GENERATIVE MODELING FOR LOW DIMENSIONAL SPEECH ATTRIBUTES WITH NEURAL SPLINE FLOWS

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ABSTRACT

Despite recent advances in generative modeling for text-to-speech synthesis, these models do not yet have the same fine-grained adjustability of pitch-conditioned deterministic models such as FastPitch and FastSpeech2. Pitch information is not only low-dimensional, but also discontinuous, making it particularly difficult to model in a generative setting. Our work explores several techniques for handling the aforementioned issues in the context of Normalizing Flow models. We also find this problem to be very well suited for Neural Spline flows, which is a highly expressive alternative to the more common affine-coupling mechanism in Normalizing Flows.

1 INTRODUCTION

Our work aims to bridge the gap between two families of text-to-speech (TTS) models: the deterministic but heavily factorized models, and the less factorized generative models. In the first group, works such as FastSpeech2 (Ren et al., 2020), FastPitch (Łańcucki, 2021), and Mellotron (Valle et al., 2020a), conditioned not only on text, but also on pitch, and sometimes energy. These models are capable of fine-tuning results for applications such as cross-speaker pitch transfer, as well as auto-tune like effects. Furthermore, while clean audio is hard to come by, acoustic features such as pitch are robust to noise and various distortions. This means that parts of these models responsible for modeling pitch distributions can incorporate large amounts of less-than-perfect training data with no loss in quality. However, being deterministic, there is a loss in realism as these models will never vary given the same prompt. On the other hand, we have generative models such as GlowTTS (Kim et al., 2020c), GradTTS (Popov et al., 2021), and RADTTS (Shih et al., 2021). These models are capable of producing diverse samples from the same prompt, but lack the aforementioned factorized benefits. What if we could have it all?

In order to achieve the same level of factorization in a generative context, one must be able to fit a generative model over fundamental frequency or pitch. However, we can quickly see why this is a difficult task. In practice, pitch information is represented by the fundamental frequency \( F_0 \) of a speaker’s voice. Consider Figure 1, which depicts the \( \log(F_0) \) of a speech sample. We can identify the following issues upon inspection:

- **Low dimensionality:** As with audio waveform data, fundamental frequency is a 1D waveform and low dimensional data is difficult to work with. For the same reason that audio waveform data is first expanded to 80+ dimensional Mel Spectrograms using STFT, we must either find a reasonable means to increase the dimensionality, or find a model architecture that excels on low dimensional data.

- **Discontinuity:** Unlike audio waveform data, fundamental frequency data is discontinuous. It comprises segments of periodic voiced regions with valid fundamental frequency interleaved by aperiodic unvoiced segments with no fundamental frequency. How one handles the unvoiced regions is important because as far as the model is concerned, all inputs are valid inputs. As a direct result of the discontinuity issue, the variance in graph appears much more than it really is, due to the artificial transitions between the valid data and placeholder values. A generative model attempts to map all

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the variance in the graph to a Gaussian. If the model is not aware of the differences between these regions, one could end with unexpected spikes and dips in the middle of the spoken segments, leading to catastrophic audio artifacts.

Our work explores several techniques for handling the aforementioned issues, using normalizing flows as our framework for generative modeling. Our contributions are as follows:

- We propose normalizing flow models that are aware of voiced/unvoiced segments, and demonstrate why this is critical.
- We compare various techniques for handling issues regarding $F_0$ data.
- We explore various model architectures, including both parallel and autoregressive normalizing flow models, as well as the use of neural spline flows in place of the standard affine-coupling.

![Figure 1: Example graph of fundamental frequency of a speech sample plotted against time in log space. Unvoiced regions are aperiodic and hence have no frequency data, depicted with a placeholder value of 0 in this graph.](image)

## 2 RELATED WORKS

**Feature Augmentation:** Normalizing flows are known to be limited to homeomorphism-preserving transformations. Prior works such as (Huang et al., 2020) and (Chen et al., 2020) propose the incorporation of additional dimensions by augmenting with random variables drawn from a different distribution. Similarly, (Dupont et al., 2019), proposes to append a vector of zeros to circumvent a similar limitation in Neural ODEs. (Kim et al., 2020a) tackles a similar problem of fitting normalizing flow models to map thin 3D structures to Gaussian priors. Instead of augmenting dimensions, they propose to dilate the data by directly adding noise, creating an augmented data distribution that is topologically closer to the target prior. Our work draws inspiration from these prior works, however our proposed approaches are more specialized to tackle the intricacies of discontinuous fundamental frequency information in speech.

**Generative Text-to-Speech:** Several recent works have tackled the problem of generative text-to-speech modeling, wherein the goal of the resulting model is to sample diverse outputs given a single text prompt. Flowtron (Valle et al., 2020b) proposes an autoregressive-flow whereas GlowTTS (Kim et al., 2020c), FlowTTS (Miao et al., 2020) both propose a Glow-style (Kingma & Dhariwal, 2018) non-autoregressive flow model for sampling text-conditional mel-spectrograms. RADTTS (Shih et al., 2021) further extends the flow-based approaches by incorporating generative duration synthesis, replacing deterministic phoneme regression used in prior methods. More recently, likelihood models based on diffusion denoising probabilistic models (Jeong et al., 2021; Popov et al., 2021) have been considered as well. Our work operates in the same vein as these prior methods, but our target pitch and energy representations occur *before* the mel-spectrogram stage, thereby allowing us to achieve diverse synthesis with the option of frame-level manual adjustment.

