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Subtitles to Segmentation: Improving Low-Resource Speech-to-Text Translation Pipelines

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Abstract

In this work, we focus on improving ASR output segmentation in the context of low-resource language speech-to-text translation. ASR output segmentation is crucial, as ASR systems segment the input audio using purely acoustic information and are not guaranteed to output sentence-like segments. Since most MT systems expect sentences as input, feeding in longer unsegmented passages can lead to sub-optimal performance. We explore the feasibility of using datasets of subtitles from TV shows and movies to train better ASR segmentation models. We further incorporate part-of-speech (POS) tag and dependency label information (derived from the unsegmented ASR outputs) into our segmentation model. We show that this noisy syntactic information can improve model accuracy. We evaluate our models intrinsically on segmentation quality and extrinsically on downstream MT performance, as well as downstream tasks including cross-lingual information retrieval (CLIR) tasks and human relevance assessments. Our model shows improved performance on downstream tasks for Lithuanian and Bulgarian.

Keywords: Speech Segmentation, Lithuanian, Bulgarian, Low-Resource Languages

1. Introduction

A typical pipeline for speech-to-text translation (STTT) uses a cascade of automatic speech recognition (ASR), ASR output segmentation, and machine translation (MT) components (Cho et al., 2017). ASR output segmentation is crucial, as ASR systems segment the input audio using purely acoustic information and are not guaranteed to output sentence-like segments (i.e., one utterance may be split if the speaker pauses in the middle, or utterances may be combined if the speaker does not pause). Since most MT systems expect sentences as input, feeding in longer unsegmented passages can lead to sub-optimal performance (Koehn and Knowles, 2017).

When the source language is a low-resource language, suitable training data may be very limited for ASR and MT, and even nonexistent for segmentation. Since typical low-resource language ASR audio datasets crawled from the web do not have hand-annotated segments we propose deriving proxy segmentation datasets from TV show and movie subtitles. Subtitles typically contain boundary information like sentence-final punctuation and speaker turn information, even if they are not exact transcriptions.

We further incorporate part-of-speech (POS) tag and dependency label information (derived from the unsegmented ASR outputs) into our segmentation model. This noisy syntactic information can improve model accuracy.

We evaluate our models intrinsically on segmentation quality and extrinsically on downstream MT performance. Since the quality of the underlying MT of low-resource languages is relatively weak, we also extrinsically evaluate our improved STTT pipeline on document and passage-level cross-lingual information retrieval (CLIR) tasks. We report results for two translation settings: Bulgarian (BG) to English and Lithuanian (LT) to English.

This paper makes the following contributions: (i) We propose the use of subtitles as a proxy dataset for ASR segmentation. (ii) We develop a simple neural tagging model using noisy syntactic features on this dataset. (iii) We show downstream performance increases on several extrinsic tasks: MT and document and passage-level CLIR tasks.

2. Related Work

Segmentation in STTT has been studied quite extensively in high resource settings. Earlier models use kernel-based SVM models to predict sentence boundaries from ngram and part-of-speech features derived from a fixed window size (Sridhar et al., 2013).

Recent segmentation models use neural architecture, such as LSTM (Sperber et al., 2018) and Transformer models (Pham et al., 2019). These models benefit from large training data available for the high-resource languages. For example, the STTT task for English audio to German include TED corpus, which contains about 340 hours of well transcribed data. To our knowledge, these data do not exist for the languages we are interested in. In addition, these models predict full punctuation marks as well as casing for words (binary classification of casing). However, since our translation models are trained on unpunctuated texts, we restrict the classification task to predicting full stop boundaries only.

Although recent works have looked at end-to-end speech-to-text translation, in a high-resource setting, these models (Vila et al., 2018) achieved at most a 0.5 BLEU score improvement over a weak cascaded model. In general, the available data for end-to-end neural models is insufficient or non-existent in all but the most specific circumstances; for any pair of languages there will inevitably be far less translated speech data available than (a) monolingual transcribed speech data; (b) monolingual language modelling training data; or (c) parallel corpora of translated text data. This means that separate ASR and MT systems will generally have the benefit of training on much larger datasets.

I think you should know something. You know. I ...

y		$=$	0	0	0	0	0	1	0	1	0	$\cdots$
	$token$	$=$	i	$think$	you	$should$	$know$	$something$	you	$know$	i	$\cdots$
x	dep	$=$	$nsubj$	$root$	$nsubj$	aux	$ccomp$	obj	$nsubj$	$acl : relcl$	$nsubj$	$\cdots$
	pos	$=$	$PRON$	$VERB$	$PRON$	AUX	$VERB$	$PRON$	$PRON$	$VERB$	$PRON$	$\cdots$

Figure 1: An excerpt of subtitles (top) and the corresponding segmentation data derived from it (bottom). Punctuation is to mark boundaries $y_i = 1$. Part-of-speech and dependency relations are parsed from each document.

