SONY

Polyphone disambiguation and accent prediction using pre-trained language models in Japanese TTS front-end

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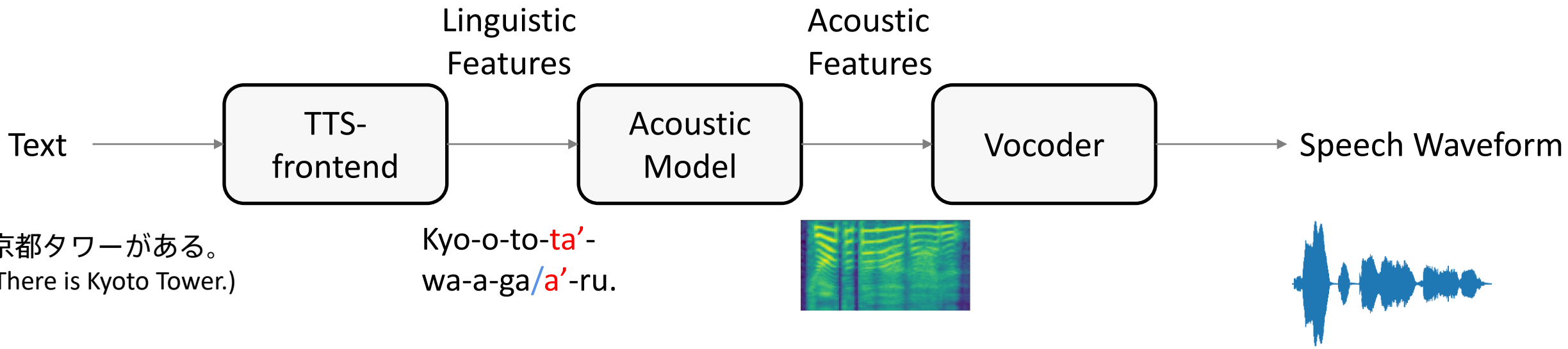
TTS frontend

TTS frontend converts text to phonetic symbol sequences.



Highly language dependent
Japanese has mainly two characteristics.

Japanese Characteristics related to TTS

- Japanese has a variety of character types and its pronunciation.
  - Some Kanji have multiple candidate pronunciations corresponding to different meanings.

このカレーは**辛い**。(This curry is **spicy**.)
- ka-ra-i (spicy)
- tsu-ra-i (hard)

➡ **Polyphone disambiguation**

- Japanese is pitch (High/Low)-accent language.
  - Some words have the same pronunciation but different accents and meanings.


chopsticks — ha / shi


bridge — ha / shi

  - The pitch accent is represented by the **accent phrase boundary** and the **accent nucleus position**.

Word		京都	タワー	が	ある
Accent	High / Low	kyo / o – to – ta / wa – a – ga			a / ru

➡ **Accent prediction**

Wrong pronunciation & accent lead wrong comprehension.
Japanese TTS system requires "**polyphone disambiguation (PD)**" and "**accent prediction (AP)**."

Motivation

Pronunciation and accent depend on context.

PD: このカレーはとても**辛い (ka-ra-i)**。 体調が悪くてとても**辛い (tsu-ra-i)**。

This curry is very **spicy**. I'm sick and it's very **hard**.

AP:

京都 (Kyoto)	タワー (tower)	上空 (above)
kyo'-o-to	ta'-wa-a	jo-o-ku-u
kyo-o-to-ta'-wa-a		jo-o-ku-u

Semantic relationship

However, existing methods only utilize local context.

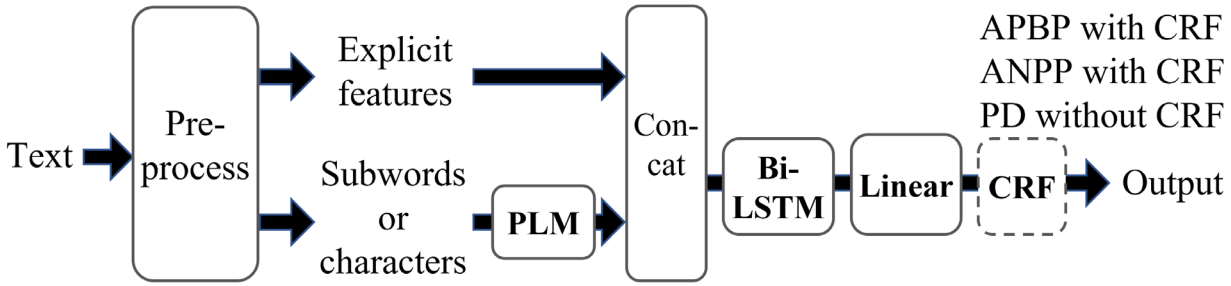
PD: KyTea[Neubig+,10] (pointwise prediction)

