# Trustworthy AI Systems

## -- Voice Conversion

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# Last Lecture

- Speech Recognition
- Speaker Recognition
  - Speaker Verification
  - Speaker Identification
- Humans as Deepfake Audio Detectors

# This Lecture

## Voice Conversion

- One-shot Voice Conversion by Separating Speaker and Content Representations with Instance Normalization (InterSpeech'2019)
- AGAIN-VC: A one-shot voice conversion using activation guidance and adaptive instance normalization. (ICASSP'2021)

- VQVC+: one-shot voice conversion by vector quantization and U-Net architecture. (ICSA'2020)
- AVQVC: One-shot voice conversion by vector quantization with applying contrastive learning. (ICASSP'2022)

- FREEVC: Towards High-quality Text-Free **One-Shot** Voice Conversion (ICASSP'2023)

# Voice Conversion (VC)

- Voice = Content Information (e.g., semantics) + Speaker Features (e.g., timbre, accent, and tones)

- Voice Conversion: transforms the source speaker's into another one's while preserving the linguistic content

# None Disentangle-based Methods

- Statistics-based Methods: need parallel data
  - Voice conversion based on maximum-likelihood estimation of spectral parameter trajectory (ICASSP'2007)
  - Voice conversion using partial least squares regression (IEEE Trans. ASLP 2010)

- Generative Models: unparalleled data (domain mapping, target speak in training)
  - GAN-based Method: around 2018
    - Cyclegan-vc: **Non-parallel** voice conversion using cycle-consistent adversarial network
    - Stargan-vc: **Non-parallel** many-to-many voice conversion using star generative adversarial networks
  - VAE-based Method: around 2018
    - **Non-parallel** many-to-many voice conversion with auxiliary classifier variational autoencoder
    - Voice conversion from unaligned corpora using variational autoencoding Wasserstein GAN

# Disentangle-based Methods

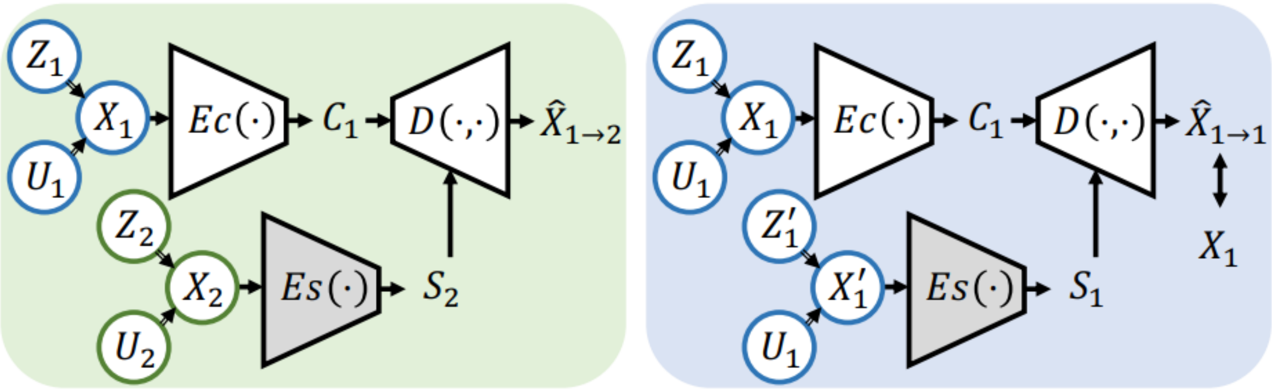
- Instance normalization (IN)
  - One-shot voice conversion by separating speaker and content representations with instance normalization (InterSpeech'2019)
  - AGAIN-VC: A **one-shot** voice conversion using activation guidance and adaptive instance normalization. (ICASSP'2021)

- Vector quantization (VQ)
  - VQVC+: **One-shot** voice conversion by vector quantization and u-net architecture. (ICSA'2020)
  - AVQVC: **One-shot** voice conversion by vector quantization with applying contrastive learning. (ICASSP'2022)

# Disentangle-based Methods: Encoder-Decoder Structure

- Encoder: Speech => Latent Representation
    - Encoding the **source** speech’s **content**
    - Encoding the source speech’s speaker features
    - Encoding the target speech’s content
    - Encoding the **target** speech’s **speaker features**
- Decoder: Latent Representation => Speech
    - Fusing the source speech’s content and target speaker features
    - Decoding the Fused Representation to Speech Data

# An Example: AutoVC (ICML'19): Layer Dimension




(a) Conversion (b) Training

E(S): Pretrained Speaker Verification Model

E(C): Content Extraction Model: to be trained Autoencoder with a carefully designed bottleneck

