Modelling Latent Translations for Cross-Lingual Transfer

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Abstract

While achieving state-of-the-art results in multiple tasks and languages, translation-based cross-lingual transfer is often overlooked in favour of massively multilingual pre-trained encoders. Arguably, this is due to its main limitations: 1) translation errors percolating to the classification phase and 2) the insufficient expressiveness of the maximum-likelihood translation. To remedy this, we propose a new technique that integrates both steps of the traditional pipeline (translation and classification) into a single model, by treating the intermediate translations as a latent random variable. As a result, 1) the neural machine translation system can be fine-tuned with a variant of Minimum Risk Training where the reward is the accuracy of the downstream task classifier. Moreover, 2) multiple samples can be drawn to approximate the expected loss across all possible translations during inference. We evaluate our novel latent translation-based model on a series of multilingual NLU tasks, including commonsense reasoning, paraphrase identification, and natural language inference. We report gains for both zero-shot and few-shot learning setups, up to 2.7 accuracy points on average, which are even more prominent for low-resource languages (e.g., Haitian Creole). Finally, we carry out in-depth analyses comparing different underlying NMT models and assessing the impact of alternative translations on the downstream performance.

1 Introduction

Cross-lingual knowledge transfer supports the development of natural language technology for many of the world’s languages (Ruder et al., 2019; Ponti et al., 2019, \textit{inter alia}). The approach currently predominant for cross-lingual transfer relies on massively multilingual pre-trained encoders (Conneau et al., 2020; Xue et al., 2020; Liu et al., 2020) that are fine-tuned on a source language and perform zero-shot (Wu and Dredze, 2019; Ponti et al., 2021) or few-shot (Lauscher et al., 2020; Zhao et al., 2020) prediction in a target language.

An alternative approach for cross-lingual transfer, \textit{translate text}, is based on translating the evaluation set into the source language and leveraging a monolingual classifier instead (Banea et al., 2008; Durrett et al., 2012; Conneau et al., 2018). This approach is currently under-investigated and usually relegated to the role of a baseline due to its lower flexibility, e.g., it is not suitable for sequence labelling tasks. Yet, it achieves the state-of-the-art results in most benchmarks for multilingual Natural Language Understanding and Question Answering tasks (Hu et al., 2020; Ponti et al., 2020; Ruder et al., 2021, \textit{inter alia}). Moreover, the availability of off-the-shelf translation models for multiple languages (Wu et al., 2016; Tiedemann and Thottingal, 2020; Liu et al., 2020) provides coverage for transfer to a large number of target languages. Indeed, very recent preliminary results suggest that the translation-based transfer might even outperform \textit{monolingual} pre-trained models in languages different from English (Isbister et al., 2021).

Translation-based transfer, however, currently suffers from two main limitations. First, the errors in translation accumulate along the pipeline. In fact, sentences that are possibly not faithful to the original in the target language and/or not grammatical in the source language are fed to the classifier, which degrades its performance. Second, only the maximum-likelihood translation is usually retrieved, which may not capture the precise meaning of the original sentence and its most relevant features for the downstream task.

In this work, we propose a method to amend these limitations and further enhance translation-based transfer. In particular, by treating the previously separate components for translation and classification as an integrated system, we re-interpret the traditional pipeline as a \textit{single model} with an intermediate \textit{latent translation} between the target text.
We propose an optimisation scheme based on MIN- XCOPA (Ponti et al., 2020) for commonsense reasoning (Yang et al., 2019) for paraphrase identification, via gradient descent, however, is often impossible due to the incompatibility of the token vocabularies of the two components. Therefore, we devise a universal method for fine-tuning that is suitable for any pair of pre-trained translator and classifier. We propose an optimisation scheme based on Minimum Risk Training (MRT; Och, 2003; Smith and Eisner, 2006; Shen et al., 2016, inter alia): it only requires the gradient of the translation scores and a reward based on downstream classification metrics.

Our evaluation is conducted on all multilingual Natural Language Understanding (NLU) tasks that are part of the popular XTREME (Hu et al., 2020) and XTREME-R (Ruder et al., 2021) cross-lingual transfer benchmarks. These include PAWS-X (Yang et al., 2019) for paraphrase identification, XCOPA (Ponti et al., 2020) for commonsense reasoning, and XNLI (Conneau et al., 2018) for natural language inference. Our model improves over standard translation-based methods in zero-shot and few-shot scenarios, up to 2.6 accuracy points on average, with peaks of 5.6 points for resource-poor languages like Haitian Creole.

As an additional contribution, we also examine for the first time the impact of translation quality (as measured by BLEU) and multilingual coverage of several models on the downstream classification performance. In particular, we compare among the Google Cloud Translation API, Marian MT (Tiedemann and Thottingal, 2020; Junczys-Dowmunt et al., 2018), and mBART (Liu et al., 2020; Tang et al., 2020), revealing substantial differences among these models. We release our code publicly at: github.com/McGill-NLP/latent-translation.

2 Latent Translation Model

In the present work, we are concerned with the problem of performing zero/few-shot inference in any given target language \( \ell_t \) by transferring knowledge from a source language \( \ell_s \). Specifically, we focus on classification tasks with data of the form \( \mathcal{D}_t \triangleq \{ (x, y) \}_1^p \), where \( x \in \Sigma_t \) is a discrete sequence of tokens from the vocabulary \( \Sigma_t \) and \( y \in \mathbb{N} \) is a label index. We further assume that a parallel corpus \( \mathcal{P} = \{ (x_{\ell_t}, x_{\ell_s}) \}_1^p \) is available. This enables translation-based transfer (Banea et al., 2008; Durrett et al., 2012), which comes in two flavours: either the evaluation set can be translated into \( \ell_s \) (translate test), or the training set can be translated into \( \ell_t \) (translate train).

