Low-Resource Text-to-Speech Synthesis **Through Language Agnostic Meta Learning** and Articulatory Features



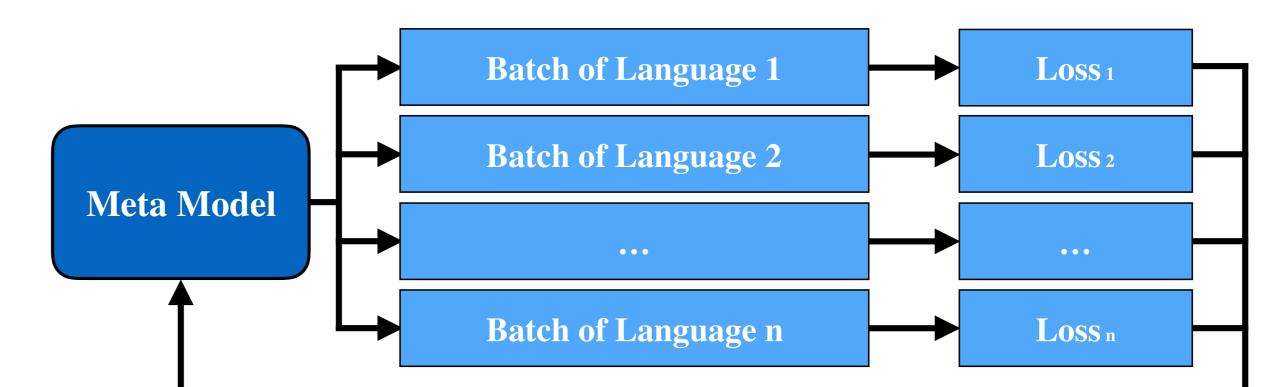
1: Introduction

Neural Text-to-Speech has made great advances, however it still requires a lot of data, which is not feasible for many languages.

Mismatch in the Input Space

We want to **share knowledge** between higher and lower resourced languages. But languages have different phoneme sets.

Language Agnostic Meta Learning



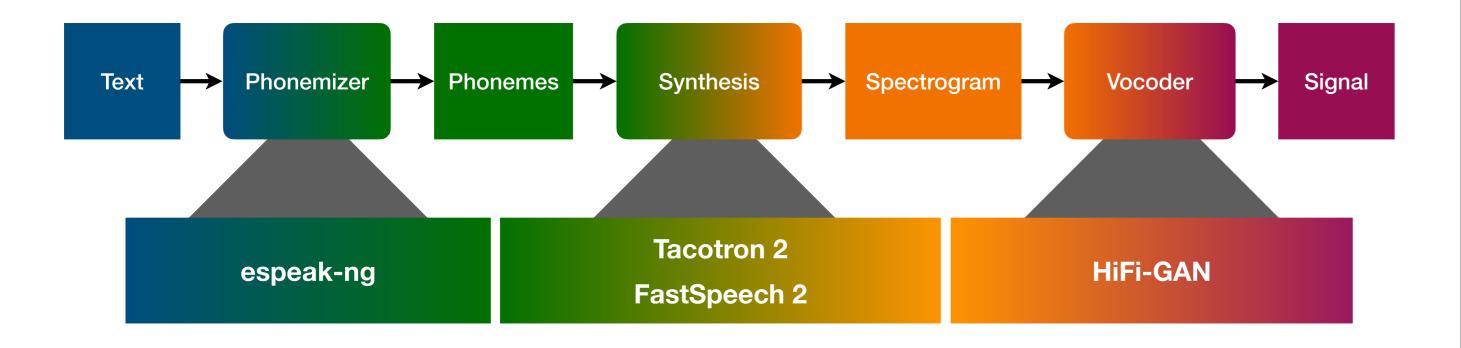
 \rightarrow Meaningful featurevectors allow to zero-shot infer phonemes! [1]

Data Need

A shared input space alone allows finetuning to a new language with less data. But it's still infeasible for many languages.

 \rightarrow Model Agnostic Meta Learning [2] (MAML) reduces data need to learn unseen tasks. We formulate our training procedure such that different languages are the tasks in a MAML like procedure. This allows us to learn new languages with just 30 minutes of speech in an unseen language.