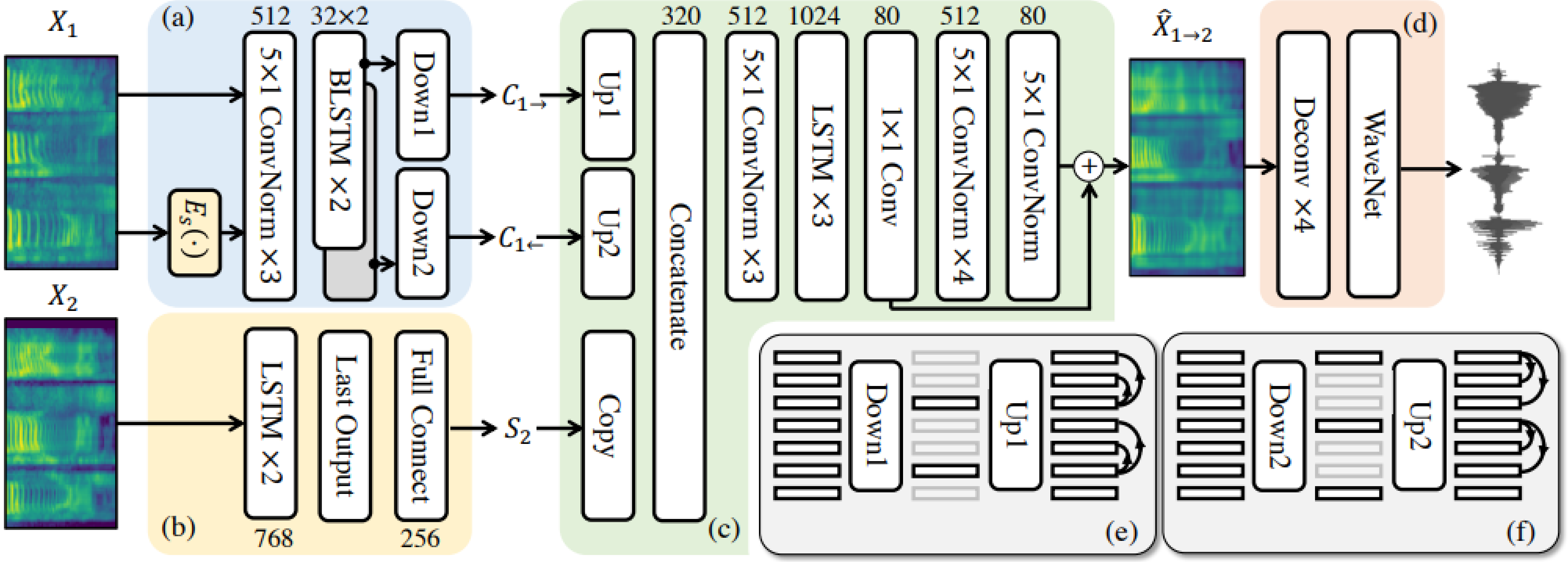
D(): Decoder

$$\min_{E_c(\cdot),D(\cdot,\cdot)} L = L_{\text{recon}} + \lambda L_{\text{content}},$$

where

$$L_{\text{recon}} = \mathbb{E}[\|\hat{X}_{1\to1} - X_1\|_2^2],$$
$$L_{\text{content}} = \mathbb{E}[\|E_c(\hat{X}_{1\to1}) - C_1\|_1].$$

# An Example: AutoVC (ICML'19)




Es and (b):The style encoder

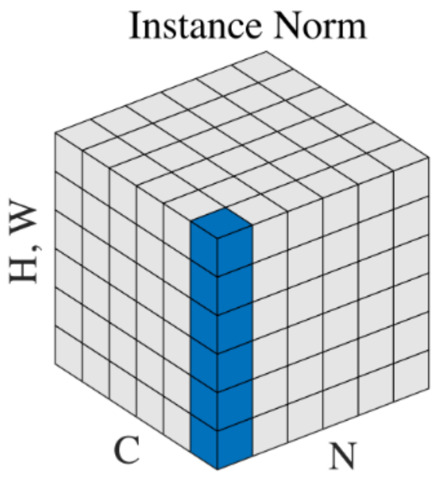
AutoVC Architecture

# Instance Normalization based Disentanglement (1)

## Instance Normalization

$$\mu_{ti} = \frac{1}{HW}\sum_{l=1}^{W}\sum_{m=1}^{H} x_{tilm}, \quad \sigma_{ti}^2 = \frac{1}{HW}\sum_{l=1}^{W}\sum_{m=1}^{H}(x_{tilm} - \mu_{ti})^2. \quad y_{tijk} = \frac{x_{tijk} - \mu_{ti}}{\sqrt{\sigma_{ti}^2 + \epsilon}},$$