AP: TASET[Suzuki+,17] (linear-chain CRF)

How to take "longer/rich context" into account?
-> Using **Pre-trained Language Models**.

Japanese TTS-frontend with Pretrained Language Models (PLMs)

Model:



Features

Explicit(EF):

features derived from morphological analysis

Implicit(PLM):

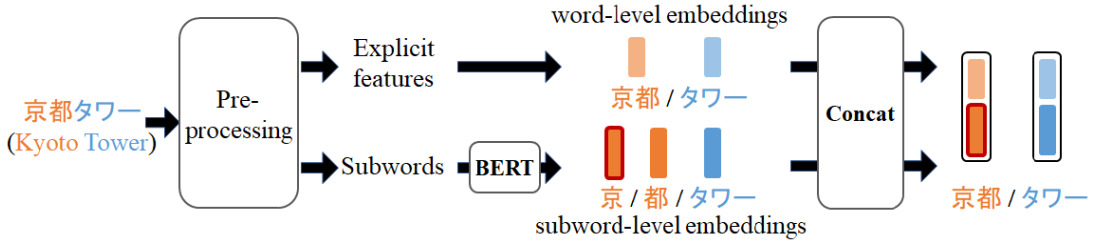
features from Pretrained Language Models

BERT: subword based masked language model

Flair: character based bidirectional encoder

Word	京都	タワー	が	ある	
POS	Noun	Noun	Particle	Verb	Explicit Features (EFs)
Original pronunciation	kyo-o-to	ta-wa-a	ga	a-ru	
Accent nucleus position of each word	kyo \ o – to	ta \ wa – a	ga	a \ ru	
Other features	・・・	・・・	・・・	・・・	

Explicit and implicit features are concatenated and input into BiLSTM.



