Unsupervised source separation with deep priors

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Contents

Abstract

Research Question

Source separation is the task of finding a set of latent sources $\boldsymbol{s} = [\boldsymbol{s}_1, \dots \boldsymbol{s}_k, \dots, \boldsymbol{s}_N]^T \in \mathbb{R}^{N \times T}$ to an observed mix of those sources $\boldsymbol{m} \in \mathbb{R}^{1 \times T}$. The induced model proposes a mixing function $\boldsymbol{m} = f(\boldsymbol{s})$. The task is to find an approximate inverse model $g(\cdot)$ which retrieves $\boldsymbol{s}$:

$$\mathbf{m} = f(\boldsymbol{s}) \tag{1}$$

$$g(\boldsymbol{m}) \approxeq \boldsymbol{s} \tag{2}$$

In this learning setting *supervision* can happen in three ways: First the source signals are identified as being from class k [1]. Second the tuples $(\boldsymbol{m}, \boldsymbol{s})$ are supervised giving us examples of mixes and their corresponding sources. And third knowing number k of sources. The first is not a supervision signal of the separation task and therefore is there something missing here? I guess so.

[1] For the setting of music think of the classes being {*guitar,piano,voice,*...}

1. Can we learn a source separation model $g(\cdot)$ by learning deep priors for the different source classes. If it is a question, it should have a question mark
2. Can we reduce this to an unsupervised setting. Unsupervised relating to the missing pairings of sources and mixes.

Background

In this section we introduce the minimally necessary background concepts our work is building upon. Our work marries two fields of research: on the one side generative, graphical models. With those one tries to model the data distribution of a n observed variable by inducing dependencies of latent (unobserved) variables generating the observed variables. Modeling those dependencies, the meaningful latent variables allow us to build an intuitive generative story for the probabilistic model of the observed data. On the other hand we introduce the recent body of of work on how to practically model sound signals, in particular how this compares differently to modeling images.

First we introduce the concept of deep latent-variable models, which important classes of models exist and how to train them. Second we will shortly draw up the difficulties of modeling sound and which recent solutions exist and how they differ.

Deep Latent-Variable Models

In this section we introduce the idea of latent variable and the idea of finding models of data using those latent variables. Further we discuss what practical ways are currently successful in estimating the model parameters and how they are trained.

For our process, we have observations from the data space $\boldsymbol{x} \in \mathcal{D}$ for which there exists an unknown data probability distribution $p^*(\mathcal{D})$. We collect a data set $\{\boldsymbol{x}_1 \dots \boldsymbol{x}_N\}$ with N samples. Further we introduce an approximate model with the density[2] $p_{\boldsymbol{\theta}}(\mathcal{D})$ and model parameters $\boldsymbol{\theta}$. Learning or modeling means finding the values for $\boldsymbol{\theta}$ which will give the closest approximation of the true underlying process:

$$p_{\boldsymbol{\theta}}(\mathcal{D}) \approx p^*(\mathcal{D}) \tag{3}$$

The model $p_{\boldsymbol{\theta}}$ has to be complex enough to be able to fit the data density while little enough parameters to be learned. Every choice for the form of the model will *induce* biases[3] about what density we can model, even before we maximize a learning objective using the parameters $\boldsymbol{\theta}$.

In the following described models we assume the sampled data points $\boldsymbol{x}$ to be drawn from $\mathcal{D}$ *independent and identically distributed*[4].

[2] We write density and distribution interchangeably to denote a probability function.

[3] called *inductive biases*

[4] meaning the sample of one datum does not depend on the other data points and we all draw them the same way

Therefore we can write the data log-likelihood as:

$$\log p_{\theta}(\mathcal{D}) = \sum_{x \in \mathcal{D}} \log p_{\theta}(x) \tag{4}$$

The maximum likelihood estimation of our model parameters maximizes this objective.

To form a latent-variable model we introduce a *latent variable*[5]. This latent variable can be any random variable underlying the generation of a data sample in $\mathcal{D}$. For example if we look at the generative story of a sound sample, a latent variable could be the sound source (the *instrument*). One can directly model the distribution of all musical notes played by all possible instruments. But we could also introduce the instrument as an underlying latent variable z, which would then lead to one distribution over this categorical variable and separate conditional densities of the sounds of each instrument. One of them then modeling the distribution of sounds made by a harp, for example.

[5] Latent variables are part of the directed graphical model but not observed.

Now the data likelihood is the marginal density of the joint latent density. With one latent variable we get:

$$p_{\theta}(x) = \int p_{\theta}(x, z) dz \tag{5}$$

Typically we introduce a factorization of the joint. The most common one and also the one from our previous example is:

$$p_{\theta}(x) = \int p_{\theta}(x|z) p(z) dz \tag{6}$$

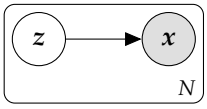


Figure 1: The graphical model with a introduced latent variable z. Observed variables are shaded.

This corresponds to the graphical model in which z is generative parent node of the observed x, see Figure 1. The density $p(z)$ is called the *prior distribution*.

If the latent is small, discrete, it might be possible to directly marginalize over it. If for example, z is a discrete random variable and the conditional $p_{\theta}(x|z)$ is a Gaussian distribution than the data model density $p_{\theta}(x)$ becomes a mixture-of-Gaussians, which we can directly estimate by maximum likelihood estimation of the data likelihood.

For more complicated models the data likelihood $p_{\theta}(x)$ as well as the model posterior $p_{\theta}(z|x)$ are intractable because of the integration over the latent z in Equation (6).

To formalize the search for an intractable posterior into a tractable optimization problem we can follow the *variational principle*[6] which introduces an approximate posterior distribution $q_{\phi}(z|x)$, also called the *inference model*. Again the choice of the model here carries inductive biases, as such that even in asymptotic expectation we can not obtain the true posterior.

[6] Jordan et al., "An Introduction to Variational Methods for Graphical Models", 1999.

Following the derivation in [[7]p. 20]kingmaIntroduction2019 we introduce the inference model into the data likelihood [8]:

[7] [.

[8] The first step is valid as q_{θ} is a valid density function and thus integrates to one.

$$\log p_{\boldsymbol{\theta}}(\boldsymbol{x}) = \mathbb{E}_{q_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\left[\log p_{\boldsymbol{\theta}}(\boldsymbol{x})\right] \tag{7}$$

$$= \mathbb{E}_{q_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\left[\log \frac{p_{\boldsymbol{\theta}}(\boldsymbol{x},z)}{p_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\right] \tag{8}$$

$$= \mathbb{E}_{q_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\left[\log \frac{p_{\boldsymbol{\theta}}(\boldsymbol{x},z)}{q_{\boldsymbol{\phi}}(z|\boldsymbol{x})}\frac{q_{\boldsymbol{\phi}}(z|\boldsymbol{x})}{p_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\right] \tag{9}$$

$$= \mathbb{E}_{q_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\left[\log \frac{p_{\boldsymbol{\theta}}(\boldsymbol{x},z)}{q_{\boldsymbol{\phi}}(z|\boldsymbol{x})}\right] + \mathbb{E}_{q_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\left[\log \frac{q_{\boldsymbol{\phi}}(z|\boldsymbol{x})}{p_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\right] \tag{10}$$

$$= \mathbb{E}_{q_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\left[\log \frac{p_{\boldsymbol{\theta}}(\boldsymbol{x},z)}{q_{\boldsymbol{\phi}}(z|\boldsymbol{x})}\right] + \mathbb{D}_{\mathrm{KL}}[q_{\boldsymbol{\phi}}(z|\boldsymbol{x})\|p_{\boldsymbol{\theta}}(z|\boldsymbol{x})] \tag{11}$$

Note that we separated the likelihood into two parts. The second part is the (positive) Kullback-Leibler divergence of the approximate posterior from the true intractable posterior. This unknown divergence states the 'correctness' of our approximation [9]. It could be clearer that the ELBO is a lower bound for the likelihood.

The first term is the *variational free energy* or *evidence lower bound* (ELBO):

$$\mathrm{ELBO}_{\boldsymbol{\theta},\boldsymbol{\phi}}(\boldsymbol{x}) = \mathbb{E}_{q_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\left[\log \frac{p_{\boldsymbol{\theta}}(\boldsymbol{x},z)}{q_{\boldsymbol{\phi}}(z|\boldsymbol{x})}\right] \tag{12}$$

We can introduce the same factorization as in Equation (6):

$$\mathrm{ELBO}_{\boldsymbol{\theta},\boldsymbol{\phi}}(\boldsymbol{x}) = \mathbb{E}_{q_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\left[\log \frac{p_{\boldsymbol{\theta}}(\boldsymbol{x}|z)p(z)}{q_{\boldsymbol{\phi}}(z|\boldsymbol{x})}\right] \tag{13}$$

$$= \mathbb{E}_{q_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\left[\log \frac{p(z)}{q_{\boldsymbol{\phi}}(z|\boldsymbol{x})}\right] + \mathbb{E}_{q_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\left[\log p_{\boldsymbol{\theta}}(\boldsymbol{x}|z)\right] \tag{14}$$

$$= -\mathbb{D}_{\mathrm{KL}}[q_{\boldsymbol{\phi}}(z|\boldsymbol{x})\|p(z)] + \mathbb{E}_{q_{\boldsymbol{\theta}}(z|\boldsymbol{x})}\left[\log p_{\boldsymbol{\theta}}(\boldsymbol{x}|z)\right] \tag{15}$$

Under this factorization, we separated the lower bound into two parts. First, the divergence of the approximate posterior from the latent prior distribution and second the data posterior likelihood from the latent [10].