We opt for the former, as it is both more efficient (due to \( |\mathcal{D}_{eval}| \ll |\mathcal{D}_{train}| \)) and effective (Conneau et al., 2018; Hu et al., 2020).

‘Translate test’ transfer relies on two main components: 1) a classifier \( f_\theta \) parameterised by \( \theta \in \mathbb{R}^d \) and trained on \( \mathcal{D}_{\ell_s} \), and 2) a translator \( f_\varphi \) parameterised by \( \varphi \in \mathbb{R}^h \) trained on \( \mathcal{P} \). These are deployed for predictive inference sequentially in the following pipeline: first, the \( i \)-th target language sentence(s) \( x_{\ell_t} \) are mapped to their translation in the source language \( x_{\ell_s} \). Afterwards, \( x_{\ell_s} \) is fed to the classifier to produce the label \( \hat{y} \).

However, this pipeline is arguably encumbered by two main limitations. Firstly, there is no information flow between the translator and the classifier; therefore, the errors in translation cannot be corrected in the subsequent step. Secondly, there may exist multiple correct translations, each reflecting different facets of the original sentence. Therefore, a single maximum-likelihood translation may not be representative of the underlying distribution, which is conceivably multi-modal.

Therefore, to grapple with both these problems, we propose to integrate both the translator and the classifier components into a unified model. This

![Figure 1: A Bayesian graph of the generative model for latent translation cross-lingual transfer.](https://cloud.google.com/translate)
amounts to treating the translations as a latent random variable $h \in \Sigma^*_\ell$, situated in between the target language sentences $x_i$ and the label $y$. From a Bayesian perspective, this is equivalent to the graphical model shown in Figure 1. Hence, if we assume the conditional independence $(y \perp x \mid h)$, posterior inference over the neural parameters $\theta$ and $\varphi$ given $D_\ell$, requires estimating:

$$p(\theta, \varphi \mid y, x) = \frac{p(y \mid x, \theta, \varphi) p(\theta) p(\varphi)}{\sum_{h \in \Sigma^*_\ell} p(y \mid h, \theta) p(h \mid x, \varphi) p(\theta) p(\varphi)}.$$  

(1)

In other words, the latent variable $h$ must be integrated out. By virtue of Equation (1), the estimate for the translator parameters $\varphi$ is influenced by the label $y$. Hence, out-of-the-box translation models can be adapted to the domain- or task-specific cues based on the feedback that downstream classification provides for any translation that they generate. Moreover, the entirety of the space $\Sigma^*_\ell$ is explored rather than just the maximum-likelihood sequence. Thus, the multi-faceted semantics of the input sentence in the target language is better preserved.

This formulation, however, poses additional challenges. First, the domain $\Sigma^*_\ell$ is countably infinite. Therefore, integrating over this space, and estimating the full probability distribution, is virtually impossible. Second, being $h$ discrete sequences, the model is not fully differentiable. Hence, training it via gradient descent is not trivial. In what follows, we propose approximate solutions in order to perform inference under our model.

### 2.1 Monte Carlo Sampling of Translations

While it may not be feasible to integrate over the space of all possible translations, we can approximate the likelihood term of Equation (1) through a finite set of $k$ Monte Carlo samples:

$$\sum_{h \in \Sigma^*_\ell} p(y \mid h, \theta) p(h \mid x, \varphi) = \mathbb{E}_{h \sim p(y \mid x, \varphi)} p(y \mid h, \theta) \approx \frac{1}{k} \sum_{i=1}^{k} p(y \mid h_i, \theta) \quad h_i \sim p(\cdot \mid x, \varphi)$$

(2)

In practice, this amounts to performing an ensemble prediction, where $k$ candidate outputs of the translator $h_i \sim p(\cdot \mid x, \varphi)$ are fed to the classifier. The predictive distributions yielded by the classifier given each candidate are then averaged:

$$\mathcal{L}(\varphi) = \min_{\varphi} \sum_{i=1}^{n} - \log \left( \sum_{j=1}^{k} \sigma(h_{ij}) \right)_{y_i}$$

where $h_{ij} \sim f_{\varphi}(x_i)$

(3)

and $y_i$ indexes the probability of the gold label of the $i$-th example and $\sigma$ is the softmax function.

### 2.2 Minimum Risk Training

The second difficulty of our integrated model lies in the fact that the latent translations are discrete sequences, which implies a non-differentiable hard decision boundary. This could be easily addressed by relaxing the tokens that are part of the translation into continuous variables (Maddison et al., 2017; Jang et al., 2017) or adopting straight-through estimators (Bengio et al., 2013; Raiko et al., 2014). Nonetheless, this may still be impractical. In fact, it is common to instantiate both the translator $f_{\varphi}$ and the classifier $f_{\theta}$ with pre-trained neural models. In this case, the output vocabulary of the former often does not coincide with the latter, due to different sub-word tokenisation strategies (Rust et al., 2020). Therefore, the domain $\Sigma^*_\ell$ of the translator output and the classifier input may also not correspond.

