δ	TR Δ	RU Δ	AR Δ	HI Δ	EU Δ	FI Δ	HE Δ	IT Δ	JA Δ	KO Δ	SV Δ	VI Δ	TH Δ	ES Δ	EL Δ	DE Δ	FR Δ	BG Δ	SW Δ	UR Δ
DEP	B	91.2	-43.9	-46.0	-28.1	-56.4	-36.1	-50.2	-30.7	-36.1	-17.1	**-60.1**	-56.1	-14.3	-	-	-	-	-	-	-	-	-
	X	92.0	**-85.4**	-44.2	-29.7	-54.6	-39	-49.5	-26.7	-39	-23.5	-80.5	-56.0	-16.3	-	-	-	-	-	-	-	-	-
POS	B	95.8	-38.0	-35.9	-16.0	-40.1	-33.4	-34.6	-21.9	-33.4	-19.8	**-46.1**	-42.0	-9.6	-	-	-	-	-	-	-	-	-
	X	96.3	-69.2	-27.7	-14.3	-37.1	-27.3	-31.9	-17.9	-27.3	-19.0	**-77.0**	-37.3	-10.7	-	-	-	-	-	-	-	-	-
NER	B	92.4	-23.3	-11.6	-10.7	**-31.7**	-11.1	-12.8	-3.8	-11.1	-2.6	-25.7	-13.8	-6.7	-	-	-	-	-	-	-	-	-
	X	91.6	**-34.8**	-6.2	-13.7	-24.6	-16.5	-8.0	-0.9	-16.5	-2.4	-30.1	-15.6	-2.2	-	-	-	-	-	-	-	-	-
XNLI	B	82.8	-13.6	-20.6	-13.5	-17.3	-21.3	-	-	-	-	-	-	-	-11.9	-28.1	-8.1	-14.1	-10.5	-7.8	-13.3	**-33.0**	-23.4
	X	84.3	-11.0	-11.3	-9.0	-13.0	-14.2	-	-	-	-	-	-	-	-9.7	-12.3	-5.8	-8.9	-7.8	-6.1	-6.6	**-20.2**	-17.3
XQuAD	B	71.1	-22.9	-34.2	-19.2	-24.7	-28.6	-	-	-	-	-	-	-	-22.1	**-43.2**	-16.6	-28.2	-14.8	-	-	-	-
	X	72.5	**-26.2**	-18.7	-15.4	-24.1	-22.8	-	-	-	-	-	-	-	-19.7	-14.8	-14.5	-15.7	-16.2	-	-	-	-

- **Huge** performance drops (both with mBERT and XLM-R) from transfer to
  (1) small languages
  (2) languages distant from English

Poor CL Transfer with MMTs

- MMTs (mBERT, XLM-R) exhibit huge performance drops in CL transfer to low-resource languages, especially if they are distant from English

- Even for large and closely-related languages (e.g., DE, ES, IT) we see drop in performance compared to English.
  - Q: Why?

- For English, we get better results by fine-tuning monolingual English BERT/RoBERTa than by fine-tuning mBERT or XLM-R.
  - Q: Why?

Poor CL Transfer with MMTs

- Part of the problem is the curse of multilinguality (Lecture 7)
  - Loss of representational accuracy for each individual language due to representing too many languages with the model of fixed capacity
- MLM training doesn't really align the representations across languages very well: clusters of language-specific subspaces visible
  - Better alignment achievable post-hoc with parallel data