The optimization of the $\mathrm{ELBO}_{\boldsymbol{\theta},\boldsymbol{\phi}}$ allows us to jointly optimize the parameter sets $\boldsymbol{\theta}$ and $\boldsymbol{\phi}$. The gradient with respect to $\boldsymbol{\theta}$ can be estimated with an unbiased Monte Carlo estimate using data samples [11]. Though we can *not* do the same for the variational parameters $\boldsymbol{\phi}$, as the expectation of the ELBO is over the approximate posterior which depends on $\boldsymbol{\phi}$. By a change of variable of the latent variable we can make this gradient tractable, the so called *reparameterization trick*[12]. We express the $z \sim q_{\boldsymbol{\theta}}$ as an random sample from a unparametrized source of entropy $\boldsymbol{\epsilon}$ and a parametrized transformation:

$$\boldsymbol{z} = f_{\boldsymbol{\eta}}(\boldsymbol{\epsilon}) \tag{16}$$

For example for a Gaussian distribution we can express $z \sim \mathcal{N}(\mu,\sigma)$ as $z = \mu + \sigma \cdot \epsilon$ with $\epsilon \sim \mathcal{N}(0,1)$ and $\eta = \{\mu,\sigma\}$.

[9] More specifically the divergence marries two errors of our approximate model. First, it gives the error of our posterior estimation from the true posterior, by definition of divergence. Second, it specifies the error of our complete model likelihood from the marginal likelihood. This is called the *tightness* of the bound.

[10] This will later be the reconstruction error. How well can we return to the data density from latent space?

[11] $\nabla_{\boldsymbol{\theta}}\,\mathrm{ELBO}_{\boldsymbol{\theta},\boldsymbol{\phi}} \approxeq \nabla_{\boldsymbol{\theta}} \log p_{\boldsymbol{\theta}}(\boldsymbol{x},\boldsymbol{z})$

[12] Kingma and Welling, "Auto-Encoding Variational Bayes", 2014.

The VAE framework

The variational autoencoder (VAE) [12][13] is the previously introduced ideas together into a trainable model.

more

[13] Rezende, Mohamed, and Wierstra, "Stochastic Backpropagation and Approximate Inference in Deep Generative Models", 2014.

Algorithm 1: Training's procedure for a variational autoencoder

while Training is not converged **do**
  $\boldsymbol{X} \sim \mathcal{D}$ ▷ Sample random mini-batch
  $\eta \leftarrow \text{EncoderNN}(\boldsymbol{X})$
  $\boldsymbol{\epsilon} \sim p(\boldsymbol{\epsilon})$
  $\boldsymbol{z} \leftarrow f_{\eta}(\boldsymbol{\epsilon})$
  $\boldsymbol{X}' \leftarrow \text{DecoderNN}(\boldsymbol{z})$
end while

The β-VAE[14] extends the VAE objective with an β hyperparameter in front of the KL divergence. The value β gives a constraint on the latent space, controlling the capacity of it. Adapting β gives a trade-off between the reconstruction quality of the autoencoder and the simplicity of the latent representations[14]. Using such a constraint is similar to the use of the information bottleneck[15].

[14] Higgins et al., "Beta-VAE", 2016.

[15] Burgess et al., "Understanding Disentangling in Beta-VAE", 2018.

Flow based models

Another class of common deep latent models is based on *normalizing* flows[16]. A normalizing flow is a function $f(\boldsymbol{x})$ that maps the input density to a fixed, prescribed density $p(\epsilon) = p(f(\boldsymbol{x}))$, in that normalizing the density [17]. They use a flow for the approximate posterior $q_{\boldsymbol{\phi}}(\boldsymbol{z}|\boldsymbol{x})$. Again this is commonly set to be a factorized Gaussian distribution.

For a finite normalizing flow, we consider a chain of invertible, smooth mappings.

NICE[18] - volume preserving transformations - coupling layer - triangular shape

Normalizing Flow[19]

RealNVP[20] builds on top of NICE creating a more general, non-volume preserving, normalizing flow.

[16] Tabak and Turner, "A family of nonparametric density estimation algorithms", 2013.

[17] The extreme of this idea is, of course, an infinitesimal, continuous-time flow with a velocity field.

[18] Dinh, Krueger, et al., "NICE", 2015.

[19] Rezende and Mohamed, "Variational Inference with Normalizing Flows", 2016.

[20] Dinh, Sohl-Dickstein, et al., "Density Estimation Using Real NVP", 2017.

$$y_{1:d} = x_{1:d} \tag{17}$$

$$y_{d+1:D} = x_{d+1:D} \odot \exp\left(s(x_{1:d})\right) + t(x_{1:d}) \tag{18}$$

$$\frac{\partial y}{\partial x^T} = \begin{bmatrix} \mathbb{1}_d & 0 \\ \frac{\partial y_{d+1:D}}{\partial x_{1:d}^T} & \operatorname{diag}\left(\exp\left(s(x_{1:d})\right)\right) \end{bmatrix} \tag{19}$$

Glow[21] extended the RealNVP by introducing invertible 1×1-convolutions. Instead of having fixed masks and permutations for the computations of the affine parameters in the coupling layer, Glow learns a rotation matrix which mixes the channels. After mixing the input can always be split into the same two parts for the

[21] Kingma and Dhariwal, "Glow", 2018.

affine transformation. Further, the authors showed that training can be helped by initializing the last layer of each affine parameter network with zeros. This ensures that at the beginning without weight update each coupling layer behaves as an identity.

Langevin dynamics

In stochastic optimization we update the parameters $\boldsymbol{\theta}$ with the gradient of the posterior using a subset of samples from our data set.

$$\Delta\boldsymbol{\theta}_t = \frac{\epsilon_t}{2}\{(\nabla \log p(\boldsymbol{\theta}_t)) + \frac{N}{n}\sum_{i=1}^{n} \nabla \log p(x_{ti}|\boldsymbol{\theta}_t)\} \tag{20}$$

This will lead to the maximum a posteriori (MAP) estimates of the parameters $\boldsymbol{\theta}$. By taking the gradient of the posterior only under a subset of the data will give us a noisy estimate of the real gradient, but is computationally cheaper. The idea is, that the noise of the noisy gradients smoothes out while sampling different subsets. When using a decaying step size ϵ_t the stochastic optimization is guareenteed to converge to a local maximum.

Now the Langevin dynamics[22] provides a Markov chain Monte Carlo (MCMC) sampling technique for estimating the parameters of a distribution without overfitting on the data(??).

[22] Neal, "MCMC Using Hamiltonian Dynamics", 2012.

$$\Delta\boldsymbol{\theta}_t = \frac{\epsilon}{2}\{(\nabla \log p(\boldsymbol{\theta}_t) + \frac{N}{n}\sum_{i=1}^{N} \nabla \log p(x_i|\boldsymbol{\theta}_i))\} + \eta_t \tag{21}$$

$$\eta_t \sim \mathcal{N}(0, \epsilon) \tag{22}$$

$$\Delta\boldsymbol{\theta}_t = \frac{\epsilon}{2}\{(\nabla \log p(\boldsymbol{\theta}_t) + \sum_{i=1}^{N} \nabla \log p(x_i|\boldsymbol{\theta}_i))\} + \eta_t \tag{23}$$

$$\eta_t \sim \mathcal{N}(0, \epsilon) \tag{24}$$

Modeling audio

In the physical world a sound signal is a change of the density of the carrier air over time. As such it is a one-dimensional temporal signal[23]. Humans sound perception is *stereo* as we have two ears and sense the changes in pressure at two different points in space simultaneously.

[23] Sound waves in gases are purely compressive, therefore they cannot be polarized which would introduce a higher complexity. In solids a sound signal can have polarization, think of an earthquake with shear and pressure components.

Representations of audio

The simplest form of digitally representing a sound signal is recording the amplitude at fixed intervals at one or multiple points in space with a microphone. This method is called Pulse-Code modulation (PCM). It introduces two parameters which will bias the result of the record. First we have to pick a temporal frequency with

which the pressure samples are taken, the so-called sample rate. The Nyquist-Shannon theorem[24] tells us that if the highest frequency in the true signal is B Hz than with a sample rate of $2 \cdot B$ Hz we will capture the complete signal with all frequencies. At a lower sample rate we might introduce aliasing effects. Second we have to represent each amplitude sample as a digital value. Most commonly the sample is encoded into a 8 bit or 16 bit integer. The microphone has a range of air pressure which w.l.o.g. we set to $[-1, 1]$, where a value of 0 is no signal, 1 shows maximum compression and -1 maximum decompression of the carrier air. The simplest form of encoding is Linear PCM. In Linear PCM amplitudes are quantized on an evenly spaced grid over the possible value range. More advanced quantization include μ-law encoding[25] in which the quantization intervals are varied with the amplitude[26]. As the human perception of loudness is logarithmic this encoding also quantizes the amplitude values on a logarithmic response curve. Simply speaking the lower amplitudes will be quantized on a finer grid than higher amplitudes. This makes it possible to achieve a higher signal-to-noise ratio at smaller encoding sizes for sound signals.

As an example, if encoding a sound signal with 8 kHz 16 bit Linear PCM we sample an amplitude value every $\frac{1}{8000}$s and quantize those into $2^{16} = 65536$ bins. A sample with 100 values is only 12.5 ms long!

A standard full piano with 88 keys tuned to 440 Hz at the A_4[27] has a frequency range of $[27.5\,\text{Hz}, 4186\,\text{Hz}]$ from the A_0 to the C_8, respectively. Therefore just for the recording of a standard piano we need a sampling rate of more than 8 kHz. Beyond the piano many instruments exhibit even larger frequency content which leads to the conclusion that not just for recording but also for our goal of modeling musical sounds a reasonably high sampling rate is crucial.

Looking at the temporal scales of musical information, on the small end we have the modeling of pitch as discussed before which happens at scales of $[10^{-1}\,\text{ms}, 10^{2}\,\text{ms}]$ over single notes happening at scales of $[10^{2}\,\text{ms}, 10^{3}\,\text{ms}]$ to the structure of melodies and full songs happening at $[10^{4}\,\text{ms}, 10^{6}\,\text{ms}]$. The modeling of music happens over 7 magnitudes of time! In **??** we will present common solutions to this difficulty.

