DISENTANGLEMENT LEARNING FOR VARIATIONAL AUTOENCODERS APPLIED TO AUDIO-VISUAL SPEECH ENHANCEMENT

Guillaume Carbajal, Julius Richter, Timo Gerkmann

Signal Processing (SP), Universität Hamburg, Germany
{guillaume.carbajal, julius.richter, timo.gerkmann}@uni-hamburg.de

ABSTRACT

Recently, the standard variational autoencoder has been successfully used to learn a probabilistic prior over speech signals, which is then used to perform speech enhancement. Variational autoencoders have then been conditioned on a label describing a high-level speech attribute (e.g. speech activity) that allows for a more explicit control of speech generation. However, the label is not guaranteed to be disentangled from the other latent variables, which results in limited performance improvements compared to the standard variational autoencoder. In this work, we propose to use an adversarial training approach based on variational autoencoders to disentangle the label from the other latent variables. At training, we use a discriminator that competes with the encoder of the variational autoencoder. Simultaneously, we also use an additional encoder that estimates the label for the decoder of the variational autoencoder. As a result, the speech generation can only partially be controlled by the label.

Disentanglement learning aims at making all the dimensions of the latent distribution independent from each other, e.g. by holding different axes of variation fixed during training. Semi-supervised disentanglement approaches, on the other hand, tackle the problem of making only some observed (often interpretable) variations in the data independent from the other latent dimensions which themselves remain entangled. In particular, some of them rely on adversarial training in the latent space for image generation.

In this work, we propose to use a semi-supervised disentanglement approach based on adversarial training in the latent space. At training, we use a discriminator that competes with the encoder of the VAE. The discriminator aims at identifying the label from the other latent dimensions, whereas the encoder aims at making it unable to estimate the label. Simultaneously, we also use an additional encoder that estimates the label for the decoder of the VAE, which proves to be crucial to learn disentanglement during training. We show the benefit of the proposed disentanglement learning when a voice activity label, estimated from visual data, is used for speech enhancement.

Index Terms—Speech enhancement, conditional generative model, variational autoencoder, disentanglement learning, adversarial training, semi-supervised learning, audio-visual.

1. INTRODUCTION

Single-channel speech enhancement consists in recovering a speech signal from a mixture signal captured with one microphone in a noisy environment. Common speech enhancement approaches estimate the speech signal using a filter in the time-frequency domain to reduce noise while avoiding speech artifacts. Under the Gaussian assumption, the optimal filter in the minimum mean square error sense requires estimating the signal variances.

Recently, deep generative models based on the variational autoencoder (VAE) have gained attention for learning the probability distribution of complex data. VAEs have been used to learn a prior distribution of clean speech, and have been combined with an untrained non-negative matrix factorization (NMF) noise model to estimate the signal variances using a Monte Carlo expectation maximization (MCEM) algorithm. However, since the VAE speech model is trained with clean speech only in an unsupervised manner, the speech prior generates a speech-like signal when only noise is present. As a result, the VAE often outputs speech-like noise when applied to noisy speech.

An increased robustness can be obtained by incorporating temporal dependencies, noise-aware training, or by conditioning the VAE on a label describing an attribute of the data that allows for a more explicit control of data generation. Various speech-related tasks, VAEs have been conditioned on a label describing a speech attribute, such as speaker identity, phoneme, or speech activity. Ideally, the label should be independent from the other latent dimensions to obtain an explicit control of speech generation. However, the semi-supervised learning of conditional VAEs does not guarantee that it will promote independence between the label and the other latent dimensions.

As a result, the speech generation can only partially be controlled by the label.

Disentanglement learning aims at making all the dimensions of the latent distribution independent from each other, e.g. by holding different axes of variation fixed during training. Semi-supervised disentanglement approaches, on the other hand, tackle the problem of making only some observed (often interpretable) variations in the data independent from the other latent dimensions which themselves remain entangled. In particular, some of them rely on adversarial training in the latent space for image generation.