**Generative F0 Modeling:** While most deep-learning based approaches have focused on deterministic regression approaches, there have been some generative autoregressive approaches, using RNNs to output stochastic states or Gaussian mixture densities (Wang et al., 2018a; 2017; 2018b). These approaches similarly separate the inference task into the voiced and unvoiced cases, which has been a commonly used formulation in parametric vocoder such as (McCree & Barnwell, 1995). Our work builds upon these methods, but we additionally explore non-autoregressive (parallel) architectures in addition to being primarily focused on overcoming the known limitation of normalizing flows on low dimensional data.
3 Methods

To construct a generative model while maintaining fine-grained adjustability over speech characteristics such as pitch and energy, we focus on fitting generative Normalizing Flow models over the fundamental frequency \((F_0)\) of audio segments, including voiced/unvoiced decisions, as well as the average energy per mel-spectrogram frame, referred to as energy for brevity. This is in contrast to most existing generative TTS models, which directly model the stochastic generation of mel-spectrogram frames. While the methods we discuss apply to both \(F_0\) and energy, we will focus our discussion on the much more problematic \(F_0\).

We will first give a brief overview of Normalizing Flows. Next, we will discuss data preprocessing techniques for resolving \(F_0\)-related issues in the context of Normalizing Flow frameworks, followed by a discussion of model design.

3.1 Normalizing Flows Overview

As with most generative models, Normalizing Flows allows us to map our data domain to a Gaussian distribution such that we can sample new data points with ease. Let \(X\) be the data domain (in our case, \(F_0\)), and \(Z\) be the normally-distributed latent space:

\[
\begin{align*}
z &\sim \mathcal{N}(0, I) \\
x &= G(z; \theta)
\end{align*}
\]

Normalizing Flows are based on the change-of-variables formula, which states that if \(G(z; \theta)\) is invertible \((z = G^{-1}(x; \theta))\), we can then optimize for its parameters \(\theta\) with exact MLE. We define \(f_Z(z)\) and \(f_X(x)\) as the probability density function in the latent (Gaussian) domain, and the unknown pdf in the data domain respectively. The change of variables gives us the following formula:

\[
\ln f_X(x) = \ln f_Z(G^{-1}(x; \theta)) + \ln \left| \det \frac{\partial G^{-1}}{\partial x} \right| (3)
\]

Using substitution, it then follows that the following objective function is the equivalent of exact maximum likelihood over the data:

\[
\hat{\theta} = \arg \max_{\theta} \ln f_Z(G^{-1}(x; \theta)) + \ln \left| \det \frac{\partial G^{-1}}{\partial x} \right| (4)
\]

Here, \(\hat{\theta}\) are the parameters of a neural architecture \(G()\), carefully constrained to guarantee invertibility.

As we are primarily interested in inferring \(F_0\) and Energy in a text-to-speech framework, \(G()\) is further conditioned on \(\Phi_{text}\), which is a matrix specifying temporally-aligned text information. As such, we have the invertible model \(G(; \theta, \Phi_{text})\), which models the conditional distribution of \(F_0\) or Energy given temporally aligned text.

3.2 Increasing Data Dimensionality

We first discuss several potential methods for tackling the low dimensionality problem with \(F_0\) and energy. Low dimensionality is particularly problematic in Normalizing Flows due to the bijectivity constraint. The bijectivity constraint limits us to homeomorphic mappings between \(X\) and \(Z\), which can be extremely limiting in low dimensions. Furthermore, we cannot simply throw in fully-connected layers to project our data to a higher dimension, as these transformations would not be invertible. Instead, we rely on the use of data grouping, auxiliary dimensions, and approximately invertible transformations.

Grouping: Grouping is a technique commonly used in fitting normalizing flow models to time-domain-based data. Let \(X = x^1, x^2, x^3 \ldots x^t \ldots x^T\) be our domain data comprising a sequence of \(T\) real values. The superscript indicates the sequence index. Each \(x \in X\) is a \(D\)-dimensional data point. We can group every \(N\) consecutive data points together in a non-overlapping fashion, thereby resulting in \(T/N\) \(ND\)-dimensional data points. For example, let \(N = 2\), then\(X' = (x^1, x^2), (x^3, x^4) \ldots (x^t, x^{t+1}), \ldots (x^{T-1}, x^T)\). While it is possible to widen indefinitely, we found that increasingly larger group sizes result in reduced variability in sampling. As such, one should go
with the minimum group size that one can get away with. A group size of 2 was sufficient for $F_0$, but a group size of 4 was necessary for modeling the energy distribution.

**Auxiliary Dimensions:** Another way to increase the dimensionality without breaking bijectivity is to tack on auxiliary dimensions, which we simply discard later during inference. We find that the approximation of the local derivative at every time step to be simple yet effective.

Continuing from the grouping example, we arrive at:

$$X' = (x^1, \frac{\partial x^1}{\partial t}, x^2, \frac{\partial x^2}{\partial t}), \ldots (x^{T-1}, \frac{\partial x^{T-1}}{\partial t}, x^T, \frac{\partial x^T}{\partial t}).$$

The derivative values work similarly to grouping, but also provide additional context information summarizing the relationship between the current group and the adjacent ones. We compute the approximate local derivative by computing the centered-difference at each timestep $t$ and scaling as necessary for model stability:

$$\frac{\partial x^t}{\partial t} = (x^t - x^{t-1}) + (x^{t+1} - x^t)$$  \hspace{1cm} (5)

An alternative to the above is to use a set of basis functions to project the signal to a higher dimension. Following FastSpeech2 (Ren et al., 2020), we also consider the continuous wavelet transformation. Similar to STFT, continuous wavelet transform (CWT) (Sun et al., 2013) can be used to convert a $F_0$ contour into a time-frequency representation, giving us more dimensions to work with. We compare this against the centered-difference auxiliary features as described above. Please check section B for further implementation details and discussion.