[24] Kotelnikov, "On the Carrying Capacity of the Ether and Wire in Telecommunications", 1933.

[25] *Pulse Code Modulation (PCM) of Voice Frequencies*, 1972.

[26] The actual formula for calculating the μ-law quantization is:

$$\mu\text{law}(x) = \text{sgn}(x) \cdot \frac{\ln(1 + \mu|x|)}{\ln(1 + \mu)}$$

[27] ISO/TC 43 Acoustics, *ISO 16 Acoustics Standard Tuning Frequency*, 1975.

Spectrograms

Commonly used alternative representations of signals in sound processing are spectrograms. Spectrograms transport the signal as it is in time-domain into the frequency domain.

Time-domain vs spectrogram, what is a spectrogram, missing phase information, complex spectrograms

Modeling raw audio

Deep learning models as used for image applications are unsuitable for raw audio signals (signals in *time-domain*). Digital audio is sampled at high sample rates, commonly 16kHz up to 44kHz. The features of interest lie at scales of strongly different magnitudes. Recognizing the local-structure of a signal, like frequency and timbre, might require features at short intervals ($\approx$ tens of milliseconds) but modeling of speech or music features happens at the scale of seconds to minutes. As such a generative model for this domain has to model at these different scales.

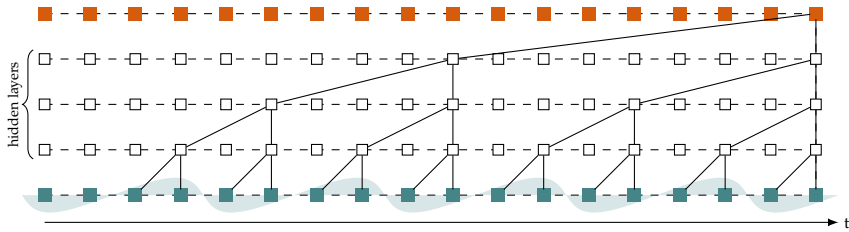


Figure 2: An example of how dilated convolutions are used in the WaveNet. We see three hidden layers with each a kernel size of two. By using the dilations the prediction of the new output element has a receptive field of 18. This convolution is *causal*, as the prediction depends only on previous input values. Causality is enforced through asymmetric padding.

The **WaveNet**[28] introduced an autoregressive generative model for raw audio. It is build upon the similar PixelCNN[29] but adapted for the audio domain. The WaveNet accomplishes this by using dilated causal convolutions.Using a stack of dilated convolutions increases the receptive field of the deep features without increasing the computational complexity, see Figure 2. Further, the convolutions are gated and the output is constructed from skip connections. For the structure of a hidden layer refer to Figure 3. A gated feature, as known from the LSTM[30], computes two outputs: one put through an sigmoid $\sigma(\cdot)$ activation and one through an $\tanh(\cdot)$ activation. The idea being that the sigmoid (with an output range of $[0, 1]$) regulates the amount of information, thereby gating it, while the tanh (with a range of $[-1, 1]$) gives the magnitude of the feature. The output of the WaveNet is the sum of outflowing skip connections added after each (gated) hidden convolution. This helps fusing information from multiple time-scales (*low-level* to *high-level*) and makes training easier[31]. The original authors tested the model on multiple audio generation tasks. They used a μ-law encoding[32] which discretizes the range $[-1, 1]$ to allow a set of μtargets and an multi-class cross-entropy training objective. While being quite unnatural this is done to avoid making any assumptions about the target distribution. Sound generation with a WaveNet is slow as the autoregressiveness requires the generation value by value. The original WaveNet setting is generating waveforms, by giving the previously generated values as the input and conditioning the process on target classes, $p(x_t|x_{1:t}, c_t)$. Therefore the generation has to happen value-by-value (autoregressive). This can be alleviated by keeping intermediate hidden activations cached[33]. The WaveNet can be conditioned by adding the weighted conditionals in the gate and feature activations

[28] Van den Oord, Dieleman, et al., "WaveNet", 2016.
[29] Van den Oord, Kalchbrenner, et al., "Conditional Image Generation with PixelCNN Decoders", 2016.
[30] Hochreiter and Schmidhuber, "Long Short-Term Memory", 1997.
[31] Szegedy et al., "Going Deeper with Convolutions", 2014.
[32] *Pulse Code Modulation (PCM) of Voice Frequencies*, 1972.
[33] Paine et al., "Fast Wavenet Generation Algorithm", 2016.

of the gated convolutions[34].

add PixelCNN++?

The first generative sounds model to employ a WaveNet is **NSynth**[35]. They construct a VAE where encoder and decoder are both WaveNet-like. The so-called *non-causal temporal encoder* uses a stack of dilated residual non-causal convolutions. The convolutions are not gated and no skip-connections are used. The decoder is a WaveNet taking the original input chunk as an input and predicts the next value of the sound sample, while being conditioned on the latent variable. The authors use this model to learn latent temporal codes from a new large set of notes played by natural and synthesized instruments. The latent of the VAE is conditioned on the pitch of these notes. While the model is difficult to train, they show great improvement of the WaveNet-based VAE compared to a spectral-based VAE.

Chorowski et al.[36] presents another WaveNet-based VAE. They are learning speech representations, unsupervised. The encoder is a residual convnet and takes the MFCC of the signal as its input. As the bottleneck they found a VQ codebook[37] to be most successful. The decoder is an autoregressive WaveNet conditioned on the latent features. Note again that this model infers the latent features from mel-cepstra but reconstructs the signal with the WaveNet in time-domain.

In Prenger et al.[38]

FloWaveNet Kim et al.[39]

[34] Van den Oord, Kalchbrenner, et al., "Conditional Image Generation with PixelCNN Decoders", 2016.

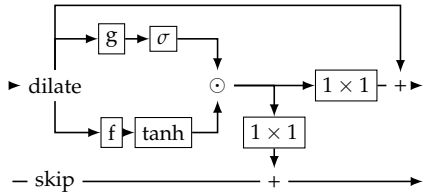


Figure 3: Hidden layer as in the WaveNet. Information flows from left, gets dilated and through the gate and filter. The result gets added to the skip flow and the hidden feature, each with a channel mixer before.

[35] Kalchbrenner et al., "Efficient Neural Audio Synthesis", 2018.

[36] Chorowski et al., "Unsupervised Speech Representation Learning Using WaveNet Autoencoders", 2019.

[37] Van den Oord, Vinyals, et al., "Neural Discrete Representation Learning", 2017.

[38] Prenger et al., "WaveGlow", 2018.

[39] Kim et al., "FloWaveNet", 2019.

Related work

In this section we give an overview of recent approaches to (sound) source separation which are related to our own approach either in the chosen model choices or implicit ideas. As the body of research into this task, especially in practical application, is vast and diverse, this overview can only be a small insight into tangentially related and recent research work.

Source separation

All here presented model maximize $p(\boldsymbol{s}|\boldsymbol{m})$ for one source (e.g. extracting only the singing voice out of a mix) or $p(\boldsymbol{s}_1, \ldots, \boldsymbol{s}_N|\boldsymbol{m})$ for multiple sources. Note that in the second case the conditional likelihood is not factorized, meaning we build a shared model for all sources.

WaveNet based

Rethage et al.[40] use a WaveNet for speech denoising. Speech denoising is a special case of source separation as the observed mix is separated into true signal and noise. The authors made the WaveNet non-causal by making the padding symmetrical. Further they used L_1-loss, instead of the multi-class μ-law objective. They show that for their case the real valued predictions behave better.

Lluís et al.[41] adapted a time-domain WaveNet for musical source separation. The non-causal [42] WaveNet directly outputs the separated sources and is trained fully supervised. They show this simple setup performing well against spectrogram based baselines. Also, the experiments show a higher performance with a network that is deeper but less wide [43].

U-Net based

Jansson et al.[44] were the first to use an U-Net architecture (see Figure 4) for musical source separation. They used a convolutional U-Net on spectrograms of musical data to extract the singing voice. Input to the network is the spectral magnitude and the output prediction is an equally-sized masked. The voice signal reconstruction is then done by multiplying the input magnitude with the predicted mask and using the original phase information from the mix, unal-

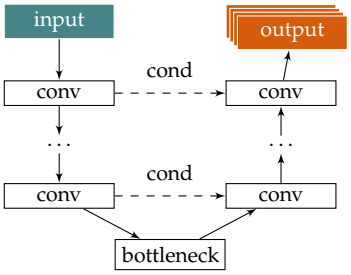


Figure 4: High level idea of a U-Net: the input gets projected into an (informational) bottleneck through some form of convolutional architecture. From this bottleneck the predictions are from an mirrored array of upsampling convolutional layer (either tuples of upsampling and convolutions or through dilated convolutions). The intermediate filter activations of the encoding are used as conditional inputs at the respective output scaling.

[40] Rethage et al., "A Wavenet for Speech Denoising", 2018.

[41] Lluís et al., "End-to-End Music Source Separation", 2019.

[42] In this setting the WaveNet can be non-causal because the prediction happens from the given mix and is not autoregressive.

[43] Deepness of a network refers to the number of hidden layers. Wideness refers to the number of kernels/features of each of these hidden layers. Making the WaveNet deeper significantly increases its receptive field.

[44] Jansson et al., "Singing Voice Separation with Deep U-Net Convolutional Networks", 2017.

tered. The training objective is the L_1 loss between the masked input spectrogram and the target signal.

The Wave-U-Net[45] brings this idea into the time-domain. The downstreaming and upstreaming layers are replaced with WaveNet style 1D convolutional layers. Further here the model is predicting multiple source signals.

[45] Stoller et al., "Wave-U-Net", 2018.

Slizovskaia et al.[46] extends the Wave-U-Net by conditioning the filter activations at the bottleneck with the instrument class label. The additional information is improving the separation quality.

[46] Slizovskaia et al., "End-to-End Sound Source Separation Conditioned On Instrument Labels", 2019.

