

XCOPA: A Multilingual Dataset for Causal Commonsense Reasoning

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Abstract

In order to simulate human language capacity, natural language processing systems must be able to reason about the dynamics of everyday situations, including their possible causes and effects. Moreover, they should be able to generalise the acquired world knowledge to new languages, modulo cultural differences. Advances in machine 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, which includes resource-poor languages like Eastern Apurímac Quechua and Haitian Creole. We evaluate a range of state-of-the-art models on this novel dataset, revealing that the performance of current methods based on multilingual pretraining and zero-shot fine-tuning falls short compared to translation-based transfer. Finally, we propose strategies to adapt multilingual 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. The XCOPA dataset is freely available at 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, and multiple modalities.

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Ultimately, it shapes the individuals’ expectations about typical situations (Shoham, 1990).¹

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.² 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 do vary across cultures (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., 2020; 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-

¹Moreover, 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*.

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

	PREMISE		CHOICE 1	CHOICE 2
qu	<i>Sipasqa cereal mikhunanpi kuruta tarirqan.</i>	R	<i>Payqa pukunman ñuqñuta churakurqan.</i>	<i>Payqa manam mikhuyta mumarqanchu.</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 (Result [R]) and backward (Cause [C]) reasoning from 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 variety over the abundance in *digital* texts. Since resource-rich languages tend to belong to a few families and areas, samples inspired by this criterion are highly biased and not indicative of true models’ performance (Gerz et al., 2018; Ponti et al., 2019a; Joshi et al., 2020; Lauscher et al., 2020). Following this guiding principle, we select 11 languages from 11 distinct families, and 5 geographical macro-areas (Africa, Eurasia, Papunesia, North America, and South America).

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., Southern 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 **4)** 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 thus indicate the limitations of current state-of-the-art multilingual models in cross-lingual transfer settings for complex reasoning tasks.

2 Annotation Design

Design Objectives. The principal objectives in devising XCOPA were: **1)** to create a *genuinely* typologically diverse multilingual dataset, aligned across target languages 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; Freitag et al., 2020).

To avoid these pitfalls, we: (i) entrusted the translation task to a single (carefully selected) translator per target language,³ 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 the Appendix.

Language Sampling. Multilingual evaluation benchmarks assess the *expected performance* of a model across languages. However, should such languages be sampled according to the distribution of digital texts or rather based on the distribution over the languages spoken around the world? The

³Crowd-sourcing offers faster annotation at a lower cost – however, in our trial experiments, chasing low annotation times and costs resulted in low translation quality. In our experiment, the average wage was £15 per hour, for a (self-paced) total time per language between 12 and 20 hours.

	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	0.5	0.6	0.66	0.66
Geography	[0, ln 6]	1.67	0.92	0.37	0	0	0

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

former strategy is unreliable, as languages rich in resources tend to belong to the same families and areas, which facilitates knowledge transfer and hence leads to an overestimation of the expected performance (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 linguistic features 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 an attribute in a language. We estimate the entropy of the distribution of values in a sample. 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.⁴

The sample of languages for XCOPA aims at maximising these indices. In particular, XCOPA includes Estonian (ET), Haitian Creole (HT), Indonesian (ID), Italian (IT), Eastern Apurímac Quechua (QU), Kiswahili (SW), Tamil (TA), Thai (TH), Turkish (TR), Vietnamese (VI), and Mandarin Chinese (ZH). These languages belong to distinct families, respectively: Uralic, Creole, Austronesian, Indo-

European, Yuman–Cochimí, Niger-Congo, Dravidian, Kra-Dai, Turkic, Austroasiatic, and Sino-Tibetan. Moreover, HT and QU are spoken in North and South America, respectively, which are both underrepresented macro-areas. We report the 3 metrics in Table 2 and compare them 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 Table 1 shows, 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. 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’ κ statistic (Fleiss, 1971): the obtained score of 0.921 for validation and 0.911 for test data reveal very high agreement (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.⁵

⁴Six macro-areas, as defined by WALS (Dryer and Haspelmath, 2013), are: Africa, Australia, Eurasia, North America, Papunesia, and South America. Whenever a language spans multiple macro-areas, we select that of the standard variety.

⁵In order to accurately represent ambiguity of the small number of disagreement labels, in the final datasets we explic-

	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. 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., e.g., *mortgage*, *lobbyist*, *gavel*); (iv) idiomatic expressions (e.g., *put the caller on hold*).