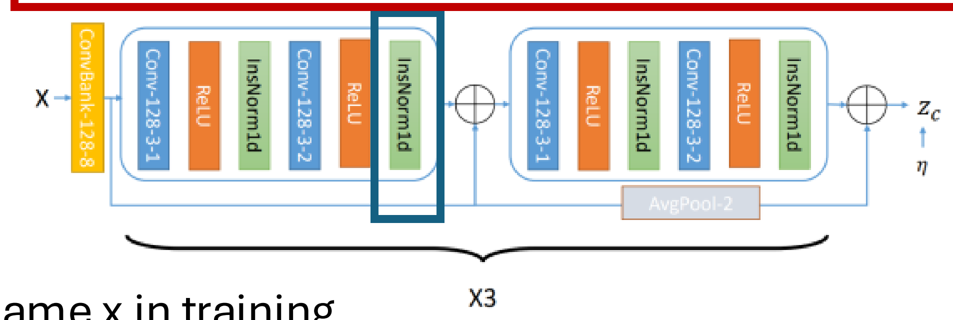
based on the description in Section 2.1. In this paper, we find that simply adding Instance normalization (IN) without affine transformation to $E_c$ can remove the speaker information while preserving the content information. Similar idea has been verified to be effective for style transfer in computer vision [28].



# Instance Normalization based Disentanglement (2)

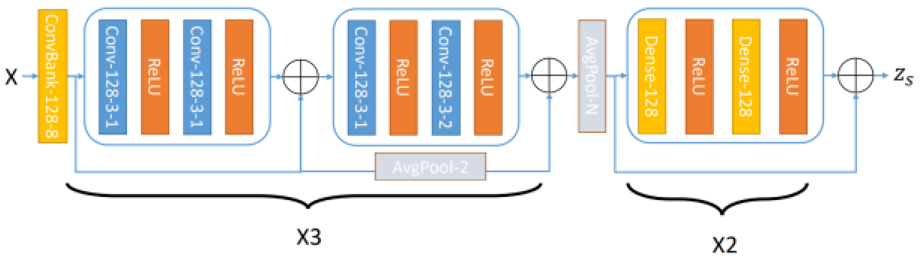
Mirror Structure

Content encoder

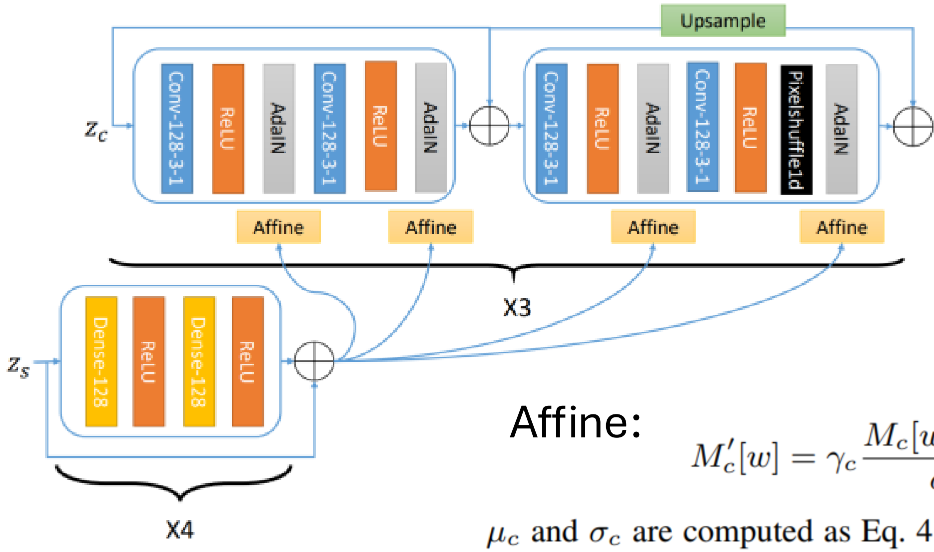



Same x in training

Speaker encoder




Decoder




Adaptive instance normalization (AdaIN) layer aligns the mean and variance of the content features with those of the style features.

Affine:

$$M'_c[w] = \gamma_c \frac{M_c[w] - \mu_c}{\sigma_c} + \beta_c. \tag{6}$$

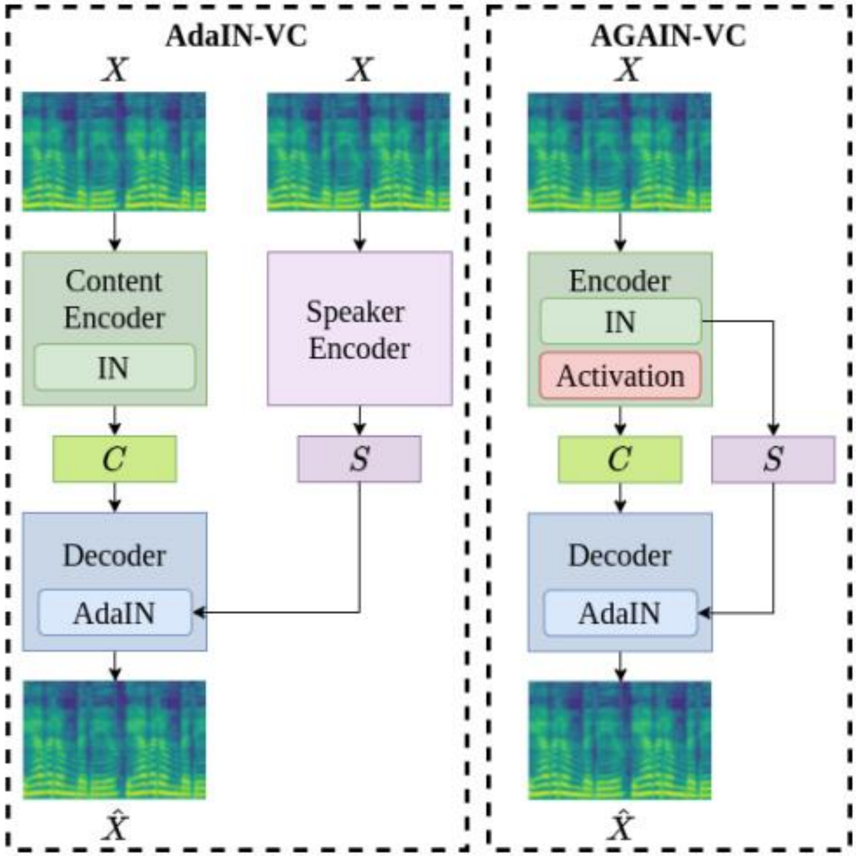
$\mu_c$ and $\sigma_c$ are computed as Eq. 4. $\gamma_c$ and $\beta_c$ for each channel are the linear transformation of the output of speaker encoder $\mathrm{E_s}$.

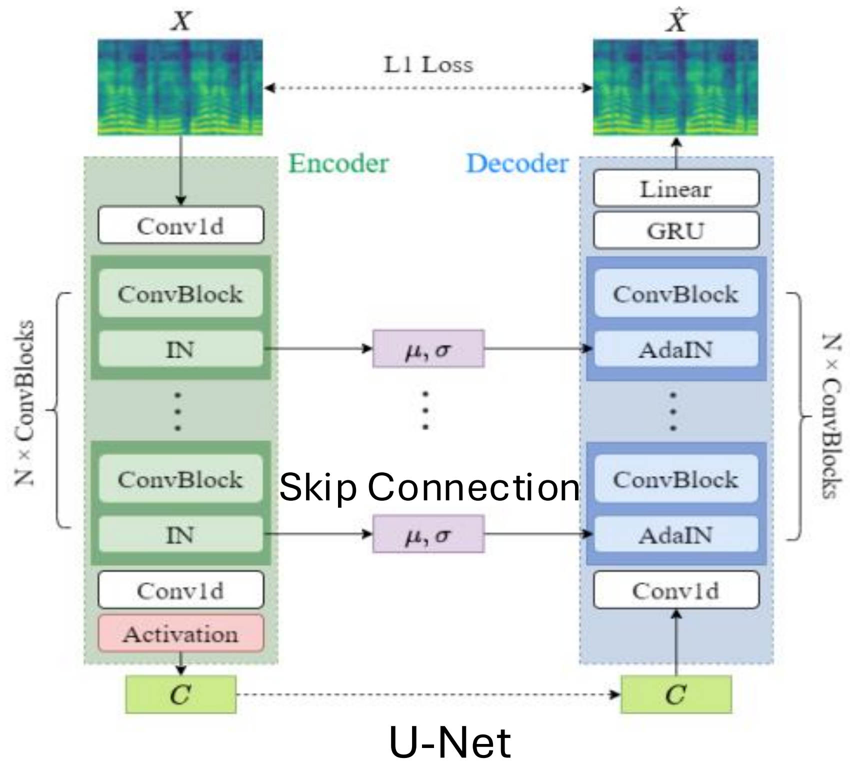
$$\min_{\theta_{\mathrm{E_s}}, \theta_{\mathrm{E_c}}, \theta_{\mathrm{D}}} L(\theta_{\mathrm{E_s}}, \theta_{\mathrm{E_c}}, \theta_{\mathrm{D}}) = \lambda_{rec} L_{rec} + \lambda_{kl} L_{kl}$$

$$L_{rec}(\theta_{\mathrm{E_s}}, \theta_{\mathrm{E_c}}, \theta_{\mathrm{D}}) = \underset{x \sim p(x), z_c \sim p(z_c|x)}{\mathbb{E}} [\| \mathrm{D}(\mathrm{E_s}(x), z_c) - x \|_1^1]. \qquad L_{kl}(\theta_{\mathrm{E_c}}) = \underset{x \sim p(x)}{\mathbb{E}} [\| \mathrm{E_c}(x)^2 \|_2^2].$$

One-shot Voice Conversion by Separating Speaker and Content Representations with Instance Normalization (InterSpeech'19)

# Instance Normalization based Disentanglement (3)




$$\mathrm{AdaIN}(\boldsymbol{H}, \mu(\boldsymbol{Z}), \sigma(\boldsymbol{Z})) = \sigma(\boldsymbol{Z})\mathrm{IN}(\boldsymbol{H}) + \mu(\boldsymbol{Z}).$$

AGAIN-VC: A one-shot voice conversion using activation guidance and adaptive instance normalization. (ICASSP'2021)

# Instance Normalization based Disentanglement (4)

Activation Guidance: With an extra activation function, the range of content embeddings is somewhat restricted.