Cohen-Hadria et al.[47] show improvements of training a Wave-U-Net when using additional data augmentation. They apply a hand-crafted set of auditory transformations (pitch-shifting, time-stretching, transforming the spectral envelope of the singing voice) to the training set of the musdb18 dataset.

[47] Cohen-Hadria et al., "Improving Singing Voice Separation Using Deep U-Net and Wave-U-Net with Data Augmentation", 2019.

Kaspersen[48] adds an bidirectional LSTM at the bottleneck of the Wave-U-Net. The BiLSTM is capable of select and keep information at the bottleneck over time and combine this memory with the new encoded information. This makes it possible for the network to keep information about the source signal at scales larger than the actual receptive field of the U-Net. The research shows an significant improvement over previous U-Net based approaches.

[48] Kaspersen, "HydraNet", 2019.

[49]

[49] Narayanaswamy et al., "Audio Source Separation via Multi-Scale Learning with Dilated Dense U-Nets", 2019.

Demucs[50] also introduces a BiLSTM at the bottleneck[51]. Additionally to the ideas from the HydraNet Demucs also adds data augmentation and makes additional internal changes to the network architecture. They simplify the layer blocks by using the simpler Gated Linear Units[52] and while the Wave-U-Net is using upsampling followed by a convolutional layer in the decoder, here the others directly use transposed convolutions to achieve the upsampling. Demucs is the first time-domain based end-to-end model that is achieving similar or better results compared to spectrogram based models.

[50] Défossez, Usunier, et al., "Demucs", 2019.

[51] Défossez, Zeghidour, et al., "SING", 2018.

[52] Dauphin et al., "Language Modeling with Gated Convolutional Networks", 2017.

Auto-encoder based

Grais et al.[53] present the first work using an auto-encoder for multi-channel sound source separation. Their auto-encoder takes raw audio as the input is using multi-scale convolutional layers (transposed in the decoder) in the encoder and decoder, combining the activations of the different scales before the activation. (Similar to Inception networks[54]).

[53] Grais et al., "Raw Multi-Channel Audio Source Separation Using Multi-Resolution Convolutional Auto-Encoders", 2018.

[54] Szegedy et al., "Going Deeper with Convolutions", 2014.

Method

In this chapter, we introduce the theoretical idea of our probability modelling of musical source separation. First, we explicitly state our chosen model of the problem, next derive a suitable optimization objective from it and then explain how we can optimize towards that.

We propose the graphical model as shown in Figure 5 as the generative story of music tracks being generated from separate source tracks. For each source, a sample is taken from the latent source distribution. The observed mix is generated deterministically from the full set of sources. Without loss of generality, we fix this function to be the mean.

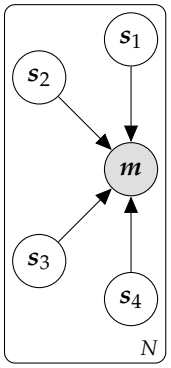


Figure 5: The used graphical model for the source separation task. We have the latent source channel variables s_k. Exemplary here, as in our data, we have four sources. The mix m is observed.

Our stated task in *Research Question* is to retreive the sources $\{s_1, \ldots, s_N\}$ from a given mix m. Our model is trained without using sample tuples

$$(m, \{s_1, \ldots, s_N\}) : f(\{s_1, \ldots, s_N\}) = m$$

which would show the relation between separate sources and mixes. The general idea is visualized in Figure 6.

Looking back at the graphical model in Figure 5, it implies the following factorization:

$$p(m) = \int^N p(s_1, \ldots, s_N, m)\, d^N s \tag{25}$$

$$= \int^N p(m|s_1, \ldots, s_N) \cdot p(s_1, \ldots, s_N)\, d^N s \tag{26}$$

$$= \int^N p(m|s_1, \ldots, s_N) \cdot p(s_1) \cdots p(s_N)\, d^N s \tag{27}$$

While the conditional $p(m|s_1, \ldots, s_N)$ is not even probabilistic, as the mix is generated deterministically with the mean of the sources, the model posterior $p(s_1, \ldots, s_N|m)$ is intractable and precisely what we are interested in. Again we want to make it clear that this setup changes the typical optimization target, as seen in other source separation approaches. We factorize the distribution $p(m)$ of mixed songs, only then to extract the most likely *latent* components that generate this mix, the sources. Therefore we are explicitly modelling the generative process of the mixed songs, and only implicitly the separation task.

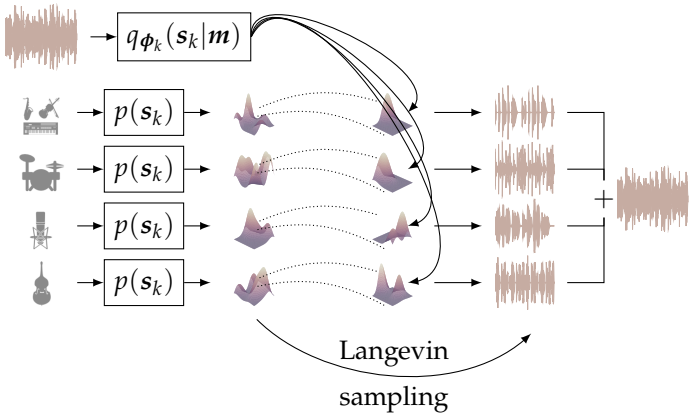


Figure 6: The method visualized, not finished yet

Already with the graphical model we introduce a fairly big assumption, namely that we can model the source distributions independently from each other when modeling the joint:

$$p(\boldsymbol{m}, \boldsymbol{s}_1, \ldots, \boldsymbol{s}_N) \equiv p(\boldsymbol{m}|\boldsymbol{s}_1, \ldots, \boldsymbol{s}_N) \cdot \prod_k^N p(\boldsymbol{s}_k) \tag{28}$$

Intuitively this assumption does not, in general, hold for the musical domain. We can expect a different behaviour for a *guitar* in a song involving a second source like a *percussion set*. The joint of those two models is different than their independent densities [55]. Nevertheless, this assumption is crucial to be able to model the prior instrumental models without needing the tuples $(\boldsymbol{s}_1, \ldots, \boldsymbol{s}_N)$ of co-occurring stems.

The general process is as follows:

First, because we assumed in our graphical model the latent sources to be independent, there exists a probability distribution $p(\boldsymbol{s}_k)$ for each source k. Thereout we need to choose a model which gives the parametrized approximated prior $p_{\boldsymbol{\theta}}(\boldsymbol{s}_k)$ with the parameters $\boldsymbol{\theta}$ which we optimize with the samples from $\mathcal{D}_k$.

Second, for each source, there exists a posterior given a mix $p(\boldsymbol{s}_k|\boldsymbol{m})$ from which we want to draw samples. Here two approaches are possible. Either we can propose an approximate posterior $q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})$, which is trained to minimize the divergence from the previously trained and fixed corresponding prior (VAE setting). Or, we can sample directly from the posterior using Stochastic Gradient Langevin Dynamics (SGLD)[56] without explicitly approximating the posterior distribution (sampling setting). Both optimization, either training or sampling, happen under the mixing constraint:

$$\sum_{k=1}^{N} \boldsymbol{s}_k = \boldsymbol{m} \tag{29}$$

When using the VAE setting we then can sample from each posterior to retrieve a set of (approximately) correct source tracks. In the

[55] A practical counter-example: If learning the behaviour of drums, only from solo drum recordings, one will encounter complex rhythms and sounds. In many rock genres drums often exhibit simpler sounds, providing beat and tempo. These two distributions are not the same.

[56] Welling and Teh, "Bayesian Learning via Stochastic Gradient Langevin Dynamics", 2011.

case of using Langevin dynamics, the iterative sampling will directly give this set from the prior distributions.

Thinking in the common terms of the VAE we need to choose:

1. a parametrization $p_{\theta}(\boldsymbol{s}_k)$ of the *prior* distribution
2. a parametrized approximate posterior distribution $q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})$ with parameters $\boldsymbol{\eta}$
3. a parametrized *encoder* which gives the parameters for the posterior distribution $\texttt{Encoder}_{\boldsymbol{\phi}}(\boldsymbol{m}) = \boldsymbol{\eta}$
4. a *decoder* which returns the input $\boldsymbol{m}$ from the latents $\texttt{Decoder}(\{\boldsymbol{s}_1, \ldots, \boldsymbol{s}_N\}) = \boldsymbol{m}$

As stated before the decoder in our case is the mean function, thus not probabilistic and without parameters. It is certainly possible to parametrize the decoder with trainable parameters. This would imply though that the latent samples are not in the *direct form* of the source sounds but under an (unknown) transformation.

Modeling the priors

The first step in the training procedure is the training of the independent source priors $p(\boldsymbol{s}_k)$. We have to choose a model for estimating the density that results in smooth, tight densities but also is capable enough to capture the complex data space of audio data. We choose to estimate the priors, with flow models for which we gave an overview in *Flow based models*. The invertibility of the flow gives us the ability to sample from the priors, which is necessary for the sampling-based approach. For the variational-based approach sampling is not necessary, nevertheless we utilize the same generative priors for both experiments. For different representations of the input, different network architectures are more suited. We experiment both with using directly the time-domain wave but also modelling on top of a spectral transformation of the time-domain data.

The two main variants of normalizing flows we build our priors from are the RealNVP and Glow. Their most important difference is the different formulation of the coupling layers. For the coupling layers, we have to split the layer input into two equally sized subsets, one of whom will be transformed using an invertible transformation parametrized by the other. The RealNVP masks the data spatially or over the channels. When done spatially a checkerboard binary mask is used (same for all channels), for the channel variant the channels are assigned in an even-odd switching. Glow, on the other hand, learns a 1×1-convolution which permutes the data channel-wise and than just splits the data along the channel dimension into two. For both RealNVP and Glow prior work exists specifically adapting the architecture to the time-series domain by integrating WaveNet modules, FloWaveNet[57] and WaveGlow[58], respectively.

Remove Glow if no experiment will use it

[57] Kim et al., "FloWaveNet", 2019.