In order to make our method as general as possible and match any pair of translator and classifier with arbitrary vocabularies, we resort instead to a reinforcement learning technique to fine-tune the translator parameters. In particular, we adopt a version of Minimum Risk Training (MRT; Shen et al., 2016): its key idea is minimising the risk (expressed as a negative reward weighted by its probability). MRT is typically harnessed for NMT as a downstream task; the reward is thus BLEU or similar metrics. However, in our setting we propose to use classification accuracy as a reward. Let $p^*(\cdot)$ represent the score (i.e. the unnormalised probability) of a translation. The loss can be formulated as follows:

$$\mathcal{L}(\varphi) = \min_{\varphi} \sum_{i=1}^{n} \sum_{j=1}^{k} \frac{p^*(h_{ij} \mid \varphi, x_i)}{\sum_{j'} p^*(h_{ij'} \mid \varphi, x_i)} \times - \log p(y_i \mid h_{ij}, \theta),$$

(4)

where $n$ is the number of training inputs (here: few-shot learning), $k$ the number of translation samples normalised sample probability. However, we found this to be detrimental to downstream performance.
generated for each input, \( h \) a latent translation, and \( \varphi \) the MT model parameters. The downstream task reward is \( R(h_{ij}) \triangleq \log p(y_i \mid h_{ij}, \varphi) \), the log-likelihood of the classifier prediction based on the \( j \)-th individual translation.\(^3\)

We optimise the parameters \( \varphi \) through gradient descent, where the gradient of the loss in Equation (4) with respect to the \( z \)-th weight \( \varphi_z \) is computed as:

\[
\frac{\partial \mathcal{L}(\varphi)}{\partial \varphi_z} = \sum_{i=1}^{n} \mathbb{E}_{h_i \mid \varphi, x_i} \left[ \frac{\partial p^*(h_i \mid \varphi, x_i)}{\partial \varphi_z} p^*(h_i \mid \varphi, x_i) \right] \times \left( R(h_i) - \mathbb{E}_{h_i \mid \varphi, x_i} [R(h_i')] \right)
\]

(5)

where the expectations are computed by explicitly enumerating the \( k \) Monte Carlo samples.

### 2.3 MAP Inference
Combining the objectives outlined in Section 2.1 and Section 2.2, we finally obtain the maximum-a-posteriori (MAP) approximation to perform posterior inference over the graphical model in Figure 1. This is expressed in the following objective, which we use for fine-tuning the classifier and translator parameters during few-shot learning:

\[
\min_{\vartheta, \varphi} \mathcal{L}(\vartheta) + \mathcal{L}(\varphi) + \frac{\lambda}{2} \Vert \vartheta \Vert_2^2 + \frac{\lambda}{2} \Vert \varphi \Vert_2^2,
\]

(6)

where \( \mathcal{L}(\vartheta) \) is taken from Equation (3) and \( \mathcal{L}(\varphi) \) is taken from Equation (4). Note that Equation (6) contains two regularisers, which correspond to the prior terms in Equation (1). In particular, we take \( \vartheta \sim \mathcal{N}(0, \lambda^{-1}) \) and \( \varphi \sim \mathcal{N}(0, \lambda^{-1}) \).

In zero-shot setups, and after that the parameters have been fine-tuned in few-shot setups, we perform predictive inference on new data points in the evaluation set through the ensemble of Monte Carlo samples, as described in Equation (2).

### 3 Experimental Setup

**Evaluation Tasks and Data.** We conduct experiments on three established cross-lingual transfer datasets for natural language understanding tasks. 1) PAWS-X (Yang et al., 2019) for paraphrase identification: given a pair of sentences, a binary label specifies whether they express an identical meaning; 2) XCOPA (Ponti et al., 2020) for commonsense causal reasoning: given a premise, a question, and a pair of (cause, effect) hypotheses, the model must determine which of the two is correct; 3) XNLI (Conneau et al., 2018) for natural language inference: a pair of sentences is classified as either an entailment, a contradiction, or a neutral relationship. Together, these 3 tasks cover a wide variety of typologically diverse languages (22 distinct ones in addition to English).

Following prior work (Hu et al., 2020; Ruder et al., 2021), English is the source language in all experiments. In all three tasks, the English training set is used to train the classifier, the English development set for hyper-parameter selection, the development sets in other languages for few-shot learning (i.e., for fine-tuning both the classifier and translator), and the test set of the target languages for evaluation.

**Machine Translation Systems.** In order to assess the impact of the underlying translation model on downstream performance, we compare three established NMT system: 1) a closed-source software, the Google Cloud Translation API.\(^4\) Moreover, we consider two open-source systems: 2) mBART (Liu et al., 2020; Tang et al., 2020), a multilingual model covering 50 languages pre-trained on a denoising objective and fine-tuned on parallel data. 3) Marian MT (Junczys-Dowmunt et al., 2018), a set of hundreds of pair-wise models which were directly trained on parallel data from OPUS (Tiedemann and Thottingal, 2020).\(^5\)

mBART is an encoder-decoder model where both the encoder and decoder have 12 Transformer layers and 16 attention heads per layer. The hidden dimension is 1024, whereas the FFN inner dimension is 4096. Marian MT is a lighter model, where all the parameters are exactly halved. Further, Marian MT varies from mBART slightly in other regards: it employs static (sinusoid) positional embeddings and does not perform layer normalisation. Several languages in our set of cross-lingual tasks are covered by some translation systems: no system currently covers QT;\(^6\) mBART also lacks BG, EL, and HT, Marian MT lacks EL, SW, and TA.\(^7\)

\(^3\)As of 6 October 2020 for XCOPA and 30 April 2021 for PAWS-X and XNLI.