Dataset for Experiments

- Polyphone disambiguation

  Focus on 92 frequently used polyphonic words

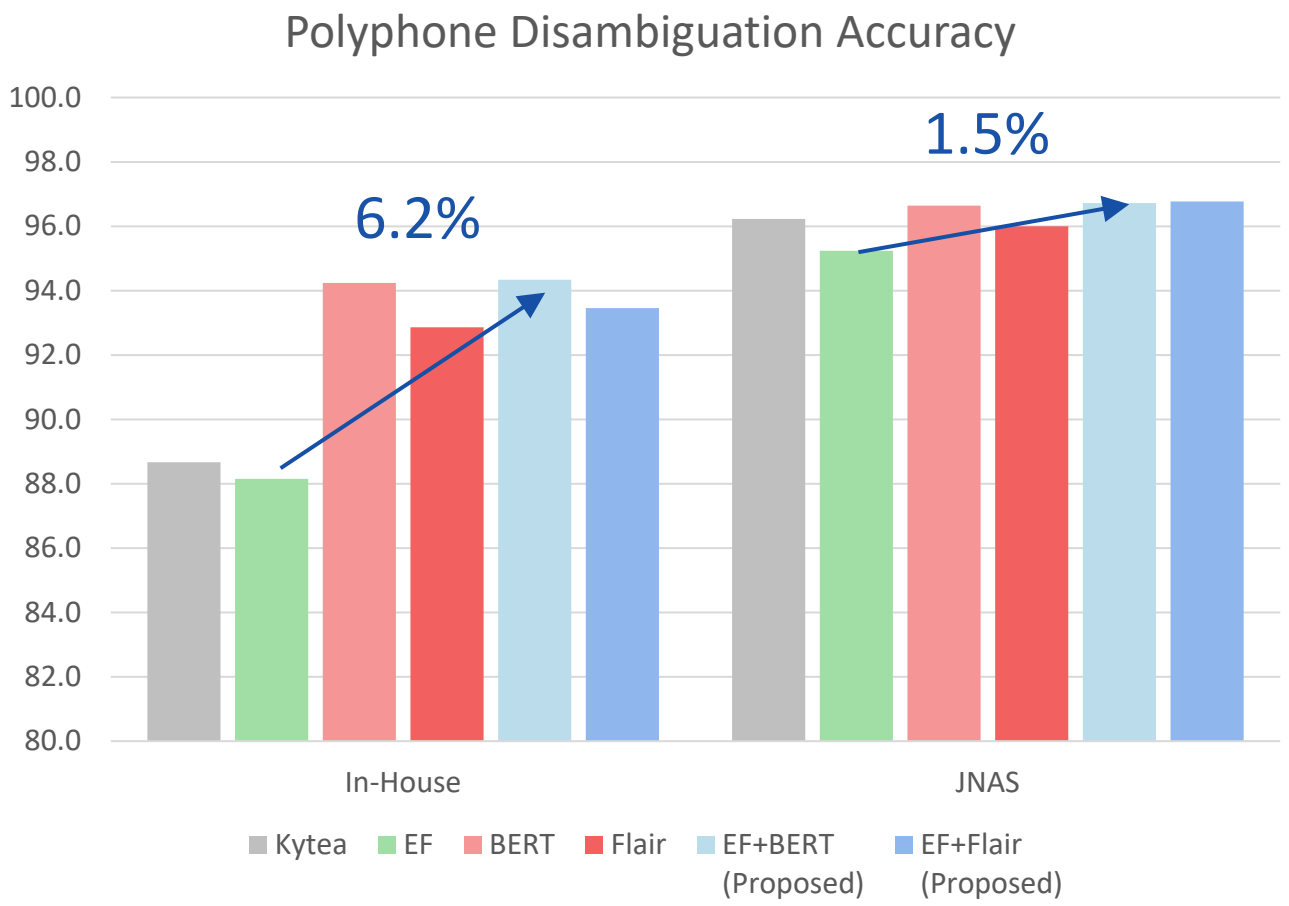
	#sentence	usage	Source
In-house	39,353 (24,117 / 5,156 / 10,080)	Train/dev/test	Wikipedia/TV captions/ novels/CSJ/JSUT
Public (JNAS)	5,642	test	JNAS

- Accent Prediction

	#sentence	usage	Source
In-house	9,497 (7,768 / 864 / 865)	Train/dev/test	TV caption
Public (JSUT)	5,000	test	JSUT