[58] Prenger et al., "WaveGlow", 2018.

For the case of the time-domain representation, the data has only one channel (mono-audio). Therefore a Glow-like shuffling of channels is not possible and we resort to using spatial masking for the coupling layers. A one-dimensional mask is used over the time dimension. In the case of using a spectral representation of the audio data, the input samples have a lower time resolution but instead the frequency distribution over a deeper channel dimension. Therefore we can also experiment with channel-shuffling.

We make it clear that the success of this method depends strongly on the expressiveness and smoothness of the learned prior models. In the case of learning the posterior, variational learning will fit the posterior distribution under the prior distribution. If the prior does not contain enough variation of the actual data distribution, the de-mixing model cannot fit a conditional posterior similar to the sample in the mixed song. In the case of the sampling approach, this constraint is even more stressed. The mixed is generated by iteratively sampling from the set of prior distributions, any possible source sample, therefore, has to be found on the manifold of the prior. If any of the priors does not capture the full variations of the data distributions, neither method will be able to extract the correct separated sources.

More practically we again point out the high difficulty of modelling audio data. As laid out in *Representations of audio* audio consists of information at greatly different resolutions. A generative model of an instrument has to model the low-range components, e.g. pitch, timbre, tremolo and high-range components, e.g. notes and rhythm.

Prior architecture

See the visualization of the prior model's architecture in Figure 7. We construct normalizing flow models, following the description in Kim et al.[59].

[59] Kim et al., "FloWaveNet", 2019.

The flow network, at the highest level, consists of n_b context blocks, each of whom contain one squeeze operation and n_f flows. The squeeze operation halves the length of the signal by doubling the number of channels. By doing so, we effectively double the receptive field of the WaveNet operators in the affine couplings. One flow contains one affine coupling layer after which the masking for the coupling (*even*/*odd*) is inverted. Before the coupling layer, we apply activation normalization[60]. The affine coupling is applying an affine transformation on the *odd* set of the input, with scale $\boldsymbol{s}$ and translation $\boldsymbol{t}$ coming from the *even* input put through a *non-causal* WaveNet.

[60] Kingma and Dhariwal, "Glow", 2018.

The *even*/*odd* masking for the coupling layer is simply achieved by splitting the channel dimension into two equal parts. Flipping the masking exchanges the top half of channels with the bottom half. No channel transformation of the channels is learned as in Glow. Further observe that through the repeated squeeze operation the

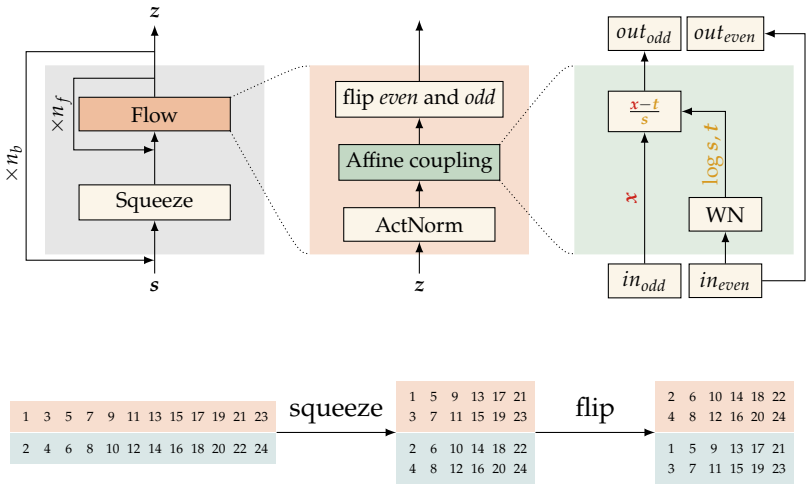


Figure 7: The building blocks for the prior model. The model consists of n_b blocks (left). Each block consists of n_f flows (middle). In each flow we apply activation normalization, followed by the affine coupling (right), after which the binary mask for the even/odd mapping is inverted. The affine coupling layer uses a WaveNet with the *even* set as the input to output scaling $\log s$ and translation t which which the *odd* set is transformed.

Figure 8: Flip and squeeze operation for the coupling layers. The squeeze operation doubles the channels and halves the length while the flip operation flips the split of channel dimension into odd and even.

masking implicitly includes a checkerboard pattern on the temporal dimension, similar to the explicit pattern used in RealNVP.

As explained in **??** the invertible flow $f(\cdot)$ network directly maps the data space into a prior distribution $p(z)$. Through the invertibility we can directly optimize the log probability with the change of variable formula:

$$\log p(\boldsymbol{x}) = \log p(f(\boldsymbol{x})) + \log \det \left(\frac{\partial f(\boldsymbol{x})}{\partial \boldsymbol{x}} \right) \tag{30}$$

Our network consists of n_b blocks with each n_f flows each with one activation normalization layer f_{AN} and an affine coupling layer f_{AC}. Therefore the log-determinant becomes:

$$\log \det \left(\frac{\partial f(\boldsymbol{x})}{\partial \boldsymbol{x}} \right) = \sum_{i}^{n_b \cdot n_f} \log \det \frac{\partial f_{\text{AN}}(\boldsymbol{x})}{\partial \boldsymbol{x}} + \log \det \frac{\partial f_{\text{AC}}(\boldsymbol{x})}{\partial \boldsymbol{x}} \tag{31}$$

The activation normalization layer f_{AN} learns an affine transformation per channel i:

$$f^i_{\text{AN}}(\boldsymbol{x}_i) = s_i \cdot \boldsymbol{x}_i + t_i \tag{32}$$

The inverse is: $f^{-1}_{\text{AN}}(\boldsymbol{y}_i) = \frac{\boldsymbol{y}_i - t_i}{s_i}$

The log-determinant is easily computed with[60]:

$$\log \det \frac{\partial f_{\text{AN}}(\boldsymbol{x})}{\partial \boldsymbol{x}} = T \cdot \sum_{i}^{C} \log |s_i| \tag{33}$$

where C is the number of channels and T is the length of the signal.

For the affine coupling layer, the log-determinant is made tractable by only transforming half the elements in each application. The coupling transforms the *odd* part as follows:

$$\log \boldsymbol{s}, \boldsymbol{t} = \text{WN}(in_{odd}) \tag{34}$$

$$out_{odd} = f_{\text{AC}}(in_{odd}) = \frac{in_{odd} - \boldsymbol{t}}{\boldsymbol{s}} \tag{35}$$

The inverse is:
$f_{\text{AC}}^{-1}(out_{odd}) = out_{odd} \cdot \boldsymbol{s} + \boldsymbol{t}$

where $\text{WN}(\cdot)$ is a WaveNet. The Jacobian of the coupling function is a lower triangular matrix[61] because of which the log-determinant becomes the product of the diagonal elements:

[61] Dinh, Sohl-Dickstein, et al., "Density Estimation Using Real NVP", 2017.

$$\log\det\frac{\partial f_{\text{AC}}(\boldsymbol{x})}{\partial \boldsymbol{x}} = -\sum \boldsymbol{s} \tag{36}$$

The purpose of the invertible flow is it to project the complex data distribution into a tractable defined prior distribution. In most cases, as in this, the prior $p(\boldsymbol{z})$ is set to be a factorized Gaussian distribution with zero mean and variance of one. As such the likelihood of $f(\boldsymbol{x}) \sim p(\boldsymbol{z})$ can be evaluated with:

$$\log p(f(\boldsymbol{x})) = -\frac{1}{2}(\log(2\cdot\pi)) + f(\boldsymbol{x})^2 \tag{37}$$

To train the model we maximize the likelihood in Equation (30) which we is the sum of the parts in Equations (33), (36) and (37). Optimization is done in mini-batches with the Adam optimzer[62] and a decaying learning rate scheme.

[62] Kingma and Ba, "Adam", 2017.

It is noted that the likelihood under the prior is computed "pixel"-wise[63]. While for the optimization the actual loss on which the optimizers performs update steps is the mean likelihood, we can use the trained prior flow to assign a likelihood map to an input signal where each log-likelihood value is depending on this values receptive field.

[63] time-points in our sound case

WaveNet

In the affine coupling layer we utilize a *non-causal* WaveNet for generating the scale $\log \boldsymbol{s}$ and translation $\boldsymbol{t}$ values. The WaveNet is non-causal because the filters are centred, as such the receptive field of an output value is symmetrically in the past and future input space. The kernel size is fixed to 3. The WaveNet is using the original gated convolution scheme described in *Background*. Appended to the last skip connection output are two additional one-dimensional convolutional layers, each preceded by a ReLU. The last convolutional layer is initialized to zero. By that we initialize the affine transformation of the coupling layer to the identity at the beginning of training, helping to stabilize optimization. The last layer outputs both scaling and translation factors. Learning those factors with weight sharing does not change the formulation of the coupling layer, as the log-determinant does not depend on the network. Learning them in the same network might increase efficiency, as well as, increasing implementation simplicity. The WaveNet completely consists of convolutional operations. As such it can be applied to one-dimensional signals of variable length.

Sampling from the posteriors

After having estimated the N prior distributions the first possibility for retrieving sample estimates $\boldsymbol{s}_k$ is sampling from the posterior

using Langevin dynamics[64]. With Stochastic Gradient Langevin Dynamics (SGLD) we can sample from $\boldsymbol{s}_i \sim p(\cdot|\boldsymbol{m})$ without computing, explicitly, the posterior $p(\boldsymbol{s}_i|\boldsymbol{m})$. For a overview of SGLD see *Langevin dynamics*.

[64] Welling and Teh, "Bayesian Learning via Stochastic Gradient Langevin Dynamics", 2011.

