DAFT-EXPRT: ROBUST PROSODY TRANSFER ACROSS SPEAKERS
FOR EXPRESSIVE SPEECH SYNTHESIS

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ABSTRACT
This paper presents Daft-Exprt, a multi-speaker acoustic model advancing the state-of-the-art on inter-speaker and inter-text prosody transfer. This improvement is achieved using FiLM conditioning layers, alongside adversarial training that encourages disentanglement between prosodic information and speaker identity. The acoustic model inherits attractive qualities from FastSpeech 2, such as fast inference and local prosody attributes prediction for finer grained control over generation. Experimental results show that Daft-Exprt significantly outperforms strong baselines on prosody transfer tasks, while yielding naturalness comparable to state-of-the-art expressive models. Moreover, results indicate that adversarial training effectively discards speaker identity information from the prosody representation, which ensures Daft-Exprt will consistently generate speech with the desired voice. We publicly release our code1 and provide speech samples from our experiments2.

Index Terms— speech synthesis, prosody transfer

1. INTRODUCTION
The first wave of neural text-to-speech systems showed the ability to synthesize natural-sounding speech [1–3]. However, these systems generate speech from text alone, offering no control over prosody (i.e., all speech information that is not contained in text, speaker identity and channel effects [4]). Harnessing prosody is instrumental for providing expressive synthetic voices in entertainment applications such as movies and video games, or to increase user engagement in human-machine interactions [5]. As a result, many recent efforts are devoted towards accurate transfer of prosodic styles on arbitrary texts [4][6][10].

One approach for prosody transfer is to capture time-independent attributes from a reference utterance to condition the generation of a new sentence. For instance, in [6], global prosodic attributes are encoded in a latent prosodic space using a mixture of learned style prototypes, while [7][9] and [10] use variational and flow-based approaches. While these methods allow for high-level prosody transfer, they usually do not offer fine-grained control over local prosodic features, unlike [11][13] which predict local prosodic attributes directly from text. Moreover, global prosodic representations tend to entangle speaker identity with prosodic information [4][9], hindering their performance when transferring prosody across speakers. This challenge is tackled in other speech applications via adversarial training [14][15].

Transferring prosody into the acoustic model is generally achieved by concatenation-based conditioning. While this is an effective method, applying feature-wise affine transformation on normalization layers has proven particularly successful in a variety of domains (e.g. image stylization [16][17] or speech [18][21]). This technique, often called conditional normalization, was later generalized by FiLM layers [22] as a general-purpose conditioning method that is decoupled from normalization operations.

This paper presents Daft-Exprt, a fast and robust multi-speaker acoustic model based on FastSpeech 2 [11]. Daft-Exprt stands for Deep affine transformations for Expressive prosody transfer. Using FiLM conditioning, Daft-Exprt can transfer detailed prosodic variations from a reference utterance. Additionally, it predicts human-readable intermediate prosodic features at the phoneme level, allowing for fine-
Daft-Exprt uses adversarial training to disentangle prosody and speaker identity, improving prosody transfer across different speakers. We compare Daft-Exprt against several strong baselines on a highly expressive multi-speaker data set and demonstrate accurate prosody transfer in challenging inter-speaker and inter-text transfer experiments, even for target speakers only trained on neutral style data. We summarize our main contributions as follows:

1. We propose a new architecture based on FiLM conditioning that enables accurate prosody transfer.
2. We show that adversarial training can disentangle speaker identity information from latent prosodic attributes.
3. We improve on state-of-the-art inter-speaker and inter-text prosody transfer with highly expressive data.

2. PROPOSED MODEL

Daft-Exprt consists of a prosody encoder and a core acoustic model, as illustrated in Figure 1. The core acoustic model generates spectrogram frames from a phoneme sequence. The prosody encoder applies feature-wise affine transformations to the core acoustic model based on a reference utterance.

2.1. Core Acoustic Model

The core acoustic model builds on FastSpeech 2 [11], a non-autoregressive transformer-based model, and comprises four parts: a phoneme encoder, a local prosody predictor, a Gaussian upsampling module and a frame decoder.