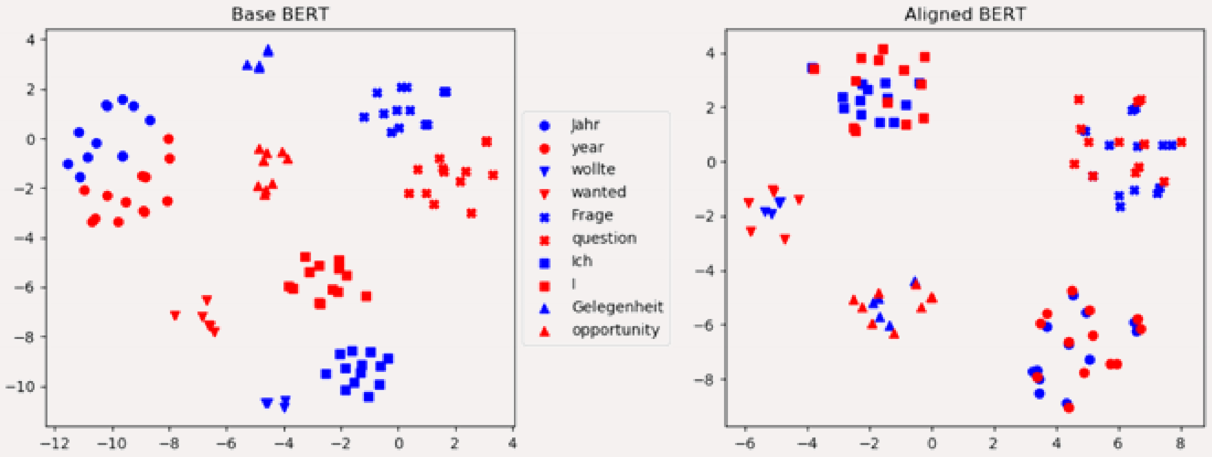


Image from: Cao, S., Kitaev, N., & Klein, D. *Multilingual Alignment of Contextual Word Representations.* In *International Conference on Learning Representations*. 2020.

Content

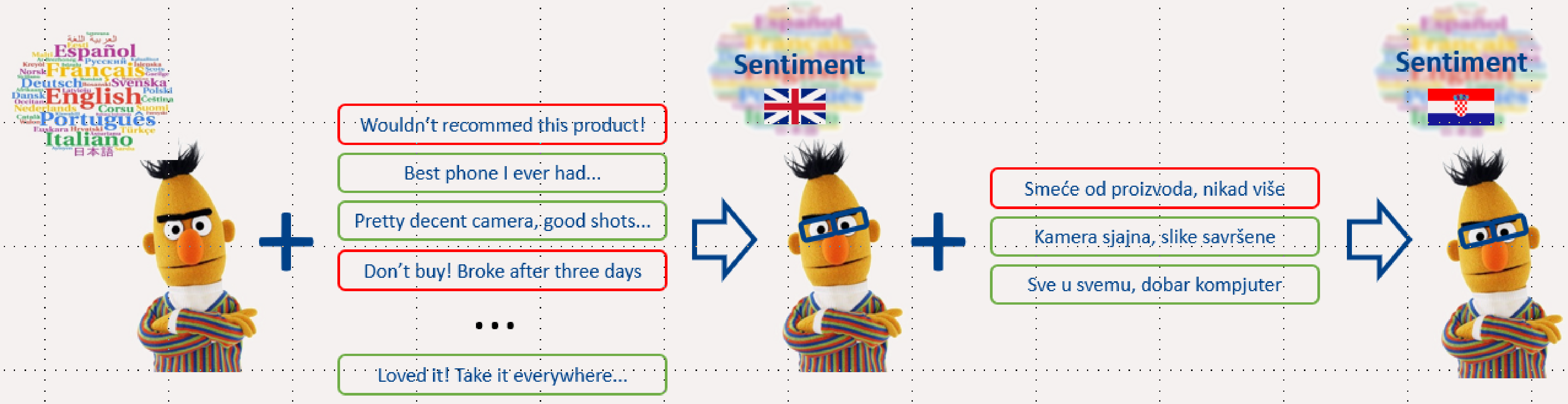
- Cross-Lingual Transfer
- CL Transfer with Massively Multilingual Transformers
- **Zero- and Few-Shot Transfer with MMTs**
- Multilingual Evaluation

Zero- vs. Few-Shot CL Transfer

- So far, we have analyzed the so-called **zero-shot transfer** setup
  - We assume **zero** labeled task instances in the target language
- In practice, it is almost always possible to annotate some small number of instances in the target language
- **Few-shot transfer**: large task-specific training dataset D_S in L_S, a few labeled instances (small dataset D_T) in L_T
  - Q: how many is „few"?
  - Depends on the task, but $|D_T| << |D_S|$

Few-Shot CL Transfer

- Sequential few-shot CL transfer
  - First fine-tune an MMT on the large D_S
  - Then fine-tune it on the small D_T