In such cases, the translators were advised to resort (in the following order of preference) 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 tag the corresponding questions with an apposite marker.

fully represent the properties of the so-called tenseless languages, we favoured the unmarked variants, with the temporal relations established by the situational context. For example, 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).

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.⁶ 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 conducted a follow-up experiment where 4 Italian native speakers labeled the translated validation and test instances. The Fleiss’ κ agreement scores were 0.926 (validation) and 0.917 (test). This corroborates our decision to override a single translator’s label with the majority label without altering the translation.

4 Experiments and Results

XCOPA is a multiple-choice classification task: given a premise and a prompt (CAUSE or RESULT), the goal is to select the more plausible of the two answer choices (see Table 1). We now benchmark

⁶Overall, there were 10 validation set questions with 1 translator out of 11 in disagreement, 5 questions with 2, and 1 question with 3.

a series of state-of-the-art models on XCOPA to provide baseline scores for future research, as well as to expose the challenging nature of the dataset. In §4.1, we list the main axes of comparison of our baselines and outline the general neural architecture for multiple-choice classification that we employ in all experiments. In §4.2, we discuss the results. Afterwards in §4.3, in order to prove that solving this task requires relying on true causal reasoning rather than spurious correlations, we test the best-performing model on ‘adversarial’ variants where either the premise or the prompt are hidden (Niven and Kao, 2019). Finally, in §4.4 we explore several strategies to adapt massively multilingual models to new languages not observed during pre-training, such as Quechua and Haitian Creole.

4.1 Baselines

We evaluate baselines in several combinations of experimental setups based on: **1)** different methods for cross-lingual transfer, either based on model transfer or machine translation; **2)** different multilingual pretrained encoders; **3)** different sources of training and validation data.

Cross-lingual Transfer Methods. We consider two high-level methods for cross-lingual transfer (Tiedemann, 2015; Ponti et al., 2019a): **1)** *multilingual model transfer* (MuMoTr), whereby a Transformer-based encoder is pretrained on multiple languages in an unsupervised fashion, and subsequently trained on English annotated data for multiple-choice classification, therefore enabling zero-shot generalisation to the other languages. **2)** *translate test* (TrTe), whereby target test data⁷ are translated into English via Google Translate. This includes all languages except for QU, for which the service is not available.

Multilingual Encoders. For model transfer, we evaluate the following state-of-the-art pretrained multilingual encoders: **1)** multilingual BERT (MBERT) (Devlin et al., 2019) and XLM-on-RoBERTa (Conneau et al., 2020), both the Base (XLM-R) and Large (XLM-R-L) variants, 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

⁷As shown by Conneau et al. (2018), translating the test data from the target language to English is more cost-effective than translating English training data into the target language.

during the task classifier’s training). Both MBERT and XLM-R include all XCOPA languages in their pretraining data spanning ~ 100 languages, except Haitian Creole and Quechua. Multilingual USE was trained on 16 languages, covering IT, TH, TR, and ZH from the XCOPA language sample.

Data Sources. The only direct in-domain data available for training is the original English COPA training set covering 400 instances. Due to data scarcity, we probe the usefulness of an intermediate training stage (Phang et al., 2018; Glavaš and Vulić, 2020) on larger multiple-choice English commonsense reasoning datasets, such as SOCIALQA (SIQA; Sap et al., 2019), before fine-tuning the model on COPA. The SIQA dataset is in a distant domain (commonsense reasoning about social interactions) with open-format prompts and three answer choices. However, it comes with a much larger training set, consisting of 33K instances. Therefore, it can provide useful learning signal also for causal commonsense reasoning in XCOPA. Moreover, we consider two different model selection regimes for hyper-parameter tuning and early stopping, namely (i) using the EN COPA validation set or (ii) target language XCOPA validation set. Table 4 lists all experimental setups.

Neural Architecture. As 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 net which produces a single scalar score for each possible answer. The scores for individual choices are then concatenated and passed to the softmax function.

As an input to the encoder, we couple each of the answer choices with the concatenation of the premise and the prompt. We feed this as a “sentence pair” input to MBERT and XLM-R, or as a single “sentence” to USE.⁸

Let c_i be the i -th answer choice of an instance of multiple-choice dataset (i.e., $i \in \{1, 2\}$ in XCOPA 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)⁹ be the en-

⁸For 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]”.