In this work, we propose to use a semi-supervised disentanglement approach based on adversarial training in the latent space. At training, we use a discriminator that competes with the encoder of the VAE. The discriminator aims at identifying the label from the other latent dimensions, whereas the encoder aims at making it unable to estimate the label. Simultaneously, we also use an additional encoder that estimates the label for the decoder of the VAE, which proves to be crucial to learn disentanglement during training. We show the benefit of the proposed disentanglement learning when a voice activity label, estimated from visual data, is used for speech enhancement.

The rest of this paper is organized as follows. In Section 2, we summarize the background related to the VAE for speech enhancement. Section 3 describes our proposed approach. The experimental setup is described in Section 4, which is followed by the evaluation in Section 5.

2. BACKGROUND

2.1. Mixture model and filtering

In the time-frequency domain using the short time Fourier transform (STFT), the mixture signal \( x_{nf} \in \mathbb{C} \) is the sum of the clean speech \( s_{nf} \in \mathbb{C} \) and the noise \( b_{nf} \in \mathbb{C} \):

\[
x_{nf} = \sqrt{g_n} s_{nf} + b_{nf},
\]

at time frame index \( n \in [1, N] \) and frequency bin \( f \in [1, F] \), where \( N \) denotes the number of time frames and \( F \) the number of frequency bins of the utterance. The scalar \( g_n \in \mathbb{R}_+ \) represents a frequency-independent but time-varying gain providing...
some robustness with respect to the time-varying loudness of different speech signals [8].

Under the Gaussian assumption, the clean speech \( s_{n,f} \) can be estimated in the minimum mean square error sense using the Wiener estimator:

\[
\hat{s}_{n,f} = \frac{\hat{v}_{n,s_{n,f}}}{\hat{v}_{n,s_{n,f}} + \hat{v}_{b,n_f}} \cdot x_{n,f},
\]

where \( \hat{v}_{n,s_{n,f}} \) and \( \hat{v}_{b,n_f} \) are the estimated variances of the clean speech \( s_{n,f} \) and the noise \( b_{n,f} \), respectively. Under a local stationary assumption, short-time power spectra \( |s_{n,f}|^2 \) and \( |b_{n,f}|^2 \) are unbiased estimates of the signal variances [24].

2.2. VAE as speech prior

2.2.1. Standard VAE

The standard VAE is used to learn a prior over clean speech [7, 8]. Fig. 1a shows the training scheme of the standard VAE. At time frame \( n \), the frequency bins of clean speech \( s_{n,f} \) in \( \mathbb{C}^F \) are modeled as

\[
p_\theta(s_{n}|z_n) = \mathcal{CN}(0, \text{diag}(D_\theta(z_n))), \quad z_n \sim \mathcal{N}(0, I),
\]

where \( z_n \in \mathbb{R}^L \) denotes a latent variable of dimension \( L \) and \( D_\theta(z_n) \in \mathbb{R}^F_+ \) is the output of the decoder network \( D_\theta(\cdot) \) parametrized by \( \theta \).

In variational inference, the posterior of \( z_n \) is approximated as

\[
q_\phi(z_n | s_n) = \mathcal{N}(\mu_\phi(|s_n|^2), \text{diag}(\nu_\phi(|s_n|^2)));
\]

where \( \mu_\phi(|s_n|^2) \in \mathbb{R}^D \) and \( \nu_\phi(|s_n|^2) \in \mathbb{R}^D_+ \) are the outputs of the encoder network \( E_{\phi,\nu}(\cdot) \) parametrized by \( \phi \).

The encoder \( E_{\phi,\nu}(\cdot) \) and decoder \( D_\theta(\cdot) \) are jointly trained by maximizing a lower bound of the marginal per-frame log-likelihood, called the evidence lower bound (ELBO):

\[
\mathcal{L}_{\text{ELBO}} = \mathbb{E}_{q_\phi(z_n | s_n)}[\log p_\theta(s_{n}|z_n)] - D_{\text{KL}}(q_\phi(z_n | s_n) || p(z_n)),
\]

where the first term is the reconstruction loss and \( D_{\text{KL}}(\cdot || \cdot) \) denotes the Kullback-Leibler divergence. However, since the training loss \( \mathcal{L}_{\text{ELBO}} \) is unsupervised, there is no explicit control of speech generation.