Few-Shot CL Transfer

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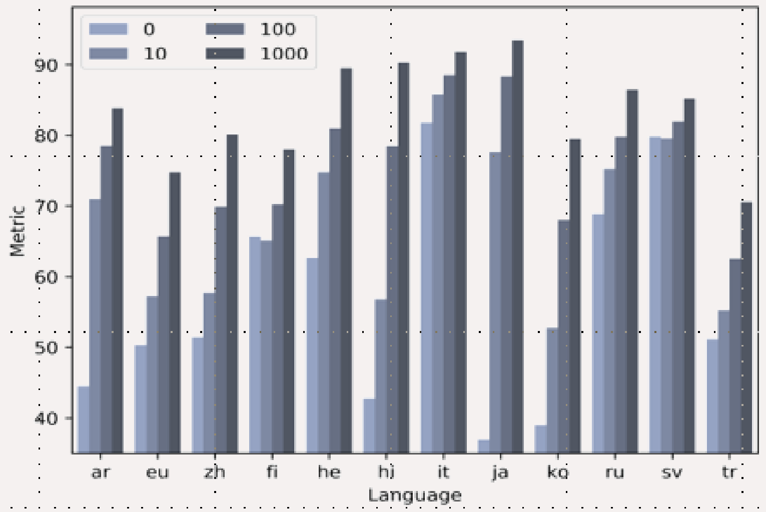
- Sequential few-shot CL transfer can bring massive gains in transfer performance compared to zero-shot CL transfer

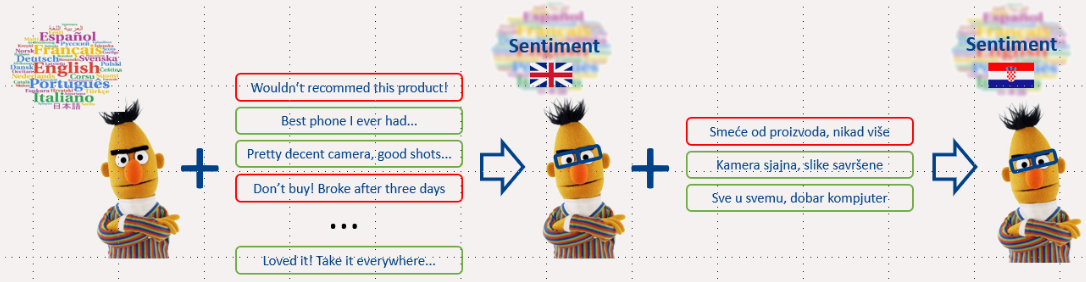
		k	$k=10$		$k=50$	
Task	Model	$k=0$	score	Δ	score	Δ
DEP	mBERT	52.96	66.69	13.73	72.67	19.70
	XLM-R	48.60	65.57	16.97	72.19	23.59
POS	mBERT	67.2	80.17	12.96	85.34	18.14
	XLM-R	65.5	80.68	15.18	85.7	20.2
NER	mBERT	79.34	83.18	3.84	84.54	5.20
	XLM-R	85.43	88.06	2.63	91.07	5.64



Dependency parsing

Few-Shot Transfer: Generality vs. Performance

- Sequential few-shot CL transfer
  (1) First fine-tune an MMT on the large D_S: computationally expensive
  (2) Then fine-tune it on the small D_T: computationally cheap
- Pro: After (1) we have a **general** task-specific model, which can be quickly fine-tuned for various target languages with few instances
- Con: The two training steps are executed sequentially, **no task-specific interaction** between the languages