\(^4\)Pre-trained models are sourced from [github.com/huggingface/transformers](https://github.com/huggingface/transformers) for Marian Helsinki-NLP/opus-mt-{src}-{tgt} whereas for mBART facebook/mbart-large-50-many-to-one-mt.

\(^5\)We refer to languages through their ISO 639-1 code.

\(^6\)Artetxe et al. (2020) noted that the joint translation of all sentences that are part of a same example (e.g., premise and hypothesis) might be beneficial, as this retains their lex-
**Classifier.** As a classifier $f_{\theta}$ for the output of all MT systems, we use RoBERTa Large (Liu et al., 2019), a 24-layer monolingual pre-trained encoder for English, with a 2-layer perceptron (MLP) head. The encoder’s hidden size is 1024, whereas the internal representation of the MLPs (both in the encoder and the head) is 1024.

In order to establish another common (and not translation-based) baseline in all evaluation tasks, we also fine-tune a multilingual encoder with an identical configuration to RoBERTa, XLM-R Large (Conneau et al., 2020). In this case, the target language text is fed directly to the classifier, without requiring translation. We label this approach ME, as opposed to ‘translate test’ (TT).\(^8\)

**Optimisation.** Both during fine-tuning on English and few-shot learning on the target language, we train all models for 5 epochs. The classifier’s parameters are optimised through Adam (Kingma and Ba, 2014) with learning rate $8 \times 10^{-6}$ and $\epsilon = 10^{-8}$, whereas the translator’s parameters through SGD with learning rate $10^{-2}$. We use a dropout of 0.1 during fine-tuning, and clip the gradient norm to 1. The maximum sequence length is 128, and the batch size is 24. Finally, for translation sampling we select the $k$ most likely sequences with a beam size of 12 and a temperature of 1. We verified empirically that probabilistic sampling performs worse (cf. Figure 3).

## 4 Results and Discussion

The main results on XCOPA, PAWS-X, and XNLI, both in zero-shot and few-shot transfer scenarios, are summarised in Table 1. In addition to the baselines, we report results on Monte Carlo sampling and MRT only for the best performing open-source model, Marian.\(^9\) The scores offer multiple axes in comparison, discussed in what follows.

**Multilingual Encoders versus Translate Test.** Inspecting the global trends in Table 1, the results mostly corroborate the received wisdom from prior work (Hu et al., 2020; Ruder et al., 2021; Ponti et al., 2020): translate test coupling Google MT with a monolingual English encoder yields stronger cross-lingual transfer performance on average than using a state-of-the-art massively multilingual encoder such as XLM-R Large. However, while the finding is true when using Google MT, we note that 1) it does not hold across the board with other NMT systems, and 2) ME-based transfer with XLM-R Large is confirmed as a strong non-MT transfer baseline. For instance, 1-best mBART falls behind XLM-R Large in all three tasks, and likewise for 1-best Marian MT in PAWS-X and XNLI.

**A Comparison of NMT Models (1-best).** Task performance varies dramatically according to the chosen MT system; what is more, it can serve as a (non-ideal) proxy of MT system quality. Google translations are by far the best (compare the average scores at the bottom of Table 1), with pronounced gains over the two competitors in all three tasks, especially in zero-shot setups. Marian MT also displays significantly better results than mBART across the board, especially on XCOPA and XNLI, despite its smaller parameter count. Arguably, this is caused by the fact that Marian MT has separate models available for each language pair, whereas mBART is massively multilingual. This effect is known as the ‘curse of multilinguality’ (Conneau et al., 2020). Finally, while Marian MT reduces the gap to Google in few-shot transfer, Google remains the strongest alternative in this setup, too, for all three tasks.