Corpus	BG		LT	
	P	U	P	U
OpenSub.	164,798	41.9	32,603	49.5
ANALYSIS	215	37.3	312	57.2
DEV	238	–	258	–

Table 1: Number of passages (P) in each dataset and average number of utterances per passage (U).

Lang.	Model	F1 ↑	WD ↓
BG	Sub	**56.78**	**33.9***
	Sub+S	56.40	34.4
LT	Sub	44.14	49.2
	Sub+S	**45.94***	**47.0***

Table 2: Intrinsic evaluation of F1 and windowdiff(WD) on ANALYSIS data. +S indicates models with syntactic features. * indicates statistical significance

3. Datasets

3.1. Segmentation Datasets

We obtain BG and LT subtitles from the OpenSubtitles 2018 corpus (Lison and Tiedemann, 2016), which contains monolingual subtitles for 62 languages drawn from movies and television. We sample 10,000 documents for BG and all available documents for LT (1,976 in total). Sentences within a document are concatenated together. Some documents are impractically long and do not match our shorter evaluation data, so we divide each document into 20 equally sized passages (splitting on segment boundaries), roughly matching the average evaluation document size. In addition to speaker turns in subtitles, we treat any of the characters *():-!?.* as segment boundaries. We split the data into a training (75%) and validation set. See Table 1 for corpus statistics.

3.2. Speech Datasets

To perform extrinsic evaluation of a STTT pipeline, we use the speech collections from the MATERIAL[1] program, which aims at finding relevant audio and text documents in low resource languages given English queries. This can be framed as an cross-language information retrieval (CLIR) task, where STTT plays a crucial part in improving the quality of downstream tasks of machine translation and information retrieval.

The speech data consists of three domains (news broadcast (NB), topical broadcast (TB) such as podcasts, and conversational speech (CS)) from multiple low-resource languages. NB and TB have one speaker and are more formal, while CS has two and is more casual. For each language, we have two collections of speech documents, the ANALYSIS and DEV sets (each containing a mix of NB, TB, and CS). Only the ANALYSIS datasets include ground truth transcriptions (including segmentation), allowing us to evaluate segmentation and translation quality. However, we can use both datasets for the extrinsic CLIR evaluation since MATERIAL provides English queries with ground truth relevance judgements.

4. Segmentation Model

We treat ASR segmentation as a sequence tagging problem. Let $x_1, \ldots, x_n \in \mathcal{V}^n$ be a passage of n ASR output tokens drawn from a finite vocabulary $\mathcal{V}$. We also define an indicator variable y_i for each token, where $y_i = 1$ indicates a segment boundary between tokens x_i and x_{i+1}. Each token x_i is additionally associated with a corresponding POS tag and dependency label. An example input and output are shown in Figure 1.

We explore a Long Short-Term Memory (LSTM)-based model architecture for this task. In the input layer we represent each word as a 256-dimensional word embedding; when using syntactic information, we also concatenate its POS tag and dependency label embeddings (both 32-dimensional). POS tags and dependency labels are obtained using the UDPipe 2.4 parser (Straka and Straková, 2017). Since we do not have punctuation on actual ASR output, we parse each document with this information removed. Conversational speech between two speakers comes in separate channels for each speaker so we concatenate the output of each channel and treat it as a distinct document when performing segmentation. The segmentation are then merged back into one document using segmentation timestamp information before being used in downstream evaluations.

We then apply a bi-directional LSTM to the input sequence of embeddings to obtain a sequence of n hidden states, each of 256 dimensions (after concatenating the output of each direction). Each output state is then passed through a linear projection layer with logistic sigmoid output to compute the probability of a segment boundary $p(y_i = 1|x)$. The log-likelihood of a single passage/boundary annotation pair is $\log p(y|x) = \sum_{i=1}^{n} \log p(y_i|x)$. All embeddings and parameters are learned by minimizing the negative log-likelihood on the training data using stochastic gradient descent.