Basic Architecture



We use FastSpeech 2 [3], Tacotron 2 [4] and HiFi-GAN [5] based on ESPnet

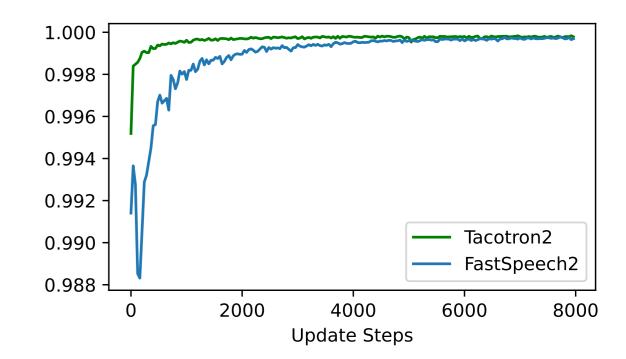
update according to $\Sigma L_{1...n}$

In terms of MAML: Every language is one task and the inner loop is run for only one step. This stabilizes training and generalizes to unseen languages.

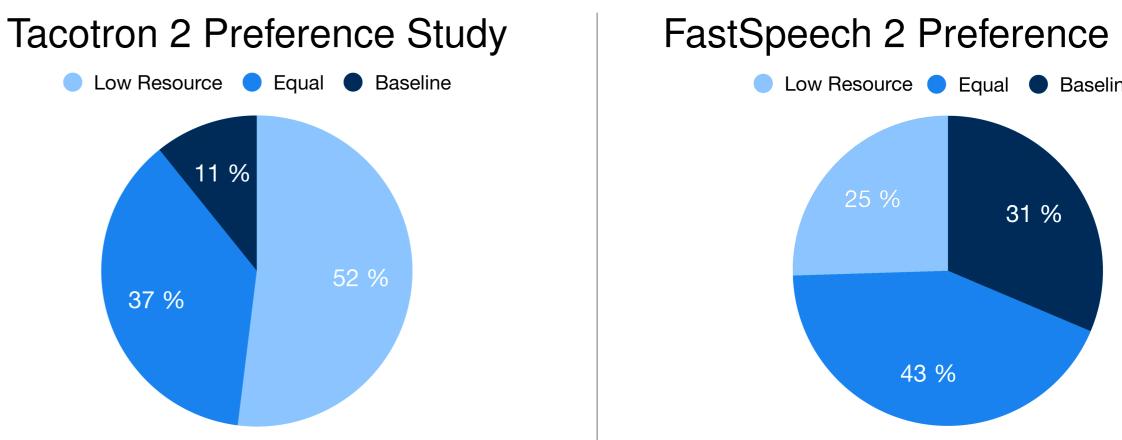
3: Evaluation

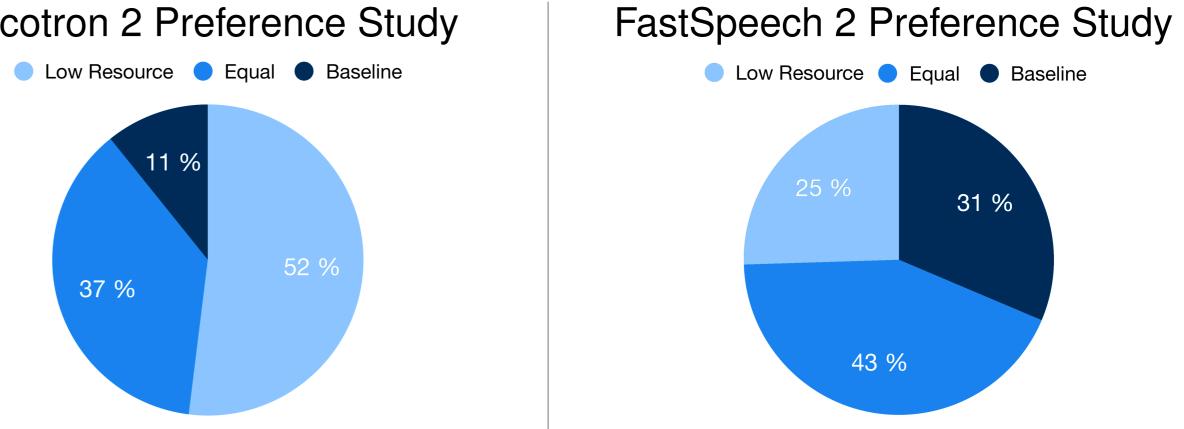
How fast does it adapt to new speakers?