2.2.2. Conditional VAE

The VAE can be conditioned on a label \( y_n \in \mathcal{Y} \) describing a speech attribute (e.g. speech activity) that allows for a more explicit control of speech generation [15]. A common approach is to make use of the label \( y_n \) by directly inputting it in both the encoder \( E_{\phi,z}(s_n, y_n) \) and the decoder \( D_\theta(z_n, y_n) \) (see Fig 1b) [15, 15]. The training loss remains the same as for the standard VAE, i.e. \( \mathcal{L}_{\text{ELBO}} \).

2.3. Non-negative matrix factorization as noise model

As in Leglaive et al. [8], the noise variance is modeled with an untrained NMF as

\[
v_{b,n_f} = \{HW\}_{n_f},
\]

where \( H \in \mathbb{R}^{N \times K} \) and \( W \in \mathbb{R}^{K \times F} \) are two non-negative matrices representing the temporal activations and spectral patterns of the noise power spectrogram. \( K \) denotes the NMF rank.

2.4. Clean speech estimation

Speech variance estimation at test time is shown in Fig. 2. First, a pretrained noise-robust classifier which is trained separately from the VAE provides the label \( \hat{y}_n \) from the mixture \( x_n \) as input for the VAE. The outputs of the encoder and decoder are then \( E_{\phi,z}(s_n, \hat{y}_n) \) and \( D_\theta(z_n, \hat{y}_n) \), respectively. Given the speech prior provided by the VAE and the noise model, the mixture signal \( s_{n,f} \) is distributed as

\[
x_{n,f} | z_n \sim \mathcal{CN}(0, g_n \{D_\theta(z_n, \hat{y}_n)\} + \{HW\}_{n_f})
\]

where \( \Theta_\omega = \{g_n, H, W\} \) are the unsupervised parameters to be estimated. Since the resulting optimization problem is intractable due to the non-linear relation between the speech variance \( v_{s,n_f} \) and the latent variable \( z_n \), an MCEM algorithm is employed to iteratively optimize the unsupervised parameters \( \Theta_\omega \) [8]. At each iteration, the estimated terms \( \hat{g}_n \{D_\theta(z_n)\} \) and \( \{HW\}_{n_f} \) are supposed to get closer to the true variances \( v_{s,n_f} \) and \( v_{b,n_f} \), respectively.

Ideally, in order to obtain an explicit control of speech generation, the label \( y_n \) should be independent from the latent variable \( z_n \). However, the training loss \( \mathcal{L}_{\text{ELBO}} \) does not guarantee that it will promote independence between the label \( y_n \) and the latent variable \( z_n \) [16]. As a result, speech generation can only partially be controlled by the label \( y_n \).

3. DISENTANGLEMENT LEARNING

Inspired by recent work on semi-supervised disentanglement learning [22, 24], we propose to use an adversarial training scheme on the latent space to disentangle the label \( y_n \) from the latent variable \( z_n \). More particularly, we propose a different training loss for the encoder of the VAE.

3.1. Architecture

Fig. 3 shows the adversarial training scheme. At training, we use a discriminator \( \delta_\varphi(\cdot) \) that competes with the encoder \( E_{\phi,z}(\cdot) \) of
the VAE, which we refer to as the adversarial-encoder. The discriminator $\delta_\phi(\cdot)$, parametrized by $\psi$, aims at identifying the label $y_n$ from the latent variable $z_n$, whereas the adversarial-encoder $E_{\phi,y}(\cdot)$ aims at making it unable to estimate the label $y_n$. Simultaneously, we also estimate the label $y_n$ using a classifier that we denote as the classifier-encoder $E_{\phi,y}(\cdot)$, parametrized by $\phi$.

Label $y_n$. We consider voice activity detection (VAD) for the label, i.e. $y_n \in \{0, 1\}$, which is here obtained from visual data.