Starting with the update step in SGLD we reformulate the update with our problem constraint:

$$\boldsymbol{s}_k^{(t+1)} = \boldsymbol{s}_k^{(t+1)} + \eta \cdot \nabla_{\boldsymbol{s}_k} \log p(\boldsymbol{s}_k^{(t)}|\boldsymbol{m}) + 2\sqrt{\eta}\epsilon_t \tag{38}$$

$$= \boldsymbol{s}_k^{(t+1)} + \eta \cdot \nabla_{\boldsymbol{s}_k} \left[\log p(\boldsymbol{m}|\boldsymbol{s}_k) + \log p(\boldsymbol{s}_k) - \log p(\boldsymbol{m})\right] + 2\sqrt{\eta}\epsilon_t \tag{39}$$

$\log p(\boldsymbol{m})$ is independent from $\boldsymbol{s}_k$ therefore no gradient.

$$= \boldsymbol{s}_k^{(t+1)} + \eta \cdot \nabla_{\boldsymbol{s}_k} \left[\log p(\boldsymbol{m}|\boldsymbol{s}_k) + \log p(\boldsymbol{s}_k)\right] + 2\sqrt{\eta}\epsilon_t \tag{40}$$

$$= \boldsymbol{s}_k^{(t+1)} + \eta \cdot \left[\|\boldsymbol{m} - \frac{1}{N}\sum_j^N \boldsymbol{s}_j^{(t)}\| + \nabla_{\boldsymbol{s}_k} \log p(\boldsymbol{s}_k)\right] + 2\sqrt{\eta}\epsilon_t \tag{41}$$

η is the update step size and $\epsilon_t \sim \mathcal{N}(0, \mathbb{1})$.

Note that the final formulation of the update step is simply a constrained greedy hill-climb under the prior model with added Gaussian noise. Intuitively the artificially noised update makes it harder for the greedy optimization to get stuck in local minima of the prior surface. See Algorithm 2 for the algorithm.

Algorithm 2: The Langevin sampling procedure for source separation is fairly straight forward. For a fixed number of steps T we sample we take a step into the direction of the gradient under the priors and the gradient of the mixing constraint while adding Gaussian noise ϵ_t.

for $t = 1 \dots T$ **do**
  for $k = 1 \dots N$ **do**
    $\epsilon_t \sim \mathcal{N}(0, \mathbb{1})$
    $\Delta \boldsymbol{s}_k^t \leftarrow \boldsymbol{s}^t + \eta \cdot \nabla \log p(\boldsymbol{s}^t) + 2\sqrt{\eta}\epsilon_t$
  end for
  for $k = 1 \dots N$ **do**
    $\boldsymbol{s}_k^{t+1} \leftarrow \Delta \boldsymbol{s}_k^t - \frac{\eta}{\sigma^2} \cdot [\boldsymbol{m} - \frac{1}{N}\sum_i^N \boldsymbol{s}_i^t]$
  end for
end for

The idea of using SGLD in combination with deep parametrized priors for source separation was, concurrently to this work, introduced in Jayaram and Thickstun[65]. The authors empirically show that

[65] Jayaram and Thickstun, "Source Separation with Deep Generative Priors", 2020.

$$\mathbb{E}\left[\|\nabla_s \log p_\sigma(\boldsymbol{s})\|^2\right] \propto 1/\sigma^2$$

They argue that this surprising proportionality is stemming from the severe non-smoothness of the prior model. If the prior model, in the extreme case, exhibits a Dirac delta peak as the probability mass, then the estimation of the gradient with added Gaussian noise will it-self be proportional to the Gaussian. From there the authors

argue, that the prior models have to be trained with noised samples, where the added noised is proportional to later used estimator noise. Will add more discussion of their results

Modeling the posteriors

Instead of formulating a sampling regime for approaching $\boldsymbol{s}_k$ we can also use the prior models to variationally train a model to estimate the parameters of an approximate posterior $q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})$. While estimating the true posterior $p(\boldsymbol{s}_k|\boldsymbol{m})$ is intractable, we choose a certain parametrized distribution as an approximation of the posterior and optimize the parameters to align with the true one.

We follow the same steps as previously shown generally for the latent variable models. First, we introduce an approximate posterior $q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})$ for each source channel. Next, we express the mix density as the expectation over those posteriors:

$$\log p(\boldsymbol{m}) = \mathbb{E}^N_{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\left[\log p(\boldsymbol{m})\right] \tag{42}$$

From here we introduce the approximate posteriors in the expectation as before, just now for N separate priors:

$$\mathbb{E}^N_{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\left[\log p(\boldsymbol{m})\right] = \mathbb{E}^N_{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\left[\log \frac{p(\boldsymbol{m}, \boldsymbol{s}_1, \dots, \boldsymbol{s}_N)}{p(\boldsymbol{s}_1, \dots, \boldsymbol{s}_N|\boldsymbol{m})}\right] \tag{43}$$

$$= \mathbb{E}^N_{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\left[\log \frac{p(\boldsymbol{m}|\boldsymbol{s}_1, \dots, \boldsymbol{s}_N) \cdot \prod_k^N p(\boldsymbol{s}_k)}{\prod_k^N q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})} + \log \frac{\prod_k^N q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}{p(\boldsymbol{s}_1, \dots, \boldsymbol{s}_N|\boldsymbol{m})}\right] \tag{44}$$

Note that again we use the assumption in Equation (28) to factorize the joint. This assumption is not being used for the independent approximate posteriors. While the true posterior certainly is the posterior of the joint source model, we choose our approximate posteriors to be independent. The expectation in (42) over those is still correct. The error arising from the independence assumption is captured in the thightness of the ELBO.

We arrive at the ELBO by leaving out the divergence of the approximate posterior to the true posterior:

$$\mathbb{E}^N_{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\left[\log p(\boldsymbol{m})\right] \geq \sum_k^N \mathbb{E}_{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\left[\log \frac{p(\boldsymbol{s}_k)}{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\right] + \mathbb{E}_{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\left[p(\boldsymbol{m}|\boldsymbol{s}_1, \dots, \boldsymbol{s}_N)\right] \tag{45}$$

The lower bound, as in the normal VAE, will be our optimization target for training the inference models that give the variational parameters $\boldsymbol{\phi}_k$. We can also formulate the objective for just one source, as the Encoders are trained independently[66]. Thus we come to:

[66] While the optimization of the Encoders is independent, the training is, of course, concurrent as the mixing condition depends on all N source samples.

$$\mathbb{E}_{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\left[\log p(\boldsymbol{m})\right] \geq \mathbb{E}_{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\left[\log \frac{p(\boldsymbol{s}_k)}{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\right] + \mathbb{E}_{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\left[p(\boldsymbol{m}|\boldsymbol{s}_1,\ldots,\boldsymbol{s}_N)\right] \tag{46}$$

$$= \mathbb{E}_{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\left[\log \frac{p(\boldsymbol{s}_k)}{q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})}\right] + \|\boldsymbol{m} - \frac{1}{N}\sum_{j}^{N}\boldsymbol{s}_j\| \tag{47}$$

The Kullback-Leibler divergence term is computationally expensive, therefore the divergence is the stochastic estimate using just one mini-batch.

As both the prior $p(\boldsymbol{s}_k)$ and the approximate posterior $q_{\boldsymbol{\phi}_k}(\boldsymbol{s}_k|\boldsymbol{m})$ are parametrized by deep neural networks, the gradient of Equation (47) is tractable with respect to the mini-batch.

Choosing a posterior

With the optimization regime set up, we have to choose a fitting posterior distribution and the deep neural network which computes its parameters from data. In many typical VAE settings, the prior density is a fixed probability distribution, typically a multivariate normal distribution and accordingly the approximate posterior also is set to be a normal distribution. As our prior is a greatly complex distribution estimated by the flow, we are not incentivized by this to choose the posterior accordingly. Nevertheless

In the case of the **real musical data** we can not construct any informed posterior distribution, as the signals do not follow any constrained prior form. For the lack of an informed decision and the computational ease of the reparametrization trick, we resort to a Gaussian posterior. More specifically we propose employing a **truncated normal distribution**. The latent sound values are restricted to $[-1, 1]$ and a with a truncated Gaussian we can restrict the support to this interval. The reparametrization trick is still applicable, for a concrete description of the sampling refer to **??**. The normal distribution is parametrized by mean and variance $\boldsymbol{\eta} = \{\sigma, \mu\}$.

Choosing an Encoder

The inference model $\texttt{Encoder}_{\boldsymbol{\phi}}(\boldsymbol{m})$ infers the parameters for the chosen posterior distribution from data. The model takes the time-domain signals as an input, therefore we use the architectural design choices as with the prior networks and employ a non-causal WaveNet architecture. As laid out before this model is fully convolutional, not autoregressive, as the prediction of the parameters is a one-to-one mapping, where each time-point is mapped to a set of parameters. As it is practice we use the same network head for both parameters and append after the last skip-connection output of the WaveNet two convolutional layers with the final one mapping to the two separate parameters. The WaveNet used here is fairly similar to the modules used in the prior flows. They employ the gated convolution and have fixed kernel sizes of 3.

We note that we fix the encoder to work in the time-domain. We propose this to have access to the phase information of the original signals during the mapping $\boldsymbol{m} \rightarrow \boldsymbol{s}_k$. This does not make it necessary, that the prior models are also working in the time-domain. The samples taken from the approximate posterior during the training of the inference model can be transformed with the same spectral transformation used to train the prior models. We can compute the gradient of the likelihood from the prior under the spectral transformation[67]. Because we are not using the generative priors to generate in this setting, the phase information lost through the transformation is not disadvantageous and still is accessible to the inference model.

[67] The `torchaudio` library provides implementations of real-valued spectrograms and a mel-transform that allow for automatic differentiation.

As we have N different sources with each a trained prior network we will also train N inference networks each with a separate approximate posterior.