### 3.3 Filling In The Holes

In addition to giving the models more dimensions to work with, it is still necessary to fill in the gaps between voiced regions of the $F_0$ data. Using a constant-value filler is problematic as it is very difficult for the Normalizing Flow model to map a segment of zero-variance data to a Gaussian. The most straightforward solution is linear interpolation, as part of the CWT transformation. However, we are also interested in potential solutions that avoid hallucinating values within the same range of valid data. This way, we can still identify unvoiced and voiced segments of the data from the graph.

**Log-Distance Transform Filler:** We consider the use of a distance transform to fill in the values for the unvoiced region, where the value at every time step is the minimum distance to the next voiced segment. We use the log of the distance transform, else the resulting value of the centered-difference auxiliary dimensions would be a constant value of $\pm 1$. Finally, we negate the values to avoid overlapping with the voiced $F_0$ values. An example can be seen in Fig. 2a.

**Unvoiced Bias:** Recall that our $F_0$ modeling task is part of a TTS pipeline, and thus the curvature is conditioned on the corresponding text (phoneme) at each time step. One potential drawback of the distance transform is that it is agnostic to the underlying phoneme sequence. As such, we
also consider a different solution – one that learns to infer negative offsets in the unvoiced regions conditioned on the phoneme sequence. An example can be seen in Fig. 2b. We will elaborate on the implementation details in section 3.4.2.

3.4 MODEL ARCHITECTURES

The focus of this work is on modeling the distribution of $F_0$ and energy in speech, conditioned on temporally aligned text. As we are working within the framework of a TTS pipeline, we assume we have the following components available:

**Timed Text Representation:** $\Phi_{text}$ is a $C \times T$ matrix that contains both textual information and the timing of individual phonemes within said text. Each slice $\Phi_{text}^t$ gives us a $C$-dimensional feature vector representing the textual information at time $t$. We visualize this in Fig 3. The goal of the model is to fit the distribution $P(X|\Phi_{text})$, where $X$ corresponds to either $F_0$ or energy ($E$).

**Pitch and Energy Conditioned Mel-Decoder:** Typically in TTS models, a decoder first maps textual inputs to mel-spectrograms, which are then converted to waveform audio using a vocoder. As with works such as FastPitch (Ła´ncucki, 2021) and FastSpeech2, we assume our mel decoder is further conditioned on pitch ($F_0$) and energy information:

$$D(\Phi_{text}, F_0, E) \rightarrow X_{Mel}$$  

To achieve this, we use a reimplementation of the RADTTS (Shih et al., 2021) architecture, modified to be further conditioned on $F_0$ and $E$. Interestingly, we found that conditioning on $F_0$ and $E$ explain
away most of the perceived variations in the resulting samples coming out of the decoder, despite RADTTS being a generative model in its own light. As such, the onus of producing diverse synthesis is now assigned to the generative F₀ and E models.

Importantly, the RADTTS alignment mechanism (in a similar fashion to GlowTTS), provides the necessary audio-text timing information necessary to construct $\Phi_{text}$.

Vocoder: Finally, we have the vocoder, which takes in $X_{mel}$ and gives us our final waveform output for audio. We use Hifi-GAN (Kong et al., 2020) for this purpose. The vocoder choice has little relevance to the focus of this work.

Given the above components, we consider two architectures for modeling pitch and energy given $\Phi_{text}$: Glow-style (Kingma & Dhariwal, 2018) bipartite model and one based on inverse-autoregressive flows (Kingma et al., 2016).

3.4.1 Bipartite Flow Model

The proposed bipartite model is structurally similar to the bipartite flow component used in RADTTS (Shih et al., 2021), with similarities to the one in GlowTTS (Kim et al., 2020b). However, the focus on modeling low dimensional discontinuous data poses additional challenges that warrant further architectural changes.

Data Format: Attempting to fit directly to raw $F₀$ and $E$ data is incredibly unstable, thereby necessitating the data transformations in Sections 3.2 and 3.3. The training is unstable in that not only does the likelihood loss have difficulty converging on training data, but that the posterior distribution of the training data struggles to conform to a standard normal. The latter indicates that the model cannot find a reasonable mapping between $f_X$ and $f_Z$, rendering the model unusable. The use of grouping and auxiliary dimension are strictly necessary for model stability, whereas additional improvements in output quality are attained through proper handling of unvoiced segments.

We train separate bipartite models for $F₀$ and $E$ respectively. We use a grouping of size 2 for $F₀$, combined with either centered-difference auxiliary features or CWT. The resulting dimensionality
at each time step is 4 and 24 respectively. We use a grouping of size 4 with centered-difference auxiliary features for $E$, giving us a dimensionality of $4 \times 2 = 8$. We found the model to be unstable with group size below 4. Difficulties in modeling $E$ possibly stem from energy being only weakly correlated with the underlying text in $\Phi_{text}$, and more strongly correlated with nearby values.

**Voiced-Aware Context:** The quality of our $F_0$ prediction plots improves with each of the aforementioned strategies. However, catastrophic errors still happen. The patterns for $F_0$ in the voiced and unvoiced segments are bimodal; they cannot be mixed. Failures occur when the model performs a misplaced transition between modes, such as in the middle of a voiced segment. Errors such as these result in outlier spikes and dips in the generated $F_0$ curvature, resulting in catastrophic audio artifacts. Examples are shown in section C.1.

Fortunately, one can easily construct a voiced/unvoiced classifier on which to condition the flow model’s output.

Conditioning on explicit voiced/unvoiced region labels prevents the flow model from performing misplaced transitions. We construct such a classifier $V = F(\Phi_{text})_{voiced}$ where $F_{voiced}$ is a regression function that predicts at every time step $t \in T$ whether we are dealing with a voiced or an unvoiced time step. Here, we assume $V$ is a binary vector of length $T$ such that $V \in \{0, 1\}^1 \times T$. We achieve this by thresholding regressed values at 0.5.