**Discriminator $\delta_\psi(\cdot)$** Similarly to Fader Networks for image generation [22], the discriminator $\delta_\psi(\cdot)$ estimates the probability that the label $y_n = 1$, i.e. $p_\psi := P(y_n = 1|z_n) = \delta_\psi(z_n)$. We use the binary cross entropy (BCE) as the learning objective:

$$L_{adv} = y_n \log p_\psi + (1 - y_n) \log(1 - p_\psi). \quad (8)$$

**Adversarial-Encoder $E_{\phi,z}(\cdot)$** To force the discriminator $\delta_\psi(\cdot)$ to make incorrect classification, adversarial approaches in image generation proposed to use $L_{adv-enc} = -L_{adv}$ as the training loss for the adversarial-encoder $E_{\phi,z}(\cdot)$ [22]. However, this loss does not make the discriminator $\delta_\psi(\cdot)$ unable to predict the label $y_n$. Instead, we thus propose to minimize the negative binary entropy function with $q_{\phi,z} := P(y_n = 1|s_n) = \delta_\psi(E_{\phi,z}(s_n^2))$:

$$L_{adv-enc} = q_{\phi,z} \log q_{\phi,z} + (1 - q_{\phi,z}) \log(1 - q_{\phi,z}). \quad (9)$$

**Classifier-Encoder $E_{\phi,y}(\cdot)$** Similarly to Creswell et al. for image generation [23], we estimate the label $y_n$ for the decoder $D_\theta(\cdot)$ using the classifier-encoder $E_{\phi,y}(\cdot)$ as $q_{\phi,y} := P(y_n = 1|s_n) = E_{\phi,y}(s_n^2)$. We use the BCE as the learning objective:

$$L_{clf-enc} = y_n \log q_{\phi,y} + (1 - y_n) \log(1 - q_{\phi,y}). \quad (10)$$

**Decoder $D_\theta(\cdot)$** Instead of using the binary label $y_n$ as an input to the decoder such that $D_\theta(z_n, y_n)$, we use the posterior probability $q_{\phi,y}$ as a soft value, such that $D_\theta(z_n, q_{\phi,y})$.

### 3.2. Adversarial training

The complete loss of the conditional VAE is as follows:

$$L_{adv-VAE} = L_{ELBO} + \alpha L_{adv-enc} + \beta L_{clf-enc}. \quad (11)$$

At each step of the training, we update the networks as follows:

1. Update $E_{\phi,z}(\cdot)$, $E_{\phi,y}(\cdot)$ and $D_\theta(\cdot)$ using $L_{adv-VAE}$
2. Update $\delta_\psi(\cdot)$ using $\alpha L_{adv-enc}$

### 3.3. Clean speech estimation

Speech variance estimation at test time is shown in Fig. 4. At test time, we estimate the label $y_n$ with a pretrained noise-robust classifier which is trained separately from the VAE on visual data. For estimating the unsupervised parameters $\Theta_u$, we use the same MCEM configuration as in Section 2.4.

---

**Dataset** For training, validation, and test we used the NTCD-TIMIT dataset [24], which consists of audio-visual recordings. The visual data consist of videos of the lip region at 30 frames-per-second (FPS). All audio signals have a sampling rate of 16 kHz. In addition to clean speech signals, we use the noisy versions, with 2 types of stationary noise (Car, White) and four types of nonstationary noises (Living Room, Cafe, Babble, Street). We evaluate on 3 signal-to-noise ratios (SNRs): $\{0, +5, +10\}$ dB. Note that these levels were computed on speech segments only. For training, the clean-speech and visual sets used are of about 5 h. For the test, the noisy speech subset consists of 15,876 utterances of about 5 s each.

**Baselines** For the noise-robust classifier estimating the label $y_n$ at test time, we use the visual-only variant of Ariav and Cohen’s audio-visual VAD classifier [25]. We pretrain the classifier on the visual training set of the NTCD-TIMIT dataset. For the baselines, we use the standard and the conditional VAEs, which we denote as VAE and CVAE, respectively, both trained using $L_{ELBO}$.