Difficulties of this method

We want to make the difficulties with this method clear and list them in the following explicitly:

1. *All sources known and trained with prior*
2. The separation capabilities in both approaches completely rely on the quality of the learned priors. The priors are learned unsupervised and unconditional from random cuts of the instruments stems. The learned manifolds are extremely complex and hard to train. There is little prior work on successfully building generative models for sound, without further conditional information.
3. We have to train a prior model for each source. In the sampling case, we concurrently sample from each of these models, in the case of the inference model we have to train an additional model for all sources. Because the separation happens under the mixing condition, at the time of training, inference or sampling all parts are used.
4. *Unstable sampling / training because of many objectives*

Experiments

As we have laid out in the previous chapter our method mainly depends on the quality of the learned source priors. The generative prior models have to provide an exhaustive and exclusive approximation of the data manifold or its data source. Therefore our experiments strongly focus on analyzing the prior densities under different training regimes and inputs. In general, we have two separate datasets with which we run the experiment, as described in the following section. TODO

Datasets

We will be working on two datasets. First, a simplified Toy dataset which reduces the problem to a minimal canonical one and second the `musdb18` dataset which is a widely-used test-set for musical source separation.

ToyData

We simplify the problem domain to create a toy-like dataset. We randomly generate waves from four simple oscillations: a sine wave, a sawtooth wave, a square wave and a triangle wave; see Figure 9. We select the period and phase of each signal in each sample independently and randomly, but fixed for the sample. The frequency is a uniformly picked form the frequency bounds of the 88 keys of an equal-temperament tuned piano. The period is also uniformly picked. Given a wave from each source, the mix is computed by simply taking the mean. In our experiments we are gonna model these sources with probability densities, looking especially at the square that will pose a problem, as those only consist of two unique values (-1 and 1). This distribution would simplify the problem too much, therefore we also vary the amplitude of the sampled signals in the uniform range $[0.8, 1.0]$. The signals are sampled with a sampling rate of 14.700Hz.

Figure 9: One period of each of the four toy sources: sinus, sawtooth, square and triangle wave.

musdb18

Further we use the `musdb18`[68] dataset published for the 2018 Signal Separation Evaluation Campaign[69]. The dataset consists of 150 full songs covering various artists and genres, split into train and test sets sized 100 and 50, respectively. Each track is separated into the

[68] Rafii et al., *MUSDB18 - a Corpus for Music Separation*, 2017.

[69] Stöter et al., "The 2018 Signal Separation Evaluation Campaign", 2018.

four sources *drums*, *bass*, *vocals* and *others*. The *others* source channel contains any remaining set of instruments not categorized under the first three ones. The song files are provided in the Stem audio file format[70] and encoded at 44.1kHz. Stem here is terming the provided source channels, we use the terms interchangeably.

The dataset consists of the 100 tracks taken from the DSD100[71] dataset and 46 track out of the MedleyDB[72] dataset. Both dataset contain tracks from a wide range of (western) musical genres, Rock, Pop, Rap, Jazz and Metal. While the upstream data sources provide more fine-grained meta-data, `musdb18` brings all tracks into the same format and stem splitting as described above.

Next to the separated stems, the dataset provides the original (studio) mix for each song. This mix is not equivalent to the simple linear mixing which we get by taking the mean. Nevertheless, the provided mix diverges only insignificantly from an auto-generated mix, as the original sources are provided in their post-compression, post-mixed form. This means that we can use the original mix and assume it to be reasonably close to the canonical linear mix.

As the songs are real natural songs, they are of different lengths. Our models will different to other recent methods, not be auto-regressive. Thus we sample fixed-length cuts from the songs as training and test samples. For the `musdb18` data, no pre-processing is applied, as the data already contains the wanted level variability, it spanning different genres and artists.

It is noted that the `musdb18` dataset while providing a remarkable diverse 10hr of real-world music, is a rather small numbered set of samples. Any data modelling from this set of data will consequently be biased. The dataset specifically is created for the accompanying separation challenge and will not translate to general music modelling.

Also for the `musdb18` dataset we downsample the signals to 14.700Hz.

[70] Native Instruments, *Stem Audio Format*, n.d.

[71] Liutkus et al., "The 2016 Signal Separation Evaluation Campaign", 2017.

[72] Bittner et al., "MedleyDB 2.0", 2016.

Figure 10: The four source channels for the `musdb18` dataset: bass ,drums, vocals and *other*.

Prior architectures

We construct two distinct prior models for the two datasets. All models follow the flow architecture described in *Method*. Table 1 gives a summary of the networks. Remember the affine transformations are parametrized by WaveNets, consisting of multiple dilated one-dimensional convolutions. We use the gated convolution and skip-connection setup as described in *Modeling raw audio*. We append two extra convolutional layers after the last dilated block with kernel size one and preceding ReLU units, respectively. The last convolutional layer is initialized to zero. This guarantees that at the beginning of training each coupling layer defaults to the identity. All other convolutional weights are initialized with He initalization[73]. The number of features in each convolutional layer is fixed throughout the whole network, as given in the table. All kernels are size 3.

[73] He et al., "Delving Deep into Rectifiers", 2015.

	blocks	flows	layers	kernel size	width
toy (time)	4	6	10	3	32
`musdb18` (time)	8	6	10	3	48

Table 1: The hyperparameters for the two network architectures. The block is the biggest unit, containing a squeeze operation and n_f flow blocks. Each flow block contains a activation normalization unit, a affine coupling layer (WaveNet) and a flip operation. The WaveNets cosist of 10 layers each with fixed kernel size and width.

Training the priors

Training of the priors is done in mini-batches with an Adam optimizer[74]. We take random fixed-length samples from the songs/signals in each mini-batch. Each sample is 16384 long with is around 1.1sec. As all models are fully convolutional the input size is in no way regimented by the architecture, only in so far that we are avoiding padding in the lower layers. The initial learning rate is set to $1e-4$. The learning rate is decreased with $=0.6$ and a fixed five-step decrease schedule. The toy model is trained with a batch size of 5 and the `musdb18` model with a batch size of 2. We train the two prior models first without any added noise for each 150.000. The training curves are shown in **??**. As also observed by prior work, the training of deep normalizing flow models behaves unstable.

[74] Kingma and Ba, "Adam: A Method for Stochastic Optimization", 2014

For practicality, the priors for all source channels are contained in one model. The PyTorch framework allows for convolutional layers to be blocked into separate groups. We are not using any operations that are dependent over the batch dimension [75]. We implement the complete flow model in such a grouped way so that the training can be done in parallel on a single GPU while the inference and the gradients for the optimizer updates are independent over the grouped blocks. For that, we also implement the utility functions, squeeze and flip in the same blocked manner.

[75] That would e.g. be batch normalization

Testing the priors

Training of the normalizing flow model combines two objectives: First, we maximize the log-determinant of the *non-volume preserving* affine coupling and the activation normalization layers. This guarantees us the invertibility of these transformations. Second, we maximize the likelihood of the projected samples under the chosen target distribution [76]. For the evaluation, we are interested in the mean average likelihood under the target distribution for different in- and out-of-distribution inputs. Remember that the flow gives a bijective mapping between the input and target space [77]. For an input of size $\boldsymbol{x} \in \mathbb{R}^{1\times L}$ the flow returns a latent $\boldsymbol{z} \in \mathbb{R}^{1\times L}$ of the same size. Each time-point latent $\boldsymbol{z}_t$ depends on the inputs from the receptive field of the flow before and after the respective input $\boldsymbol{x}_t$ but is evaluated under the independent margin $\boldsymbol{z}_t \sim \mathcal{N}(0,1)$. Because therefore the factorized multivariate Gaussian prior is equivalent to a set of one-dimensional Gaussians, the flow is also not size restricted. All transformations in the network are convolutional and use appropriate padding. L can be any chosen length. We want to set the input length larger than the receptive field of the network.

[76] The target distribution is the prior to our prior model. It is set to a factorized Gaussian.

[77] necessitated by the invertibility

The latents on either end side of the sample will be based on the larger amount of padded input, while the center values from the sample receive the full receptive field. The size of the receptive field is regimented by the depth and kernel sizes used in the convolutions of the coupling layers and the number of squeeze operations in the blocks (see Figure 8). For an exact derivation of the receptive field size see Appendix recp size.

We show an example of sampling from the toy data priors in Figure 11. It should be unsurprising that the drawn samples are not returning a consistent curve. All the latents are from i.i.d. distributions that contribute to the generation of the data output in the bounds of its receptive field. The overlapping receptive fields generate locally consistent curves. This is not a hindrance as our method does not rely on sampling from the priors unconstrained.

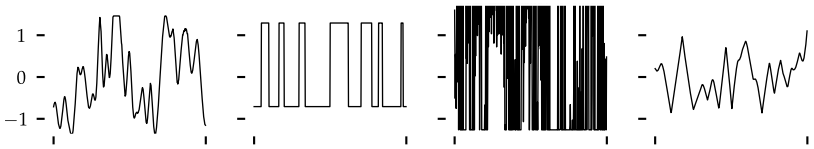


Figure 11: Samples from the prior trained on the toy data.

Testing cross-likelihood

In the full model, each prior is used to extract its source channel separately. Through their training, they explicitly contract the density for the positive, in-class examples. During separation, the priors therefore, encounter negative, out-of-distribution samples for the first time. To be useful for separation, the priors have to give a low likelihood to samples from the other classes of the dataset.

We test for this by calculating the mean log-likelihood of the test data set under each prior, for each source channel separately. What we anticipate is that the samples from the priors training source are of high likelihood while all other sources are of low likelihood. In **??** we show the source dependent likelihoods for the Toy Data. The in-distribution samples are all of high likelihood while all out-of distribution samples are highly un-likely. The Flow model therefore, was able to detect out-of-distribution samples while only being trained on in-distribution samples [78]. The estimated densities are discriminative.

[78] Something psychological research has shown, humans being able to do.

When running the same experiment for the `musdb18` the discriminative power does not hold up, see **??**. All signal sources are about equally likely under each prior density. We hypothesize this stems from the fact that the real musical data is severely more complicated compared to the Toy Data. The Flows model the appearance of sound in general, as the in-class variability of sounds is already high, without knowing anything about the *discriminative* differences between the instruments and does not infer the distribution from those features.

