

# XCOPA: A Multilingual Dataset for Causal Commonsense Reasoning

Edoardo M. Ponti<sup>1\*</sup>, Goran Glavaš<sup>2\*</sup>, Olga Majewska<sup>1</sup>,  
Qianchu Liu<sup>1</sup>, Ivan Vulić<sup>1</sup>, Anna Korhonen<sup>1</sup>

<sup>1</sup>Language Technology Lab, TAL, University of Cambridge, UK

<sup>2</sup>Data and Web Science Group, University of Mannheim, Germany

<sup>1</sup>{ep490,om304,ql261,iv250,alk23}@cam.ac.uk

<sup>2</sup>goran@informatik.uni-mannheim.de

## Abstract

In order to simulate human language capacity, natural language processing systems must complement the explicit information derived from raw text with the ability to reason about the possible causes and outcomes of everyday situations. Moreover, the acquired world knowledge should generalise to new languages, modulo cultural differences. Advances in machine commonsense reasoning and cross-lingual transfer depend on the availability of challenging evaluation benchmarks. Motivated by both demands, we introduce Cross-lingual Choice of Plausible Alternatives (XCOPA), a typologically diverse multilingual dataset for causal commonsense reasoning in 11 languages. We benchmark a range of state-of-the-art models on this novel dataset, revealing that current methods based on multilingual pretraining and zero-shot fine-tuning transfer suffer from the curse of multilinguality and fall short of performance in monolingual settings by a large margin. Finally, we propose ways to adapt these models to out-of-sample resource-lean languages where only a small corpus or a bilingual dictionary is available, and report substantial improvements over the random baseline. XCOPA is available at [github.com/cambridgeltl/xcopa](https://github.com/cambridgeltl/xcopa).

## 1 Introduction

Commonsense reasoning is a critical component of any natural language understanding system (Davis and Marcus, 2015). Contrary to textual entailment, commonsense reasoning must bridge between premises and possible hypotheses with *world knowledge* that is not explicit in text (Singer et al., 1992). Such world knowledge encompasses, among other aspects: temporal and spatial relations, causality, laws of nature, social conventions, politeness, emotional responses, multiple modalities.

Hence, it corresponds to the individuals’ expectations about typical situations (Shoham, 1990).<sup>1</sup>

A seminal work on the quantitative evaluation of commonsense reasoning is the Choice Of Plausible Alternatives dataset (COPA; Roemmele et al., 2011), which focuses on cause–effect relationships. In recent years, more datasets have been dedicated to other facets of world knowledge (Sakaguchi et al., 2020; Bisk et al., 2020; Bhagavatula et al., 2020; Rashkin et al., 2018; Sap et al., 2019, *inter alia*). Unfortunately, the extensive efforts related to this thread of research have so far been limited only to the English language.<sup>2</sup> Such a narrow scope not only curbs the development of natural language understanding tools in other languages (Bender, 2011; Ponti et al., 2019a), but also exacerbates the Anglo-centric bias in modeling commonsense reasoning. In fact, the expectations about typical situations vary cross-culturally (Thomas, 1983).

Datasets that cover multiple languages for other natural understanding tasks, such as language inference (Conneau et al., 2018), question answering (Lewis et al., 2019; Artetxe et al., 2020a; Clark et al., 2020), and paraphrase identification (Yang et al., 2019b) have received increasing attention. In fact, the requirement to generalise to new languages encourages the development of more versatile language understanding models, which can be ported across different grammars and lexica. These efforts have recently culminated in the integration of several multilingual tasks into the XTREME evaluation suite (Hu et al., 2020). However, a compre-

<sup>1</sup>Moreover, there are often multiple legitimate chains of sentences that can be invoked in between premises and hypotheses. In short, commonsense reasoning does not just involve understanding what is possible, but also ranking what is most *plausible*.

<sup>2</sup>The only exception is direct translation of the 272 paired English Winograd Schema Challenge instances to Japanese (Shibata et al., 2015), French (Amsili and Seminck, 2017), and Portuguese (Melo et al., 2020).

\*Equal contribution.

	PREMISE		CHOICE 1	CHOICE 2
qu	<i>Sipasqa cereal mikhunanpi kuruta tarirqan.</i>	R	<i>Payqa pukunman ñuqñuta churakurqan.</i>	<i>Payqa manam mikhuyta munarqanchu.</i>
en	The girl found a bug in her cereal.		She poured milk in the bowl.	She lost her appetite.
th	ตาของฉันแดงและบวม	C	ฉันร้องไห้	ฉันหัวเราะ
en	My eyes became red and puffy.		I was sobbing.	I was laughing.

Table 1: Examples of forward and backward reasoning (Result [R] and Cause [C]) in the XCOPA validation sets.

hensive multilingual benchmark for commonsense reasoning in particular is still missing.

In order to address this gap, we develop a novel dataset, **XCOPA** (see examples in Table 1), by carefully translating and re-annotating the validation and test sets of English COPA into 11 target languages. A key design choice is the selection of a typologically diverse sample of languages. In particular, we privilege internal variety over the abundance of digital resources in each language. Since resource-rich languages tend to belong to only a few families and areas, their sample is highly biased and is not indicative of the expected model performance (Gerz et al., 2018; Ponti et al., 2019a; Joshi et al., 2020). Following this guiding principle, we select 11 languages from 11 distinct families, and 4 geographical macro-areas (Africa, South America, Eurasia, Southeast Asia and Oceania).

We leverage XCOPA to benchmark a series of state-of-the-art pretrained multilingual models, including XLM-R (Conneau et al., 2020), MBERT (Devlin et al., 2019), and multilingual USE (Yang et al., 2019a). Two XCOPA languages (i.e., Quechua and Haitian Creole) are out-of-sample for the pretrained models: this naturally raises the question of how to adapt the pretrained models to such unseen languages. In particular, we investigate the resource-lean scenarios where either some monolingual data or a bilingual dictionary with English (or both) are available for the target language.

In summary, we offer the following contributions. **1)** We create the first large-scale multilingual evaluation set for commonsense reasoning, spanning 11 languages, and discuss the challenges in accounting for world knowledge across different cultures and languages. **2)** We propose quantitative metrics to measure the internal variety of a language sample, which can guide the design of any multilingual dataset in the future. **3)** We benchmark pretrained state-of-the-art models in cross-lingual transfer of commonsense knowledge, and investigate how to (post-hoc) improve transfer for languages unseen at pretraining time.

In order to rise to the challenge of this dataset,

models must be able not only to combine textual evidence with world knowledge – which makes commonsense reasoning challenging *per se* (Talmor et al., 2019; Rajani et al., 2019), but they must also transfer the acquired causal reasoning abilities across languages. The results we obtain on XCOPA may thus indicate the limitations of current state-of-the-art multilingual models in cross-lingual transfer for complex reasoning tasks.

## 2 Annotation Design

**Design Objectives.** The principal objectives in XCOPA creation were: **1)** to create a *genuinely* typologically diverse multilingual dataset, aligned across target languages in order to make performance scores comparable, and **2)** to ensure high quality, naturalness and idiomacity of each monolingual dataset. While the commonly used translation approach addresses the former objective, it is prone to compromise the latter goal, bending the target language to the structural and lexical properties of the source language: the resulting evaluation benchmarks thus fail to measure system performance adequately (Koppel and Ordan, 2011; Volansky et al., 2015; Artetxe et al., 2020a).