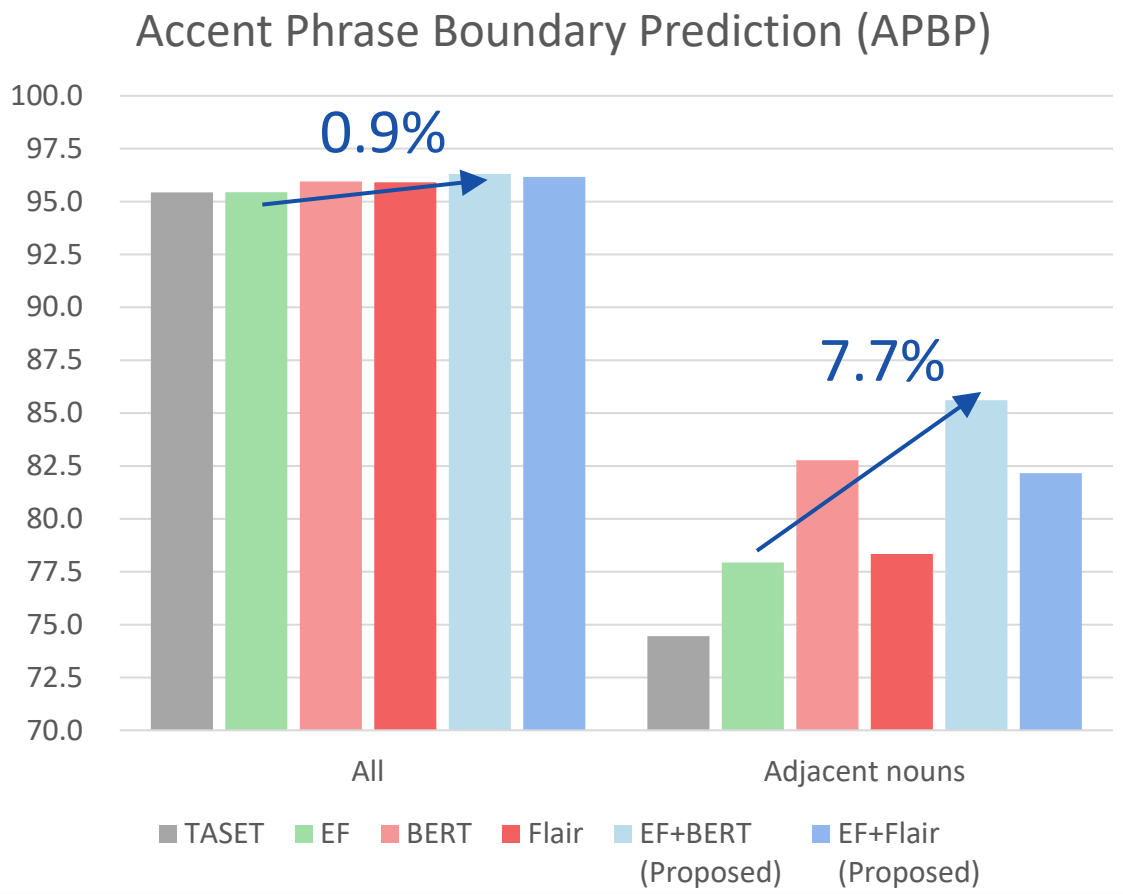
1: K. Maekawa, “Corpus of spontaneous Japanese: its design and evaluation,” in ISCA/IEEE Workshop on Spontaneous Speech Processing and Recognition, 2003, pp. 7–12.
2 : R. Sonobe, S. Takamichi, and H. Saruwatari, “JSUT corpus: free largescale Japanese speech corpus for end-to-end speech synthesis,” arXiv preprint arXiv:1711.00354, 2017.
3: ASJ Japanese Newspaper Article Sentences Read Speech Corpus (JNAS), http://research.nii.ac.jp/src/JNAS.html.

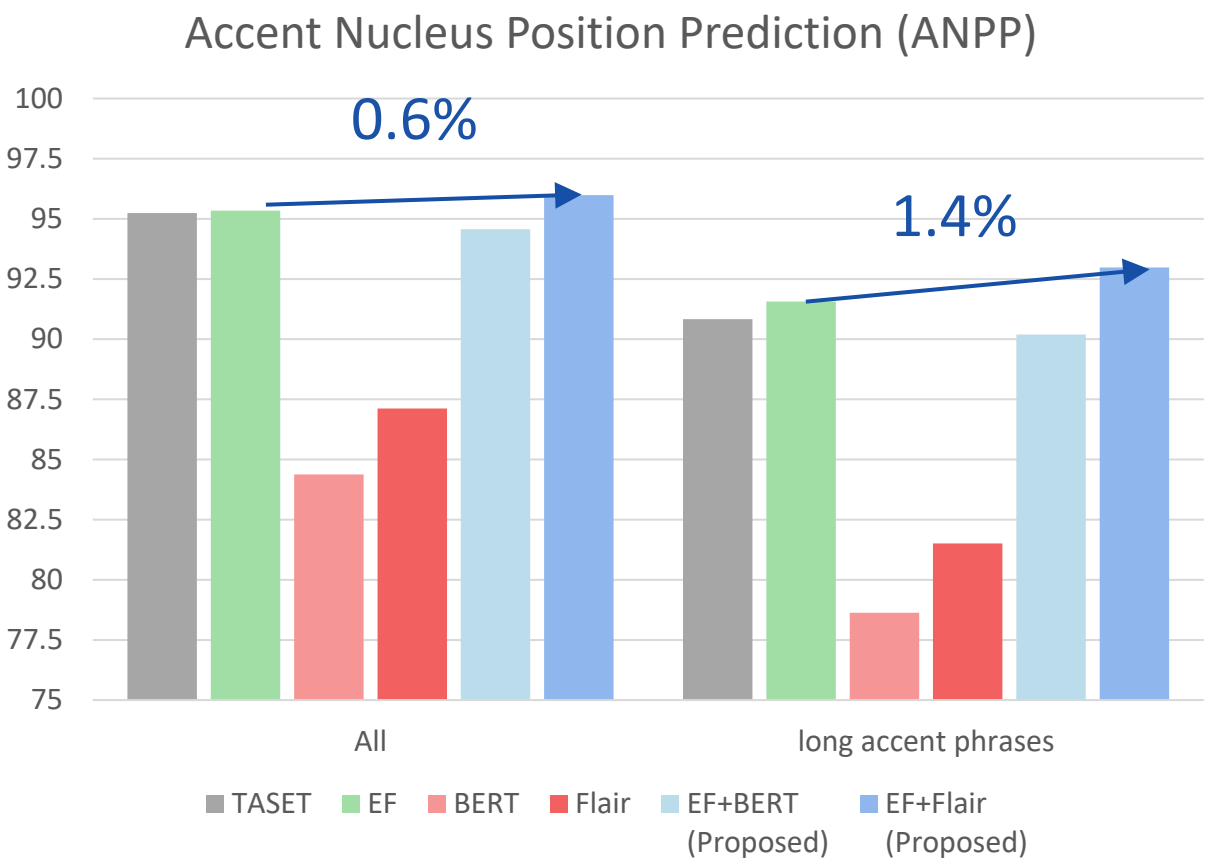
Comparison w/ & w/o PLMs on Polyphone disambiguation