Even above that, the results exhibit an additional failing for the

`musdb18` dataset. The third stem in the dataset files *other* is filled with a smorgasbord of different instruments. With our training regime, we are implying we can model the sound this set of unrelated instruments with only in-distribution samples with a resulting distribution which is discriminative against another set of unrelated instruments. Intuitively this already fails to be reasonable. Because of this, the results show the unintuitive result that the test samples from the *other* class are *less likely* under its own prior model compared to the out-of-distribution samples. While this makes it rather final that the at hand dataset is not completely suitable to out trainings regime, it is a data-dependent restriction that would not correspond to our hypothesized application.

Similar results were shown before in

cite some OOD VAE stuff

.

The results for both datasets are similar for all tested model architectures and input domains. See Appendix

add results

for the full results.

Noise-conditioning

We fine-tune the noise-less flow models by continuing the training with added Gaussian noise on the input samples. Fine-tuning[79] the noise-less model instead of retraining the model is considerably cheaper and the noised distribution we want to approximate is close to the noise-free distribution of the initial training. We follow Jayaram and Thickstun[80] in evaluating the noised distribution at variances in 5 steps from 0 to 1, geometrically increasing. The signals with added noised are not capped to the range $[0, 1]$ as to not bias the signals towards the bounds of the interval.

We find that fine-tuning converges quickly at —-.

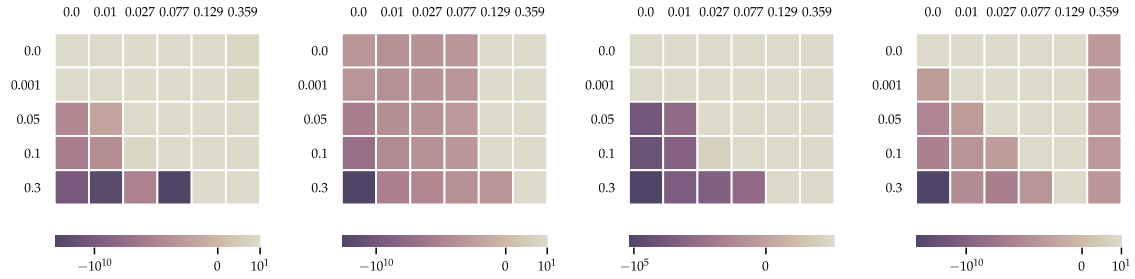
Conditioning the prior distributions on noised samples is supposed to reduce local peaks in the latent space. Nalisnick et al.[81] points to the general problem that maximizing the Jacobian of the determinant in the objective of normalizing flows encourages the learned distribution to be sensitive to perturbations of inputs. They warn precisely of assuming anything about the density of a generative model outside of its training data-distribution. Jayaram and Thickstun[80] experimentally shows that for their source separation method the same problem can be alleviated by fine-tuning on noised samples. Figuratively speaking the Gaussian noise in data space translates to Gaussian smoothing of the peaks in the probability distribution. For our comparatively more complicated models, we want to assess the success of this step.

In Figure 12 we show the mean average log-likelihood of the test data set with different levels of added noised under the priors fine-tuned with increasing levels of noise. We see that with the noiseless model the likelihood of noised samples quickly decreases with the

[79] Yosinski et al., "How Transferable Are Features in Deep Neural Networks?", 2014.

[80] Jayaram and Thickstun, "Source Separation with Deep Generative Priors", 2020.

[81] Nalisnick et al., "Do Deep Generative Models Know What They Don't Know?", 2019.

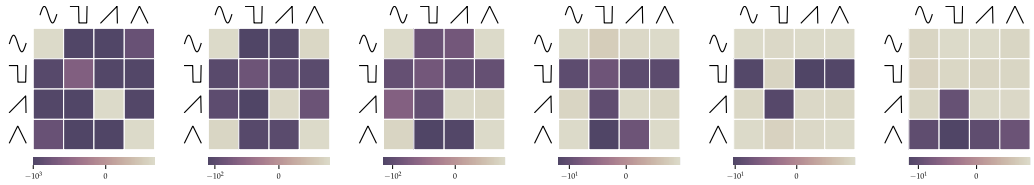


(a) sin (b) square (c) saw (d) triangle

Figure 12: The log likelihood of the test data set with different levels of noise $\mathcal{N}(0, \sigma)$ for the prior models fine-tuned on pertubated data with increasing levels of Gaussian noise.

increasing variance of the noise. Conditioning on a higher variance of noise levels out the likelihood for the lower levels of noise variances. This is not surprising as with the noise conditioning we explicitly model the noised distribution. Consider though the priors conditioned on the noise levels 0.027 or 0.077. The noised distribution is getting likely for noise levels beyond the conditioned level of noise. Now one might argue that the result, while unexpected, is not prohibitive as the whole point of noise-conditioning is too make 'close-to' in-distribution data around as likely as in-distribution data. We argue that our results do show that noise-conditioning the flow distribution is not a pertinent approach to reduce the contractiveness of the latent distribution. Conditioning the noiseless model on low levels of noised data quickly *destroys* the previously learned spiked latent distribution.

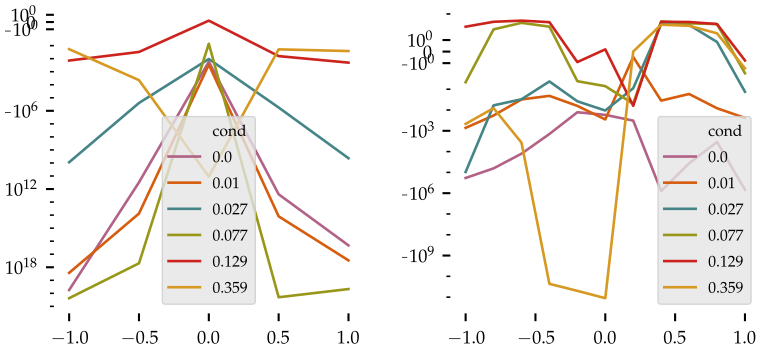
We show this failing more pronounced in Figure 13. Here we plot the mean average likelihood of the different source channels under each prior with widening noise-conditioning. The expectation is to preserve the discriminative power of the different source priors while reducing the sensitivity to noise. The results clearly show that trying to slowly decrease the sensitivity, quickly destroys any discriminative power the generative priors exhibit in the noiseless model.



(a) 0.0 (b) 0.01 (c) 0.027 (d) 0.077 (e) 0.129 (f) 0.359

Figure 13: The cross-likelihood of the toy source channels under each prior model after conditioning the distribution on different levels of noise.

With the noiseless model **??** the distribution is discriminative against the samples from the other sources. With increasing noise-conditioning the discriminative power is lost going to **??**. The noising of the input data results in the latent distribution to flatten out to the point of not being able to differ between any of the signal channels.



(a) Noise (b) Const

Figure 14: Noise Const

Random and constant inputs

82,83,84

[82] Nalisnick et al., "Do Deep Generative Models Know What They Don't Know?", 2019.

[83] Sønderby et al., "Amortised MAP Inference for Image Super-Resolution", 2017.

[84] Van den Oord, Li, et al., "Parallel WaveNet", 2017.

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Noise-conditioning

	0.0	0.01	0.027	0.077	0.129	0.359
0.000	4.8e+00	5.4e+00	5.3e+00	4.9e+00	5.3e+00	1.4e+00
0.001	4.3e+00	5.4e+00	5.3e+00	4.9e+00	5.3e+00	1.4e+00
0.050	-1.7e+02	-3.4e-02	4.5e+00	5.3e+00	5.3e+00	2.7e+00
0.100	-7.0e+03	-2.2e+01	1.9e+00	5.0e+00	5.2e+00	3.1e+00
0.300	-1.8e+10	-2.4e+13	-1.1e+03	-3.5e+14	4.1e+00	3.7e+00

Table 2: The numerical data as visualized 12 for the source `sin`.

	0.0	0.01	0.027	0.077	0.129	0.359
0.000	-1.8e+00	-1.3e+01	-9.3e+00	-2.9e+00	1.9e+00	2.1e+00
0.001	-2.9e+00	-1.2e+01	-9.3e+00	-2.9e+00	1.9e+00	2.1e+00
0.050	-2.3e+03	-1.8e+01	-7.0e+00	-7.3e-01	2.0e+00	2.2e+00
0.100	-6.8e+05	-8.1e+01	-1.3e+01	-1.1e+00	1.8e+00	2.6e+00
0.300	-5.4e+13	-2.0e+03	-1.5e+02	-1.2e+01	-2.0e+00	2.6e+00

Table 3: The numerical data as visualized 12 for the source `square`.

	0.0	0.01	0.027	0.077	0.129	0.359
0.000	4.1e+00	3.8e+00	3.9e+00	4.1e+00	3.4e+00	2.9e+00
0.001	3.5e+00	3.8e+00	3.9e+00	4.1e+00	3.4e+00	2.9e+00
0.050	-9.2e+02	-7.7e+00	3.7e+00	4.1e+00	3.4e+00	2.9e+00
0.100	-3.7e+03	-5.6e+01	5.2e-01	4.1e+00	3.4e+00	3.0e+00
0.300	-2.2e+05	-2.2e+02	-1.1e+02	-6.4e+00	2.8e+00	3.0e+00

Table 4: The numerical data as visualized 12 for the source `saw`.

	0.0	0.01	0.027	0.077	0.129	0.359
0.000	4.0e+00	4.8e+00	4.8e+00	4.9e+00	4.5e+00	-3.1e+00
0.001	-1.8e+00	4.8e+00	4.8e+00	4.9e+00	4.5e+00	-3.1e+00
0.050	-5.5e+03	-2.0e+00	3.8e+00	4.8e+00	4.8e+00	-3.3e+00
0.100	-1.9e+04	-2.8e+01	-8.9e-01	4.5e+00	4.7e+00	-3.4e+00
0.300	-1.3e+16	-4.6e+02	-3.2e+04	-1.6e+01	3.5e+00	-8.7e+00

Table 5: The numerical data as visualized 12 for the source `triangle`.