⁹For MBERT Base and XLM-R Base, $H = 768$; for XLM-R Large, $H = 1,024$; for multilingual USE Large, $H = 512$.

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

Table 4: Different experimental setups for data sources. CO=COPA; SI=SIQA; ZS=Zero-Shot; TLV=Target Language Validation (Set).

coding of its corresponding input consisting of the premise, prompt and the answer itself, as explained above.¹⁰ 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 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 classification dataset. We minimise the cross-entropy loss function via stochastic gradient descent.

4.2 Results and Discussion

We first present the results for model transfer based on multilingual pretrained encoders. Table 5 shows the aggregate accuracy of MBERT, XLM-Rs and USE over 11 XCOPA languages for each of the previously described training setups from Table 4. We first compare our cross-lingual average XCOPA results in the best setup with the English COPA performance of the monolingual English BERT (Base) reported by Sap et al. (2019), namely 63 accuracy in COPA-only fine-tuning (+7%) and 80 after sequential SIQA + COPA fine-tuning (+17%). 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.

Multilingual Encoders. XLM-R (both Base and Large) outperforms MBERT and USE in all setups, but the gains are pronounced only where the models were first fine-tuned on SIQA (SI-ZS, SI+CO-ZS, and SI+CO-TLV). USE outperforms MBERT often, which is especially surprising in the

¹⁰For MBERT and XLM-R \mathbf{x}_i is the transformed representation of the sequence start token. For USE, \mathbf{x}_i is the average of contextualised vectors of all tokens.

Setup	Model	All	MBERT \cap XCOPA	USE \cap XCOPA
		CO-ZS	XLM-R	55.6
	XLM-R-L	52.4	52.5	52.1
	MBERT	54.1	54.4	55.7
	USE	54.7	56.0	58.1
CO-TLV	XLM-R	55.1	56.4	55.2
	XLM-R-L	51.6	51.7	52.1
	MBERT	54.2	54.5	55.8
	USE	54.8	55.4	59.0
SI-ZS	XLM-R	60.1	62.3	62.9
	XLM-R-L	68.4	72.1	72.9
	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
	XLM-R-L	67.3	70.8	71.8
	MBERT	55.8	56.8	57.9
	USE	54.1	54.9	58.9
SI+CO-TLV	XLM-R	60.7	63.5	63.6
	XLM-R-L	69.1	72.8	74.6
	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.

few-shot learning setup of COPA-only, as it contradicts the received wisdom that a larger amount of trainable parameters guarantees higher sample efficiency (Kaplan et al., 2020). What is more, USE in some setups even surpasses 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 a combination of two effects: (1) the infamous “curse of multilinguality” (Conneau 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.

Unsurprisingly, XLM-R Large substantially outperforms its Base counterpart in all setups with SIQA training. Due to almost 3 times more parameters (355M vs. 125M), XLM-R-L stores more language-specific information during pretraining. The large parameter space, however, also causes XLM-R-L to under-perform XLM-R in COPA-only setups (CO-ZS and CO-TLV), with the small COPA fine-tuning dataset.

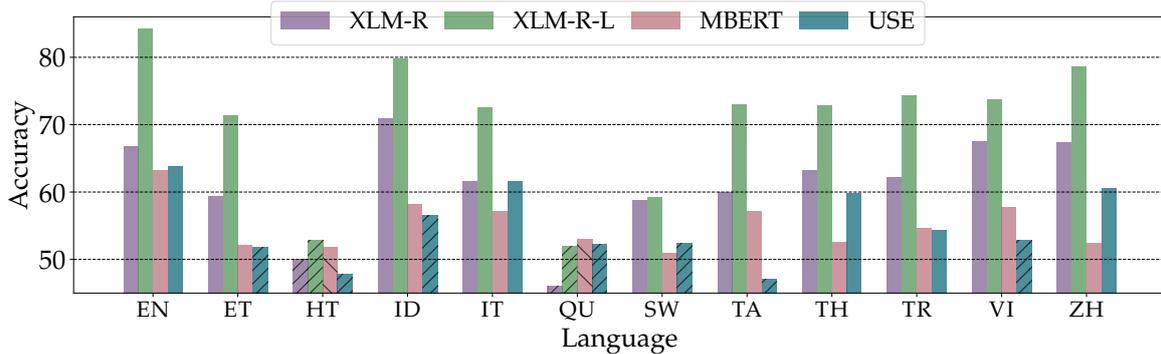


Figure 1: Per-language XCOPA results for XLM-R, MBERT, and USE in the SIQA + COPA-TLV setup. Striped bars correspond to language-model pairs where the language was not included in model pretraining.

