INSTANCE-BASED MODEL ADAPTATION FOR DIRECT SPEECH TRANSLATION

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ABSTRACT

Despite recent technology advancements, the effectiveness of neural approaches to end-to-end speech-to-text translation is still limited by the paucity of publicly available training corpora. We tackle this limitation with a method to improve data exploitation and boost the system’s performance at inference time. Our approach allows us to customize “on the fly” an existing model to each incoming translation request. At its core, it exploits an instance selection procedure to retrieve, from a given pool of data, a small set of samples similar to the input query in terms of latent properties of its audio signal. The retrieved samples are then used for an instance-specific fine-tuning of the model. We evaluate our approach in three different scenarios. In all data conditions (different languages, in/out-of-domain adaptation), our instance-based adaptation yields coherent performance gains over static models.

Index Terms—End-to-end neural speech translation

1. INTRODUCTION

The technology advancements in end-to-end speech-to-text translation (ST) recently allowed to reduce the performance gap with classic cascade solutions combining separate automatic speech recognition (ASR) and machine translation (MT) components. However, despite its advantages in terms of architectural simplicity and reduced error propagation, direct ST still suffers from drawbacks related to its limited data effectiveness [1]. A general problem is that neural approaches are per se data-hungry and the publicly available ST corpora are still orders of magnitude smaller than those released for ASR and MT [2]. The data demand issue is exacerbated by the fact that, being a higher-level task than ASR and MT, direct ST requires higher abstraction capabilities to capture relevant features of the input (audio signals) and learn the mapping into proper output representations (texts in the target language). Learning this mapping end-to-end is usually more complex and data demanding than exploiting the intermediate representations of separate, individually trained components.

Previous solutions to cope with data scarcity focused on two orthogonal aspects: improving the learning process and increasing the training material. On the learning side, [3,4,5] exploited transfer learning from ASR and MT showing, for instance, that pre-training the ST encoder on ASR data can yield significant improvements. On the data side, the most promising approach is data augmentation, which has been experimented via knowledge distillation from a neural MT (NMT) model [9], synthesizing monolingual MT data in the source language [10], multilingual training [11], or translating monolingual ASR data into the target language [10][12][3]. Nevertheless, despite some claims of big industrial players operating in rich data conditions [10], top results at recent shared tasks [13] show that effectively exploiting the scarce training data available still remains a crucial issue to reduce the performance gap with cascade ST solutions.

Along this direction, we propose a general framework for maximizing data exploitation and customizing an existing ST model to each incoming translation request at inference time. In a nutshell, given a generic model Mₚ and an ST data pool D, each translation request r is handled by a two-step process. First, a set of (audio, translation) pairs is retrieved from D based on the similarity between their audio element and r. Then, the retrieved pairs are used to adapt Mₚ via fine-tuning. The underlying intuition is that the similarity of the new samples with the input audio can be used at run-time to overfit Mₚ to samples similar to r, and influence its behaviour towards a better translation.

We explore this idea in different scenarios considering different language directions and experimenting in intra-, multi- and cross-domain adaptation. Our results show that, compared to static ST models, instance-based on-the-fly adaptation yields variable but coherent improvements, with larger gains in cross-domain scenarios where the mismatch between the training and test domains makes ST more challenging.

2. DIRECT SPEECH TRANSLATION

In direct speech translation, a single neural model is trained end-to-end on the speech-to-text translation task. Given an input audio segment X representing a speech in a source language e, and an output text Y representing the translation of X in a target language f, a direct ST model is trained by optimizing the log-likelihood function in Equation 1, where B is the size of a batch, lₑ is the length of the target sequence at position b, and θ is the vector of model’s parameters.
\[
L = - \sum_{b=0}^{B} \sum_{i=0}^{l_b} y_{ib} \log(p(\tilde{y}_{ib}|X, y_{<i,b}; \theta))
\] (1)

Models for this task have a sequence-to-sequence architecture \[14\] with at least one encoder that processes the audio input, and one decoder that generates the output, one token at a time, in an autoregressive manner. In this work, we use S-Transformer \[15\], an adaptation of Transformer \[16\] to the ST task. In addition to the original Transformer, S-Transformer elaborates the input spectrograms with ad-hoc layers. The input is first processed by two stacked 2D CNNs with stride \((2, 2)\), which also reduce the input sequence length by a factor of 4. Then, the output of the second CNN is fed to a stack of two 2D Self-Attention \[17\]. The goal of the 2D Self-Attention is to model the bi-dimensional dependencies along the spectrogram’s time and frequency dimensions. 2D Self-attention layers process the input with 2D CNNs and compute attention among both matrix directions. All CNNs are followed by batch normalization \[18\] and ReLU nonlinearity. Moreover, to focus the encoder on short-range dependencies, a distance penalty mechanism is added in every self-attention layer of the encoder. Given a position \(i\) in the query vector, and a position \(j\) in the key vector, with \(i \neq j\) we compute \(\text{pen} = \log(|i - j|)\) and subtract \(\text{pen}\) from the attention scores before softmax normalization.