Tacotron 2 reaches excellent speaker similarity after just 1000 steps, Fast-Speech 2 takes roughly 5000. In both cases, speaker similarity is excellent before overfitting problems become apparent.



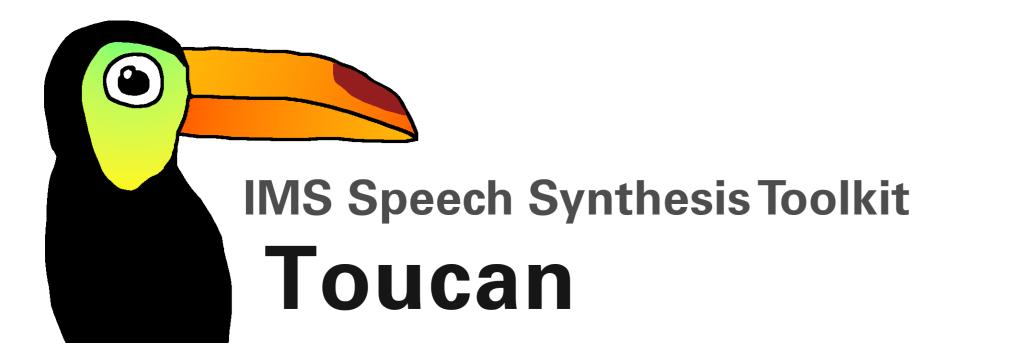
How is the quality compared to high-resource?





[6] implementations. We use single speaker modeling only to get the most general speech production knowledge possible in the pretraining.