Bi-LSTM w/ EF+BERT improves by 6.2/1.5% from only EF.

Comparison w/ & w/o PLMs on Accent Prediction





Bi-LSTM w/ EF+PLM improves by 0.9/7.7% on APBP, 0.6/1.4% on ANPP from only EF.
BERT for APBP, Flair for ANPP

TTS quality subjective evaluation

TTS settings

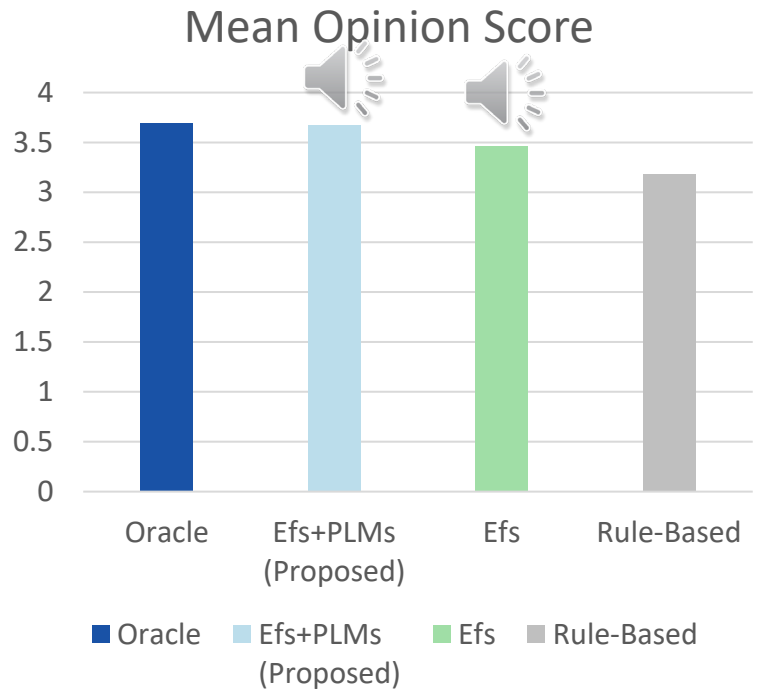
- Acoustic model: Tacotron2 w/ Global Style
- Token[Shen+,18. Wang+,18]
- Vocoder: Parallel WaveGAN [Yamamoto+, 20]
- Training data: Sub-corpus of JSUT for both models

Evaluator

- 30 native Japanese Speakers

Evaluation text

- 25 utterance samples from in-house data



Proposed method achieved almost the same speech quality as Oracle.

Summary

We proposed the method which incorporates implicit/explicit features in PD/AP.

- The combination of explicit and implicit features improves both PD/AP performance.
- Methods showed better performance on MOS than conventional TTS-frontend.
- The effectiveness of PLMs type (BERT/Flair) depends on tasks.

Future Work

・Using pre-trained model from both of grapheme & phoneme

References

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