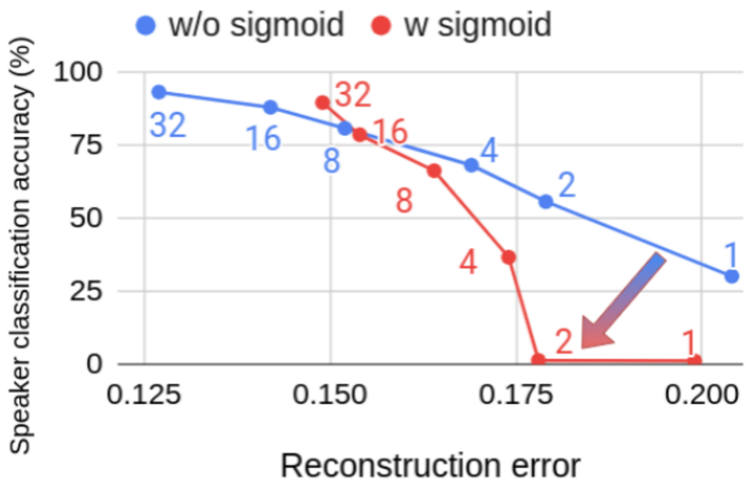



**Fig. 3**: The trade-off between the reconstruction error and the speaker classification accuracy on $C$. The numbers here represent the channel size of $C$. Besides, the arrow stands for the direction of improvement of the models we do care.

Both of them should be as low as possible

**Table 1**: Comparison between the models with different activation functions. $C$ and $S$ are the speaker classification accuracy on content embeddings and speaker embeddings, respectively, and Rec. represents the reconstruction error. * is our proposed method.

| Activation | $C$ (Acc.%) ↓ | $S$ (Acc.%) ↑ | Rec. ↓ |
|---|---|---|---|
| None | 68.6 | 92.6 | 0.161 |
| ReLU | 51.9 | 92.2 | 0.174 |
| ELU | 69.2 | 91.5 | 0.167 |
| Tanh | 57.3 | 91.7 | 0.165 |
| Sigmoid ($\alpha = 1$) | 30.5 | 90.0 | 0.167 |
| Sigmoid ($\alpha = 0.1$) * | **1.7** | **93.2** | **0.151** |
| Sigmoid ($\alpha = 0.01$) | **1.7** | 91.1 | 0.222 |

# Vector Quantization based Disentanglement (1)

Vector Quantization:

- The content information can be represented by discrete codes;
- The speaker information can be viewed as the difference between the continuous representations and the discrete codes.

$$\boldsymbol{V} = enc(\boldsymbol{X}),$$
$$\boldsymbol{C} = Quantize(\boldsymbol{V}),$$
$$\boldsymbol{s} = \mathbb{E}_t[\boldsymbol{V} - \boldsymbol{C}], \quad \boldsymbol{S} = \{\underbrace{\boldsymbol{s}, \boldsymbol{s}, ..., \boldsymbol{s}}_{T\ times}\},$$

$$Quantize(\boldsymbol{V}) = \{\boldsymbol{q}_0, \boldsymbol{q}_1, ..., \boldsymbol{q}_T\}, \quad \boldsymbol{q}_j = \arg\min_{\boldsymbol{q} \in Q}(||\boldsymbol{v}_j - \boldsymbol{q}||_2^2).$$

Q: quantization codebook

VQVC+: one-shot voice conversion by vector quantization and U-Net architecture. (ICSA'2020)

# Vector Quantization based Disentanglement (2)

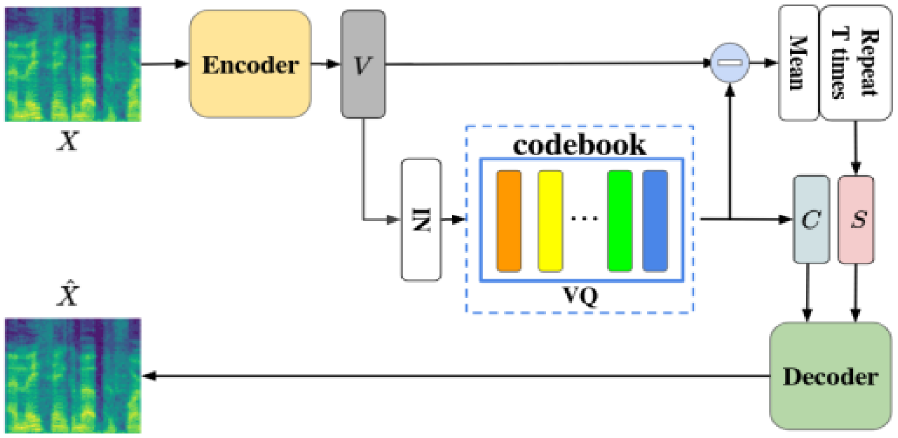



Figure 1: *The VQVC architecture. VQ is the vector quantization layer, and IN is the instance normalization layer. VQVC applies IN+VQ layers to separate the content and the speaker information to achieve voice conversion.*