The phoneme encoder extracts a sequential latent representation from an embedded phoneme sequence using Feed-Forward Transformer (FFT) blocks. A FFT block implements a multi-head self-attention and two 1D-convolution layers, each followed by a residual connection and layer normalization, as depicted in Figure 2a.

Next, the local prosody predictor estimates a duration, energy, and pitch scalar value for each phoneme. The architecture, shown in Figure 2b, is similar to the variance adaptor of [11] but without the length regulator. All prosodic features are predicted using shared parameters. Following [12], we predict prosodic features at the phoneme level because it is more intuitive than at the frame level.

Daft-Exprt uses the Gaussian upsampling module in Figure 2c to address the length mismatch between phoneme and spectrogram sequences. Gaussian upsampling [13] replaces the length regulator of FastSpeech 2 to improve naturalness. First, three 1D-convolution layers project duration, energy and pitch to match the dimension of the phoneme representation. A range predictor then sums the projections and encoded phonemes before predicting a sequence of ranges using a linear layer with SoftPlus activation. Finally, a Gaussian upsampling layer adds the energy and pitch projections to the encoded phonemes and upsamples the sequence using integer frame durations as means and ranges as standard deviations.

As a last step, the frame decoder predicts spectrogram frames from the upsampled hidden sequence by applying several FFT blocks followed by a linear layer.

2.2. Prosody Encoder

The core acoustic model is conditioned in three strategic places: the phoneme encoder, the local prosody predictor and the frame decoder. The prosody encoder, illustrated in Figure 2d, applies affine transformations to the intermediate features of specific layers. These transformations, illustrated as FiLM layers [22] in Figure 2a and 2b, are conditioned on prosodic information extracted from a reference utterance in the form of energy, pitch and spectrogram sequences.

First, the spectrogram is encoded through three 1D-convolution layers, each followed by ReLU activation and layer normalization. Two 1D-convolution layers also project
pitch and energy. The hidden sequences are then summed and fed to FFT blocks to produce a sequential intermediate representation. A latent prosody vector, summarizing the prosody of the whole utterance, is obtained by averaging over the sequence, and a speaker embedding is added to the prosody vector to specify the identity of the target voice. Finally, a linear layer predicts a $\beta$ and a $\gamma$ value for each conditioned feature in the core acoustic model. The $\gamma$ and $\beta$ values correspond to the scaling and bias performed by the FiLM layer. As in [23], for regularization, each FiLM layer has a scaling value $s_\gamma$ and $s_\beta$ applied to all its $\gamma$ and $\beta$. These scaling values are not predicted, but learned during training.

### 2.3. Training Loss

We use four loss terms for training: two regularization terms, $\mathcal{L}_r$ and $\mathcal{L}_f$, alongside a prediction error $\mathcal{L}_e$ and an adversarial loss $\mathcal{L}_a$. The relative importance of all terms is adjusted through $\lambda_f$, $\lambda_a$ and $\lambda_r$:

$$\mathcal{L} = \mathcal{L}_e + \lambda_f \mathcal{L}_f - \lambda_a \mathcal{L}_a + \lambda_r \mathcal{L}_r$$  \hspace{1cm} (1)

The prediction error $\mathcal{L}_e$ is the mean squared error for the mel-spectrogram, duration, energy and pitch predictions. We also add mean absolute error on mel-spectrogram predictions.

As in [23], we observe that regularization ensures better generalization with FiLM conditioning. We follow [23] and use $\mathcal{L}_f$ to penalize the $\ell^2$-norm of the scaling parameters $s_\gamma$ and $s_\beta$. We also further regularize using weight decay $\mathcal{L}_r$.

Finally, the adversarial loss $\mathcal{L}_a$ encourages disentanglement between the prosody vector and the speaker embedding. During training, reference and target speakers are the same, which causes the prosody encoder to capture speaker identity. We use adversarial speaker-invariant learning to address this challenge [14][15]. A classifier predicts the speaker identity from the prosody vector and the error is propagated through a gradient reversal layer [23]. In other words, the classifier penalizes the prosody encoder if the prosody vector contains information about the speaker from the reference utterance. The classifier consists of three linear layers with ReLU activations and we use the cross-entropy loss for $\mathcal{L}_a$.