[1] www.iarpa.gov/index.php/research-programs/material

Lang.	Model	EDI-NMT			UMD-NMT			UMD-SMT		
		NB	TB	CS	NB	TB	CS	NB	TB	CS
BG	Acous.	24.49	24.65	7.13	**33.25**	29.82	10.32	**35.30**	31.11	11.08
	Sub	24.83	**25.28**	**8.07**	32.89	**30.35**	11.10	35.15	**31.55**	11.32
	Sub+S	**24.90**	25.25	8.04	32.96	30.23	**11.24**	35.16	**31.55**	**11.57**
LT	Acous.	**16.03**	**17.00**	**6.53**	**16.31**	**18.67**	**5.92**	**16.52**	**17.60**	**6.34**
	Sub	14.83	15.59	6.33	15.41	17.47	4.66	15.93	17.14	5.86
	Sub+S	14.97	15.77	6.43	15.40	17.54	5.11	15.76	17.19	6.00

Table 3: Document level BLEU scores on ANALYSIS set. +S indicates model with syntactic features.

Lang.	Model	EDI-NMT			UMD-NMT			UMD-SMT		
		NB	TB	CS	NB	TB	CS	NB	TB	CS
BG	Acous.	0.289	**0.482**	0.052	0.394	0.175	0.005	0.426	0.355	0.148
	Sub	0.289	0.435	**0.127**	0.475	0.19	**0.111**	**0.433**	0.361	**0.245**
	Sub+S	**0.312**	0.443	0.014	**0.498**	**0.247**	0.074	**0.433**	**0.368**	**0.245**
LT	Acous.	0.293	**0.304**	0.005	0.356	0.291	0.0	0.359	**0.484**	0.0
	Sub	0.293	0.266	0.011	**0.393**	0.278	0.0	**0.484**	0.42	0.0
	Sub+S	**0.365**	0.254	**0.111**	0.377	**0.305**	0.0	0.459	0.382	0.0

Table 4: AQWV scores on ANALYSIS set. +S indicates model with syntactic features.

5. Experiments and Results

Pipeline Components All pipeline components were developed by participants in the MATERIAL program (Oard et al., 2019). We use the ASR system developed jointly by the University of Cambridge and the University of Edinburgh (Ragni and Gales, 2018; Carmantini et al., 2019).

We evaluate with three different MT systems. We use the neural MT model developed by the University of Edinburgh (EDI-NMT) (Junczys-Dowmunt et al., 2018) and the neural and phrase-based statistical MT systems from the University of Maryland, UMD-NMT and UMD-SMT respectively (Niu et al., 2018).

For the IR system, we use the bag-of-words query model implemented in Indri (Strohman et al., 2005).

5.1. Intrinsic Evaluation

We evaluate the models on F-measure of the boundary prediction labels, as well as WindowDiff (Pevzner and Hearst, 2002), a metric that penalizes difference in the number of boundaries between the reference and predicted segmentation given a fixed window. We obtain a reference segmentation as described in subsection 3.1. We indicate our models without and with syntactic features as Sub and Sub+S respectively. Table 2 shows our results on the ANALYSIS data. For BG, which is trained on an order of magnitude more data, the model without syntactic information performs slightly better. Meanwhile, in the lower-data LT setting, adding syntactic cues yields a 2.2 point improvement on WindowDiff.

5.2. Extrinsic Evaluations

We perform several extrinsic evaluations using a pipeline of ASR, ASR segmentation, MT, and information retrieval (IR) components.

5.2.1. MT Evaluation

Our first extrinsic evaluation measures the BLEU (Papineni et al., 2002) score of the MT output on the ANALYSIS sets, where we have ground truth reference English translations. As our baseline, we compare the same pipeline using the segmentation produced by the acoustic model of the ASR system, denoted Acous.

Since each segmentation model produces segments with different boundaries, we are unable to use BLEU directly to compare to the reference sen- tences. Thus, we concatenate all segments of a document and treat them as one segment, which we refer to as "document-level" BLEU score.

Table 3 shows our results.

For BG, both Sub and Sub+S models improve BLEU scores over the baseline segmentation on the more informal domains (TB, CS). Across all MT systems, Sub+S performs best on conversations (CS), while Sub performs best on topical monologues (TB).

For LT, the segmentation models do not provide any improvement on BLEU scores. However, there is generally an increase in BLEU with the syntactic features, consistent with the intrinsic results.

5.2.2. Document-level CLIR Evaluation

Our second extrinsic evaluation is done on the MATERIAL CLIR task. We are given English queries and asked to retrieve conversations in either BG or LT. In our setup, we only search over the English translations produced by our pipeline. We evaluate the performance of CLIR using the Actual Query Weighted Value (AQWV) (NIST, 2017).

