PROSODY-AWARE NEURAL MACHINE TRANSLATION FOR DUBBING

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ABSTRACT
We introduce the task of prosody-aware machine translation which aims at generating translations suitable for dubbing. Dubbing of a spoken sentence requires transferring the content as well as the prosodic structure of the source into the target language to preserve timing information. Practically, this implies correctly projecting pauses from the source to the target and ensuring that target speech segments have roughly the same duration of the corresponding source segments. In this work, we propose an implicit and explicit modeling approaches to integrate prosody information into neural machine translation. Experiments on English-German/French with automatic metrics show that the simplest of the considered approaches works best. Results are confirmed by human evaluations of translations and dubbed videos.

Index Terms— Machine Translation, Prosody, Automatic Dubbing

1. INTRODUCTION
Recent advancements in machine translation (MT), largely due to the success of transformer models, have improved the quality of MT significantly [1]. However, when MT is applied to specific use cases, like subtitle translation or automatic dubbing [2] [3] [4], translation quality is not the only dimension by which a model’s performance is evaluated. In subtitles, translation of a source sentence should fit into a certain amount of characters [5]. In dubbing, the translation of a dialogue line should match the timing of the original version to achieve isochrony, i.e. the dubbed version should match the speech-pause temporal arrangement of the original audio [6]. This means, pauses in the source dialogue should be projected into the target dialogue in relatively similar positions [7].

Currently, in an automatic dubbing [6] [8] pipeline, a source transcript with time stamps is first translated and then segmented and time aligned by a prosodic alignment (PA) model that splits the translation into phrases and pauses following the temporal arrangement of the transcript [4][6]. In these two steps, two distinct models are deployed, one for translating and one for segmenting, which is clearly a sub-optimal solution. Our hypothesis is that, better and more suitable translations could be generated by taking into account the prosodic structure to be targeted. In this paper, we propose to combine the two steps into a single MT model that directly generates translations including pause markers. We, therefore, introduce the new task of Prosody Aware MT (PAMT) where MT system should jointly transfer both the meaning and the prosodic information (pause markers, segment duration and speaking rate) from the source to the target.

The task of PAMT is challenging in different ways: 1) MT needs to learn two distinct modeling problems (MT and PA); 2) While projecting pause information MT should not deteriorate translation quality; 3) MT should temporally map source text segments into target segments of similar duration. In particular, the latter challenge requires MT controlling the translation length at the segment level rather than at the sentence level [8].

To our knowledge this is the first work that combines prosody and verbosity control into neural MT. We investigate several approaches and report experimental results on a publicly available speech translation data set [2] for two translation directions, English-French and English-German. Besides introducing a new MT task, we also provide a suite of automatic metrics to evaluate translation quality, prosody alignment, and verbosity of the translation. Finally, we also run subjective human evaluations to measure the impact of our solutions on automatic dubbing.

2. RELATED WORK
The automatic dubbing pipeline introduced by [10] extends a speech-to-speech translation pipeline by incorporating MT with verbosity control [11] and PA [4] modules. More recently, [8] proposed a better verbosity control mechanism on MT so that the length (in characters) of the source and target sentences would match. Specifically, they add an embedding at the beginning of the sentence that indicates whether the target sequence is shorter, the same, or longer than the source sequence. The model is trained with the verbosity embedding corresponding to the actual verbosity level observed in the reference translation. During inference the model is instead run with a “fixed” verbosity-level embedding. As alternatives to the verbosity embedding, other approaches in [11] and [12] inject length control information using positional encoding of the self-attention [1]. Improving over [7], [6] introduced new prosodic alignment approaches that project more accurately the source speech segments into the target translation. Regarding learning distinct tasks with a single model, a closely related work is [13] which trains MT to translate subtitles and to segment them into chunks to fit the screen size.

3. PROSODY-AWARE MACHINE TRANSLATION
The task of Prosody Aware MT involves translating sentences in source language containing pause marker information correctly to target which includes 1) projection of the pauses and 2) verbosity control of phrases across the languages (see Fig. [2]). We refer to phrase as the text between two pauses, and not necessarily a group of words acting as a grammatical unit.

*This work was done during an internship at Amazon.

1We interchangeably use phrase and segment throughout the paper.
No one’s gonna bat an eye. But I gotta ask you a question. You bring what’s left to the commercial disposal outfits you use for work? [pause] ¿Traes lo que queda de los trajes de eliminación comercial que usas para trabajar?

3.1. Dataset

The HEROES data set released by Oktem et. al. (2018) is the only publicly available data for the task of prosody aware MT for English-Spanish but it just contains 7,000 samples in total which renders it rather small to train any NMT model. MustC Cinemas dataset on the other hand has 200,000 samples for 7 language pairs but it is created specifically for the subtitling translation task which is different from PAMT in that subtitling segments the translation on the basis of fixed length constraints (e.g. 42 characters), while PAMT segments input on the basis of pause information contained in the source (audio).