In order to avoid these pitfalls, we: (i) entrusted the translation task to a single (but carefully selected) translator for each target language,<sup>3</sup> and (ii) offered enough leeway for necessary target-language adjustments (e.g., substitutions with culture-specific concepts and multi-word paraphrases, wherever the original text eluded direct translation). Detailed translation guidelines are available in Appendix A.

**Language Sampling.** Multilingual evaluation benchmarks assess the *expected performance* of a model across languages. However, should such languages be randomly sampled from the distribution of digital texts? Or rather, should the sample represent the distribution over the languages spoken

<sup>3</sup>Crowd-sourcing offers faster annotation at a lower cost – however, in our trial experiments, chasing low annotation times and costs resulted in low translation quality.

	Range	XCOPA	TyDiQA	XNLI	XQUAD	MLQA	PAWS-X
Typology	[0, 1]	0.41	0.41	0.39	0.36	0.32	0.31
Family	[0, 1]	1	0.9	0.78	0.6	0.66	0.66
Geography	[0, log <sub>2</sub> 6]	1.79	1.16	0.95	0.72	0.66	0

Table 2: Indices of typological, genealogical, and areal diversity for the language samples of a set of NLU datasets.

around the world? Resource-rich languages tend to belong to the same families and areas, which facilitates knowledge transfer and leads to an overestimation of the expected performance in the second sense (Gerz et al., 2018; Ponti et al., 2019a). Moreover, rather than samples that account for independent and identically distributed draws from the ‘true’ language distribution (known as *probability* sampling), we opt for a *uniform* distribution of linguistic phenomena, which encourages the inclusion of outliers (known as *variety* sampling; Rijkhoff et al., 1993; Dryer, 1989). Thus, the performance on XCOPA also reflects the *robustness* of a model, i.e. its resilience to phenomena that are unlikely to be observed in the training data.

Inspired by Rijkhoff et al. (1993) and Miestamo (2004), we propose a series of simple and interpretable metrics that quantify diversity of a language sample independent of its size: **1)** a *typology* index based on 103 typological features of each language from URIEL (Littell et al., 2017), originally sourced from the World Atlas of Language Structures (WALS; Dryer and Haspelmath, 2013). Each feature is binary and indicates the presence or absence of a phenomenon in a language. We estimate the entropy of the distribution of values in a sample, as shown in the heatmap of Figure 2 in the Appendix. Afterwards, we average across all 103 feature-specific entropies. Intuitively, if all values are equally represented, the entropy is high. If all languages have identical features, the entropy is 0; **2)** The *family* index is simply the number of distinct families divided by the sample size. **3)** The *geography* index is the entropy of the distribution over macro-areas in a sample.<sup>4</sup>

The sample of languages for XCOPA aims at maximising these indices. In particular, XCOPA includes Estonian (ET), Indonesian (ID), Italian (IT), Cusco-Collao Quechua (QU),<sup>5</sup> Kiswahili (SW), Tamil (TA), Thai (TH), Turkish (TR), Vietnamese (VI), and Mandarin Chinese (ZH). These languages belong to distinct families, respectively:

<sup>4</sup>Six macro-areas, as defined by Dryer (1989), are Africa, Eurasia, Southeast Asia and Oceania, Australia and New Guinea, North America, and South America.

<sup>5</sup>The translator is an Eastern Apurímac Quechua speaker.

Uralic, Creole, Austronesian, Indo-European, Yuman–Cochimí, Niger-Congo, Dravidian, Kra-Dai, Turkic, Austroasiatic, and Sino-Tibetan. Moreover, QU and HT are spoken in South America, which is an underrepresented macro-area. We report the 3 metrics in Table 2 and compare it to samples from other standard multilingual NLU datasets. XCOPA offers the most diverse sample in terms of typology (on a par with TyDiQA), family, and geography.

**Final Dataset.** As shown in Table 1, each (X)COPA instance corresponds to a premise, a question (“What was the CAUSE?” or “What happened as a RESULT?”), and two alternatives. The task is framed as binary classification where the machine has to predict the more plausible choice. For each target language, XCOPA comprises 100 annotated data instances in the validation set and 500 instances as the test set, which are translations from the respective English COPA validation and test set, see Table 1 again. Our translators performed labeling prior to translation, deciding on the correct alternative for the English premise and preserving the correctness of the same alternative in translation. We measure inter-translator agreement using the Fleiss’  $\kappa$  statistic (Fleiss, 1971): the obtained score of 0.921 for development data and 0.911 for test data reveal very high agreement between translators (i.e., Landis and Koch (1977) define  $\kappa \geq 0.81$  as almost perfect agreement).

From the 11 sets of annotation labels we obtain the majority labels (i.e., 6+ translators agree). We observe perfect agreement between our majority labels and the English COPA labels for development data. We then compute the percentage of annotated labels which agree with the majority label for each language individually, reported in Table 3, and find very high agreement across 11 languages. The small discrepancies in label choices in our work stem not only from the actual semantic ambiguity of the original English question, but also reflect the translators’ different cultural frames of reference and patterns of association. On average, 2.1% of labels in the validation set and 2.4% of labels in the test set do not match the majority label.<sup>6</sup>

<sup>6</sup>In order to accurately represent ambiguity of the small

	ET	HT	ID	IT	QU	SW	TA	TH	TR	VI	ZH
<i>val</i>	97.0	97.0	99.0	98.0	98.0	99.0	100.0	99.0	97.0	97.0	96.0
<i>test</i>	98.2	96.4	100.0	97.0	94.8	99.0	98.6	98.2	96.4	98.4	96.6

Table 3: Percentage of annotated labels in each language agreeing with the majority label. Note that the majority label is highly reliable, as we observed a 100% agreement with the development set labels in the original COPA.

### 3 Qualitative Analysis

As highlighted in §2, our guidelines anticipated that the adopted translation approach may entail language-specific challenges, e.g., the lack of equivalent concepts or the grammatical expression of tense and aspect. We now analyse the main design challenges and the adopted solutions.

**Cultural Context.** The scenarios included in English COPA were authored by American English speakers with a particular cultural background. It is therefore inevitable that some concepts, intended as commonplace, sound unusual or even completely foreign in the target language. The examples include: (i) concrete referents with no language-specific term available (e.g., *bowling ball*, *hamburger*, *lottery*); (ii) systems of social norms absent in the target culture, e.g., traffic regulations (e.g., *parallel parking*, *parking meter*); (iii) social, political, and cultural institutions and related terminology (e.g., *mortgage*, *lobbyist*, *gavel*); (iv) idiomatic expressions (e.g., *put the caller on hold*).

In such cases, the translators were advised to resort to (i) paraphrasing; (ii) substitutions with similar concepts, e.g., ‘faucet’ is replaced with ‘pipe’ in Tamil (கூழாய், *kulāy*) and Haitian Creole (*tiyo*); or (iii) phonetically transcribed loan words, e.g., in Tamil: பெளலிங் பந்து (*paulin pantu*, ‘*bowling ball*’), சோப்பு (*cōppu*, ‘*soap*’).