3. INSTANCE-BASED MODEL ADAPTATION

Algorithm 1 illustrates our instance-based model adaptation procedure. Its goal is to improve the performance of a pre-trained ST model \(M_g\) by fine-tuning it at inference time on \((\text{audio}, \text{translation})\) pairs in which the audio is similar to the input translation request \(r\). These pairs are retrieved from a data pool \(D\), which can either be the same training set used for \(M_g\) or a new dataset. In the former case, instance-based adaptation aims to maximize the exploitation of the training data. In the latter case, the goal is to exploit newly available data to also cover new domains. Our experiments \((14)\) will address both the scenarios.

**Data pool.** \(D\) consists of \((\text{audio}, \text{translation})\) pairs, in which the audio element is also used as a retrieval key for the pair. For our experiments, the audio segments are stored either \(i)\) as a spectrogram \(S\) with \(N\) time frames and \(k\) features (Raw Features in Table 1), or \(ii)\) as a function \(E(S)\) obtained by processing \(S\) with the model’s encoder (Encoder Features). The generated segments are stored in order to be retrieved during translation.

**Similarity.** The similarity between the query audio segment \(r\) and the audio segments in \(D\) is computed as the cosine similarity between the pairs of vectors \((z_r, z_1), \ldots, (z_r, z_n)\) \(\in R^k\), where \(k\) is the number of features of the chosen segment representations. Each \(z_i\) is obtained by summing all the time frames of its sequence along the time axis. The advantage of this similarity is its applicability in a direct ST scenario, where no intermediate transcription step is involved.

**Retrieval.** The retrieval procedure receives as argument the translation request \(r\), the data pool \(D\) and a similarity threshold \(\tau\). It returns the set of \((\text{audio}, \text{translation})\) pairs \((D_r)\) for which the similarity of the audio element with \(r\) is above \(\tau\).

**Adaptation.** If \(D_r\) is not empty, the generic model \(M_g\) is fine-tuned for \(e\) epochs on the top \(n\) samples to obtain the adapted model \(M_r\) used to translate \(r\). In our experiments, \(e\) and \(n\) are fixed hyperparameters. After translating \(r\), the adapted model is discarded so that, for the next input query, the process restarts from the initial generic model \(M_g\).

4. EXPERIMENTS

4.1. Datasets

We use two datasets. One is MuST-C \[2\], a multilingual ST corpus containing English speech (TED Talks) translated into 8 European languages. Data size ranges from 385 hours for English→Portuguese to 504 hours for English→Spanish. The other corpus is How2 \[19\], a multimedia corpus for English→Portuguese also including ST data (300 hours). In both corpora, the speech segments are in the form of log MEL filterbanks with time width 25ms and step of 10ms.

A comparison between the target side of the En-Pt section of MuST-C and How2 shows that they have a different level of text repetitiveness (How2 has a repetition rate \[20\] that is 40% higher) and vocabulary overlap (27% of the MuST-C terms appear in How2, while 48% of the How2 terms are also in MuST-C). Other differences in terms background noise and number of non-native speakers (both higher in MuST-C) suggest that the How2 data are in general easier to handle for ST.
3 Epochs

Table 1. BLEU results on MuST-C and How2 in the intra-domain scenario. The retrieval is based on either MEL filter-banks or the encoder’s output representations.

|       | Baseline | Raw Features | Encoder Features |
|-------|----------|--------------|------------------|
| De    | 17.0     | 16.9         | 17.3             |
| Es    | 21.5     | 21.5         | 22.0             |
| Fr    | 27.0     | 27.1         | 27.4             |
| It    | 17.5     | 17.8         | 18.0             |
| Nl    | 21.8     | 21.9         | 22.0             |
| Pt    | 21.5     | 21.4         | 21.7             |
| Ro    | 16.4     | 16.4         | 16.8             |
| Ru    | 12.2     | 12.3         | 12.4             |
| How2  | 39.4     | 39.9         | 40.1             |

Table 2. BLEU results on MuST-C running the adaptation for 1, 3 and 5 epochs on the least similar pair retrieved from $D$.