Given our predicted voiced/unvoiced mask $V$ and our context matrix $\Phi_{text}$, one could simply concatenate them and condition the flow model on the concatenated result. However, concatenation runs the risk of the model choosing to ignore single-channel $V$, which has a negligible vector norm compared to each slice in $\Phi_{text}$, set to 512 channels in our implementation. Instead, we learn separate affine transformations for voiced and unvoiced regions to apply directly on $\Phi_{text}$ to get $\hat{\Phi}_{text}$, similar to conditional instance normalization used in style transfer literature (Dumoulin et al., 2017). Let $V^t$ be the binary voiced/unvoiced indicator at timestep $t$. $s_{voiced}$, $b_{voiced}$, $s_{unvoiced}$, and $b_{unvoiced}$ are $C$-dimensional embedding vectors, matching the dimensions in $\Phi_{text}$. They represent the learned scale ($s$) and bias ($b$) for voiced and unvoiced regions. We perform the voiced-conditional affine transformation of $\Phi_{text}$ as follows:
The result is a per-channel affine transformation over $\hat{\Phi}_{text, voice}$, with different affine parameters for voiced and unvoiced regions, allowing us to condition on timed text and whether a time segment is voiced. We can use the ground truth voiced/unvoiced area mask during training, and the output of $F_{voiced}$ during inference.

### 3.4.4 Autoregressive Flow Model

Our autoregressive flow model for modeling $F_0$ and $E$ is based on the bidirectional autoregressive flow architecture used in Flowtron (Valle et al., 2020b; Papamakarios et al., 2017). As with before, we train separate models for $F_0$ and $E$. A high level description of how the model works can be seen in Figure 6 with a more detailed description of the forward and inverse process given in section D.1.

Following the implementation in (Valle et al., 2020b), the neural network architecture comprises a 2-layer LSTM followed by a final non-linear projection over the hidden state to produce the affine or spline transformation parameters. The full model comprises two such models: one running from left-to-right, and a second identical model running from right-to-left on the output of the first, similar to a bi-directional LSTM.

The autoregressive transformation is more expressive than the bipartite transformation as the corresponding Jacobian matrix of the autoregressive transform is much more dense compared to that of a bipartite model (Ping et al., 2020). This difference is especially significant on low-dimensional data such as what we are attempting in this work.

**Learning the Unvoiced Bias:** Similarly to the bipartite model, the autoregressive model is unstable on raw $F_0$ data due to unvoiced phonemes. Drawing inspiration from mixed excitation synthesizers (McCree & Barnwell, 1995) in which unvoiced sounds were represented as a distribution over frequency band and width, we learn a negative bias term for each unvoiced phoneme.

Let $\phi_{text}$ represent the sequence of duration agnostic phoneme embeddings in an utterance. We design a regression function $b_{unvoiced} = -ReLU(F(\phi_{text})_{bias})$ that predicts a per-phoneme negative or zero bias given phoneme embedding. The voiced/unvoiced mask described in 3.4.1 operates at a frame basis, hence we first align the unvoiced bias with the $F_0$ contour by using “ground truth” phoneme durations. Then we apply the voiced mask to the unvoiced bias and finally bias the $F_0$ contour. We optimize $F_{Bias}$ by backproping through the $F_0$ of the conditional decoder. As this is ReLU-based, we still end up with some zeros in the unvoiced regions. Nevertheless, the autoregressive model worked well with this setup.
Further improvements in handling the voiced and unvoiced region transitions come from incorporating the same voiced-aware context as described in the bipartite model description. Without it, the model relies heavily on its hidden states, which are far less reliable.

Worth noting that while the learned bias worked well for the autoregressive model, the phoneme-agnostic distance transform filler resulted in unnatural-sounding $F_0$ contours. Conversely, the bipartite model was somewhat more stable using the distance transform than the learned bias, as the latter may still have zeros in the unvoiced region. We speculate that the difference in behavior is due to the distinct differences in learned data associations between an autoregressive process and a conv-net-style bipartite model.

3.4.3 Improved Model Fitting with Neural Splines

Both normalizing flow architectures we examine rely on coupling-based transforms. The most commonly used implementation is the affine-coupling function, which splits the data along the channel dimension and uses the one split to infer a set of affine parameters for the other:

$$x \rightarrow \text{split } x_a, x_b$$
$$f(x_b) \rightarrow D, \beta$$
$$x_a^* = Dx_a + \beta$$

(10)

(11)

(12)

$$\text{concat}(x_a^*, x_b) \rightarrow x^*$$

(13)

Here, $D$ is a diagonal matrix of inferred scaling values to simplify the inversion and log-determinant calculation process, which are $1/D$ and the sum of the diagonal terms on $\log D$ respectively. As $x_b$ is unaltered, we can recover $D$ and $\beta$ to invert the transformation on $x_a$.

One potential limiting factor of affine coupling is that the set of transformation parameters is uniform for all possible values in $x_a$. This is relevant to our case because, as previously stated, our $F_0$ data representation is bimodal. It would not make sense to use the same affine parameters for both voiced and unvoiced values.

For this reason, we consider Neural Splines as an alternative to affine coupling. Neural Splines, as originally proposed by (Müller et al., 2019) and further extended by (Durkan et al., 2019), replace the affine function with a monotonic piecewise polynomial function. This function is monotonic and its input and output are bounded, thereby allowing for easy invertibility. Importantly, the piecewise spline transformation comprises of a series of connected polynomial functions. A value in $x_a$ will receive different treatment based on which spline’s bin it falls into. Critically, this allows the model to learn multi-modal transformations necessary for multi-modal inputs.