**Multiple Samples and MRT.** Our latent-based translation approach yields consistent gains over the base 1-best MT system in all three tasks: the improvements of 12-best Marian over its 1-best variant are observed in all zero-shot and few-shot runs. The further inclusion of MRT in few-shot setups results in additional small but consistent boosts, again in all evaluation tasks. This confirms that both components, as discussed in Section 2, indeed focus on mitigating distinct limitations of the standard translation-based approach, and thus offer complementary benefits to the final task performance. Using multiple samples with MRT, an initially weaker NMT system can recover several points of performance, even outperforming an initially stronger NMT system for some tasks and languages. For instance, MRT with 12 samples is the peak-scoring variant for TR by 2 points, despite “starting” 2 points behind the Google 1-best baseline. We observe similar trends, among others, for
| ME  | TTE: RoBERTa+ |
|-----|--------------|
| NLI-R | mBART | Google | Marian-1 | Marian-12 |
| EN | 85.4 | 89.8 | 89.8 | 89.8 |
| ET | 72.6 | 69.8 | 82.2 | 83.4 | 84.4 |
| HT | * | * | 75.4 | 56.0 | 61.6 |
| ID | 81.8 | 80.6 | 83.8 | 82.2 | 85.2 |
| TH | 77.0 | 74.0 | 85.8 | 80.6 | 79.8 |
| QU | * | * | * | * | * |
| SW | 62.8 | 50.2 | 76.6 | * | * |
| TA | 71.2 | 69.8 | 81.8 | * | * |
| TH | 72.4 | 62.6 | 76.4 | 74.6 | 77.2 |
| TR | 71.6 | 74.6 | 83.4 | 79.6 | 83.0 |
| VI | 77.6 | 76.2 | 83.0 | 76.0 | 79.2 |
| ZH | 80.2 | 82.8 | 85.2 | 82.4 | 85.2 |
| avg | 74.1 | 71.2 | 81.4 | 76.9 | 79.5 |
| ME  | TTE: RoBERTa+ |
| NLI-R | mBART | Google | Marian-1 | Marian-12 |
| EN | 97.10 | 96.85 | 96.85 | 96.85 | 96.85 |
| DE | 90.60 | 89.54 | 91.25 | 91.05 | 91.40 |
| ES | 91.60 | 87.79 | 92.05 | 91.45 | 91.80 |
| FR | 92.30 | 89.94 | 92.20 | 91.40 | 91.90 |
| JA | 81.59 | 77.49 | 81.09 | 72.89 | 74.54 |
| KO | 83.04 | 74.59 | 81.49 | 73.04 | 73.24 |
| ZH | 84.34 | 82.04 | 85.24 | 82.44 | 82.64 |
| avg | 89.58 | 87.23 | 89.55 | 87.62 | 88.18 |
| ME  | TTE: RoBERTa+ |
| NLI-R | mBART | Google | Marian-1 | Marian-12 |
| EN | 88.84 | 91.24 | 91.24 | 91.24 | 91.24 |
| AR | 79.58 | 72.83 | 82.27 | 78.60 | 79.98 |
| BG | 83.21 | * | 85.21 | 84.43 | 85.01 |
| DE | 82.97 | 82.71 | 85.45 | 84.49 | 85.37 |
| EL | 82.03 | * | 84.09 | * | * |
| ES | 84.27 | 78.56 | 86.88 | 85.73 | 86.44 |
| FR | 82.95 | 82.35 | 85.33 | 84.51 | 85.09 |
| HI | 76.48 | 73.25 | 77.26 | 63.71 | 65.14 |
| RU | 79.34 | 77.98 | 82.23 | 79.68 | 81.13 |
| SW | 72.19 | 34.66 | 75.12 | * | * |
| TH | 76.92 | 45.28 | 77.40 | 75.34 | 75.34 |
| TR | 78.94 | 74.15 | 81.57 | 79.88 | 80.57 |
| UR | 72.57 | 60.55 | 71.79 | 55.30 | 55.44 |
| VI | 80.12 | 75.86 | 81.79 | 77.70 | 78.80 |
| ZH | 80.00 | 78.34 | 81.73 | 79.02 | 79.78 |
| avg | 82.05 | 75.05 | 84.00 | 81.43 | 82.34 |

Table 1: Results (Accuracy × 100) in zero-shot (left columns) and few-shot (right columns) scenarios for XCOPA (top tables), PAWS-X (centre tables), and XNLI (bottom tables). *MT system does not cover the target language. The numbers after each MT system refer to the number of translation samples k (see Section 3).
with target languages more dissimilar to English (arguably most complex) XCOPA task. Here, the
(e.g., compare the scores of
Performance across Languages. The scores over
individual target languages of all translate-test variants also reveal the presence of ample headroom under English performance in all three tasks. This is due to “information lost” owing to imperfect translation. As expected, larger gaps are detected with target languages more dissimilar to English (e.g., compare the scores of JA, KO, and ZH versus ES, FR, DE on PAWS-X), and for lower-resource languages with smaller amounts of parallel data (e.g., HT in XCOPA, SW in XCOPA and XNLI).

Performance across Tasks. Finally, a cross-task comparison reveals that the largest benefits of the translation-based approaches are observed on the (arguably most complex) XCOPA task. Here, the gains with Google 1-best and Marian 1-best over the ME approach are pronounced in both zero-shot and few-shot setups. Moreover, the use of multiple samples plus MRT yields further performance gains, highest across all tasks. The benefits of the TT approach compared to ME are smaller on XNLI, and non-present on the PAWS-X task, which is the most saturated and least linguistically diverse (Ruder et al., 2021). However, the results across all three tasks do confirm the benefits of the proposed latent translation-based approach, which always improves over the base MT system.

5 In-Depth Analysis

Number of Samples. We plot the effect of varying the number of translation samples from 1 to 12 on XCOPA accuracy in Figure 3. As it emerges, the performance metric increases monotonically. The lack of a plateau in the considered interval suggests that larger numbers could ameliorate accuracy even further. Moreover, note that k-best deterministic sampling appears superior to probabilistic sampling for all k’s.

Translation Quality. In Figure 2, we report the BLEU scores\(^\text{11}\) of the 1-best translation of all NMT systems on the development sets of all languages. We source the gold references from the English datasets (COPA, PAWS, and SNLI) from which XCOPA, PAWS-X, and XNLI, respectively, were manually translated. The violin plot reveals large gaps in BLEU based on the distance from English. This is most evident in PAWS-X, with JA, KO, and ZH on the bottom and DE, ES, FR on the top. Moreover, BLEU levels vary by task: while XCOPA has the shortest sentences, it is also the most typologically diverse. This makes the dataset easier to translate in some respects, but harder in others.

Hence, one might wonder what is the relationship between these 1-best BLEU scores and gains

\(^{10}\)In addition to MRT, we considered fine-tuning the translator through self-training (Sennrich et al., 2016) and learning a re-ranker for weighted ensemble prediction (Dong et al., 2017). Compared to MRT, both yield sub-par results, which are reported in Table 3 in Appendix.

\(^{11}\)Evaluated through sacrebleu (Post, 2018).
due to multiple samples. Figure 4 depicts these two quantities. For XCOPA and XNLI, there is a trend for higher gains with lower translation quality. HT is the clearest example, with only 12.6 BLEU and a Δ of around 5 points in accuracy. However, for PAWS-X we observe almost no linear correlation, which might be caused by overall gains being much smaller. There might also be a minimum translation quality below which multiple samples cannot bring benefits, which would explain the outlier UR in XNLI. On the other extreme, in a few languages with best-quality MT, such as IT for XCOPA and DE for PAWS-X, multiple samples seem to mislead the classifier in few-shot transfer.