|       | 1 Epoch | 3 Epochs | 5 Epochs |
|-------|---------|----------|----------|
| De    | 15.8    | 13.1     | 10.0     |
| Es    | 21.0    | 19.8     | 19.0     |
| Fr    | 26.3    | 22.5     | 18.8     |
| It    | 17.0    | 15.0     | 13.2     |
| Nl    | 21.5    | 20.1     | 18.0     |
| Pt    | 21.2    | 19.6     | 17.7     |
| Ro    | 15.8    | 13.7     | 11.4     |
| Ru    | 11.9    | 9.7      | 7.3      |

4.2. Settings

We trained S-Transformer on all the datasets with the following hyper-parameters: 2D CNNs have kernels of size $3 \times 3$ and stride $(2, 2)$, 2D self-attentions have internal 2D CNNs with 4 output channels (and thus 4 heads in multi-head attention), and 64 output channels in the last layer. Transformer layers have size $512 \times 8$ heads in multi-head attention and 1024 units in the hidden feed-forward sub-layers. Dropout is set to 0.1 after each layer. For training, we used the Adam optimizer [21] with noam decay [16] using initial learning rate 0.0003, 4000 warm-up steps and maximum learning of 0.001. The loss we used is cross-entropy with label smoothing [22]. For each setting, we perform hyperparameter search in the validation set, then the best selection is applied on the test set. We perform instance-based adaptation with the Adam optimizer [21] and choose the best set of hyperparameters among learning rates $\{1, 2, 3\} \times 10^{-3, 4, 5}$, number of retrieved samples $\{1, 5, 10\}$, and number of tuning epochs $\{1, 3, 5\}$. Additionally, we filter out the retrieved samples whose cosine similarity score is below a threshold $\tau$. After an initial exploration, we found out that a threshold $\tau = 0.5$ allows the systems to keep the best performance while reducing the tuning time. As an additional note, we found that the SGD optimizer does not work as well as the Adam optimizer, particularly for the multi/cross-domain adaptation experiments.

4.3. Experiments

We evaluate our instance-based model adaptation approach in three scenarios. In the first scenario ("intra-domain"), the data pool used for retrieval ($D$) is the same corpus used to train the initial ST model $M_g$. These experiments aim to evaluate whether instance adaptation helps to make better use of the training data. In the second scenario ("multi-domain"), $M_g$ is trained on data from two domains ($D_1$+$D_2$) and the goal is to maximize performance on both. In this case, the adaptation is performed using as a data pool either the domain-specific material from the same domain of the query $r$, or the whole data from the two domains. In the last scenario ("cross-domain"), $M_g$ is trained on data from one domain only, and it has to be adapted to a new domain. We consider two variants of this scenario. In the first variant, an in-domain data pool from the same domain of the test set is available for retrieval. In the second variant, the data pool contains only the original, out-of-domain training data. The latter variant, in which $M_g$ has to be adapted to unseen test data by only exploiting out-of-domain material, represents the hardest condition from an on-field deployment standpoint.

For each setting, we compute BLEU on the validation set, then the best selection is applied on the test set. We perform instance-based adaptation with the Adam optimizer [21] and choose the best set of hyperparameters among learning rates $\{1, 2, 3\} \times 10^{-3, 4, 5}$, number of retrieved samples $\{1, 5, 10\}$, and number of tuning epochs $\{1, 3, 5\}$. Additionally, we filter out the retrieved samples whose cosine similarity score is below a threshold $\tau$. After an initial exploration, we found out that a threshold $\tau = 0.5$ allows the systems to keep the best performance while reducing the tuning time. As an additional note, we found that the SGD optimizer does not work as well as the Adam optimizer, particularly for the multi/cross-domain adaptation experiments.

5. RESULTS

Intra-domain. The results of the intra-domain experiments are shown in Table 1. In general, the performance on MuST-C is lower than on How2. As pointed out in [11], despite the smaller size of the training corpus, the higher repetitiveness of How2 creates a favourable evaluation condition. Instance-based adaptation, however, provides small but coherent improvements on all the language pairs and on both corpora (from 0.2 to 0.5 for MuST-C and 0.7 for How2). Since the Encoder Features are slightly better than the Raw Features, they will be used in the rest of the experiments. To better understand the effectiveness of our approach, Table 2 shows the impact of adapting on the least similar pair retrieved from the pool, for different numbers of epochs and for each language direction of MuST-C. These results are always higher than the baseline and, by increasing the number of epochs, they deteriorate up to $-7.5$ BLEU points on Fr with 5 epochs. This suggests that instance-based adaptation is sensitive to the quality (i.e., the similarity) of the retrieved material and that our approach is able to identify pairs that are useful to the model, resulting in variable performance gains in all the experiments.