We use piecewise quadratic splines for our work, simply adjusting the parameter predictor in (12) to output the spline parameters instead of affine. One limitation of neural spline coupling layers is that the input and output are bounded. While it is customary to simply to use the identity function for anything outside of bounds, this can be problematic if too much (or sometimes all) of the data ends up outside of bounds. For the bipartite architecture, we replace the affine coupling transform in the 4 out of 6 flow steps closest to the latent space with neural splines, leaving the 2 steps closest to the training data as affine coupling. Having the neural splines deal directly with the bimodal $F_0$ data can potentially lead to some instabilities. The two simpler, but also more stable affine coupling flow steps serve to massage the data slightly for the spline functions. The autoregressive architecture comprises only two affine coupling blocks, one for each direction in the bidirectional procedure. We replace each with neural splines, carefully scaling the input data to fall within the spline’s bounds.

Our experiments will later demonstrate that the introduction of neural splines greatly improve the model’s ability to map the training data to the standard normal prior.

4 Experiments

We conduct our experiments on the LJSpeech dataset (Ito & Johnson, 2017). The following section includes ablation studies on various design choices, as well as comparisons against deterministic baselines. All experiments, we use “ground-truth” phoneme durations obtained from the RADTTS alignment framework to avoid introducing additional variables into the study. Our experiments focus
on the quality of resampled $F_0$ and energy, with timing held as a constant. FastPitch (FP) uses a checkpoint available provided by the author (Ła´ncucki, 2021). Our FastSpeech2 (FS2) (Ren et al., 2020) is based on a third-party open-source implementation from (Chien, 2022), modified and replicated to the best of our ability.

When full-audio synthesis is necessary, synthesized features from our models are decoded using a reimplementation of the RADTTS mel spectrogram decoder, modified to further condition on $F_0$ and $\mathcal{E}$. A full study on its acoustic feature fidelity is provided in section A.

To go from mel spectrograms to waveform, all models share a single HiFi-GAN (Kong et al., 2020) checkpoint trained on LJSpeech as provided by the authors (Kong, 2022). We do not fine-tune HiFi-GAN (HG) on synthesized mel-spectrograms because it would turn HG into a mel-spectrogram enhancer and introduce confounding factors into the analysis. For brevity, the bipartite model will be referred to as BGAP (bipartite generative attribute predictor) and the autoregressive architecture AGAP. We use the acronym RADTTS to refer to (Shih et al., 2021), RADDAP to refer to RADTTS with deterministic attribute predictors, BGAP and AGAP to refer to bipartite and autoregressive flow models, whereas ablated model names are specified in the legend of Fig. 8.

4.1 $F_0$ AND $\mathcal{E}$ DISTRIBUTION EVALUATION

We attempt to quantitatively evaluate how well our models are able to accurately reproduce the true distribution of the low-level acoustic features we are modeling.

4.1.1 SPLINES IMPROVE FIT TO PRIOR

Normalizing flows fit a transformation, mapping the input data distribution to a (usually) a standard normal. We observed that the distribution of the projected latent values per training batch would quickly conform to a standard normal, whereas unstable models would not. Figure 7 tracks the value $\frac{1}{2}||z||_2$ taken from the normalizing flow loss function. This value also corresponds to $\frac{1}{2}$ the variance of a zero-mean Gaussian, which means we should expect it to stabilize at exactly 0.5. We observe that in the bipartite case, the introduction of neural splines significantly improve the rate at which the projected training data conform to a standard normal. The baseline model using only affine transforms never conform to a standard normal even at convergence. However, the same comparison on the autoregressive architecture resulted in little to no difference, as both affine-only and spline architectures had no trouble transforming the distribution.

4.1.2 STATISTICAL MOMENTS

Following (Ren et al., 2020), we compare statistical moments $\mu_n$ of the ground truth $F_0$ distribution, represented as midi notes (Moog, 1986) ($m = 12 \times \log_2\left(\frac{f}{440}\right) + 69$) against the synthetic pitch distribution from several models. Whereas the first two statistical moments provide a measure of what an average note is and how much variation there is, the third statistical moment highlights if notes lower than the mean are more frequent than notes higher than the mean, while the fourth moment highlights how often outlier notes are present and how high they are.
For these experiments, we use $\sigma_{F_0} = 1$ to sample from all generative $F_0$ predictors and $\sigma_{(E)} = 1$ and $\sigma_{(E)} = 0.3$ for the autoregressive and the bipartite generative models. All models use voiced-aware context (Vpred). BGAP models use centered-difference first-order auxiliary features (FoF) in all cases except when continuous wavelet transforms (CWT) are used. We also ablate the use for distance transform filler data (DTx) for BGAP models. Our results in Table 1 show that with our method we effectively model the statistical moments without sacrificing quality. Our autoregressive flow model achieves the highest similarity with the target distribution in 4 out of 4 statistical moments, notably outperforming our internal deterministic RADDAP, which uses the same decoder and vocoder.

We hypothesize that the high kurtosis values on BGAP spline models are an artifact from instabilities due to the high $\sigma$ value, specially given the relatively small second moment. On the other hand, a comparison of the affine and spline BGAP models (rows 3 and 4) makes it evident that by adding the distance transform we are able to improve the third and fourth moments.