**Grammatical Tense.** The temporal contiguity between two events and their duration is crucial in establishing their causal relationship (Bohnenmeyer et al., 2011). A number of languages in our sample (i.e., TH, VI, ID, ZH) do not have the grammatical category of tense and express temporality by means of aspect, mood or lexical items and expressions referring to time (e.g., adverbs), or rely entirely on pragmatic context to provide sufficient information for the interpretation of the utterance. Even if aspectual viewpoint markers exist, they are optional, e.g., the perfective marker 了 (*le*) in ZH. To ensure naturalness of the translated sentences and faithfully represent the properties of the so-called

tenseless languages, we favoured the unmarked variants, with the temporal relations established by the situational context (e.g., compare: (a) 我想节约能源。 , *Wǒ xiǎng jiéyuē néngyuán.*, ‘I want(ed) to conserve energy.’ (no perfective marker), and (b) 学生拼错了这个词。 , *Xuéshēng pīn cuòle zhège cí.*, ‘The student misspelled the word.’, (with completed action marker). Further considerations on anteriority and aspect are provided in Appendix B.

**Label Discrepancies.** The analysis of inter-translator agreement in §2 revealed a small number of COPA scenarios with discrepancies in annotations across languages. To better understand the source of such disagreements, we identified all the validation set instances on which one or more translators diverged from the majority label.<sup>7</sup> We identified two cases where the translator’s experience and cultural frame of reference played a role (as attested in translator feedback), which required, for instance, understanding of the procedures and structure of U.S. court trials (e.g., *The judge pounded the gavel*. CAUSE: (a) *The courtroom broke into uproar*. (b) *The jury announced its verdict*.).

Most disagreement cases (87.5%), however, seem to be culturally independent and concern genuinely ambiguous cases (e.g. *The detective revealed an anomaly in the case*. RESULT: (a) *He finalized his theory*. (b) *He scrapped his theory*.). To verify this in a monolingual setting, we carried out a follow-up experiment where 4 Italian native speakers labeled the translated validation and test set instances. The Fleiss’  $\kappa$  agreement scores were 0.926 (validation) and 0.917 (test), respectively. This corroborates our decision to override a single translator’s label with the majority label without altering the translation.

### 4 Experiments and Results

We now benchmark a series of state-of-the-art multilingual models on XCOPA to provide baseline scores for future research, as well as to exhibit the

<sup>7</sup>Overall, there were 10 validation set questions with 1 translator out of 11 in disagreement, 5 questions with 2, and 1 question with 3.



challenging nature of the dataset. The only direct in-domain data available are: **1)** the original English COPA training set covering 400 instances and **2)** validation sets in English and all target languages spanning 100 instances each.

We evaluate the following state-of-the-art pre-trained multilingual encoders: **1)** multilingual BERT (MBERT) (Devlin et al., 2019) and XLM-on-RoBERTa (XLM-R) (Conneau et al., 2020) in the standard *fine-tuning regime* (i.e., their parameters are fine-tuned together with the task classifier’s parameters), and **2)** multilingual Universal Sentence Encoder (USE) (Yang et al., 2019a) in the *feature-based regime* (i.e., its parameters are fixed during the task classifier’s training). Both MBERT and XLM-R include all XCOPA languages in their pre-training data spanning  $\sim 100$  languages, except for Haitian Creole and Quechua. Multilingual USE was trained on 16 languages, covering IT, TH, TR, and ZH from the XCOPA language sample.

#### 4.1 Multiple-Choice Classification

COPA and XCOPA are multiple-choice classification tasks: given a premise and a prompt (CAUSE or RESULT), the goal is to select the more meaningful of the two choices (see Table 1). Due to training data scarcity in COPA, we probe the usefulness of first “pretraining” the classifier on larger multiple-choice English commonsense reasoning datasets, such as SOCIALIQA (SIQA; Sap et al., 2019) or WINOGRANDE (Sakaguchi et al., 2020). As different multiple-choice selection tasks differ in the number of choices (e.g., there are 2 possible answers in COPA, whereas there are 3 in SIQA), a classifier with a fixed number of classes is not a good fit for this scenario. We thus follow Sap et al. (2019) and couple the (pretrained) encoder with a feed-forward network which produces a single scalar score for each of the possible answers. The scores for individual choices are then concatenated and passed to the softmax function.

**Encoder Input.** For each instance, we couple each of the answer choices with the concatenation of the premise and the prompt and feed that as a “sentence” pair input to MBERT and XLM-R, or as a single “sentence” to USE.<sup>8</sup>

**Classifier Head.** Let  $c_i$  be the  $i$ -th answer choice

<sup>8</sup>For MBERT and XLM-R, we insert the standard special tokens. For example, for the last example from Table 1 and Choice 1, the input for MBERT would be as follows: [CLS] My eyes became red and puffy. What was the cause? [SEP] I was sobbing. [SEP]

Setup	Train dataset		Model selection	
	SIQA	COPA	EN	target
CO-ZS		✓	✓	
CO-TLV		✓		✓
SI-ZS	✓		✓	
SI+CO-ZS	✓	✓	✓	
SI+CO-TLV	✓	✓		✓

Table 4: Different fine-tuning and transfer setups. CO=COPA; SI=SIQA; ZS=Zero-Shot; TLV=Target Language Validation (Set).

of an instance of multiple-choice dataset (i.e.,  $i \in \{1, 2\}$  in COPA and  $i \in \{1, 2, 3\}$  in SIQA) and let  $\mathbf{x}_i \in \mathbb{R}^H$  (with  $H$  as the vector size of the encoder) be the encoding of its corresponding input consisting of the premise, prompt and the answer itself, as explained above.<sup>9</sup> The predicted score  $\hat{y}_i$  for the answer  $c_i$  is then obtained with the following feed-forward net:  $\hat{y}_i = \mathbf{W}_o \tanh(\mathbf{W}_h \mathbf{x}_i + \mathbf{b}_h)$ , with  $\mathbf{W}_h \in \mathbb{R}^{H \times H}$ ,  $\mathbf{b}_h \in \mathbb{R}^H$  and  $\mathbf{W}_o \in \mathbb{R}^{1 \times H}$  as parameters. We obtain the score  $\hat{y}_i$  for each answer  $c_i$  and concatenate them into a prediction vector to which we apply a softmax normalisation:  $\hat{\mathbf{y}} = \text{softmax}([\hat{y}_1, \dots, \hat{y}_N])$ , where  $N$  is the number of answers in the multiple-choice selection dataset. The loss for the training instance is then the standard cross-entropy classification loss.

**Experimental Setup.** We rely on the following pretrained Transformer-based encoder configurations: multilingual BERT (Base,  $H = 768$ ), XLM-R (Base,  $H = 768$ ), and multilingual USE (Large,  $H = 512$ ). We evaluate them in different transfer learning setups based on **1)** different sources of training data: SIQA,<sup>10</sup> COPA, or both; and **2)** different model selection regimes for hyper-parameter tuning and early stopping (based on English or target language validation set). The resulting combinations are shown in Table 4.

#### 4.2 Results and Discussion

Table 5 shows the aggregate accuracy of MBERT, XLM-R and USE over 11 XCOPA languages for each of the previously described training setups from Table 4. We first compare our XCOPA re-

<sup>9</sup>For MBERT and XLM-R  $\mathbf{x}_i$  is the transformer representation of the sequence start token. For USE,  $\mathbf{x}_i$  is the average of contextualised vectors of all tokens.