$$L_{rec}(\mathcal{Q}, \theta_{enc}, \theta_{dec}) = \mathbb{E}_{\boldsymbol{X} \in \mathcal{X}} \left[ ||\hat{\boldsymbol{X}} - \boldsymbol{X}||_1^1 \right].$$

$$L_{latent}(\theta_{enc}) = \mathbb{E}_t[||IN(\boldsymbol{V}) - \boldsymbol{C}||_2^2].$$

$$L = L_{rec} + \lambda L_{latent}.$$

Two 3X1 1D-convolution layers, an IN layer, and a vector quantization layer

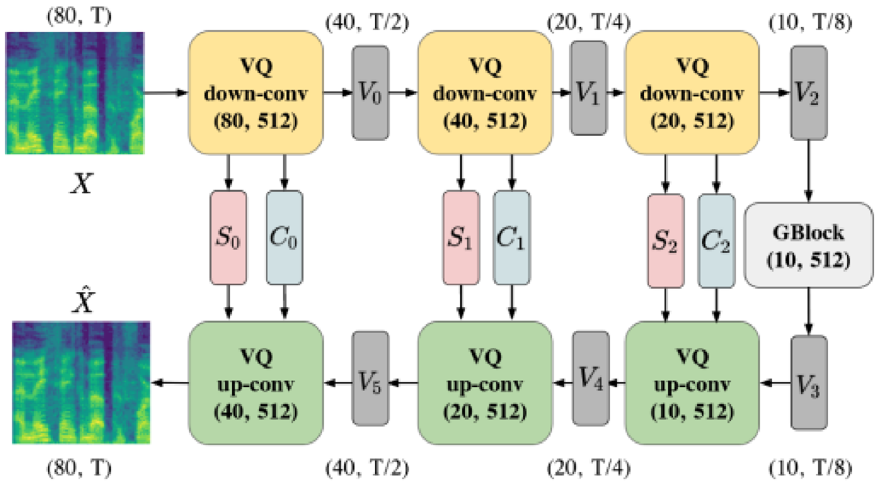



Figure 2: *The VQVC+ architecture. VQVC+ applies the U-Net architecture to improve quality, and each sub-module in the encoder is a variant of the VQVC encoder. Quantized output* $\boldsymbol{C}$ *and the speaker embedding* $\boldsymbol{S}$ *are skip-connected to the decoder instead of the continuous embedding* $\boldsymbol{V}$.

Up-conv: Two 3X1 1D-convolution layers, and time upsampling, frequency upsampling

# Vector Quantization based Disentanglement (3)

The experiment on the output of each encoder layer C_0, C_1, C_2:

| Method | $C_0$ / $C_1$ / $C_2$ (%) | L1Loss |
|---|---|---|
| VQVC | 16.0 | 0.262 |
| Q32 | 19.5 / 11.8 / 6.8 | 0.210 |
| Q64 | 23.2 / 16.6 / 7.0 | 0.188 |
| Q128 | 33.3 / 17.0 / 10.3 | 0.180 |
| Q256 | 35.8 / 18.1 / 12.5 | 0.165 |
| IN-only | 71.2 / 36.8 / 5 | 0.145 |

Table 1: *Accuracy of identifying speakers on the content embedding and the speaker embedding with different methods. VQVC is the model without skip-connection design. QN means that the size of codebook, Q, in VQVC+ is N. IN-only means no quantization in U-Net. L1Loss is the L1 reconstruction loss.*

| Method | $S_0/S_1/S_2$ (%) |
|---|---|
| VQVC | 96.6 |
| Q64 | 98.3 / 72.2/ 45.4 |
| IN-only | 97.4/ 80.1 / 23.1 |

Table 2: *Accuracy of identifying speakers on the speaker embedding* $\boldsymbol{S}$.