### Table 1: Statistical moments computed over midi notes. Closer to the GT value is better. Model numbers correspond to the same numbering as used in the Fig.8 legend.

| Model   | $\mu_1$ | $\mu_2$ | $\mu_3$ | $\mu_4$ |
|---------|---------|---------|---------|---------|
| GT      | 55.47   | 4.06    | 0.36    | 0.50    |
| HG      | 55.49   | 4.00    | 0.26    | -0.16   |
| 1 BGAP-AVDF | 55.79 | 3.53    | -1.10   | 18.30   |
| 2 BGAP-SVC | 56.41 | 3.32    | -0.04   | -0.05   |
| 3 BGAP-SVDF | 55.63 | 3.07    | -6.67   | 196.01  |
| 4 BGAP-SVF | 55.63 | 3.21    | -10.81  | 396.56  |
| 5 AGAP-SV | **55.56** | **4.08** | **0.33** | **0.70** |
| 6 AGAP-AV | 55.27   | 4.89    | 0.52    | 1.06    |
| 7 AGAP-SVC | 56.00   | 3.92    | -0.09   | 0.05    |
| 8 RADDAP | 56.36   | 2.90    | 0.04    | 0.28    |
| 9 FS2    | 53.06   | 6.86    | -0.81   | -0.47   |
| 10 FP    | 55.15   | 4.37    | -1.30   | 3.05    |

#### 4.1.3 Sample Error

We now look at mean squared error with respect to the ground truth on the LJS 100 validation set. We evaluate Voiced $F_0$ Error (VFE): the $F_0$ mean-squared error limited to the voiced segments of the data. Next we have the predicted energy error (ENR): the MSE between predicted energy and ground truth. Finally, we have Voicing Decision Errors (VDE) (Nakatani et al., 2008): mean-absolute error between predicted and ground truth voiced-region masks. As generative models do not predict the best sample everytime, we synthesize 30 samples per utterance to cover the distribution of errors given the same utterance. We use $\sigma_{F_0} = 1$ for both models, and $\sigma_{(E)} = 1$ and $\sigma_{(E)} = 0.3$ for AGAP and BGAP respectively. Our primary deterministic baseline is RADDAP. While we include results for FP and FS2, their mel spectrogram decoders have lower acoustic feature fidelity, see Appendix A, and thus cannot be directly compared against.

Figure 8 provides violin plots of the distribution of VFE, VDE and ENR computed over a set of models, with the vertical axis in log space. By comparing models AGAP models 5 and 6, we can see the effect of replacing affine couplings layers with spline coupling layers. Incorporating splines considerably lowers the error distribution compared to the affine-coupling baseline.

The plot on the second row shows that our models in general have lower average VDE errors compared to other models, most notably our internal RADDAP baseline. We hypothesize this is due to the voiced-aware context we proposed. We also hypothesize that the relatively large error outliers in ENR for AGAP models compared to come from the difference in $\sigma_{(E)}$ between AGAP and BGAP models.
Figure 8: Distribution of VFE, VDE and ENR between ground truth and synthesized samples. A comparison of the distribution of FDE in deterministic and generative models highlights that generative modelling of $F_0$ is possible without loss in quality. In addition, the VDE error distributions suggest our context-aware context decreases voicing decision errors. The vertical axis is in log space.

5 Conclusion

To the best of our knowledge, our work is the first to propose an explicit generative model for $F_0$ and Energy. We resolve the issue of generative modelling of low dimensional speech attributes by proposing solutions using both autoregressive and bipartite normalizing flow models. Stability is achieved through voiced/unvoiced segment awareness, as well as several techniques for handling issues regarding discontinuities and zero derivative regions in $F_0$ data. Furthermore, we identify spline coupling layers as a powerful invertible transformation, particularly well suited for our task.
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Xin Wang, Shinji Takaki, Junichi Yamagishi, Simon King, and Keiichi Tokuda. A Vector Quantized Variational Autoencoder (VQ-VAE) Autoregressive Neural SF_0S Model for Statistical Parametric Speech Synthesis. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 2018b. ISSN 2329-9290. doi: 10.1109/taslp.2019.2950099.
A Acoustic Feature Fidelity

We use acoustic feature fidelity to denote how well a speech synthesis model preserves $F_0$ and $E$ as specified by the conditioning values. This is important because it describes how speech synthesis models interfere with the conditioning variables and quantifies how much control in fact is available to the end-user.

We evaluate the acoustic fidelity of different models by deconstructing LJSpeech’s validation audio files into their extracted phoneme durations, $F_0$, and $E$, and attempt to reconstruct the original using the RADTTS, FP, and FS2 decoders followed by the Hifi-Gan vocoder.

We provide quantitative results that compare voiced $F_0$ Relative Frame Error (FRE) Kawahara et al. (2005), Voicing Decision Error (VDE) Nakatani et al. (2008), Energy Error (ENR), and Mel-Spectrogram Error (MER). In addition to results for FP, FS2, the RADTTS decoders, we also measure the irreducible error from the HG vocoder by use of ground-truth mel-spectrograms. This serves as a lower bound to the reconstruction error. All $F_0$ and voicing decisions are extracted using the pYIN algorithm Mauch & Dixon (2014).

The results in Table 2 show that the RADTTS (RAD) decoder has the lowest reconstruction error in all acoustic features measured. Our results show that RAD performs at least twice as well with respect to $F_0$ fidelity, a significant improvement specially in artistic endeavours where pitch fidelity is of utmost importance.$^1$

Finally, we include a parameter sweep study of the effect of the sampling noise level on acoustic feature fidelity in Fig.9. As observed, several metrics do improve at lower noise levels. However, the lower noise levels also introduce noticeable audio artifacts.