<sup>10</sup>The SIQA dataset is similar in nature to COPA (i.e., it is a multiple-choice dataset for commonsense reasoning about social interactions, with open-format prompts and three answer choices). It comes with a much larger training set, consisting of 33K instances and therefore can provide useful learning signal also for causal commonsense reasoning in XCOPA.

Setup	Model	All	MBERT $\cap$ XCOPA	USE $\cap$ XCOPA
CO-ZS	XLM-R	55.6	56.9	55.4
	MBERT	54.1	54.4	55.7
	USE	54.7	56.0	58.1
CO-TLV	XLM-R	55.1	56.4	55.2
	MBERT	54.2	54.5	55.8
	USE	54.8	55.4	59.0
SI-ZS	XLM-R	60.1	62.3	62.9
	MBERT	54.7	55.6	56.4
	USE	55.0	56.4	60.1
SI+CO-ZS	XLM-R	59.0	60.7	61.9
	MBERT	55.8	56.8	57.9
	USE	54.1	54.9	58.9
SI+CO-TLV	XLM-R	<b>60.7</b>	<b>63.5</b>	<b>63.6</b>
	MBERT	54.4	54.8	54.2
	USE	54.3	55.2	59.1

Table 5: Summary of XCOPA results. **All**: average over all 11 XCOPA languages; **MBERT  $\cap$  XCOPA**: average over 9 XCOPA languages (without HT and QU) included in MBERT and XLM-R pretraining; **USE  $\cap$  XCOPA**: average over 4 XCOPA languages (IT, TH, TR, and ZH), included in the USE pretraining.

sults with the English COPA performance of the monolingual English BERT (Base) reported by Sap et al. (2019): 63% accuracy in COPA-only fine-tuning and 80% after sequential SIQA+COPA fine-tuning, which is approximately 7% (COPA-only) and 17% (SIQA + COPA) better than our best average XCOPA performances in the respective setups. This contributes to recent suspicions (Cao et al., 2020; Hu et al., 2020) that massively multilingual pretrained transformers do not offer a completely satisfactory solution for language transfer.

XLM-R outperforms MBERT and USE in all setups, but the gains are pronounced only in setups in which the models were first fine-tuned on SIQA (SI-ZS, SI+CO-ZS, and SI+CO-TLV). USE outperforms MBERT surprisingly often. This might have been expected in the COPA-only setups (CO-ZS and CO-TLV) where the small COPA training set is insufficient to meaningfully fine-tune MBERT transformer parameters. However, the finding that MBERT does not benefit more than USE from prior SIQA training is surprising and warrants further investigation. What is more, USE in some setups even outperforms MBERT for some of the languages (e.g., ID, TA, SW) on which MBERT was pretrained and USE was not (cf. the scores in the MBERT  $\cap$  XCOPA column). We speculate that this is due to the combination of two effects: (1) the infamous “curse of multilinguality” (Con-

neau et al., 2020) is much more pronounced for MBERT (which is pretrained on 104 languages) than for USE, pretrained on only 16 languages; and (2) there are subword-level similarities between XCOPA target languages and the 16 languages used in USE pretraining.

We also note that training models only on SIQA yields performance that is comparable (and for MBERT and USE often better) to performance we obtain with additional COPA training (setups SI + CO-ZS and SI + CO-TLV). While this is in part due to the limited size of the COPA training set, it confirms the assumption that SIQA and COPA are highly compatible tasks. We also note that only slight gains are achieved by hyper-parameter tuning on the target language validation set (TLV).

In Figure 1, we display per-language performance in the best setup, SIQA + COPA-TLV, while detailed results for all other setups are available in Appendix D. As expected, all models fluctuate around random-level performance on out-of-sample languages, HT and QU. For all other languages, XLM-R outperforms MBERT. Surprisingly, we also observe that for some languages (ID, VI, ZH) performance of transfer from English is slightly higher than the actual performance in English, without transfer. Another observation is that the transfer performance is often better for some languages typologically distant from English than for languages closer to English (e.g., TH, VI, ZH versus IT). This might be partially due to good representation of languages such as ZH and TH in the pretrained models due to their large training data and very specific scripts.

### 4.3 Adaptation to Unseen Languages

Even massively multilingual pretrained encoders like MBERT and XLM-R, pretrained on corpora of over 100 languages, cover a fraction of the world’s 7000+ languages. Pretraining a multilingual encoder covering the majority of the world languages is infeasible: we thus explore several resource-lean approaches for extending it post-hoc to support transfer to languages not observed during pretraining, such as QU and HT in XCOPA.

**Adaptation Strategies.** We rely on XLM-R, as the best-performing multilingual encoder in XCOPA evaluation (see Figure 1) and probe several strategies for adapting it to the two unseen XCOPA target languages. In all strategies, we simply continue training the XLM-R model via masked lan-

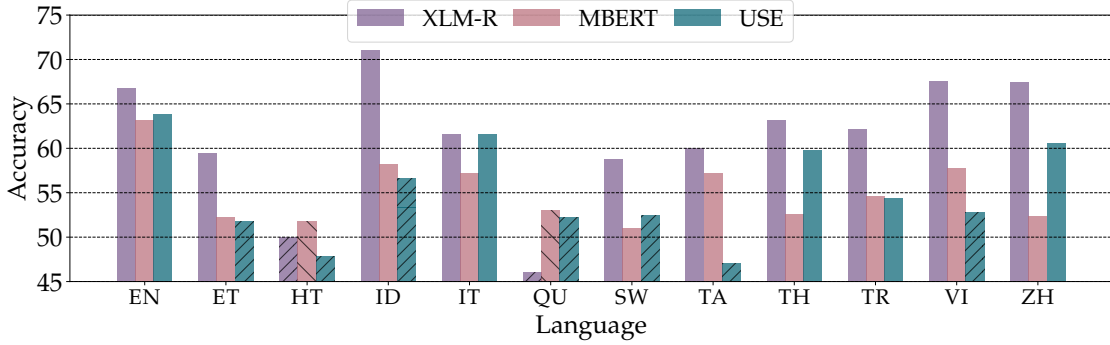


Figure 1: Per-language XCOPA results for XLM-R, MBERT, and USE in the SIQA + COPA-TLV setup. Striped bars correspond to language-model pairs where the language was not included in model pretraining.

guage modeling (MLM) on different combinations of data, and in particular:

**1) T.** Sentences in the target language. We create the monolingual corpora for HT and QU by concatenating their respective Wikipedia dumps with their respective text from the JW300 corpus (Agić and Vulić, 2019). In total, the training size is 5,710,426 tokens for HT, and 2,263,134 tokens for QU.

**2) S.** Sentences in English (EN). This could prevent (catastrophic) forgetting of the source language while fine-tuning, which presumably may occur with T only. We create the English corpus of comparable size to HT and QU corpora by randomly sampling 200K sentences from EN Wikipedia.

**3) D.** A bilingual EN-HT and EN-QU dictionary. The dictionaries were extracted from PanLex (Kamholz et al., 2014): we retain the 5k most reliable word translation pairs according to the available PanLex confidence scores. We create a synthetic corpus from the dictionary (termed *D-corpus* henceforth) by concatenating each translation pair from the dictionary into a quasi-sentence.