**Hyperparameter settings** The STFT is computed using a 64 ms Hann window with 75% overlap, resulting in $F = 513$ unique frequency bins and an audio frame rate of 62.5 FPS. To obtain the same visual frame rate as the audio frame rate, we use FFmpeg [27]. This guarantees that the audio and visual frames are synchronized. To obtain the ground truth for the VAD label $y_n$, we use simple thresholding in the time domain.

For a fair comparison between all the approaches, we consider a similar architecture for each subnetwork. Tab. 1 shows the configuration of the models. We set the dimension of the latent space $s$ to $L = 16$. For the loss, we empirically found that $\alpha = \beta = 10$ provides excellent performance. We use the Adam optimizer with standard configuration [28]. We set the batch size to 128. Early stopping with a patience of 10 epochs is performed using $L_{adv-enc}$ on the validation set. For the MCEM we follow the settings of Leglaive et al. and set the NMF rank to $K = 10$ [8].

**Metrics** To evaluate speech enhancement performance, we use the scale-invariant signal-to-distortion ratio (SI-SDR) measured in dB [29], raw scores of the extended short-time objective intelligibility (ESTOI) with values between 0 and 1 [30], and the perceptual objective listening quality analysis (POLQA) score with values between 1 and 5 [31]. To evaluate the classification performance of the visual-only VAD classifier used at test time, we use the F1-score which combines the precision and recall rates.

### 4. EXPERIMENTAL SETUP

| Subnetwork | Hidden layers | Output layer | act. fn | act. fn |
|------------|--------------|--------------|---------|---------|
| $\delta_\psi(\cdot)$ | 2 128 | ReLU | sigmoid |
| $E_{\phi,z}(\cdot)$ | 2 128 | tanh | identity |
| $E_{\phi,y}(\cdot)$ | 2 128 | ReLU | sigmoid |
| $D_\theta(\cdot)$ | 2 128 | tanh | exp |

Table 1: Model configurations.

---

1. $\alpha$ is related to $L_{adv-enc}$ and proved to provide better results in practice.
5. RESULTS

5.1. Average performance

The visual-only VAD classifier gives F1-score = 88% on the test set. Fig. 2 shows an example of the reconstructed spectrograms by the VAEs, i.e., without using the MCEM algorithm. The proposed CVAE + \( \mathcal{L}_{\text{adv-VAE}} \) is the only approach with a meaningful output when speech absence is detected, i.e., \( \hat{y}_n = 0 \). This illustrates that disentanglement works with the proposed approach.

Tab. 2 shows the average results for nonstationary noises. CVAE + \( \mathcal{L}_{\text{adv-VAE}} \) outperforms both VAE + \( \mathcal{L}_{\text{ELBO}} \) and CVAE + \( \mathcal{L}_{\text{ELBO}} \) in terms of SI-SDR. This is again explained by our successful disentanglement which prevents CVAE + \( \mathcal{L}_{\text{adv-VAE}} \) from outputting a noise-like signal when speech absence is detected, i.e., \( \hat{y}_n = 0 \). Conversely, VAE + \( \mathcal{L}_{\text{ELBO}} \) and CVAE + \( \mathcal{L}_{\text{ELBO}} \) often outputs speech-like noise when \( \hat{y}_n = 0 \). Note that, unlike SI-SDR, the benefits of the proposed approach can not be visible with ESTOI and POLQA because these metrics are only computed in speech presence.

Table 2: Average performance for nonstationary noises. ESTOI and POLQA are only evaluated during speech activity while the proposed disentanglement yields strong improvements in speech absence.

| Model            | SI-SDR (dB) | ESTOI   | POLQA   |
|------------------|-------------|---------|---------|
| Mixture          | -1.3 ± 0.1  | 0.38 ± 0.00 | 1.40 ± 0.01 |
| VAE + \( \mathcal{L}_{\text{ELBO}} \) | 3.9 ± 0.1   | 0.36 ± 0.00 | 1.52 ± 0.01 |
| CVAE + \( \mathcal{L}_{\text{ELBO}} \) | 4.6 ± 0.1   | 0.38 ± 0.00 | 1.57 ± 0.01 |
| CVAE + \( \mathcal{L}_{\text{adv-VAE}} \) | 5.3 ± 0.1   | 0.38 ± 0.00 | 1.56 ± 0.01 |

