Detecting Pause Anomalies in Read Japanese L2 Speech

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Background and Objectives

Pronunciation feedback has been shown to be effective in second-language pronunciation training, but it can be difficult to obtain. Software-based mispronunciation feedback can fill this need.

Here we focus on two types of errors in speakers' pause patterns:

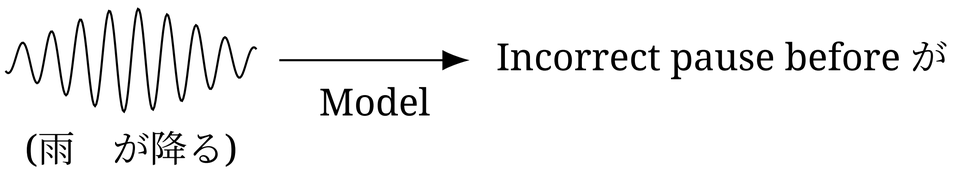
Incorrect Pause

A word boundary where the speaker paused, but L1 (native) speakers would normally not pause (e.g. 雨|が降る)

Missing Pause

A word boundary where the speaker did not pause, but most L1 speakers would pause (e.g. 美しい∧本当に 今日の景色は。)

We'd like to build the "Model" in the following figure:



Method

We use two main components:

- **Forced aligner**: detects pauses in the input
- **Pause model**: predicts where native speakers would pause, outputting a classification PAUSE / NO_PAUSE for every word boundary

We use an off-the-shelf forced aligner, but for the pause model, we tried two approaches:

Full Cascade

We apply ASR to the input utterance and then feed the result to a separate pause model that predicts the word boundaries in the transcription where a native speaker would have paused.

$$\text{AUDIO} \xrightarrow{\text{ASR}} \text{TEXT} \xrightarrow{\text{PM}} \text{PAUSE PATTERN}$$

The pause pattern is a sequence of inferred pause probabilities, one for each word boundary.

Fused Model

We use a single model that transcribes the utterance, interspersing the transcript with pause markers.

$$\text{AUDIO} \xrightarrow{\text{ASR\_PM}} \text{TEXT W/ PAUSE MARKERS}$$

For example, if the input audio contains the phrase つ ま り 彼 は 来 な い, then we should get つまり [PAUSE] 彼は来ない, regardless of the observed pause pattern.

To get a final output, we compare the *predicted* typical pause locations and the *actual* pauses found by the forced aligner:

Pred	うん	|	大学	を	やめて	ね	|	会社	を	作る	らしい	よ
Actual	うん		大学	を	やめて	ね	|	会社	を	| 作る	らしい	よ
	うん	∧	大学	を	やめて	ね	|	会社	を	| 作る	らしい	よ

Experiment

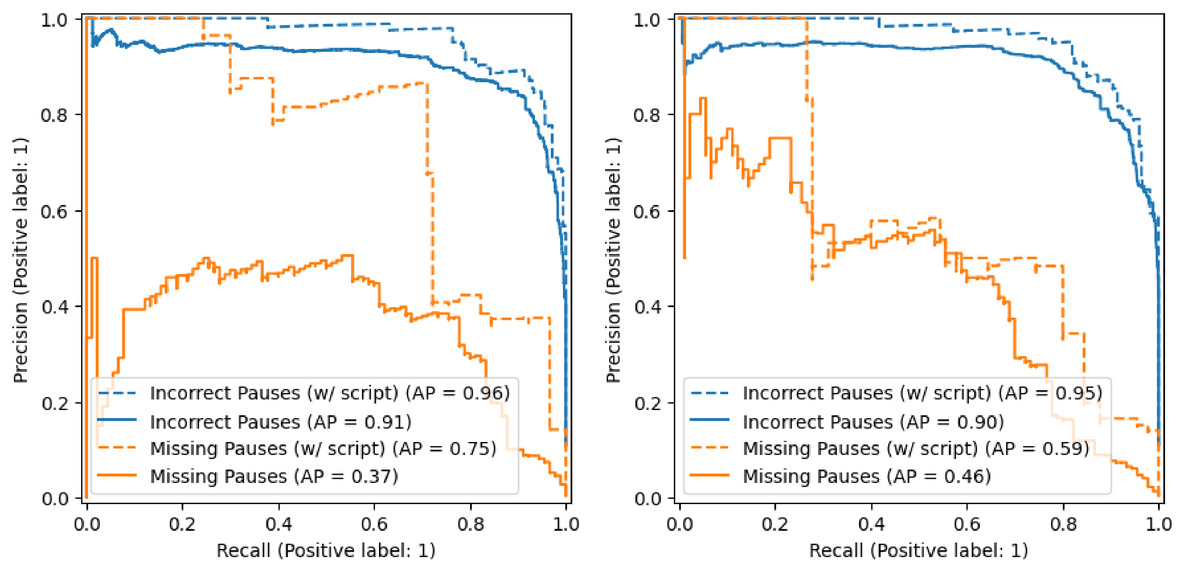
We use reazonspeech-espnet-v2 for ASR and the Montreal Forced Aligner.

For the full-cascade pause model, we fine-tune XLM-RoBERTa based on a subset of the JVS, JSUT, and UME-JRF corpuses.

We build two fused pause model+FA models, trained only on UME-JRF:

- a w2v-BERT 2.0-based model trained with CTC loss
- a Whisper (small)-based model. In this case, we additionally experiment with forcing Whisper to produce the correct transcription when the script is available (denoted *w/ script* in the results).

Results



Precision-recall curves for the **fully-cascaded** model in two training conditions

(*left*: average pause pattern, *right*: one utterance, one sample)

Model Name	Condition	Precision	Recall	F1-Score
Whisper small	Incorrect Pauses	0.64	0.96	**0.77**
	Missing Pauses	0.15	0.50	0.24
	Incorrect Pauses (w/ script)	0.66	0.93	0.78
	Missing Pauses (w/ script)	0.17	0.66	0.27
w2v-BERT 2.0	Incorrect Pauses	0.57	0.96	0.71
	Missing Pauses	0.18	0.62	**0.28**

Results for **pause model+FA** models

To provide a flavor for the kinds of sentences that are difficult, here are some patterns where the text-based pause model struggled:

- **Overindexing on particles**: our models tended to incorrectly predict a pause after an early particle, making mistakes like "それは|たいてい一時間にも及ぶ" or "イランに|天気予報はない". We saw a similar phenomenon with words like もちろん that appeared in the training set often and were usually followed by a pause.
- **Missing semantic pauses**: some words like 何げなく and まるで break up a sentence, but these happened to show up only in our validation set, so the model did not do well on such examples.
- **Lists**: when multiple nouns are listed (e.g. 生活扶助医療扶助住宅扶助など) the model struggles to break them up properly.

Discussion

Since we only need to catch some pausing mistakes, the **full-cascade** model, when operating on the left side of the curve, is **usable in practice**.

The performance of the pause model+FA approach is **less exciting**, but our models were trained on less data. Our evaluation was also a bit unfair to these models, since the outputs had to be aligned with the reference script, where in practice this wouldn't be the case.

Our **evaluation method** has room for improvement. By averaging pause probabilities over multiple utterances, **we assume that pauses** at one word boundary **are independent** of pauses at others. For a simple counter-example, notice that pauses are unlikely to occur in succession. To test whether this is a significant effect, we compared the accuracy of the two training conditions of the fully cascaded models on predicting the pause patterns of held-out native utterances. Both have similar performance, even though only the *one utterance, one sample* model can capture pauses that are not independent of each other.