### 3. EXPERIMENTS AND RESULTS

#### 3.1. Experimental Setup

The same training data is used in all experiments. We combine the LJ Speech data set [25] with a 12 speaker internal data set containing 47 hours of recordings. We capture highly expressive performances in various styles from 7 of the speakers. The remaining speakers recorded only neutral lines.

We extract 80 bin mel-spectrograms from the recordings using a $\sim$46ms Hann window and a hop size of $\sim$12ms. We extract phoneme durations using MFA$^3$ to estimate log-pitch with REAPER$^4$ and use the $\ell^2$-norm of the spectrogram frames to measure energy. We average energy and log-pitch per phoneme and normalize them per speaker.

The core acoustic model is configured as in [11]. However, we use a kernel size of 3 for all 1D-convolution layers. We also decrease the hidden dimension from 256 to 128 for the phoneme embedding, phoneme encoder, and frame decoder for improved generalization.

We build the prosody encoder with a kernel size of 3 for all 1D-convolutions, and encode mel-spectrograms using 1024 channels. The prosody encoder maps inputs to a 128 dimension hidden representation, which is passed through 4 FFT blocks with 8 attention heads. Finally, we learn a 128 dimension speaker embedding. The classifier used for adversarial training is also made of 128-dimensional layers.

We train Daft-Exprt with a batch size of 48 and use the Adam optimizer, configured as in [11]. We linearly increase the learning rate from 1e-4 to 1e-3 during the first 10k steps before decaying. For the loss, we set $\lambda_f$ to 1e-3, $\lambda_r$ to 1e-6, and linearly increase $\lambda_a$ from 0 to 1e-2 during the first 10k steps. Finally, we use a dropout rate of 0.1 for all self-attention and 1D-convolution layers.

We compare Daft-Exprt against 3 strong baseline models: GST-Tacotron [6], VAE-Tacotron [7] and Flowtron [10]. We add multi-speaker support to GST-Tacotron and VAE-Tacotron, as done in [10]. For Flowtron, we fine-tune a model pre-trained on LibriTTS [26] that has been made available by the authors. All models are trained for 300 epochs on our data. Once training is finished, we fine-tune a pre-trained 22kHz universal HiFi-GAN vocoder$^5$ [22] for each acoustic model during 1M iterations.

#### 3.2. Evaluation Setup

Our subjective evaluations focus on expressive inter-speaker and inter-text prosody transfer. We compare the models conditioning on 30 utterances from speakers seen during training and 30 utterances from speakers unseen during training. All the reference utterances used for evaluation are excluded from training data. For unseen speakers, we draw expressive samples from the 2013 Blizzard Challenge [28] and RAVDESS [29] data sets. For each reference utterance, we randomly select a text line and a target speaker. We generate using the 4 models and submit the speech samples to human raters.

MUSHRA-like tests [30] evaluate prosody transfer, while mean opinion scores (MOS) evaluate naturalness. As a low anchor for MUSHRA, we condition Daft-Exprt on a neutral reference utterance, randomize phoneme durations and flatten pitch curve. Each audio is rated by at least 8 different self-reported native English speakers. We report mean scores and 95% confidence intervals. We discard raters giving very high scores to low quality anchors and low naturalness scores.

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$^3$https://github.com/MontrealCorpusTools/Montreal-Forced-Aligner

$^4$https://github.com/google/REAPER

$^5$https://github.com/jik876/hifi-gan
to lines recorded by professional actors. We use the CAQE Toolkit\(^6\) as the experiment interface.

### 3.3. Prosody Transfer

Table 1 reports MUSHRA scores obtained when comparing models on inter-speaker and inter-text prosody transfer. Raters were asked to evaluate speech samples based on their prosody similarity with a reference utterance, while ignoring speaker identity, audio quality or pronunciation mistakes.

| Method        | MUSHRA | MOS  |
|---------------|--------|------|
| GST-Tacotron  | 40.9 ± 2.0 | 2.86 ± 0.08 |
| VAE-Tacotron  | 37.9 ± 1.8 | 3.36 ± 0.08 |
| Flowtron      | 36.2 ± 1.9 | 3.47 ± 0.08 |
| Daft-Exprt    | 58.0 ± 2.0 | 3.28 ± 0.08 |
| Ground truth + HiFi-GAN | - | 3.85 ± 0.07 |
| Ground truth  | -      | 4.42 ± 0.05 |

Table 1: MUSHRA scores on inter-speaker prosody transfer and naturalness MOS on the same examples.