5.2. Analysis of the training scheme

While the above results show the performance of CVAE with the proposed training scheme using \( \mathcal{L}_{\text{adv-VAE}} \), we need further analysis regarding what contributes to the performance of the proposed training scheme CVAE + \( \mathcal{L}_{\text{adv-VAE}} \). Since the proposed disentanglement yields strong improvements in speech presence while ESTOI and POLQA are only evaluated during speech presence, we only consider SI-SDR here.

\[ \text{https://uhh.de/inf-sp-disentangled2021} \]

6. CONCLUSION

In this work, we propose to use adversarial training to learn disentanglement between a label describing speech activity and the other latent variables of the VAE. We showed the beneficial effect of learning disentanglement when reconstructing clean speech from noisy speech. In the presence of nonstationary noise, the proposed approach outperforms the standard and conditional VAEs, both trained using the ELBO as loss function, in terms of SI-SDR. Our proposed approach is particularly interesting for audio-visual speech enhancement, where speech activity can be estimated from visual information, which is not affected by the noisy environment.
7. REFERENCES

[1] E. Vincent, T. Virtanen, and S. Gannot, Eds., Audio Source Separation and Speech Enhancement. Hoboken, NJ: John Wiley & Sons, 2018.

[2] R. C. Hendriks, T. Gerkmann, and J. Jensen, DFT-Domain Based Single-Microphone Noise Reduction for Speech Enhancement: A Survey of the State-of-the-Art, ser. Synthesis Lectures on Speech and Audio Processing. Williston, VT: Morgan & Claypool, 2013, no. 11.

[3] C. Breithaupt, T. Gerkmann, and R. Martin, “Cepstral Smoothing of Spectral Filter Gains for Speech Enhancement Without Musical Noise,” IEEE Signal Processing Letters, vol. 14, no. 12, pp. 1036–1039, Dec. 2007.

[4] C. Févotte, N. Bertin, and J.-L. Durrieu, “Nonnegative Matrix Factorization with the Itakura-Saito Divergence: With Application to Music Analysis,” Neural Computation, vol. 21, no. 3, pp. 793–830, Mar. 2009.

[5] T. Gerkmann and R. C. Hendriks, “Unbiased MMSE-Based Noise Power Estimation With Low Complexity and Low Tracking Delay,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 20, no. 4, pp. 1383–1393, May 2012.

[6] D. P. Kingma and M. Welling, “An Introduction to Variational Autoencoders,” Foundations and Trends in Machine Learning, vol. 12, no. 4, pp. 307–392, 2019.

[7] Y. Bando, M. Mimura, K. Itoyama, K. Yoshii, and T. Kawahara, “Statistical Speech Enhancement Based on Probabilistic Integration of Variational Autoencoder and Non-Negative Matrix Factorization,” in ICASSP, Apr. 2018, pp. 716–720.

[8] S. Leglaive, L. Girin, and R. Horaud, “A variance modeling framework based on variational autoencoders for speech enhancement,” in MLSP, Sept. 2018, pp. 1–6.

[9] Y. Bando, K. Sekiguchi, and K. Yoshii, “Adaptive neural speech enhancement with a denoising variational autoencoder,” in ISCA Interspeech, 2020, pp. 2437–2441.

[10] J. Richter, G. Carbajal, and T. Gerkmann, “Speech Enhancement with Stochastic Temporal Convolutional Networks,” in ISCA Interspeech, Oct. 2020, pp. 4516–4520.

[11] H. Fang, G. Carbajal, S. Wermter, and T. Gerkmann, “Variational autoencoder for speech enhancement with a noise-aware encoder,” in ICASSP, 2021, pp. 676–680.

[12] D. P. Kingma, S. Mohamed, D. Jimenez Rezende, and M. Welling, “Semi-supervised learning with deep generative models,” in NeurIPS, vol. 27. Curran Associates, Inc., 2014, pp. 3581–3589.