Table 2: The RADTTS decoder has the highest acoustic feature fidelity and lowest mel-spectrogram reconstruction error.

| Model | FRE  | VDE  | ENR  | MER  |
|-------|------|------|------|------|
| HG    | 0.019| 0.045| 0.051| 0.286|
| RADTTS| 0.026| 0.067| 0.270| 0.735|
| FP    | 0.055| 0.128| 0.355| 0.833|
| FS2   | 0.050| 0.150| 0.350| 0.758|

B Continuous Wavelet Transform Implementation Details and Discussion

We follow the exact implementation as used in FastSpeech2, first filling in the unvoiced areas with linear interpolation, standardizing the data to be zero mean unit variance, then applying CWT to give us a 10D representation. Finally, we append the original mean and variance, replicated along the time axis, to achieve a 12D representation. This final step is necessary as the mean and variance are required to undo the standardization step.

There are several drawbacks of this approach. First of all, the CWT is not a lossless procedure, as the reconstruction has a tendency to produce a smoother curvature than the original data. Next, while interpolation is necessary for CWT to be stable, it also means that we lose track of the location of the unvoiced regions. Furthermore, it is possible that the interpolated values may introduce noise into the training data as it falls within the same range as the valid data. Nevertheless, accounting for these drawbacks, we observe improved training stability and output quality due to the dimensionality increase as we will demonstrate later.

$^1$In musical terms, 0.05 FRE is equivalent to singing half-a-step out of tune, turning a professional singer into an amateur.
C Bipartite Model Details

The bipartite model architecture closely follows that which was used in RADTTS Shih et al. (2021), using steps of flow comprising $1 \times 1$ invertible convolutions and Coupling transforms. As mentioned in the main text, the proposed architecture replaces 4 out of the 6 steps of flow nearest to the latent space with quadratic splines.

Data Scaling: Training data should be scaled to be reasonably close in scale to the target standard normal distribution for stability. Centered-difference features are computed on $\log F_0$ and kept at their original scale. $\log F_0$ values are then divided by 6 before being used in the model. $E$ values are kept at their original values, but the corresponding centered-difference features on $E$ are multiplied by 10.

Spline Details: Our work uses quadratic splines in all cases. Previously we have experimented with linear splines, but found quadratic splines to have much better convergence. The splines for the bipartite model operate within the bound $[-3, 3]$ with 24 bins. All values that fall outside of the bounds are passed through with identity, but eventually handled by the $1 \times 1$ invertible convolution blocks.

C.1 Qualitative Analysis

Several ablations for the bipartite model were not included in the main studies, as the results were obviously poor. However, we can qualitatively observe the effect of various design choices in Fig. 10. We display the direct output of the model in this figure. In other words, if distance transform filler data was used, it should be reproduced by the model during inference, as we see in the top two rows. In practice, these filler values will be easily thresholded away before plugging into the decoder.

The first thing to observe is the accuracy of how the accuracy of the voiced/unvoiced region segments is affected by the removal of the voiced-aware context. The full model at the top contains voiced-aware contexts, distance transform filler in the unvoiced regions, and centered-difference features. In the second row, we start to see unnatural spikes in the middle of a voiced segment, indicating the model was not certain which mode of behavior to go with at that time step.
Figure 10: Qualitative ablation of how feature transformations affect $F_0$ prediction quality. The top row is the full model, containing voiced-aware contexts, distance transform filler in the unvoiced regions, and centered-difference features. As voiced prediction and distance transform filler are removed, the model becomes incapable of modeling the unvoiced segments.

Moving down to the third row, we see how the removal of the distance transform context further degrades the model’s ability to model unvoiced regions. Notably, notice that without the distance transform filler data, there are no more long unvoiced segments. We can compare against the ground truth in the fourth row to see that only the full model, and to a lesser extent, the second row with distance transform filler, is able to somewhat accurately model the longer unvoiced segments. However, we note than even in the full model, we can identify false-positive voiced regions at the end of the sample as compared to the ground truth.

D AUTOREGRESSIVE MODEL DETAILS

The autoregressive model architecture closely follows that which was used in Flowtron Valle et al. (2020b). With this setup, it is also possible to reverse the ordering of the attributes in time without loss of generality. We reverse the order of frames on even steps of flow, defining a step of flow as a full pass over the input sequence. This allows the model to learn dependencies both forward and backwards in time while remaining causal and invertible. Our proposed autoregressive flow architecture uses 2 steps of flow, each with 2 LSTMs over the data, the second one also conditioned on the context.

Data Scaling: Similarly to the Bipartite flow model, training data was scaled to be reasonably close in scale to the target standard normal distribution for stability.

Spline Details: Our work uses quadratic splines in all cases. The splines for the autoregressive model operate within the bound $[-6, 6]$ with 24 bins. Wider bounds are necessary as we do not incorporate 1x1 invertible convolutions as a catch-all for out-of-bound values.
D.1 Forward and Inverse Procedures

Here, we provide additional background on the forward and inverse procedure for the autoregressive architecture. For simplicity, we will use affine transforms as an example, but the same procedure holds for the neural spline operation. Here, superscripts indicate positional indices, not to be confused with exponents.

Let $X$ be the sequence $x^0 \ldots x^T$. We first augment it with a constant value at the beginning:

$$X = 0, x^0, \ldots, x^T$$  \hfill (14)

Let $NN()$ be the autoregressive transformation parameter predictor that will run through the data from $0$ to $x^T$. Our first iteration is as follows:

$$s^0, b^0 = NN(0)$$  \hfill (15)

$$z^0 = (x^0 - b^0) / s^0$$  \hfill (16)

and subsequent steps:

$$s^t, b^t = NN(0 \ldots x^{t-1})$$  \hfill (17)

$$z^t = (x^t - b^t) / s^t$$  \hfill (18)

Our end result is a vector $Z = z^0 \ldots z^T$. To reverse the process, we again start with $0$ as follows:

$$s^0, b^0 = NN(0)$$  \hfill (19)

$$x^0 = s^0 z^0 + b^0$$  \hfill (20)

and with $x^0$ available, we can then proceed with subsequent steps:

$$s^t, b^t = NN(0 \ldots x^{t-1})$$  \hfill (21)

$$x^t = s^t z^t + b^t$$  \hfill (22)

For further information, please see Valle et al. (2020b) and Papamakarios et al. (2017).