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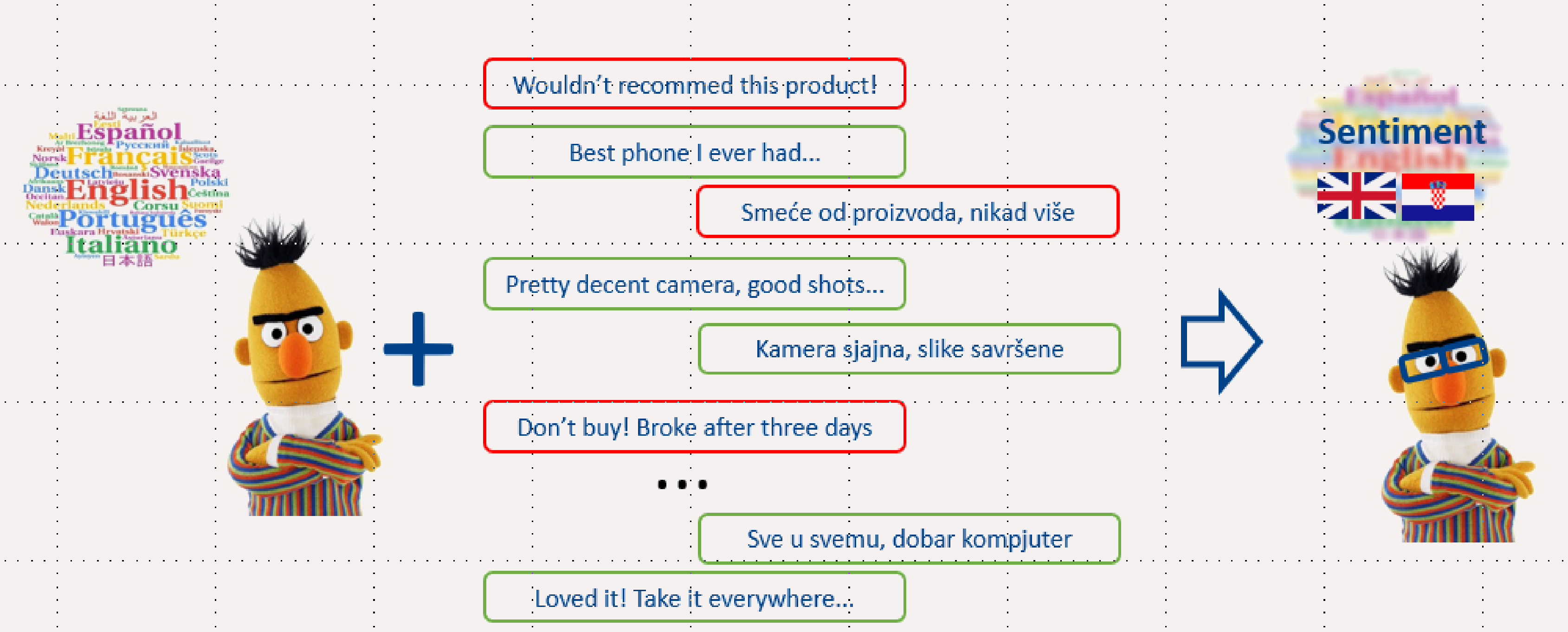
- Simultaneous fine-tuning on (many) instances from L_S and (few) from L_T



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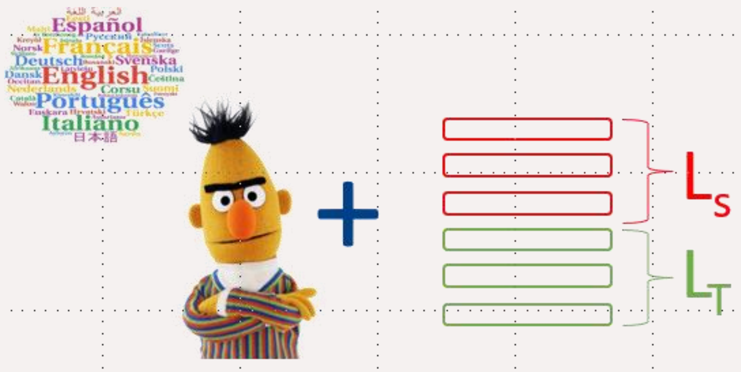
- Simultaneous fine-tuning on (many) instances from L_S and (few) from L_T

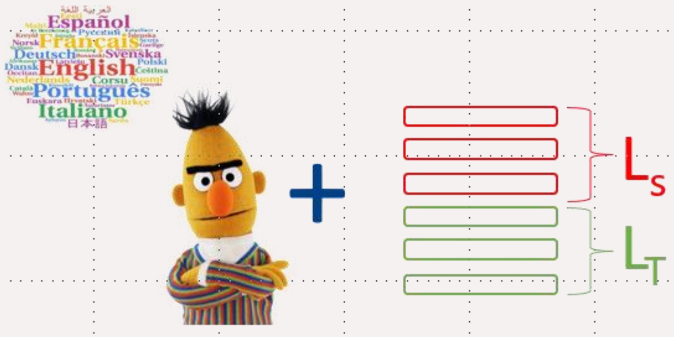
Important: **batch balancing** between L_S and L_T

- Few target language instances will repeat much more often
- But will be „regularized" with different source language instances in different bathes
  → less overfitting, better generalization in L_T



Few-Shot Transfer: Generality vs. Performance

- Joint few-shot CL transfer
- Pro: Task-specific interaction between L_S and L_T, leads to **better performance** on L_T
- Con: For each L_T we have to carry out the fine-tuning on $|D_S| + |D_T|$ instances
  - Effectively $2*|D_S|$ instances in training
    - Because we're repeating D_T instances to balance batches



Content

- Cross-Lingual Transfer
- CL Transfer with Massively Multilingual Transformers
- Zero- and Few-Shot Transfer with MMTs
- **Multilingual Evaluation**