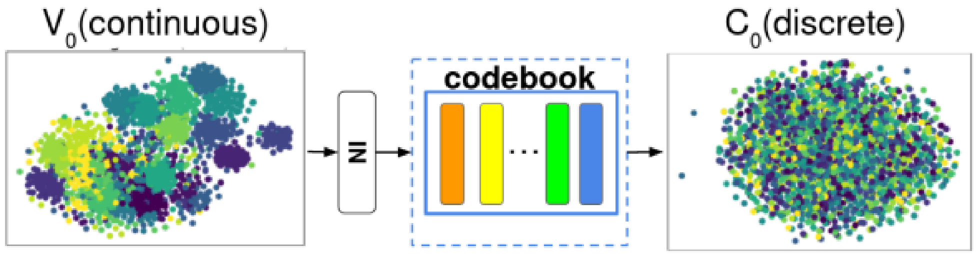



Figure 6: *quantization*

# Vector Quantization based Disentanglement (4)

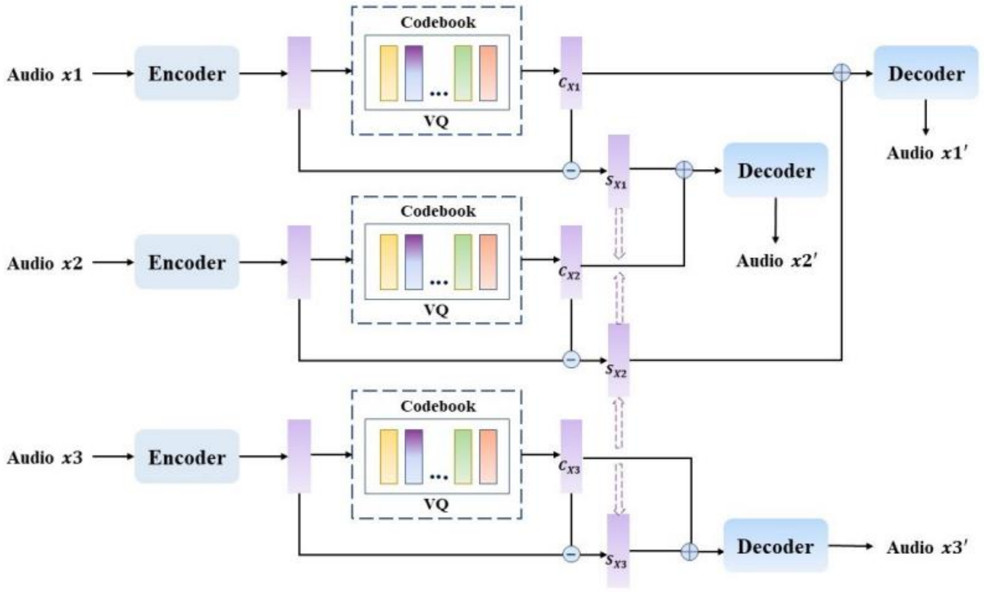



**Fig. 2**. Framework of AVQVC. Both $x_1$ and $x_2$ are produced by the same speaker, but their text content are different, while $x_3$ belongs to another speaker. $\boldsymbol{C}_X$ is a discrete variable generated by looking up the *codebook*. And, $\boldsymbol{S}_X$ denotes speaker embedding, which is produced by the mean difference between encoder output and $\boldsymbol{C}_X$.

$$\mathcal{L}_{\text{recon}} = \|x_1' - x_1\|_1^1 + \|x_2' - x_2\|_1^1 + \|x_3' - x_3\|_1^1$$

$$\begin{aligned}\mathcal{L}_{\text{latent}} = &\|enc(x_1) - C_{x_1}\|_2^2 \\ &+ \|enc(x_2) - C_{x_2}\|_2^2 + \|enc(x_3) - C_{x_3}\|_2^2\end{aligned}$$

$$\mathcal{L}_{\text{speaker}} = \|S_{x_2} - S_{x_1}\|_1^1$$

$$\mathcal{L}_{\text{diff}} = -(\|S_{x_2} - S_{x_3}\|_1^1 + \|S_{x_1} - S_{x_3}\|_1^1)$$

$$L = \mathcal{L}_{\text{recon}} + \alpha\mathcal{L}_{\text{latent}} + \beta\mathcal{L}_{\text{speaker}} + \lambda\mathcal{L}_{\text{diff}}$$

AVQVC: **One-shot** voice conversion by vector quantization with applying contrastive learning.

# Vector Quantization based Disentanglement (5)

**Table 1**. Comparison of different models in traditional VC and one-shot vc.

| **Methods** | **Traditional VC** | | | **One-Shot VC** | | | |
|---|---|---|---|---|---|---|---|
| | MCD | MOS | VSS | MCD | MOS | VSS | MODEL-SIZE |
| VQVC | $8.16 \pm 0.31$ | $2.28 \pm 0.99$ | $3.47 \pm 0.82$ | $8.12 \pm 0.14$ | $2.06 \pm 0.84$ | $2.97 \pm 0.75$ | **5.71M** |
| VQVC+ | $7.08 \pm 0.22$ | $3.31 \pm 0.90$ | $3.42 \pm 0.85$ | $8.41 \pm 0.08$ | $2.75 \pm 0.84$ | $3.11 \pm 0.88$ | 388M |
| AutoVC | $\mathbf{4.34 \pm 0.12}$ | $\mathbf{3.81 \pm 1.14}$ | $3.45 \pm 0.76$ | $7.66 \pm 0.17$ | $2.61 \pm 0.73$ | $2.91 \pm 0.72$ | 339M |
| StarGAN-VC2 | $6.28 \pm 0.09$ | $3.45 \pm 1.01$ | $3.59 \pm 0.87$ | — | — | — | 56.45M |
| **AVQVC(512)** | $5.19 \pm 0.29$ | $3.57 \pm 0.91$ | $\mathbf{3.70 \pm 0.71}$ | $\mathbf{5.04 \pm 0.13}$ | $\mathbf{3.20 \pm 0.91}$ | $\mathbf{3.29 \pm 0.64}$ | 5.77M |

The Mel-Cepstral Distortion(MCD) between converted speech and the ground truth target speech

$$\frac{10\sqrt{2}}{\ln 10}\frac{1}{T}\sum_{t=1}^{T}\sqrt{\sum_{i}\left(C_{ti}-\hat{C}_{ti}\right)^{2}}.$$

The mean opinion score(MOS) test, which is used to evaluate the quality of converted speech

The voice similarity score(VSS) test, which measures how similar the timbre of the converted voice is to that of the ground truth.