Training of PAMT models requires source and target sentences to contain pause markers information so that model can learn to translate the content and project the pause markers. However, since this information is unavailable from any of the open source data sets, we leverage MustC data set. One natural way to find pauses in a sentence would be to treat punctuation markers as pause breaks. However, after force aligning the audio and text (in the source language) on a small subset of the data, we noticed that speakers do not necessarily pause in correspondence of punctuation markers or other linguistic cues in the text. Rather, they can stop at any point of time - for e.g. to catch their breath or get a glass of water in a talk. To this end, we were motivated to insert the pause markers in the source text with a random scheme. We used a segmented data set from MustC to compute the distribution of phrase lengths and randomly sampled a phrase length every time we insert a pause marker. We then run a light weight PA module which does not use any of the speech information extracted from the source audio.

3.2. Evaluation Metrics

Given that PAMT extends the complexity of the translation task, we introduce additional automatic metrics to measure three attributes: i) translation quality at phrase level, ii) pause project accuracy, and iii) length similarity across source and target.

We leverage BLEU [17] to measure overall translation quality (at corpus level) while at phrase level we evaluate translation quality with ChrF score [18] as precision for higher order n-grams might be skewed towards zero (ChrF-Phrase). To measure the accuracy of the projection of pauses, we compute the percentage of sentences for which the number of pauses in the target is the same as in the source (PPA, pause projection accuracy). To measure length similarity at the phrase level, we consider the percentage of sentences

| Method       | MT+PA | MT+[pause] | MT+DIS Emb | MT+DIS Att |
|--------------|-------|------------|------------|------------|
| PPA          | 100   | 98.9       | 30.1       | 30.1       |

Table 1. Preliminary results on En-De showing that approaches using disentangled features (MT+DIS) with embedding concatenation (Emb) or cross-attention (Att) under perform in terms of pause projection accuracy.

where length of every target phrase is within 10% of the length (in characters) of the corresponding (order wise) source phrase (PhraseVC). Implicitly, PhraseVC also takes into account that number of pause on either side should be the same. We combine phrase-level translation quality with length similarity into a single metric by multiplying ChrF with PhraseVC and name it Acceptability score. We evaluate our proposed models in Section 4 on all five metrics.

4. PROSODY-AWARE MT MODELS

In this section we introduce our baseline model and different modeling techniques to implicitly and explicitly control verbosity of phrases.

4.1. Baseline (MT+PA)

Our baseline model is a two step approach system where we first translate the source text with no pause information using an MT model trained on MustC data and then project the pause markers using the light weight PA module [6], i.e. not leveraging timing and speech information extracted from the source audio.

4.2. Implicit Control of Prosody

4.2.1. Prosody Token (MT+[pause])

Injecting meta information or linguistic markers in NMT is a well studied topic [19, 20, 21]. A straightforward approach is to insert these markers in the text being generated. To project pause markers from source to target language, we simply add a [pause] token to delineate pauses in the source and target sentences. And then, let the NMT model learn the phrase boundaries implicitly by learning the [pause] token positions along with target token sequence. This way we incorporates pauses directly into the vocabulary of the model and allows it to learn semantics of the marker itself, at the same time model also implicitly learns to control the length of the phrase by demarcating the phrase boundaries.

4.2.2. Disentangling Feature (MT+DIS*)

Other approaches of injecting information in NMT use factors [22, 23] either as separate source streams [24, 25] and/or as separate target streams [25]. This approach disentangles the pause marker from the regular text, by adding a binary feature indicating whether there is a pause marker after the current token. Then, the model uses these disentangled features to output two predictions: the next token, and whether there is a pause marker after the next token. We experiment with two ways of modeling these two features: 1) concatenating the embeddings of features and tokens in the input layer, and 2) having distinct encoders and decoders for tokens and features, connected by cross attention to model interactions between tokens and features.

We ran preliminary experiments with the disentangling approach (see Table 1), and compared pause projection accuracy of the baseline (MT+PA) and MT+[pause] models. As it turns out, the accuracy
goes down significantly for the disentangling feature model, thus, we did not pursue this approach any further.

4.3. Explicit Control of Prosody

A drawback of the above approaches is the lack of explicit control over the length of each phrase between the pauses at generation time. While the projection of pause markers is important, we also need to control for the verbosity of phrases to achieve isochrony \[26\]. As a result, we further consider the objective of controlling the verbosity of each segment and as a by product, we can also maximize the accuracy of generating the same number of phrase segments in the target with respect to the source (i.e. PPA metric).