Translation Ranking. The fact that lower-scoring translations positively contribute during ensemble prediction is counter-intuitive. Yet, we verify that among the k-best translations, higher-ranking ones are not necessarily associated with better classification accuracy, even when their log-probability is significantly greater (see Figure 5 in Appendix). Table 2 shows an example for TR in XCOPA, where lower-ranking translations turn the ensemble decision correct when the highest rank translation leads to the wrong classification. In this case, they resolve an incorrect disambiguation of gender. However, in other cases it is hard to interpret how minor lexical changes affect the ensemble prediction.

These insights offer a provocative question for future work: can similar application-oriented evaluations of MT systems reach beyond standard intrinsic evaluation protocols such as BLEU (Papineni et al., 2002) or METEOR (Banerjee and Lavie, 2005)? In other words, assessing how well the NMT models support cross-lingual transfer might provide additional empirical evidence on their translation abilities.

6 Conclusion and Future Work

We proposed a new method to perform translation-based cross-lingual transfer, by treating the translation of the input text in a target language as a latent random variable. This unifies under a single model both components (a translator and a classifier) of the traditional pipeline, which were previously learned separately and deployed in consecutive steps. As a consequence, in our model, 1) multiple translations can be generated with Monte Carlo sampling to better render the original meaning and 2) the translator can be adapted to the downstream task and correct its errors based on the feedback from the classifier through a variant of Minimum Risk Training. We demonstrate the effectiveness of our method on several benchmarks for natural language understanding, including commonsense causal reasoning, paraphrase identification, and natural language inference. Furthermore, we find that classification performance varies dramatically according to the translation quality of the underlying translator model, whereas its internal ranking of k-best translations plays almost no role. We hope that our findings will provide an incentive to improve language coverage and quality of (especially public) NMT models to support a wide array of multilingual NLP applications.
References

Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2020. Translation artifacts in cross-lingual transfer learning. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 7674–7684, Online. Association for Computational Linguistics.

Abhishek Arun, Barry Haddow, and Philipp Koehn. 2010. A unified approach to minimum risk training and decoding. In Proceedings of the Joint Fifth Workshop on Statistical Machine Translation and MetricsMATR, pages 365–374, Uppsala, Sweden. Association for Computational Linguistics.

Carmen Banea, Rada Mihalcea, Janyce Wiebe, and Samer Hassan. 2008. Multilingual subjectivity analysis using machine translation. In Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing, pages 127–135, Honolulu, Hawaii. Association for Computational Linguistics.

Satanjeev Banerjee and Alon Lavie. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

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 the 58th Annual Meeting of the Association for Computational Linguistics, pages 8440–8451, Online. Association for Computational Linguistics.

Li Dong, Jonathan Mallinson, Siva Reddy, and Mirella Lapata. 2017. Learning to paraphrase for question answering. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 875–886, Copenhagen, Denmark. Association for Computational Linguistics.

Greg Durrett, Adam Pauls, and Dan Klein. 2012. Syntactic transfer using a bilingual lexicon. In Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, pages 1–11, Jeju Island, Korea. Association for Computational Linguistics.

Sergey Edunov, Myle Ott, Michael Auli, David Grangier, and Marc’Aurelio Ranzato. 2018. Classical structured prediction losses for sequence to sequence learning. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 355–364, New Orleans, Louisiana. Association for Computational Linguistics.

Akiko Eriguchi, Melvin Johnson, Orhan Firat, Hideto Kazawa, and Wolfgang Macherey. 2018. Zero-shot cross-lingual classification using multilingual neural machine translation. arXiv preprint arXiv:1809.04686.

Di He, Yingce Xia, Tao Qin, Liwei Wang, Nenghai Yu, Tie-Yan Liu, and Wei-Ying Ma. 2016. Dual learning for machine translation. Advances in neural information processing systems (NeurIPS), 29:820–828.

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 generalisation. In International Conference on Machine Learning, pages 4411–4421.

Tibor Kádár, Fedrik Carlsson, and Magnus Sahlgren. 2021. Should we stop training more monolingual models, and simply use machine translation instead?

Eric Jiang, Shixiang Gu, and Ben Poole. 2017. Categorical reparameterization with Gumbel-Softmax. In Proceedings of the 5th International Conference on Learning Representations (ICLR 2017).

Laura Jehl, Carolin Lawrence, and Stefan Riezler. 2019. Learning neural sequence-to-sequence models from weak feedback with bipolar ramp loss. Transactions of the Association for Computational Linguistics, 7:233–248.

Marcin Junczys-Dowmunt, Kenneth Heafield, Hieu Hoang, Roman Grundkiewicz, and Anthony Aue. 2018. Marian: Cost-effective high-quality neural machine translation in C++. In Proceedings of the 2nd Workshop on Neural Machine Translation and Generation, pages 129–135, Melbourne, Australia. Association for Computational Linguistics.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Julia Kreutzer, Shahramp Khadivi, Evgeny Matusov, and Stefan Riezler. 2018. Can neural machine translation be improved with user feedback? In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume
3 (Industry Papers), pages 92–105, New Orleans - Louisiana. Association for Computational Linguistics.

Anne Lauscher, Vinit Ravishankar, Ivan Vulić, and Goran Glavaš. 2020. From zero to hero: On the limitations of zero-shot language transfer with multilingual Transformers. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 4483–4499, Online. Association for Computational Linguistics.