Results indicate a statistically significant improvement on prosody transfer when comparing Daft-Exprt to all baseline models. The large margin between scores is explained by the ability of Daft-Exprt to accurately transfer expressive prosodies, even to target speakers for which the data set contains only neutral utterances. Our demo page showcases some of these examples. We hypothesize that conditioning with affine transformations allows for independent targeting of different parts of the core acoustic model, which translates into semantically meaningful modulations.

#### 3.4. Naturalness

Naturalness MOS for all models and the ground truth recordings are reported in Table 1. Ground truth utterances are all expressive and are used as references for prosody transfer. We also measure the impact of the vocoder on audio quality by evaluating re-synthesized ground truth spectrograms. Results show that the vocoder significantly degrades speech quality. As observed in \(^6\), vocoders produce more artifacts on highly expressive speech than on neutral voices.

VAE-Tacotron, Flowtron and Daft-Exprt get comparable results. However, sources of imperfection are different from one model to another. Daft-Exprt is not attention-based, unlike all baseline models, thus less prone to attention failure problems like word skipping or repetitions. On the other hand, the baseline models are autoregressive which has been shown to improve naturalness \(^2\). Finally, naturalness is measured on samples produced by attempting to transfer expressive prosodies, which cause more artifacts during vocoding. This negative effect is proportional to the prosody transfer capabilities of each model, which disadvantages Daft-Exprt because it can transfer more accurately expressive prosodies.

### 3.5. Prosody and Speaker Identity Disentanglement

| Method        | MUSHRA | Accuracy |
|---------------|--------|----------|
| Daft-Exprt \( \lambda_a = 0 \) | 61.1 ± 1.8 | 40.5%    |
| Daft-Exprt \( \lambda_a = 0.01 \) | 55.0 ± 1.8 | 97.6%    |
| Daft-Exprt \( \lambda_a = 1 \) | 35.2 ± 1.7 | 100.0%   |

Table 2: MUSHRA scores and target speaker classification accuracy on inter-speaker prosody transfer.

As explained in Section 2.3, the adversarial loss term encourages disentanglement between prosody and speaker identity. Here, we study the impact of this loss term by varying its importance weight \( \lambda_a \) in equation 1. We conduct MUSHRA tests to evaluate prosody transfer quality, as explained in section 3.3. Similar to \( \text{\textsection 2.3} \), we also report the accuracy of a classifier predicting the identity of the target speaker from the generated spectrogram. The classifier consists of the prosody encoder in Section 2.2, ignoring energy and pitch sequences, combined with the speaker classifier described in Section 2.3. We train the classifier on ground truth mel-spectrograms until reaching a 100% test set accuracy. We evaluate the accuracy for each model on 15k inter-speaker generated spectrograms.

Results in Table 2 confirm that adversarial training effectively encourages disentanglement between prosody and speaker identity. When \( \lambda_a = 0 \), the prosody encoder is free to capture reference speaker identity information. The high MUSHRA score indicates that prosody is accurately transferred. However, the low classifier accuracy means that the model fails to generate with the desired speaker voice. As \( \lambda_a \) increases, disentanglement is encouraged at the expense of accurate prosody transfer. We empirically searched for the best trade-off between prosody transfer and disentanglement and found \( \lambda_a = 0.01 \) yields best results.

### 4. CONCLUSION

This paper introduced Daft-Exprt, a multi-speaker acoustic model combining FiLM conditioning layers and adversarial training for accurate inter-speaker and inter-text prosody transfer. Our experiments showed that Daft-Exprt advances the state-of-the-art on inter-speaker and inter-text prosody transfer, while delivering high quality speech. We also measured the benefits of adversarial training on disentanglement between speaker identity and prosody. As future work, we intend to replace our speaker encoding scheme to synthesize with any target speaker voice, and increase spectrogram prediction accuracy for higher final sound quality.

\(^6\)https://github.com/interactiveaudiolab/CAQE
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