Motivated by prior work on MT-verbosity control \[8\], we apply the same idea at the phrase level. Although this is a more complex level of verbosity control, it aligns with the objective of integrating prosody in MT model. We look at the problem of transferring prosody information from source to target language as a modeling problem which we can control during training. We propose to train a model that jointly learns to project pause markers as well as controlling the verbosity of phrases. We use the simulated training data (refer Sec. 3.1) for this process.

4.3.1. Semi-Autoregressive Modeling (MT+NAR)

Ideally we could approach this problem as a non-autoregressive translation, where we first deterministically project the pause markers at the same position in target sequence as in the source, and then continue generating the tokens non-autoregressively similar to \[27\]. This allows the model to condition on the location of the pause markers and since the model knows the start/end positions it should account for the verbosity from the beginning of the generation step. However, non-autoregressive generation is known to have significantly lower performance than autoregressive generation \[28\].

In lieu of that, instead of training a fully non-autoregressive model that can generate any token in any order, we train the model in a semi-auto regressive manner where we first project the pause markers deterministically from source to target (i.e. the same position as target) and then generate tokens in an auto-regressive manner from left to right. This way, the model is still auto-regressive but it can condition on future pause marker positions, we call this approach \(\text{MT+NAR}\). A target sequence \(X\) condition on future pause marker positions, we call this approach \(\text{MT+NAR}\). A target sequence \(X = [x_0, x_1, \text{[pause]}, x_3]\), in this approach will be generated using Eq. 2 whereas in traditional auto-regressive approach the same sequence will be generated using Eq. 1.

\[
P(X) = P(x_0)P(x_1|x_0)P(x_2 = \text{[pause]}|x_1, x_0)
\]

\[
P(x_3|x_2 = \text{[pause]}, x_1, x_0)
\]

\[
P(X) = P(x_0|x_2 = \text{[pause]}|x_1, x_0)P(x_1|x_0, x_2 = \text{[pause]})
\]

\[
P(x_3|x_2 = \text{[pause]}, x_1, x_0)
\]

4.3.2. Auto-Regressive Modeling (MT+LC)

We also explore a fully auto-regressive approach (MT+LC) inspired by the work of \[29\] where they control verbosity by having an additional length-dependent positional encoding. The main difference from their work is that in PAMT we have to control for verbosity at phrase level. Similar to \[11\], we first compute the ratio of number of characters left to generate in the target sequence:

\[
\frac{1}{\text{# total_char}} \text{ generated - # total_char}
\]

where \(\text{total_char}\) is the length of the target phrase (pre-determined from the source length). These floating point ratios on intervals of 0.1 from 0 to 1 are then quantized to an integer value between 0 and 10. The final embedding is the sum of token embeddings with its positional embeddings along with its length dependent positional embeddings.

During inference, the model uses the total number of characters in the source to compute the ratio of characters left to generate. During training, the model uses the total number of characters in the reference target to compute the ratio of characters left to generate. We cannot use the number of characters in the source in training because the model is trained to generate the reference target itself. Different than previous works which stopped generating at end-of-sequence token, we stop generating when the ratio of characters left to generate is zero. This acts as a hard constraint, whereas previous models \[29\] use a soft constraint.

We ran preliminary experiments comparing MT+NAR with MT+LC and find the NAR approach to be quite aggressive in dropping content in translation due to which the quality of translation goes down significantly by 7% in terms of BLEU score. We therefore drop evaluating NAR model in further iterations.

5. RESULTS

5.1. Automatic Evaluation

Table 2 shows automatic metric results defined in Sec. 3.2 for the various approaches used to model prosody-aware MT. We evaluate all models on \textit{MustC-495} test set \[6\], a post-edited subset of original MustC test set \[16\]. We additionally compare our models against the state of art approach of Lakew et. al. \[8\] for MT verbosity control cascaded with light-weight PA.

Looking at BLEU and Acceptability, the approach of \[8\] shows the highest scores. This is expected given multiple hypotheses generation for re-ranking and leveraging the PA module for phrase segmentation. Our aim is not to improve over \[8\], rather get as close as possible since using a re-ranker function is an orthogonal way to improve over our approach.