[13] H. Kameoka, L. Li, S. Inoue, and S. Makino, “Supervised determined source separation with multichannel variational autoencoder,” Neural Computation, vol. 31, no. 9, pp. 1891–1914, Sept. 2019.

[14] Y. Du, K. Sekiguchi, Y. Bando, A. A. Nugraha, M. Fontaine, K. Yoshii, and T. Kawahara, “Semi-supervised Multichannel Speech Separation Based on a Phone- and Speaker-Aware Deep Generative Model of Speech Spectrograms,” in EU-SIPCO, Jan. 2021, pp. 870–874.

[15] G. Carbajal, J. Richter, and T. Gerkmann, “Guided variational autoencoder for speech enhancement with a supervised classifier,” in ICASSP, June 2021, pp. 681–685.

[16] N. Siddharth, B. Paige, J.-W. van de Meent, A. Desmaison, N. Goodman, P. Kohli, F. Wood, and P. Torr, “Learning disentangled representations with semi-supervised deep generative models,” in NeurIPS, vol. 30. Curran Associates, Inc., 2017.

[17] I. Higgins, L. Matthey, A. Pal, C. Burgess, X. Glorot, M. Botvinick, S. Mohamed, and A. Lerchner, “β-VAE: Learning basic visual concepts with a constrained variational framework,” in ICLR, 2017.

[18] H. Kim and A. Mnih, “Disentangling by factorising,” in Int. Conf. Machine Learning, vol. 80. PMLR, July 2018, pp. 2649–2658.

[19] R. T. Q. Chen, X. Li, R. B. Grosse, and D. K. Duvenaud, “Isolating sources of disentanglement in variational autoencoders,” in NeurIPS, vol. 31. Curran Associates, Inc., 2018.

[20] E. Mathieu, T. Rainforth, N. Siddharth, and Y. W. Teh, “Disentangling Disentanglement in Variational Autoencoders,” vol. 97. PMLR, June 2019, pp. 4402–4412.

[21] F. Locatello, M. Tscharnmann, S. Bauer, G. Rätsch, B. Schölkopf, and O. Bachem, “Disentangling Factors of Variation Using Few Labels,” in ICLR, 2020.

[22] G. Lample, N. Zeghidour, N. Usunier, A. Bordes, L. Denoyer, and M. Ranzato, “Fader networks: Manipulating images by sliding attributes,” in NeurIPS, vol. 30. Curran Associates, Inc., 2017, pp. 5969–5978.

[23] A. Creswell, Y. Mohamied, B. Sengupta, and A. A. Bharath, “Adversarial Information Factorization,” arXiv:1711.05175 [cs], Sept. 2018.

[24] A. Liutkus, R. Badeau, and G. Richard, “Gaussian Processes for Underdetermined Source Separation,” IEEE Transactions on Signal Processing, vol. 59, no. 7, pp. 3155–3167, July 2011.

[25] A. H. Abdelaziz, “NTCD-TIMIT: A New Database and Baseline for Noise-Robust Audio-Visual Speech Recognition,” in ISCA Interspeech, Aug. 2017, pp. 3752–3756.

[26] I. Ariav and I. Cohen, “An End-to-End Multimodal Voice Activity Detection Using WaveNet Encoder and Residual Networks,” IEEE Journal of Selected Topics in Signal Processing, vol. 13, no. 2, pp. 265–274, May 2019.

[27] FFmpeg Developers, “ffmpeg (version 4.3.2),” 2021. [Online]. Available: http://ffmpeg.org/

[28] D. P. Kingma and J. Ba, “Adam: A Method for Stochastic Optimization,” in ICLR, Dec. 2014.

[29] J. L. Roux, S. Wisdom, H. Erdogan, and J. R. Hershey, “SDR – Half-baked or Well Done?” in ICASSP, May 2019, pp. 626–630.

[30] J. Jensen and C. H. Taal, “An Algorithm for Predicting the Inter-telligibility of Speech Masked by Modulated Noise Maskers,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 24, no. 11, pp. 2009–2022, Nov. 2016.

[31] Int. Telecomm. Union (ITU-T) Rec., “Recommendation P.863: Perceptual objective listening quality assessment,” 2011.