**4) T-REP.** T data with all occurrences of target language terms from the 5K dictionary replaced with their English translations.

We select 5k target language sentences as the development corpus and use it for early stopping of the MLM training (i.e., we measure perplexity).

#### 4.4 Results and Discussion

The performance of the five adaptation variants with XLM-R on HT and QU in the zero-shot XCOPA evaluation setups is reported in Table 6. When using sufficiently large fine-tuning datasets (SI-ZS and SI+CO-ZS setups) all adaptation methods yield substantial improvements over the base XLM-R model. The improvements are less consis-

Setup	Model	HT	QU
CO-ZS	XLM-R	49.4	50.7
	+T	<b>53.8</b>	49.8
	+S+T	52.8	54.0
	+D	52.2	51.2
	+S+T+D	53.6	52.0
	+T-REP	49.6	<b>55.0</b>
SI-ZS	XLM-R	49.2	51.0
	+T	<b>56.2</b>	<b>57.9</b>
	+S+T	55.2	55.0
	+D	55.4	57.4
	+S+T+D	56.4	53.5
	+T-REP	<b>58.6</b>	57.7
SI+CO-ZS	XLM-R	51.4	51.2
	+T	57.8	54.0
	+S+T	55.8	55.2
	+D	57.8	<b>57.9</b>
	+S+T+D	55.4	54.0
	+T-REP	<b>58.4</b>	54.4

Table 6: XCOPA accuracy scores of different transfer variants that adapt to out-of-sample languages.

tent in the COPA-ZS setup. However, we attribute it to the limited size of the English COPA dataset (only 400 instances) used for fine-tuning rather than to the ineffectiveness of the adaptation strategies. A comparison between XLMR+T and XLMR+S+T suggests that additional MLM pretraining on a moderately sized target language corpus does not lead to forgetting of the source language information.

The results of the light-weight post-hoc XLM-R adaptations for HT and QU are quite encouraging,<sup>11</sup> as they bypass retraining the encoder from scratch while achieving downstream results almost comparable with seen languages. Moreover, the results from Table 6 suggest that leveraging additional knowledge from a general bilingual dictionary can lead to further benefits: e.g., note the results of XLMR+T-REP in SIQA-ZS and SIQA+COPA-ZS

<sup>11</sup>Note that the unseen languages, however, must rely on seen scripts (e.g., both HT and QU are written in Latin script).

transfer setups. Further, the results with the most resource-lenient method (XLMR+D) also reveal positive trends. Further adaptation strategies (Ponti et al., 2019b) and downstream tasks warrant future investigation.

## 5 Related Work

**Evaluation of Commonsense Reasoning.** Besides COPA, another important early dataset that instigated computational modeling of commonsense reasoning is the Winograd Schema Challenge (WSC) (Levesque et al., 2012; Morgenstern and Ortiz, 2015). WSC targets a pronoun coreference resolution task with paired instances, and has been recently expanded into the WinoGrande dataset (Sakaguchi et al., 2020) through crowd-sourcing, now spanning 44k paired instances.

Recent advances across a range of NLP tasks driven by large pre-trained language models (Wang et al., 2019; Ruder et al., 2019) has spurred further interest in this area as a way to probe their reasoning abilities. Some evaluation sets target particular well-defined aspects of commonsense, such as the physical aspect (Bisk et al., 2020), abductive reasoning (Bhagavatula et al., 2020),<sup>12</sup> intents and reactions to events (Rashkin et al., 2018), social interactions (Sap et al., 2019), or visual commonsense (Zellers et al., 2019a). Other recent datasets such as CommonsenseQA (Talmor et al., 2019), SWAG (Zellers et al., 2018), and Hel-laSWAG (Zellers et al., 2019b) are cast as open-ended multiple-choice problems where the system is expected to choose the most sensible option. Another line of evaluation targets commonsense-enabled reading comprehension and question answering (Ostermann et al., 2018; Zhang et al., 2018; Huang et al., 2019).

**Multilingual Evaluation of Natural Language Understanding.** While all these datasets for commonsense reasoning are limited to English, several multilingual datasets for other natural language understanding tasks are available. These include lexical semantic similarity (Multi-SimLex) (Vulić et al., 2020), document classification (MLDoc) (Schwenk and Li, 2018), sentiment analysis (Barnes et al., 2018), and natural language inference (XNLI) (Conneau et al., 2018). Other recent multilingual datasets target the QA task based on reading comprehension. MLQA (Lewis et al., 2019) includes 7

languages; XQuAD (Artetxe et al., 2020b) spans 10 languages; TyDiQA (Clark et al., 2020) covers 11 typologically diverse languages. Further, PAWS-X (Yang et al., 2019b) evaluates paraphrase identification over 6 languages. A standard and pragmatic approach to multilingual dataset creation is translation from an existing (English) dataset: Multi-SimLex was created starting from the extended English SimLex-999 (Hill et al., 2015), XNLI from MultiNLI (Williams et al., 2018), XQuAD from SQuAD (Rajpurkar et al., 2016), and PAWS-X from PAWS (Zhang et al., 2019). On the other hand, TyDiQA was built independently in each language. Finally, a large number of tasks has been recently integrated into a unified multilingual evaluation suite, XTREME (Hu et al., 2020).

## 6 Conclusion

We presented the Cross-lingual Choice of Plausible Alternatives (XCOPA), a multilingual evaluation benchmark for causal commonsense reasoning. All XCOPA instances are aligned across 11 languages, which enables cross-lingual comparisons. The language selection was informed by variety sampling, in order to maximise the diversity in terms of typological features, geographical macro-area, and family. This allows for assessing the robustness of machine learning models to an array of rare phenomena displayed by the languages in the sample.

We also ran a series of cross-lingual transfer experiments, evaluating state-of-art transfer methods based on multilingual pretraining and fine-tuning on English. We observed that, although these methods perform better than chance, they still lag significantly behind the monolingual supervised learning setting. Overall, the scores are held down by the ‘curse of multilinguality’, the need to account for a wide sample of languages in pretraining. In addition, the transfer seems not to depend that much on the distance from the source, but rather on the abundance of monolingual target language data for multilingual pretraining. Finally, we investigated how to adapt pretrained multilingual models to new out-of-sample languages in resource-lean scenarios where only a small monolingual corpus and/or a bilingual English–target dictionary are available, with notable gains reported.

We hope that this new challenging evaluation set will foster further research in multilingual commonsense reasoning and cross-lingual transfer.

<sup>12</sup>Abductive reasoning is inference to the most plausible explanation of incomplete observations (Peirce, 1960).



## Acknowledgements

This work is supported by the ERC Consolidator Grant LEXICAL (no 648909). EMP, IV, and AK are also funded through the Google Faculty Research Award 2018 for Natural Language Processing. GG is supported by the Eliteprogramm of the Baden-Württemberg Stiftung (AGREE Grant). Heartfelt thanks to Ulla Meeri Petti and Fangyu Liu for their invaluable help.