The most interesting finding is the proposed PAMT approaches

Table 2. Results comparing the proposed PA-MT approaches, MT+[pause] and LC= Length Control against the current best MT output length control mechanism of Lakew et. al. \[8\], on MustC-495 test set \[6\]. PPA= PauseProjectionAccuracy.

| Method           | BLEU  | ChrF-Phrase | PPA | PhraseVC | Acceptability |
|------------------|-------|-------------|-----|----------|---------------|
| MT + PA          | 27.5  | 58.3        | 100 | 16.1     | 9.6           |
| MT + [pause]     | 27.8  | 59.5        | 99.8| 19.7     | 11.7          |
| MT + LC          | 26.5  | 50.4        | 100 | 39.1     | 17.9          |
| Lakew et. al. [8] PA | 28.8  | 51.2        | 100 | 43       | 22            |

| Method           | Acceptable | Fixable | Wrong |
|------------------|------------|---------|-------|
| MT + [pause]     | 26.2       | 35.3    | 38.5  |
| MT + LC          | 12.1       | 29.0    | 58.9  |
| Lakew et. al. [8]| 26.8       | 36.7    | 36.5  |

Table 3. Human evaluation of MT using 200 randomly selected unique samples from the post-edited benchmark.
Table 3 show results comparing two of our proposed approaches against the state-of-the-art Lakew et al. [8] for MT-verbosity control, that leverages N-best list re-scoring. For En-De, MT+[pause] shows comparable performance with acceptable translations at 26.2% with respect to [8] at 26.8%. For En-Fr, MT+[pause] drops by 5.4% from the best performing [8]. For the MT+LC model, we observed a large drop in the acceptable translations, which we regard as the outcome of an aggressive length control that pushes the model to drop certain tokens. With the absence of N-best list re-scoring from the proposed approaches, we found the human evaluation as a confirmation to the promising direction of the prosody-aware MT.

Table 4. (I) Automatic smoothness metric and (II) Subjective user preferences (% of Wins) for automatic dubbing in a head to head comparison of: (A) MT + PA, (B) MT + [pause], (C) MT + LC, and (D) Lakew et al. [8]+PA. Models B′, D′ are versions of models B, D that also apply the relaxation mechanism in [8]. Significance testing is done for the Wins metric with levels p < 0.05 (*) and p < 0.01 (**).

| (I) | Smoothness | A | B | C | D |
|-----|------------|---|---|---|---|
| en-fr | 44.8 | 53.1 | 60.0 | 40.0 | 55.2 |
| en-de | 51.9 | 56.3 | 65.6 | 48.4 | 56.6 |

| (II) | Wins | A vs. B | A vs. C | B vs. C | D vs. B | D vs. B |
|------|------|---------|---------|---------|---------|---------|
| en-fr | 36.9 | 38.2 | 61.4 | 23.8 | 60.9 | 22 |
| en-de | 32.0 | 41.0 | 48.4 | 30.8 | 51.7 | 30.1 |

Part (I) of Table 4 shows results for automatic evaluation with the Smoothness metric that computes the stability of TTS speaking rate across contiguous target phrases. Part (II) shows the results for subjective human evaluation with the Wins metric. For both automatic and human metrics model B outperforms model A on both languages with relative improvements for Smoothness (fr: +18.5%, de: +8.5%) and Wins (fr: +3.5%, de: +28.1%) with statistically significant (p < 0.01) difference in Wins for de. Model B also outperforms model C with statistically significant difference for both languages for Wins (fr: +137.9%, +57.1%). Though C has the better Smoothness compared to B, as shown in Section 5.2.2, C trades off translation quality for improved Smoothness and hence results in dubs of lower quality.

We select model B and run another set of evaluations comparing B with the state-of-the-art model D. For fair comparison, we use the same light-weight PA for D that was used to generate the training data set. As shown in Table 4, B beats D on both Smoothness (fr: +21.0%, de: +16.3%) and significant Wins (fr: +45.2%, +17.5%) for both languages. This shows that our (simple) MT model with prosody token outperforms the rest of the approaches.

To further test these models, we apply the time-boundary relaxation mechanism [6] that was introduced to improve speaking rate smoothness. We denote with B′ and D′ dubbing obtained with conditions B and D after applying the relaxation mechanism. Notice also that for B′ we apply the full fledged PA segmentation model, also including audio features. From the results, we observe that Smoothness of D′ and B′ is improved as expected compared to D and B. Additionally Smoothness of D′ and B′ are now on par. Also, D′ beats B′ for Wins for on fr (+28.2%, p < 0.01) and obtains comparable Wins for de. The reason is that after adding relaxation, while both conditions reach comparable smoothness, D actually provides more acceptable translations than B (cf. Table 3). In fact, in order to generate good dubs, both correct translations and smooth speaking rates are necessary, which is the main challenge for prosody-aware MT.

6. CONCLUSION

In this work, we extend the task of machine translation by also transferring prosodic information from the source to the target sentence, specifically speech pause markers. We proposed approaches that try to predict the correct number of prosody markers, their positions, and that try control verbosity at the level of phrase segments. We compared these models against strong baselines that decouple the machine translation and prosodic alignment tasks. We conducted automatic and human evaluations both of MT quality and on automatic dubbing, which relies on prosodic and temporal information projected from the source. Our findings confirm the viability of integrating prosodic information in the machine translation process.
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