Data Sources. 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 compatible tasks. We also note that only slight gains are achieved by hyper-parameter tuning on the target language validation set (TLV).

Per-Language Performance. In Figure 1, we report the language-specific performances for the best setup, SIQA + COPA-TLV, while we provide detailed results for all other setups in the Appendix. As expected, all models fluctuate around random-level accuracy on the two out-of-sample languages, HT and QU. 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. Moreover, the scores are often better for languages typologically distant from English than for closer ones (e.g., TH, VI, ZH vs. IT). We speculate that this is due to the fact that languages such as ZH and TH are better represented in the pretrained models due to their unique scripts, which are shared with few other languages and therefore prevent lexical interferences.

Cross-Lingual Transfer Methods. Finally, in Table 6 (bottom) we compare the best setup for multilingual model transfer (XLM-R-L encoder with SIQA + COPA-TLV) with the method based on machine translation of the test set into English. In particular, for machine translation we consider both the massively multilingual (XLM-R-L) and the monolingual (RoBERTa Large, R-L) versions of the best encoder found in previous ex-

periments.¹¹ No clear pattern emerges as the same model, XLM-R-L, is superior in 5 languages under the translation-based setup, and in 4 languages for the multilingual model transfer setup. A boost in accuracy, however, is especially evident for SW, with a gain of 13.8 points (+25%). On the other hand, the translation-based setup largely outpaces multilingual model transfer when paired with a monolingual encoder, R-L. This baseline surpasses the others in all languages except for TH. This brings us to the conclusion that it is not the cross-lingual transfer method in itself, but rather the avoidance of the ‘curse of multilinguality,’ that makes translation-based cross-lingual transfer superior.

4.3 Adversarial Variants

After detecting an effective baseline, we ‘stress test’ its robustness to prove that true causal reasoning is needed to solve our task. Recently, [Niven and Kao \(2019\)](#) demonstrated that state-of-the-art pretrained encoders tend to rely on spurious correlations in natural language understanding datasets. Inspired by their work, we create two ‘adversarial’ variants of XCOPA (and SIQA) where part of the input is masked. In the first variant (NoP), we hide premises; in the second (NoQ), we hide prompts.

The results of the best configuration for multilingual model transfer are reported in Table 6 (top). Clearly, without premises the performance is not much better than chance (accuracy of 50.0). Without prompts (CAUSE and EFFECT for XCOPA), performance is higher but still lags behind the original variant with full inputs. Hence, we may conclude that solving this task requires causal reasoning over all components of the event dynamics.

¹¹As a caveat, note that these results are not perfectly comparable as Google Translate was trained on different (possibly more abundant) data, in addition to parallel texts.

Setup	Variants	Model	EN	ET	HT	ID	IT	SW	TA	TH	TR	VI	ZH
MuMoTr	NoP	XML-R-L	63.0	56.2	-	62.4	56.6	56.0	60.2	60.6	58.8	60.2	63.2
MuMoTr	NoQ	XML-R-L	76.2	63.8	-	73.4	72.8	59.0	64.4	70.2	69.2	69.8	70.8
MuMoTr	Full	XML-R-L	84.2	71.4	-	79.8	72.6	59.2	73.0	72.8	74.4	73.8	78.6
TrTe	Full	XML-R-L	84.2	76.8	70.0	79.6	74.6	74.0	74.0	71.4	72.8	77.8	78.4
TrTe	Full	R-L	88.4	81.0	73.8	82.2	77.8	74.2	79.6	71.4	79.6	81.0	86.0

Table 6: Detailed per-language XCOPA results of the best cross-lingual transfer setups (bottom). Performance with two adversarial variants of the dataset where premises and prompts are hidden, respectively (top).

4.4 Adaptation to Unseen Languages

Even massively multilingual encoders like MBERT and XLM-R, pretrained on corpora of over 100 languages, cover only a fraction of the world’s 7,000+ languages. In fact, the majority of the world languages suffer from data paucity (Kornai, 2013): we thus explore several resource-lean approaches for extending encoders post-hoc to support transfer to languages not observed during pretraining, such as QU and HT in XCOPA.