Chunxi Liu, Qiaochu Zhang, Xiaohui Zhang, Kritika Singh, Yatharth Saraf, and Geoffrey Zweig. 2020. Multilingual graphemic hybrid ASR with massive data augmentation. In Proceedings of the 1st Joint Workshop on Spoken Language Technologies for Under-resourced languages (SLTU) and Collaborating and Computing for Under-Resourced Languages (CCURL), pages 46–52, Marseille, France. European Language Resources association.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. RoBERTa: A robustly optimized BERT pretraining approach. arXiv preprint arXiv:1907.11692.

Chris J Maddison, Andriy Mnih, and Yee Whye Teh. 2017. The concrete distribution: A continuous relaxation of discrete random variables. In Proceedings of the 5th International Conference on Learning Representations (ICLR 2017).

Peter Makarov and Simon Cleamteide. 2018. Neural transition-based string transduction for limited-resource setting in morphology. In Proceedings of the 27th International Conference on Computational Linguistics, pages 83–93, Santa Fe, New Mexico, USA. Association for Computational Linguistics.

Takuya Makino, Tomoya Iwakura, Hiroya Takamura, and Manabu Okumura. 2019. Global optimization under length constraint for neural text summarization. In Proceedings of the 57th Annual Meeting of the Association of Computational Linguistics, pages 1039–1048, Florence, Italy. Association for Computational Linguistics.

Dipendra Misra, Ming-Wei Chang, Xiaodong He, and Wen-tau Yih. 2018. Policy shaping and generalized update equations for semantic parsing from denotations. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2442–2452, Brussels, Belgium. Association for Computational Linguistics.

Franz Josef Och. 2003. Minimum error rate training in statistical machine translation. In Proceedings of the 41st Annual Meeting of the Association for Computational Linguistics, pages 160–167, Sapporo, Japan. Association for Computational Linguistics.

Nikolaos Panagiaris, Emma Hart, and Dimitra Gkatzia. 2020. Improving the naturalness and diversity of referring expression generation models using minimum risk training. In Proceedings of the 13th International Conference on Natural Language Generation, pages 41–51, Dublin, Ireland. Association for Computational Linguistics.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Edoardo M. Ponti, Ivan Vulić, Ryan Cotterell, Marinela Parovic, Roi Reichart, and Anna Korhonen. 2021. Parameter Space Factorization for Zero-Shot Learning across Tasks and Languages. Transactions of the Association for Computational Linguistics, 9:410–428.

Edoardo Maria Ponti, Goran Glavaš, Olga Majewska, Qianchu Liu, Ivan Vulić, and Anna Korhonen. 2020. XCOPA: A multilingual dataset for causal commonsense reasoning. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2362–2376, Online. Association for Computational Linguistics.

Edoardo Maria Ponti, Helen O’Horan, Yevgeni Berzak, Ivan Vulić, Roi Reichart, Thierry Poibeau, Ekaterina Shutova, and Anna Korhonen. 2019. Modeling language variation and universals: A survey on typological linguistics for natural language processing. Computational Linguistics, 45(3):559–601.

Matt Post. 2018. A call for clarity in reporting BLEU scores. In Proceedings of the Third Conference on Machine Translation: Research Papers, pages 186–191, Brussels, Belgium. Association for Computational Linguistics.

Tapani Raiko, Mathias Berglund, Guillaume Alain, and Laurent Dinh. 2014. Techniques for learning binary stochastic feedforward neural networks. arXiv preprint arXiv:1406.2989.

Marc’Aurelio Ranzato, Sumit Chopra, Michael Auli, and Wojciech Zaremba. 2016. Sequence level training with recurrent neural networks. In Proceedings of the International Conference on Learning Representation (ICLR), San Juan, Puerto Rico.

Sebastian Ruder, Noah Constant, Jan Botha, Aditya Siddhant, Orhan Firat, Jinfan Fu, Pengfei Liu, Junjie Hu, Graham Neubig, and Melvin Johnson. 2021. XTREME-R: Towards more challenging and nuanced multilingual evaluation. arXiv preprint arXiv:2104.07412.

Sebastian Ruder, Ivan Vulić, and Anders Søgaard. 2019. A survey of cross-lingual word embedding models. Journal of Artificial Intelligence Research, 65:569–631.
Phillip Rust, Jonas Pfeiffer, Ivan Vulič, Sebastian Ruder, and Iryna Gurevych. 2020. How good is your tokenizer? on the monolingual performance of multilingual language models. arXiv preprint arXiv:2012.15613.

Danielle Saunders, Felix Stahlberg, and Bill Byrne. 2020. Using context in neural machine translation training objectives. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7764–7770, Online. Association for Computational Linguistics.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Improving neural machine translation models with monolingual data. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 86–96, Berlin, Germany. Association for Computational Linguistics.

Shiqi Shen, Yong Cheng, Zhongjun He, Wei He, Hua Wu, Maosong Sun, and Yang Liu. 2016. Minimum risk training for neural machine translation. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1683–1692, Berlin, Germany. Association for Computational Linguistics.

Aditya Siddhant, Melvin Johnson, Henry Tsai, Naveen Ari, Jason Riesa, Ankur Bapna, Orhan Firat, and Karthik Raman. 2020. Evaluating the cross-lingual effectiveness of massively multilingual neural machine translation. In Proceedings of the AAAI Conference on Artificial Intelligence, pages 8854–8861.