Table 4 shows the results of the CLIR ANALYSIS evaluation.

Similar trends are found on the DEV set. On BG, our models yield large increases in AQWV for both UMD MT models, especially on CS, where the gains are on the order of 0.1 absolute points. Syntactic information also proves use-

Lang.	Model	EDI-NMT			UMD-NMT			UMD-SMT		
		NB	TB	SMT	CS	TB	CS	NB1	TB	CS
BG	Acous.	0.583	0.258	0.065	**0.716**	**0.305**	**0.075**	0.725	0.312	**0.139**
	Sub	**0.774**	**0.266**	0.071	0.658	0.296	0.037	**0.675**	0.383	0.076
	Sub+S	**0.774**	0.186	**0.074**	0.658	0.273	0.054	**0.675**	**0.407**	0.105
LT	Acous.	0.161	0.195	0.262	**0.325**	0.307	0.19	**0.372**	**0.404**	0.262
	Sub	**0.348**	0.314	**0.333**	0.271	0.385	**0.262**	0.304	0.386	0.262
	Sub+S	0.269	**0.317**	**0.333**	**0.300**	**0.390**	**0.262**	0.320	0.385	0.262

Table 5: AQWV scores on DEV set. +S indicates model with syntactic features.

Lang.	MT	Relevance	
		A	M
BG	EDI-NMT	0.564	**0.566**
	UMD-NMT	0.572	**0.615**
	UMD-SMT	0.593	**0.658**
	Reference	0.862	
LT	EDI-NMT	**0.576**	0.554
	UMD-NMT	**0.663**	0.593
	UMD-SMT	**0.681**	0.614
	Reference	0.9	

Table 6: Passage-level evaluation comparing relevance using the Sub+S model (M), the acoustic baseline (A).Evaluation of reference translation is also provided for each language.

ful, as Sub+S performs best in six of nine settings. Despite the lack of increase in BLEU for LT, the segmentation models show large increases in AQWV over the baseline, especially on UMD-SMT/NB where the Sub model improves AQWV by 0.125 points absolutely. Only EDI-NMT was able to yield nonzero retrieval scores for the CS domain, with Sub+S improving by 0.106 points.

5.2.3. Passage-level CLIR Evaluation

We also conduct a human evaluation to compare our segmentation model with acoustically-based segmentation and investigate which makes it easier for annotators to determine MT quality and query relevance. To this end, we collect relevant query/passage pairs and ask Amazon Mechanical Turk Workers[2] to judge quality and relevance.

The MT quality judgments were done on a 7-point scale (integer scores from -3 to 3 inclusive), and the query relevance judgments on a 3-point scale (0, 0.5, and 1). A perfect pipeline should achieve 3 in MT quality and 1 in query relevance. We give each HIT (each containing five passages) to three distinct Workers. Figure 2 shows the detailed instruction we have for the HIT. Also see Figure 3 for an example passage as displayed in a HIT.

We require Workers to have a minimum lifetime approval rate of 98% and number of HITs approved greater than 5000. Workers that provide the same quality score for all snippets in a HIT are manual checked by the author.

To generate our evaluation data, we use YAKE! (Campos et al., 2018) to extract keywords from documents in the ANALYSIS dataset. We then collect 3-segment passages of each document and pair them with a keyword that appears in the middle utterance in the ground truth transcription; these will become the passages and queries we give to Workers. We match the timestamps of these passages in the ground truth transcription with the output of the Sub+S model and the Acous. model, and feed those segments through MT. We randomly sample 200 passages each from BG and LT and present them in three conditions (ground truth or pipeline with either our segmentation, or acoustic segmentation). Please refer to Figure 2 and Figure 3 in the appendix for the instruction and example provided for the Mechanical Turk task.

Table 6 shows the results. We omit the differences in quality because they were not significant. The human reference transcriptions received 0.917 (BG) and 1.153 (LT) out of a maximum of 3.0, suggesting that speech excerpts, even when well translated, are hard to understand out of context. On the relevance assessment, we see consistent improvements in BG using the Sub+S model, regardless of the MT system, although only UMD-SMT is statistically significant.[3]

We do not see improvements on relevance on LT, although no differences are significant. While this might seem counter-intuitive, given that the Sub+S model leads to consistent improvement in LT CLIR, it is corroborated by the lower BLEU scores on LT, suggesting the CLIR pipeline is less affected by poor fluency than are actual human users who need to read the output to determine relevance.