Adaptation Strategies. We use XLM-R, the best-performing among the “base size” multilingual encoders on XCOPA, 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 the masked language modeling (MLM) objective on different combinations of data (Pfeiffer et al., 2020), 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.

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

Table 7: XCOPA accuracy scores of different transfer variants that adapt to out-of-sample languages.

We select 5k target language sentences as the development corpus and use it for early stopping the MLM training (with perplexity as a metric).

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 7. When using sufficiently large fine-tuning datasets (SI-ZS and SI+CO-ZS setups) all adaptation methods yield substantial improvements over the XLM-R Base model. The improvements are less consistent in the COPA-ZS setup. However, we attribute this to the limited size of the English COPA training set (which contains mere 400 instances) used for fine-tuning rather than to the ineffectiveness of the proposed adaptation strategies. A comparison between XLM-R+T and XLM-R+S+T suggests that additional MLM pretraining on a moderately sized target language corpus does not lead to catastrophic forgetting of the source language information.

The results of the light-weight post-hoc XLM-R adaptations for HT and QU are encouraging,¹² as

¹²Note that the unseen languages, however, must rely on

they bypass retraining the encoder from scratch while achieving downstream results almost comparable with seen languages. Also, the results in Table 7 suggest that leveraging additional knowledge from a general bilingual dictionary can lead to further benefits: e.g., note the results of XLM-R+TRP in SIQA-ZS and SIQA+COPA-ZS transfer setups, as well as XLM-R+D. Building on this proof-of-concept experiment, further adaptation strategies for zero-shot learning may be explored in the future, such as conditioning parameters on typological features (Ponti et al., 2019b).

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 consists in a pronoun coreference resolution task with paired instances, and has been recently expanded into the WinoGrande dataset (Sakaguchi et al., 2020) through crowd-sourcing.

Several recent evaluation sets target particular aspects of commonsense, e.g., abductive reasoning (Bhagavatula et al., 2020),¹³ intents and reactions to events (Rashkin et al., 2018), social (Sap et al., 2019) and physical (Bisk et al., 2020) interactions, or visual commonsense (Zellers et al., 2019a). Others, e.g., CommonsenseQA (Talmor et al., 2019), SWAG (Zellers et al., 2018), and HellaSWAG (Zellers et al., 2019b) are cast as open-ended multiple-choice problems where the most sensible option is chosen. Another line of evaluation involves 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 the above commonsense reasoning datasets are limited to English, several multilingual datasets for other natural language understanding tasks are available, e.g., 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 sets target the QA task based on reading comprehen-

seen scripts (e.g., both HT and QU are written in Latin script).

¹³Abductive reasoning is inference to the most plausible explanation of incomplete observations (Peirce, 1960).

sion: MLQA (Lewis et al., 2020) in 7 languages, XQuAD (Artetxe et al., 2020b) in 10; and TyDiQA (Clark et al., 2020) in 11 typologically diverse languages. Further, PAWS-X (Yang et al., 2019b) evaluates paraphrase identification in 6 languages. A standard and pragmatic approach to multilingual dataset creation is translation from an existing (English) dataset, e.g., Multi-SimLex 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). TyDiQA, however, was built independently in each language. Finally, a large number of tasks has been recently integrated into unified multilingual evaluation suites, XTREME (Hu et al., 2020) and XGLUE (Liang et al., 2020).

6 Conclusion and Future Work

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 diversity in terms of typological features, geographical macro-area, and language family. This allows us to test the robustness of machine learning models for an array of rare phenomena displayed by the chosen languages.

We also ran a series of cross-lingual transfer experiments, evaluating state-of-the-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 setting where test data are translated into English, due to the ‘curse of multilinguality.’ In addition, we verified that spurious correlations are insufficient to solve this new task by creating ‘adversarial’ variants of the dataset, where premises or prompts are masked, thus showing that robust causal reasoning is indeed required to solve XCOPA. Finally, we investigated resource-lean adaptation of pretrained multilingual models to out-of-sample languages, exploiting only small monolingual corpora and/or bilingual dictionaries, reporting notable gains.