David A. Smith and Jason Eisner. 2006. Minimum risk annealing for training log-linear models. In Proceedings of the COLING/AACL 2006 Main Conference Poster Sessions, pages 787–794, Sydney, Australia. Association for Computational Linguistics.

Artem Sokolov, Felix Hieber, and Stefan Riezler. 2014. Learning to translate queries for clir. In Proceedings of the 37th Annual ACM SIGIR Conference.

Yuqing Tang, Chau Tran, Xin Li, Peng-Jen Chen, Namn Goval, Vishav Chaudhary, Jiatao Gu, and Angela Fan. 2020. Multilingual translation with extensible multilingual pretraining and finetuning. arXiv preprint arXiv:2008.00401.

Jörg Tiedemann and Santhosh Thottingal. 2020. OPUS-MT – building open translation services for the world. In Proceedings of the 22nd Annual Conference of the European Association for Machine Translation, pages 479–480, Lisboa, Portugal. European Association for Machine Translation.

Chaojun Wang and Rico Sennrich. 2020. On exposure bias, hallucination and domain shift in neural machine translation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 3544–3552, Online. Association for Computational Linguistics.

John Wieting, Taylor Berg-Kirkpatrick, Kevin Gimpel, and Graham Neubig. 2019. Beyond BLEU: training neural machine translation with semantic similarity. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4344–4355, Florence, Italy. Association for Computational Linguistics.

Sam Wiseman and Alexander M. Rush. 2016. Sequence-to-sequence learning as beam-search optimization. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 1296–1306, Austin, Texas. Association for Computational Linguistics.

Shijie Wu and Mark Dredze. 2019. Beto, bentz, becas: The surprising cross-lingual effectiveness of BERT. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 833–844, Hong Kong, China. Association for Computational Linguistics.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. 2016. Google’s neural machine translation system: Bridging the gap between human and machine translation. arXiv preprint arXiv:1609.08144.

Linting Xue, Noah Constant, Adam Roberts, Mihar Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. 2020. mT5: A massively multilingual pre-trained text-to-text transformer.

Yinfei Yang, Yuan Zhang, Chris Tar, and Jason Baldridge. 2019. PAWS-X: A cross-lingual adversarial dataset for paraphrase identification. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3687–3692, Hong Kong, China. Association for Computational Linguistics.

Mengjie Zhao, Yi Zhu, Ehsan Shareghi, Roi Reichart, Anna Korhonen, and Hinrich Schütze. 2020. A closer look at few-shot crosslingual transfer: Variance, benchmarks and baselines. CoRR, abs/2012.15682.
A  Translation Quality Across Ranks

Figure 5 shows how in XNLI the share of correct predictions are relatively stable across translations of different ranks within each language. For some languages the top-ranking translations are the best candidate (e.g. ES, UR), but for others it may be lower-ranked translation (e.g. 3rd best for HI or 8th best for TH).

B  Additional Results

| ME | mBART | Marian +Self-train | Marian +Re-ranker |
|----|-------|-------------------|-------------------|
| EN | 77.0  | 89.6              | 89.6              |
| ET | 56.2  | 86.6              | 70.4              |
| HT | 52.8  | 86.6              | 59.6              |
| ID | 61.2  | 85.4              | 64.6              |
| IT | 54.4  | *                  | *                  |
| QU | 61.4  | 86.6              | 70.4              |
| SW | 67.4  | 85.4              | 64.8              |
| ZH | 67.4  | 78.4              | 59.4              |
| TR | 64.6  | 84.8              | 77.2              |
| VI | 67.6  | 78.0              | 60.6              |
| avg| 63.7  | 79.3              | 64.5              |

Table 3: Additional few-shot learning results on XCOPA for alternative multilingual encoders pre-trained on NMT (mBART) and alternative auxiliary objectives (self-training and re-ranking).

C  Related Work

Minimum Risk Training (MRT) is a technique used for tuning MT models towards given evaluation metrics, and was introduced for statistical MT models (Och, 2003; Arun et al., 2010; Smith and Eisner, 2006) and adapted for NMT (Shen et al., 2016; Edunov et al., 2018; Wieting et al., 2019; Wang and Sennrich, 2020; Saunders et al., 2020). The advantages over classic maximum likelihood training with reference translations are that it mitigates exposure bias and addresses the loss-evaluation mismatch (Ranzato et al., 2016; Wiseman and Rush, 2016; Wang and Sennrich, 2020) by incorporating the evaluation metric directly into the loss, rewarding high-scoring model outputs and penalizing lower-scoring ones. This metric does not need to be differentiable (e.g. BLEU), and gradients are approximated with Monte-Carlo sampling. MRT has been found effective not only in NMT, but other sequence-to-sequence NLP tasks such as abstractive summarization (Edunov et al., 2018; Makino et al., 2019), string transduction (Makarov and Clematide, 2018), and referring expression generation (Panagiaris et al., 2020). While each task comes with its own evaluation metrics, the rewards can also be received from other neural models (He et al., 2016; Wieting et al., 2019), user feedback (Kreutzer et al., 2018), or a downstream task such as the success of execution of a semantic parse (Misra et al., 2018; Jehl et al., 2019) or cross-lingual information retrieval (Sokolov et al., 2014). The latter works are similar to ours in that we leverage downstream task signals to adapt the MT model.

D  Details for Reproducibility

We carried out all our experiments on a single 48GB RTX 8000 GPU with Turing architecture. On average, runtime is ∼ 3 hours for fine-tuning on the English training set, ∼ 10 minutes per language for fine-tuning on the target language development set (few-shot learning), and ∼ 5 minutes per language for evaluation.