5.3. Discussion

Overall, when subtitle data is plentiful, as is the case with BG, we see consistent improvements on downstream MT and CLIR tasks. Moreover, we find consistent improvements in the CS domain where acoustic segmentation is likely to produce choppy, non-sentence-like segments. Even on LT, where there is not enough data to realize gains in translation, it still has positive effects on the document-level CLIR task.

6. Conclusion

We present an approach for ASR segmentation for low-resource languages for the task of STTT. On extrinsic evaluations of MT, IR, and human evaluations, we are able to

[2] `https://www.mturk.com/`

[3] Using the approximate randomization test at the $\alpha = .05$ level (Riezler and Maxwell, 2005).

show improvements in the downstream MT and CLIR. In future work, we hope to explore methods to make the tagger model more robust to noise, since word-error rates of ASR in the low-resource condition tend to be high

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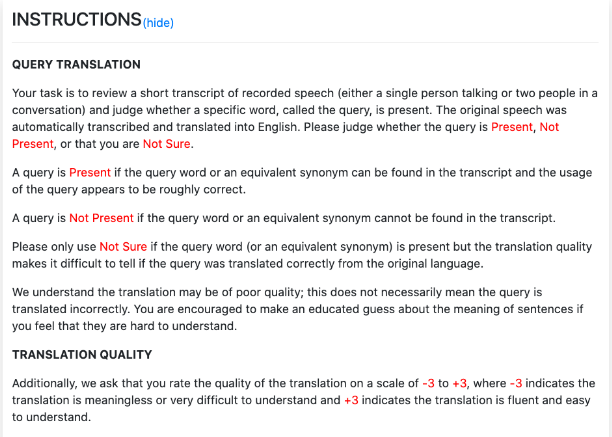
A. Additional Document-level CLIR Evaluation



INSTRUCTIONS (hide)

QUERY TRANSLATION

Your task is to review a short transcript of recorded speech (either a single person talking or two people in a conversation) and judge whether a specific word, called the query, is present. The original speech was automatically transcribed and translated into English. Please judge whether the query is Present, Not Present, or that you are Not Sure.

A query is Present if the query word or an equivalent synonym can be found in the transcript and the usage of the query appears to be roughly correct.

A query is Not Present if the query word or an equivalent synonym cannot be found in the transcript.

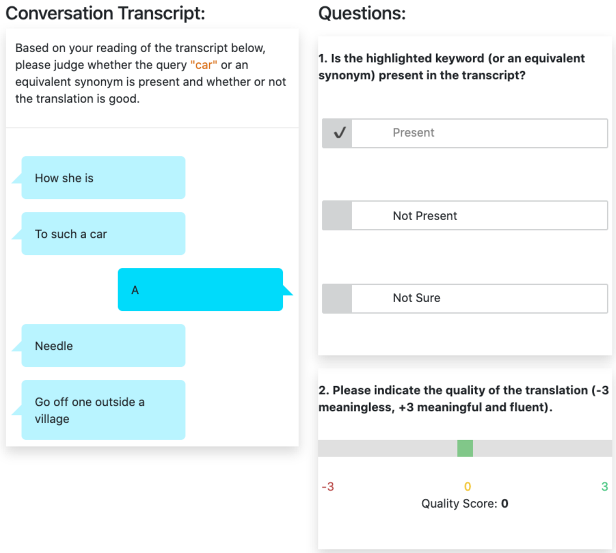
Please only use Not Sure if the query word (or an equivalent synonym) is present but the translation quality makes it difficult to tell if the query was translated correctly from the original language.

We understand the translation may be of poor quality; this does not necessarily mean the query is translated incorrectly. You are encouraged to make an educated guess about the meaning of sentences if you feel that they are hard to understand.

TRANSLATION QUALITY

Additionally, we ask that you rate the quality of the translation on a scale of -3 to +3, where -3 indicates the translation is meaningless or very difficult to understand and +3 indicates the translation is fluent and easy to understand.

Figure 2: The instructions we provided for the Mechanical Turk task.



Conversation Transcript:

Based on your reading of the transcript below, please judge whether the query "car" or an equivalent synonym is present and whether or not the translation is good.

How she is

To such a car

A

Needle

Go off one outside a village

Questions:

1. Is the highlighted keyword (or an equivalent synonym) present in the transcript?

☑ Present

☐ Not Present

☐ Not Sure

2. Please indicate the quality of the translation (-3 meaningless, +3 meaningful and fluent).

-3 0 3

Quality Score: **0**

Figure 3: An example of our Amazon Mechanical Turk relevance and quality judgment task.