## References

- Željko Agić and Ivan Vulić. 2019. [JW300: A wide-coverage parallel corpus for low-resource languages](#). In *Proceedings of ACL*, pages 3204–3210.
- Pascal Amsili and Olga Semnck. 2017. [A Google-proof collection of French Winograd schemas](#). In *Proceedings of the 2nd Workshop on Coreference Resolution Beyond OntoNotes (CORBON 2017)*, pages 24–29.
- Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2020a. [Translation artifacts in cross-lingual transfer learning](#). *arXiv preprint arXiv:2004.04721*.
- Mikel Artetxe, Sebastian Ruder, and Dani Yogatama. 2020b. [On the cross-lingual transferability of monolingual representations](#). In *Proceedings of ACL*.
- Jeremy Barnes, Roman Klinger, and Sabine Schulte im Walde. 2018. [Bilingual sentiment embeddings: Joint projection of sentiment across languages](#). In *Proceedings of ACL*, pages 2483–2493.
- Emily M. Bender. 2011. [On achieving and evaluating language-independence in NLP](#). *Linguistic Issues in Language Technology*, 6(3):1–26.
- Chandra Bhagavatula, Ronan Le Bras, Chaitanya Malaviya, Keisuke Sakaguchi, Ari Holtzman, Hannah Rashkin, Doug Downey, Scott Wen-tau Yih, and Yejin Choi. 2020. [Abductive commonsense reasoning](#). In *Proceedings of ICLR*.
- Yonatan Bisk, Rowan Zellers, Ronan Le Bras, Jianfeng Gao, and Yejin Choi. 2020. [PIQA: Reasoning about physical commonsense in natural language](#). In *Proceedings of AAAI*.
- Jürgen Bohnemeyer, Nick Enfield, James Essegbey, and Sotaro Kita. 2011. The macro-event property: The segmentation of causal chains. *The Mental Lexicon*.
- Steven Cao, Nikita Kitaev, and Dan Klein. 2020. [Multilingual alignment of contextual word representations](#). In *Proceedings of ICLR*.
- Jonathan H. Clark, Eunsol Choi, Michael Collins, Dan Garrette, Tom Kwiatkowski, Vitaly Nikolaev, and Jennimaria Palomaki. 2020. [TyDiQA: A benchmark for information-seeking question answering in typologically diverse languages](#). *Transactions of the ACL*.
- Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. [Unsupervised cross-lingual representation learning at scale](#). In *Proceedings of ACL*.
- Alexis Conneau, Ruty Rinott, Guillaume Lample, Adina Williams, Samuel Bowman, Holger Schwenk, and Veselin Stoyanov. 2018. [XNLI: Evaluating cross-lingual sentence representations](#). In *Proceedings of EMNLP*, pages 2475–2485.
- Ernest Davis and Gary Marcus. 2015. [Commonsense reasoning and commonsense knowledge in Artificial Intelligence](#). *Communications of the ACM*, 58(9):92–103.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. [BERT: Pre-training of deep bidirectional transformers for language understanding](#). In *Proceedings of NAACL-HLT*, pages 4171–4186.
- Matthew S Dryer. 1989. Large linguistic areas and language sampling. *Studies in Language. International Journal sponsored by the Foundation “Foundations of Language”*, 13(2):257–292.
- Matthew S. Dryer and Martin Haspelmath, editors. 2013. [WALS Online](#). Max Planck Institute for Evolutionary Anthropology, Leipzig.
- Joseph L Fleiss. 1971. Measuring nominal scale agreement among many raters. *Psychological bulletin*, 76(5):378.
- Daniela Gerz, Ivan Vulić, Edoardo Maria Ponti, Roi Reichart, and Anna Korhonen. 2018. [On the relation between linguistic typology and \(limitations of\) multilingual language modeling](#). In *Proceedings of EMNLP*, pages 316–327.
- Andrew Gordon and Reid Swanson. 2009. [Identifying personal stories in millions of weblog entries](#). In *Third International Conference on Weblogs and Social Media, Data Challenge Workshop, San Jose, CA*, volume 46.
- Felix Hill, Roi Reichart, and Anna Korhonen. 2015. [SimLex-999: Evaluating semantic models with \(genuine\) similarity estimation](#). *Computational Linguistics*, 41(4):665–695.
- Paul J. Hopper. 1979. Aspect and foregrounding in discourse. In *Discourse and Syntax*, pages 211–241. Brill.
- Junjie Hu, Sebastian Ruder, Aditya Siddhant, Graham Neubig, Orhan Firat, and Melvin Johnson. 2020. [XTREME: A massively multilingual multi-task benchmark for evaluating cross-lingual generalization](#). *arXiv preprint arXiv:2003.11080*.

- Lifu Huang, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. 2019. [Cosmos QA: Machine reading comprehension with contextual commonsense reasoning](#). In *Proceedings of EMNLP-IJCNLP*, pages 2391–2401.
- Pratik Joshi, Sebastin Santy, Amar Budhiraja, Kalika Bali, and Monojit Choudhury. 2020. [The state and fate of linguistic diversity and inclusion in the NLP world](#). In *Proceedings of ACL*.
- David Kamholz, Jonathan Pool, and Susan Colowick. 2014. [PanLex: Building a resource for panlingual lexical translation](#). In *Proceedings of LREC*, pages 3145–3150.
- Diederik P Kingma and Jimmy Ba. 2015. [Adam: A method for stochastic optimization](#). In *Proceedings of ICLR*.
- Moshe Koppel and Noam Ordan. 2011. [Translationese and its dialects](#). In *Proceedings of the ACL-HLT*, pages 1318–1326.
- J Richard Landis and Gary G Koch. 1977. The measurement of observer agreement for categorical data. *Biometrics*, pages 159–174.
- Hector Levesque, Ernest Davis, and Leora Morgenstern. 2012. [The Winograd schema challenge](#). In *Proceedings of the 13th International Conference on the Principles of Knowledge Representation and Reasoning*.
- Patrick Lewis, Barlas Oğuz, Ruty Rinott, Sebastian Riedel, and Holger Schwenk. 2019. MLQA: Evaluating cross-lingual extractive question answering. *arXiv preprint arXiv:1910.07475*.
- Patrick Littell, David R. Mortensen, Ke Lin, Katherine Kairis, Carlisle Turner, and Lori Levin. 2017. [Uriel and lang2vec: Representing languages as typological, geographical, and phylogenetic vectors](#). In *Proceedings of EACL*, pages 8–14.
- Gabriela Melo, Vinicius Imaizumi, and Fábio Cozman. 2020. [Esquemas de Winograd em português](#). In *Proceedings of the 16th Encontro Nacional de Inteligência Artificial e Computacional (ENIAC 2020)*, pages 787–798.
- Matti Miestamo. 2004. *Clausal negation: A typological study*. Ph.D. thesis, University of Helsinki.
- Leora Morgenstern and Charles L. Ortiz. 2015. [The Winograd Schema Challenge: Evaluating progress in commonsense reasoning](#). In *Proceedings of AAAI*, pages 4024–4026.
- Simon Ostermann, Ashutosh Modi, Michael Roth, Stefan Thater, and Manfred Pinkal. 2018. [MCScript: A novel dataset for assessing machine comprehension using script knowledge](#). In *Proceedings of LREC*.
- Charles Sanders Peirce. 1960. *Collected papers of Charles Sanders Peirce*, volume 2. Harvard University Press.
- Edoardo Maria Ponti, Helen O’Horan, Yevgeni Berzak, Ivan Vulić, Roi Reichart, Thierry Poibeau, Ekaterina Shutova, and Anna Korhonen. 2019a. [Modeling language variation and universals: A survey on typological linguistics for natural language processing](#). *Computational Linguistics*, 45(3):559–601.
- Edoardo Maria Ponti, Ivan Vulić, Ryan Cotterell, Roi Reichart, and Anna Korhonen. 2019b. [Towards zero-shot language modeling](#). In *Proceedings of EMNLP-IJCNLP*, pages 2893–2903.
- Nazneen Fatema Rajani, Bryan McCann, Caiming Xiong, and Richard Socher. 2019. [Explain yourself! Leveraging language models for commonsense reasoning](#). In *Proceedings of ACL*, pages 4932–4942.
- Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. [SQuAD: 100,000+ questions for machine comprehension of text](#). In *Proceedings of EMNLP*, pages 2383–2392.
- Hannah Rashkin, Maarten Sap, Emily Allaway, Noah A. Smith, and Yejin Choi. 2018. [Event2Mind: Commonsense inference on events, intents, and reactions](#). In *Proceedings of ACL*, pages 463–473.
- Jan Rijkhoff, Dik Bakker, Kees Hengeveld, and Peter Kahrel. 1993. A method of language sampling. *Studies in Language*, 17(1):169–203.
- Melissa Roemmele, Cosmin Adrian Bejan, and Andrew S. Gordon. 2011. [Choice of plausible alternatives: An evaluation of commonsense causal reasoning](#). In *Proceedings of the 2011 AAAI Spring Symposium Series*.
- Sebastian Ruder, Matthew E. Peters, Swabha Swayamdipta, and Thomas Wolf. 2019. [Transfer learning in Natural Language Processing](#). In *Proceedings of NAACL-HLT: Tutorial Abstracts*, pages 15–18.
- Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. 2020. [WinoGrande: An adversarial Winograd Schema Challenge at scale](#). In *Proceedings of AAAI*.
- Maarten Sap, Hannah Rashkin, Derek Chen, Ronan Le Bras, and Yejin Choi. 2019. [Social IQa: Commonsense reasoning about social interactions](#). In *Proceedings of EMNLP-IJCNLP*, pages 4463–4473.
- Holger Schwenk and Xian Li. 2018. [A corpus for multilingual document classification in eight languages](#). In *Proceedings of LREC*.
- Tomohide Shibata, Shotaro Kohama, and Sadao Kurohashi. 2015. [日本語 Winograd Schema Challenge の構築と分析](#). 言語処理学会第 21 回年次大会論文集, pages 493–496.
- Yoav Shoham. 1990. Nonmonotonic reasoning and causation. *Cognitive Science*, 14(2):213–252.