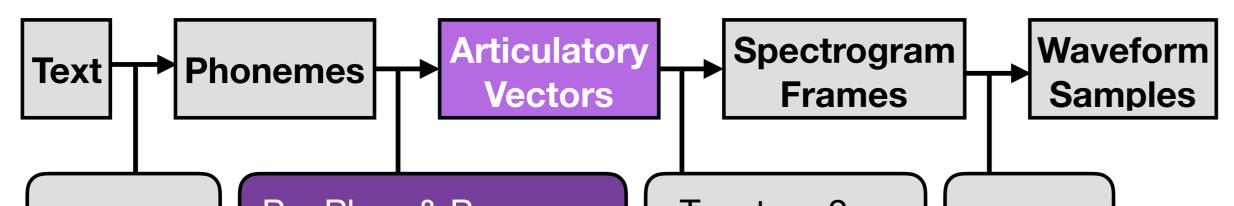
Code and Models are Public





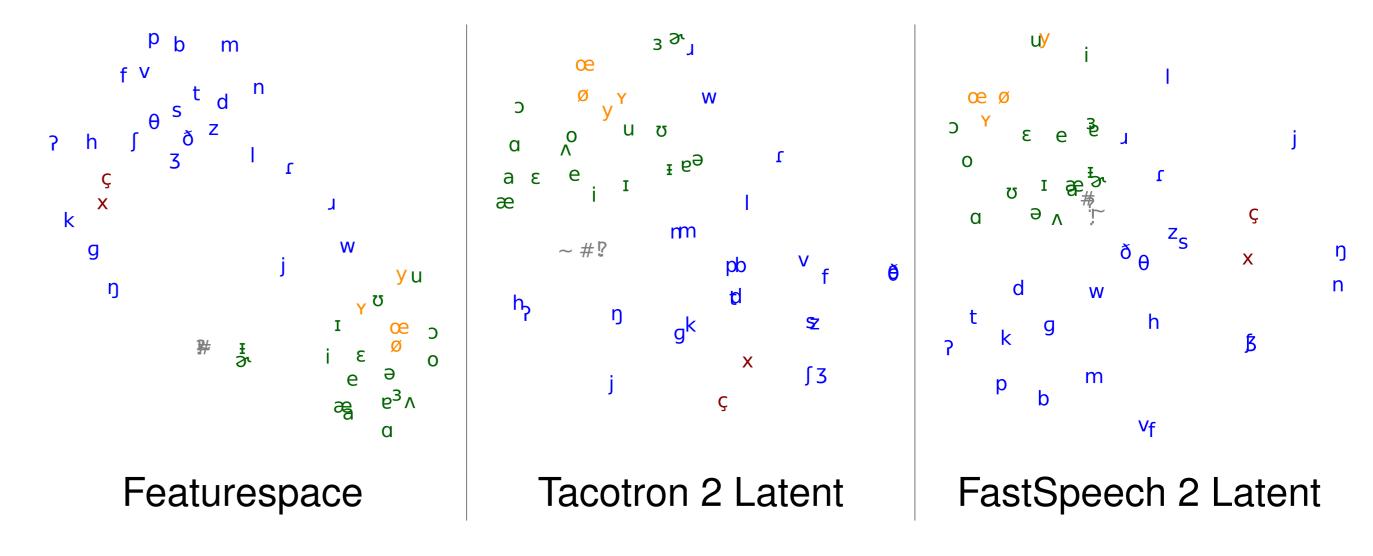
2: Proposed Approach

Articulatory Features

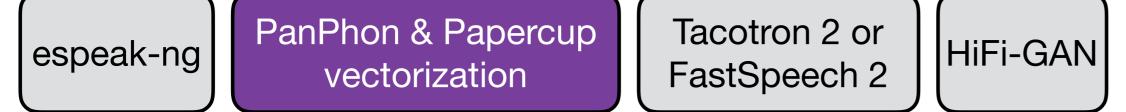


For both Tacotron 2 and FastSpeech 2, more than half of the 102 ratings by the 34 raters say that the low-resource model trained on 30 minutes is better or equal to one trained on 29 hours without pretraining.

Can it handle unseen phonemes?



Consonants are blue, vowels are green. Unseen vowels are orange and unseen consonants are red. Unseen phonemes get placed in meaningful positions in the latent space.



Contains features such as the type of the symbol (vowel, consonant, other), the position of articulation (e.g. palatal, alveolar, glottal), whether it's voiced or unvoiced, if there is friction noise, the position of the tongue, tongue tenseness, whether the mouth is rounded and some more.

R	symbol_type	= phoneme	i	symbol_type	= phoneme
	vowel_consonant	= consonant		vowel_consonant	= vowel
	voicedness	= voiced		voicedness	= voiced
	consonant_place	= uvular		vowel frontness	= central
	consonant_manner	= fricative		vowel_openness	= close
L			1	vowel_roundedness	= unrounded

Take Home: Using articulatory phoneme descriptions as input and training on multiple languages simultaneously without conditioning leads to a language agnostic TTS model initialization.



- [1] M. Staib, T. H. Teh, A. Torresquintero, D. S. R. Mohan, L. Foglianti, R. Lenain, and J. Gao, "Phonological Features for 0-Shot Multilingual Speech Synthesis," Interspeech, 2020.
- [2] C. Finn, P. Abbeel, and S. Levine, "Model-agnostic meta-learning for fast adaptation of deep networks," in ICML, 2017.
- [3] Y. Ren, C. Hu, X. Tan, T. Qin, S. Zhao, Z. Zhao, and T.-Y. Liu, "FastSpeech 2: Fast and High-Quality End-to-End Text to Speech," in ICLR, 2020.
- [4] Y. Wang, R. Skerry-Ryan, D. Stanton et al., "Tacotron: Towards End-to-End Speech Synthesis," Interspeech, 2017.
- [5] J. Kong, J. Kim, and J. Bae, "HiFi-GAN: Generative adversarial networks for efficient and high fidelity speech synthesis," Advances in Neural Information Processing Systems, vol. 33, 2020.
- [6] T. Hayashi, R. Yamamoto, K. Inoue, T. Yoshimura et al., "ESPnet-TTS: Unified, reproducible, and integratable open source end-to-end text-to-speech toolkit," in ICASSP, 2020.