D.2 Qualitative Analysis

Figure 11 depicts three autoregressive models. The first two use the full set of proposed autoregressive design choices, but one uses affine coupling and the second uses splines. The qualitative difference between the affine and spline full models is very minimal, supporting the observation that autoregressive are much better suited for the task. In the third row, we have an ablation where voiced-context is removed. We immediately see that there are now more discrepancies between the third row and the ground truth in the fourth. Here, the model must infer voiced-unvoiced state changes based on its internal hidden state, which we suspect is much less reliable than a simple fully-supervised classifier. Nevertheless, we note that the autoregressive result without voiced prediction is still much cleaner than the one from the bipartite model.
Figure 11: Qualitative analysis of $F_0$ synthesis from the autoregressive architecture. While the autoregressive architecture benefits from the use of voiced-aware context, it performs acceptably well compared to a bipartite model without voiced-aware context.
Subjective scoring is performed by crowd-sourcing pairwise preferences between models, as mean opinion scores are not suited for fine-grained differences. Listeners were pre-screened with a hearing test based on sinusoid counting. Qualified raters were repeatedly given two synthesized utterances of the same text, picked at random from 100 LJ test samples and asked to select samples with best overall quality, defined by accuracy of text, pleasantness, and naturalness. All the model details were hidden from the human raters. Approximately 150 scores per model were collected. Table 3 demonstrates the results of the pairwise preference test conducted against specific model combinations.

First, we observe that the spline flow models are preferred over affine flow based models when sampled with standard deviation 0.5 as well as 1.0. The preference is more profound for standard deviation 1.0. We believe this is a consequence of splines fitting the prior better than affine transforms.

Next, we compare the models from autoregressive and bipartite flow based generative models against RADDAP, a model with deterministic feature prediction in RADTTS. We observe that in both cases the deterministic feature prediction model is preferred by human raters however there is a confidence interval overlap between the two models. This shows that the generative feature predictors are close in human perception to deterministic feature predictor models. We also observe that the autoregressive spline flow model fares better than the bipartite spline flow model. We also directly compare the autoregressive spline flow model to bipartite spline flow models sampled at standard deviation 0.5, and observe the same conclusion. The autoregressive feature prediction models outperform parallel feature prediction models and are preferred by human raters.

We compare the speech quality of our generative models using spline and affine transform based flow models against FastPitch and FastSpeech2 baselines. We observe that in almost all cases, our deterministic feature prediction model RADDAP as well as generative feature prediction models (spline flow and affine flow models) outperform FastSpeech2 in the perceived speech quality of the samples. In certain cases, the FastPitch model is preferred over our generative feature prediction models but with overlapping confidence intervals. Our deterministic feature prediction model (RADDAP) outperforms both FastPitch and FastSpeech2. Considering all these comparisons, we observe that the RADDAP model is preferred the most among all models considered in this evaluation. However, the spline flow based autoregressive and parallel generative feature prediction models provide a comparable speech synthesis quality with the added benefits of supporting synthesis of diverse samples.

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2 We re-implemented FastSpeech2 to the best of our ability, but due to lack of source code and pretrained models, we had a hard time matching the quality of samples reported by the authors. This comparison was done using our implementation of FastSpeech2.
Table 3: Pairwise preference scores by human raters, shown with 95% confidence intervals of model A (left) vs model B (right). Scores above 0.5 indicate model A was preferred by majority of raters over model B.

| Model Pair                                      | Pairwise Preference | Preferred Model |
|------------------------------------------------|---------------------|-----------------|
| BGAP Spline (\(\sigma = 0.5\)) vs BGAP Affine (\(\sigma = 0.5\)) | 0.567 ± 0.0766      | BGAP Spline     |
| BGAP Spline (\(\sigma = 1.0\)) vs BGAP Affine (\(\sigma = 1.0\)) | 0.647 ± 0.0774      | BGAP Spline     |
| RADDAP vs AGAP Spline (\(\sigma = 0.5\))           | 0.562 ± 0.0740      | RADDAP (CI Overlap) |
| RADDAP vs BGAP Spline (\(\sigma = 0.5\))           | 0.671 ± 0.0707      | RADDAP          |
| AGAP Spline (\(\sigma = 0.5\)) vs BGAP Spline (\(\sigma = 0.5\)) | 0.680 ± 0.0652      | AGAP Spline     |
| BGAP Spline (\(\sigma = 0.5\)) vs FastPitch       | 0.391 ± 0.0525      | FastPitch (CI Overlap) |
| BGAP Spline (\(\sigma = 0.5\)) vs FastSpeech2     | 0.831 ± 0.0669      | BGAP Spline     |
| BGAP Affine (\(\sigma = 0.5\)) vs FastPitch      | 0.393 ± 0.0819      | FastPitch       |
| BGAP Affine (\(\sigma = 0.5\)) vs FastSpeech2     | 0.785 ± 0.0716      | BGAP Affine     |
| AGAP Spline (\(\sigma = 0.5\)) vs FastPitch      | 0.537 ± 0.0688      | AGAP Spline (CI Overlap) |
| AGAP Spline (\(\sigma = 0.5\)) vs FastSpeech2     | 0.771 ± 0.1464      | AGAP Spline     |
| RADDAP (\(\sigma = 0.5\)) vs FastPitch           | 0.586 ± 0.0692      | RADDAP          |
| RADDAP (\(\sigma = 0.5\)) vs FastSpeech2          | 0.849 ± 0.0891      | RADDAP          |