Multi-domain. To evaluate instance-based adaptation in the
Table 3. Results on mixed- and cross-domain experiments.

|        | Train | Test | Pool | D1: How2 | D1: MuST-C | D2: How2 |
|--------|-------|------|------|----------|------------|----------|
| Multi-Domain |      |      |      |          |            |          |
| 1      | D1 + D2 | D1   | -    | 22.7     | 41.0       |
| 2      | D1 + D2 | D1   | D1   | 23.6     | 41.8       |
| 3      | D1 + D2 | D1   | D1+D2| 23.5     | 41.8       |
| Cross-Domain |     |      |      |          |            |          |
| 4      | D1     | D2   | -    | 9.90     | 14.1       |
| 5      | D1     | D2   | D2   | 11.1     | 21.6       |
| 6      | D1     | D2   | D1   | 10.5     | 14.4       |

In this case, instance-based adaptation can account for the data, it is stronger due to its higher generalization capability. When a model has been trained on larger and more diverse data, it is stronger due to its higher generalization capability. In this case, instance-based adaptation can account for the domain shift without performance loss in the initial domains.

Cross-domain. As mentioned in §4.3, we also run our domain-adaptation experiments by training the ST model in one domain and testing it on the other. The similar pairs can be retrieved either from the same domain of the test set or from the training data only. In general, when training and test data come from different domains (Table 3, line 4), the non-adapted models show a significant drop in performance (-1.6 BLEU points for the MuST-C test set and -25.3 for How2). Retrieving from the same domain (line 5) helps with gains over the static model of 1.2 BLEU points for the MuST-C test set and +7.5 for How2. These results are promising but still far from the baseline values reported in Table 1. However, it is important to remark that our baselines have access to the in-domain data in advance, so they work in a more favorable condition. For the sake of comparison, we fine-tuned the baseline models on the incoming pool of in-domain data, but this results in models with performance comparable to the baselines for the new domain without pre-training. Retrieving similar pairs from a different domain (line 6) is extremely difficult, in particular considering the differences between the two datasets (see §4.1). Also in this case, however, instance selection is able to leverage the training data to produce translations that are slightly better than those obtained from the static system (+0.6 on MuST-C and +0.3 on How2).

6. RELATED WORKS AND OPEN ISSUES

The idea of instance-based adaptation exploiting information retrieval dates back to [24], in which it was developed to dynamically customize a language model for ASR. In statistical MT, it was applied for the same purpose in [25, 26] and later, in [27], for domain adaptation. More recently, different variants of the approach have been proposed for neural MT [28, 29, 30, 31] and MT-related tasks [32]. However, differently from ST, all the previously explored translation scenarios involve managing textual data for domain adaptation purposes. These aspects mark the main differences with our work, which, to the best of our knowledge, is the first attempt to apply instance-based adaptation to cope with data paucity in a speech-related task.

On this front, it is worth remarking that the challenges posed by speech input data can not be addressed with the mere application of previous text-based techniques. Indeed, differently from MT that only deals with what a sentence says in terms of content, the ST (or ASR) input has a more complex nature. Together with the conveyed meaning, it also provides information about the acoustic properties of the spoken utterances (e.g. speaker’s voice, recording conditions) describing how meaning is expressed. This adds additional challenges to instance-based adaptation, where fine-tuning can exploit the retrieval of “similar” instances from the point of view of the audio (e.g. a similar voice), the content (a similar meaning), or both. This paper provides a first exploration along this direction, in which the two aspects are not decoupled. A strand of future works will focus on better understanding and balancing their contribution, as well as dynamically leveraging the notion of similarity (e.g. by a similarity-informed setting of the model’s hyper-parameters).

The deeper exploration of different domain-adaptation strategies represents another promising strand of research. In principle, besides maximizing data exploitation in scarce resource conditions, instance-based adaptation would allow to simultaneously manage multiple domains with one single ST system. This is a crucial feature from the industrial standpoint, where training and maintaining domain-dedicated models is costly and time-consuming. We demonstrated the feasibility of the approach with initial experiments but several technical aspects still remain to be explored (e.g. whether to “reset” the model after each update to preserve its performance on all the domains or to keep the updated one so to favour knowledge transfer across domains when processing new translation requests).

7. CONCLUSIONS

We proposed a method to maximize data exploitation in the scarce resource conditions posed by end-to-end ST. The method is based on fine-tuning at inference time a pre-trained model on a set of instances retrieved from the original training data or from an external corpus based on their similarity with the input audio. We evaluated our approach in different data conditions (different languages, in/out-of-domain adaptation) reporting coherent improvements over generic ST systems and highlighting promising research directions for the future.
Acknowledgements

This work is part of a project financially supported by an Amazon AWS ML Grant.

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