- Murray Singer, Michael Halldorson, Jeffrey C Lear, and Peter Andrusiak. 1992. Validation of causal bridging inferences in discourse understanding. *Journal of Memory and Language*, 31(4):507–524.
- Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. 2019. [CommonsenseQA: A question answering challenge targeting commonsense knowledge](#). In *Proceedings of NAACL-HLT*, pages 4149–4158.
- Jenny Thomas. 1983. Cross-cultural pragmatic failure. *Applied linguistics*, 4(2):91–112.
- Vered Volansky, Noam Ordan, and Shuly Wintner. 2015. [On the features of translationese](#). *Digital Scholarship in the Humanities*, 30(1):98–118.
- Ivan Vulić, Simon Baker, Edoardo Maria Ponti, Ulla Petti, Ira Leviant, Kelly Wing, Olga Majewska, Eden Bar, Matt Malone, Thierry Poibeau, et al. 2020. [Multi-SimLex: A large-scale evaluation of multi-lingual and cross-lingual lexical semantic similarity](#). *arXiv preprint arXiv:2003.04866*.
- Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2019. [SuperGLUE: A stickier benchmark for general-purpose language understanding systems](#). In *Proceedings of NeurIPS*, pages 3261–3275.
- Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. [A broad-coverage challenge corpus for sentence understanding through inference](#). In *Proceedings of NAACL-HLT*, pages 1112–1122.
- Yinfei Yang, Daniel Cer, Amin Ahmad, Mandy Guo, Jax Law, Noah Constant, Gustavo Hernandez Abrego, Steve Yuan, Chris Tar, Yun-Hsuan Sung, et al. 2019a. [Multilingual universal sentence encoder for semantic retrieval](#). *arXiv preprint arXiv:1907.04307*.
- Yinfei Yang, Yuan Zhang, Chris Tar, and Jason Baldridge. 2019b. [PAWS-X: A cross-lingual adversarial dataset for paraphrase identification](#). In *Proceedings of EMNLP*, pages 3687–3692.
- Rowan Zellers, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019a. [From recognition to cognition: Visual commonsense reasoning](#). In *Proceedings of CVPR*, pages 6720–6731.
- Rowan Zellers, Yonatan Bisk, Roy Schwartz, and Yejin Choi. 2018. [SWAG: A large-scale adversarial dataset for grounded commonsense inference](#). In *Proceedings of EMNLP*, pages 93–104.
- Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019b. [HellaSwag: Can a machine really finish your sentence?](#) In *Proceedings of ACL*, pages 4791–4800.
- Sheng Zhang, Xiaodong Liu, Jingjing Liu, Jianfeng Gao, Kevin Duh, and Benjamin Van Durme. 2018. ReCoRD: Bridging the gap between human and machine commonsense reading comprehension. *arXiv preprint arXiv:1810.12885*.
- Yuan Zhang, Jason Baldridge, and Luheng He. 2019. [PAWS: Paraphrase adversaries from word scrambling](#). In *Proceedings of NAACL-HLT*, pages 1298–1308.

## A Detailed Translation Guidelines

Translation of the English COPA validation and test set instances into each of the 11 languages was carried out by a single translator per language, meeting the following eligibility criteria: (i) a native speaker of the target language, (ii) fluent in English, (iii) with minimum undergraduate education level. Each translator was presented with translation guidelines and a spreadsheet accessible online, containing one English premise-hypothesis triple per line, followed by an empty line where target translations were entered. The task consisted in (a) identifying the correct alternative for the English premise and (b) translating the premise and both alternatives into the target language, preserving the causal relations present in the original (see §3 for discussion of ambiguous and problematic cases). Each translator worked independently (using any external resources, such as English-target language dictionaries, if needed) and completed the task in its entirety, producing 100 validation and 500 test instance translations, and a label for each. To ensure the output preserves the lexical, temporal, and causal relations present in the original triples, the guidelines instructed to:

- i. maintain the original correspondence relations between lexical items, i.e., if the same English word appeared both in the premise and the alternatives (Premise: *The friends decided to share the hamburger.*; A1: *They cut the hamburger in half.*; A2: *They ordered fries with the hamburger.*), it was translated into the same target-language equivalent in all three translated sentences;
- ii. ensure that the original chronology and temporal extension of events is preserved through appropriate choice of verbal tense and aspect in the target language, e.g., maintaining the distinction between perfective and imperfective aspect (Premise: *My eyes became red and puffy.* [PERF], A1: *I was sobbing.* [IMPERF], A2: *I was laughing.* [IMPERF]; See §3 for discussion of the challenges posed by tenseless languages);
- iii. in case of English words with no exact translations in the target language or referring to concepts absent from the target language culture (e.g., *peach*), the following solutions were to be adopted, in order of preference: (1) using a common loanword from another language,

provided it is understood by the general population of target-language speakers; (2) using a periphrasis to describe the same concept (e.g., *a juicy fruit*); (3) substituting the original concept with a similar one that is more familiar to the target language speaker community (e.g., *santol*), provided that it can play a similar role in the causal relations captured by the original premise-hypothesis triple;

The translators were encouraged to split the workload into multiple sessions with breaks in between. On average, the task took 20 hours of work to complete. Additionally, translators were encouraged to provide feedback, commenting on translation challenges and chosen solutions, which we discuss in §3.