Multilingual Evaluation

- In the last few years, a lot of new multilingual evaluation datasets and benchmarks in NLP
- Some multilingual datasets (single task)
  - Americas NLI: evaluation dataset for natural language inference (NLI), covering 10 low-resource indigenous languages of the Americas
  - MaskhaNER: evaluation dataset for named entity recognition (NER) covering 10 low-resource African languages
  - TyDiQA: question answering (QA) dataset covering 11 typologically diverse languages
  - XCOPA: causal commonsense reasoning for 11 genealogically, geographically, and typologically diverse languages

Multilingual Evaluation

- Q: How to select languages for a multilingual dataset/benchmark?
  - Based on what criteria?
- Historically, multilingual evaluations included predominantly large languages with substantial digital footprint
  - These tend to be predominantly Indo-European (IE)
- We've seen that transfer (usually from English, which is IE) works best when transferring to other IE languages
- Datasets/benchmarks that include predominantly IE and/or large langs **overestimate** the general/global multilingual abilities of models

Multilingual Evaluation

Ponti, E. M., Glavaš, G., Majewska, O., Liu, Q., Vulić, I., & Korhonen, A. (2020). XCOPA: A Multilingual Dataset for Causal Commonsense Reasoning. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP) (pp. 2362-2376).

- Quantifying diversity of language samples in multilingual datasets
- Typological index
  - Based on URIEL typological vectors of languages: 103 binary features
  - Compute entropy for each feature, and then mean entropy across feats.
- Family index
  - Number of distinct language families in the language sample
- Geography index
  - Entropy of the distribution over the 6 global geographic macro-regions

Multilingual Benchmarks

- In the age where how we address NLP tasks has been largely unified, it is common to evaluate models on a collection of tasks
- Multilingual benchmark: a collection of multilingual datasets
  - Not all datasets (need to) cover the same set of languages
- Some multilingual benchmarks (single task)
  - XGLUE: 11 tasks, 19 languages in total
  - XTREME: 9 tasks, 40 languages (from 12 language families)
  - XTREME-R: 10 tasks, 50 languages

Creating Multilingual Datasets

- Q: How do we normally create multilingual datasets?
  - Most commonly by translating dev/test portions of English datasets

1. Completely manual translation
   - If the original dataset has a lot of culture-specific concepts that don’t have a direct translation or don’t exist in the target language
   - E.g., in XCOPA: „bowling“, „parking meter“ …
2. Machine translation + manual post-editing
   - Human annotator fixes the errors of automatic translation
   - Cheaper than manual trans. if the MT model $L_S \rightarrow L_T$ is good enough

- In both cases we need bilingual annotators
  - Difficult to find for low-resource languages

Model Selection in CL Transfer

- When we train ML models, we leverage a validation (aka development) dataset D_V for **model selection**
  - Selecting optimal hyperparameter values, early stopping, etc.
- When we fine-tune neural LMs for CL transfer, the language of the validation dataset plays a huge role
  - Target language performance much better if D_V in L_T
  - If D_V in L_S, we're selecting the model checkpoint that's optimal for the source language (usually EN) performance
- Q: Think of zero-shot CL transfer. What is the problem with having a validation dataset in the target language (i.e., D_V is in L_S)?

Model Selection in CL Transfer

- Q: Think of zero-shot CL transfer. What is the problem with having a validation dataset in the target language?
  - Not real zero-shot transfer! Relies on labeled instances in L_T
    - Just not directly for model training, but for model selection
- Most multilingual datasets offer both validation and test (final evaluation) data in L_T
  - Allows for unfair zero-shot transfer evaluation (labeled data in L_T)
  - Q: What if we did not need D_V in L_T for model selection?
    - We could use those $|D_V|$ in L_T for **training** instead → few-shot transfer
    - And few-shot is always better than zero-shot!

Model Selection in CL Transfer

Schmidt, F. D., Vulić, I., & Glavaš, G. (2023). Free Lunch: Robust Cross-Lingual Transfer via Model Checkpoint Averaging. Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (ACL). *To appear*.

- **Checkpointing**: as we train the model on the training data, we periodically (e.g., every N training steps) store the parameter values
  - This is called a checkpoint (or snaphot) of the model
- **Checkpoint averaging**: the final model is the average of all checkpoints during training (rather than just the last checkpoint)
- Checkpoint averaging in CL transfer (zero-shot and few-shot) leads to more robust training behaviour and removes the need for D_V in L_T

Image: Alexander Mikhalchyk