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

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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 in the alternative choices (Premise: *The friends decided to share the hamburger.*; A1: *They cut the hamburger in half.*; A2: *They ordered fries with the hamburger.*), it was mapped 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 also §3 and Appendix B 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–prompt–answers triple.

The translators were encouraged to split the workload into multiple sessions with breaks in between. Additionally, translators were encouraged to provide feedback, commenting on translation challenges and 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 detached from the present and those with persisting effects on the present. Both contrast with the im-

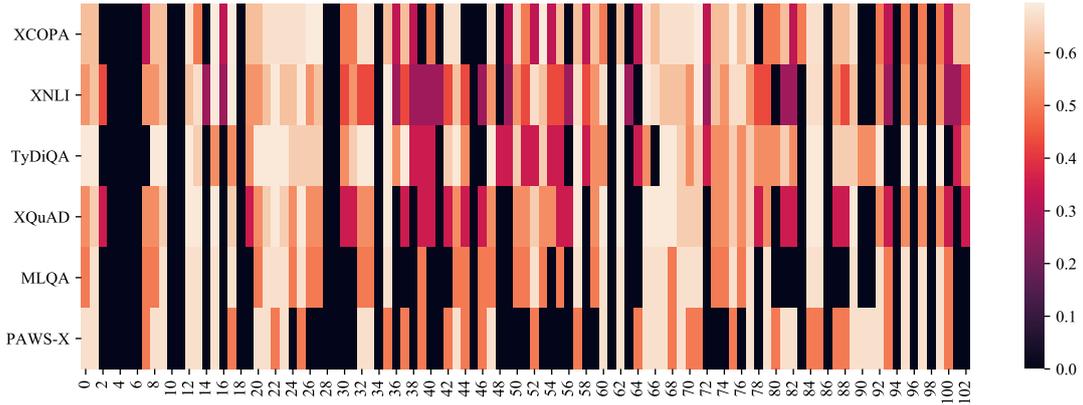


Figure 2: Heatmap of the entropy of the distributions of WALS features (x axis) in language samples from famous cross-lingual datasets outlined in §5 (y axis).

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
	XLM-R-L	53	49.6	55.8	53	52.4	48	54	51.4	51.8	51	56	53
	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
	XLM-R-L	53	49.4	47.8	51.4	53.6	54.2	50	47.8	53	50.6	58.2	51
	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
	XLM-R-L	85	70.4	53.4	79.4	72.8	50.2	60.8	71	69.4	71.2	76	78.2
	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
	XLM-R-L	84.2	68.8	52.8	79.8	72.4	50.7	59.4	68.2	67.2	71.2	73.8	76.2
	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
	XLM-R-L	84.2	71.4	52.8	79.8	72.6	52	59.2	73	72.8	74.4	73.8	78.6
	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 8: Detailed per-language XCOPA results for multilingual model transfer. None of the encoders was exposed to HT and QU during pretraining. USE was exposed only to IT, TH, TR, and ZH.

Name	Languages	Vocab	Params	URL
mBERT	104	119K	125M	https://huggingface.co/bert-base-multilingual-cased
XLM-R	100	250K	125M	https://huggingface.co/xlm-roberta-base
XLM-R-L	100	250K	355M	https://huggingface.co/xlm-roberta-large

Table 9: Pretrained transformers used in our study.

perfect, which emphasises the event’s extension or repetition in time. Given that the opposition is a matter of the speaker’s perspective on events and partially 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 hyper-parameter 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 after 10 consecutive evaluations. In all setups, we optimise the parameters with the Adam algorithm (Kingma and Ba, 2015) with $\epsilon = 10^{-8}$, no weight decay, and no warm-up. We clip the norms of gradients in single updates to 1.

D Full Results (Per Language)

Table 8 contains the detailed per-language results of multilingual model transfer for all XCOPA languages and all five of our evaluation setups (CO-ZS, CO-TLV, SI-ZS, SI+CO-ZS, SI+CO-TLV).

E Code and Dependencies

Our code is built on top of the HuggingFace Transformers framework¹⁴ and USE¹⁵ and is available at github.com/cambridgeltl/xcopa. Table 9 details the pretrained models that we exploited in this work. Besides these, our code relies only on standard Python’s scientific computing libraries (e.g., `numpy`).

¹⁴github.com/huggingface/transformers

¹⁵tfhub.dev/google/universal-sentence-encoder-multilingual-large/
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