## B Why is Grammatical Tense Problematic for XCOPA?

The scenarios included in COPA refer to events that took place in the past and are formulated in what can be described as a narrative register (one of the sources from which question topics were drawn was a corpus of personal stories published online (Gordon and Swanson, 2009)). This is grammatically rendered exclusively by means of past simple (preterite) or past continuous (imperfect) verb forms. Temporal anteriority of a hypothesis sentence with respect to the premise is not grammatically marked (e.g., with a past perfect verb form) and can only be deduced based on the prompt (“What was the CAUSE of this?”). The preterite-imperfect contrast used in English to distinguish background states (imperfective) from the main event (perfective) (e.g., *I was expecting company.* IMPERF vs. *I tidied up my house.* PERF) is not universally applicable and different languages employ different discourse grounding strategies (Hopper, 1979), which has interesting implications for the multilingual extension of COPA to XCOPA.

In the languages with grammatical tense different strategies are employed to capture the perfective-imperfective distinction, which is prominent in COPA. For example, in Haitian Creole, the simple past marker *te* is used to indicate a bounded event in the past, while the continuous aspect is signaled with an *ap* marker. Italian additionally distinguishes between two perfective past tenses, expressed by means of a simple and compound past (*vidi* - *ho visto*, ‘I saw’). The opposition is between completed actions whose effects are de-



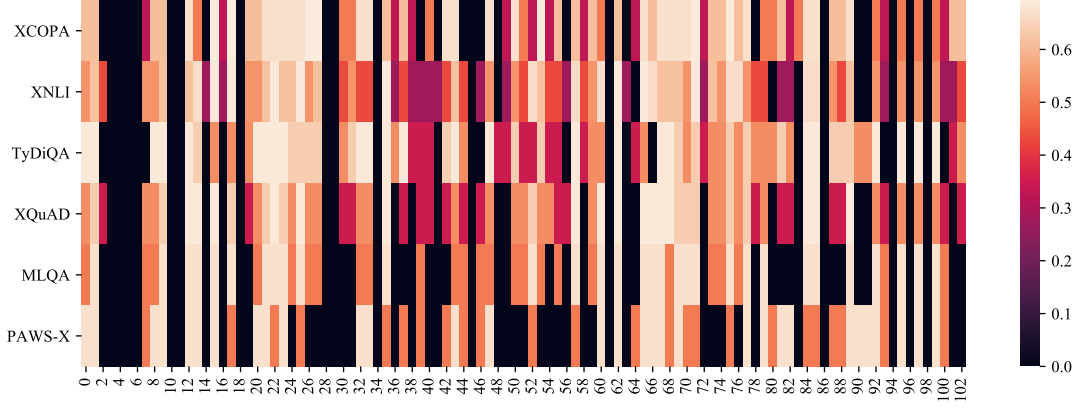


Figure 2: Heatmap of the entropy of the distributions of WALS features (x axis) in language samples from famous cross-lingual datasets outlined in §5 (y axis).

Setup	Model	EN	ET	HT	ID	IT	QU	SW	TA	TH	TR	VI	ZH
CO-ZS	XLM-R	57.6	59.8	49.4	58	56	50.7	57.2	56.6	52.8	56.2	58.5	56.6
	MBERT	62	50.6	51.4	55	53.8	54.7	53.6	52	53.2	56.8	55.4	59
	USE	63	53.8	49.4	57.6	60	48.3	52.2	53	57.2	55	54.8	60.2
CO-TLV	XLM-R	57.6	57.8	48.6	60.8	54.4	49.5	55.4	55.8	54.2	54.8	57.6	57.2
	MBERT	62	52	52.6	58.2	55	52.7	53	52	52.4	53.8	52.6	61.8
	USE	63	49.4	49.6	57.6	62	54	50.8	53.6	58.6	56.2	51.4	59.2
SI-ZS	XLM-R	68	59.4	49.2	67.2	63.6	51	57.6	58.8	61.6	60.4	65.8	66
	MBERT	62.2	55.2	51.4	57	57	50.2	51	52.2	51	53.2	59.2	64.4
	USE	62.6	51.6	46.8	60.2	61.8	50.5	52.4	48.8	60.8	54.6	54.8	63
SI+CO-ZS	XLM-R	66.8	58	51.4	65	60.2	51.2	52	58.4	62	56.6	65.6	68.8
	MBERT	63.2	52.2	54	59.4	57.2	48	56	54.6	51.2	57.4	58	65.6
	USE	63.8	51.2	48.4	57.6	61.8	52	51.8	47	58	55.6	51	60.2
SI+CO-TLV	XLM-R	66.8	59.4	50	71	61.6	46	58.8	60	63.2	62.2	67.6	67.4
	MBERT	63.2	52.2	51.8	58.2	57.2	53	51	57.2	52.6	54.6	57.8	52.4
	USE	63.8	51.8	47.8	56.6	61.6	52.2	52.4	47	59.8	54.4	52.8	60.6

Table 7: Detailed per-language XCOPA results. None of the models was exposed to HT and QU in pretraining. USE was exposed in pretraining only to IT, TH, TR, and ZH.

tached from the present and those with persisting effects on the present. Both contrast with the imperfect, which emphasises the event’s extension or repetition in time. Given that the opposition is a matter of the speaker’s perspective on events rather than based on deixis (remote versus proximate past), the translator opted for the most natural choice given a specific context/situation.

## C Hyper-Parameter Search

For MBERT and XLM-R we searched the following hyperparameter grid in both SIQA and COPA training: learning rate  $\in \{5 \cdot 10^{-6}, 10^{-5}, 3 \cdot 10^{-5}\}$ , dropout rate (applied to the output layer of the transformer and the hidden layer of the feed-forward scoring net)  $\in \{0, 0.1\}$ , and batch size  $\in \{4, 8\}$ . For USE, we searched over different values for the learning rate,  $\{10^{-3}, 10^{-4}, 10^{-5}\}$ . We evaluate

the performance on the respective development set every 500 updates for SIQA and every 10 updates for COPA and stop the training if there is no improvement over 10 consecutive evaluations. In all setups, we optimize the parameters with the Adam algorithm (Kingma and Ba, 2015) ( $\epsilon = 10^{-8}$ , no weight decay nor warmup) and clip the norms of gradients in single updates to 1.0.

## D Full Results (Per Language)

Table 7 contains the detailed per language results for all XCOPA languages and all five of our evaluation setups (CO-ZS, CO-TLV, SI-ZS, SI+CO-ZS, SI+CO-TLV).