# FreeVC

Limitations of existing work:

- Extract dirty content information with speaker information leaked in (text-free/disentanglement)
- Demand a large amount of annotated data for training (text-based VC)
- The quality of reconstructed waveform can be degraded

Two steps of VC:

1. A conversion model converts the source acoustic features into target speaker's voice
2. A pre-trained vocoder transforms the converted features into waveform
   - A different distribution from that the vocoder uses during training ➔ degrading the quality

FREEVC: Towards High-quality Text-Free **One-Shot** Voice Conversion

# FreeVC (1)

Bottleneck extractor extracts content information

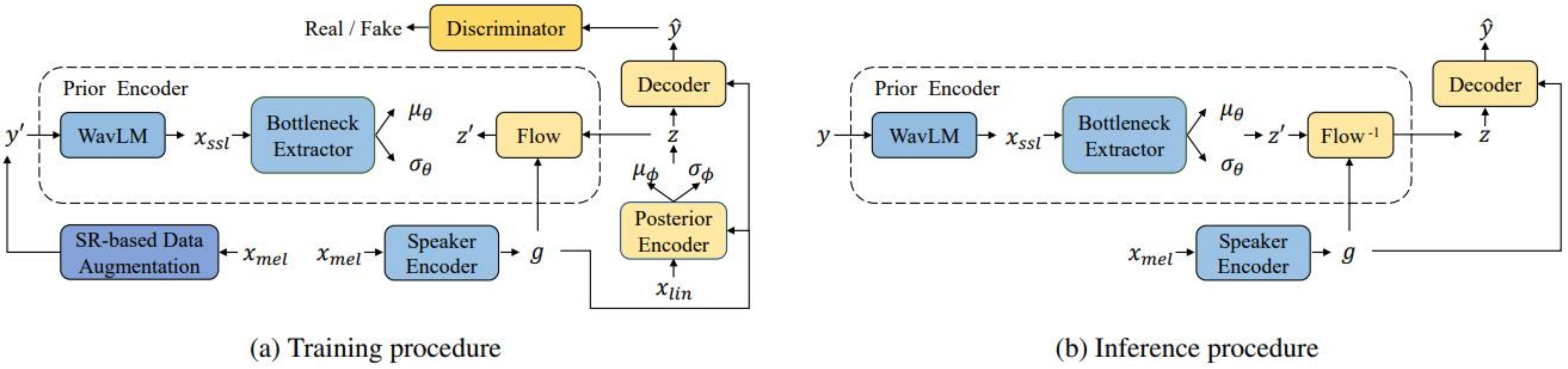
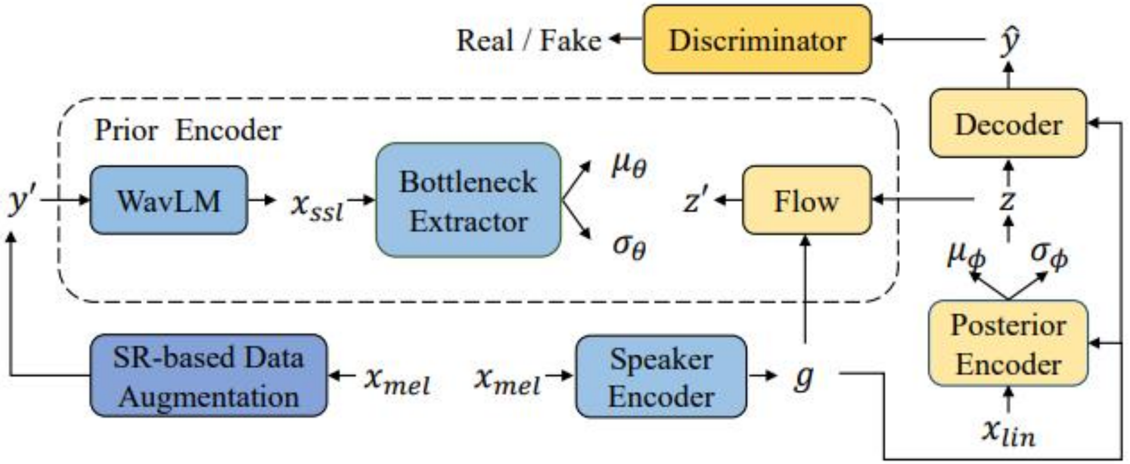


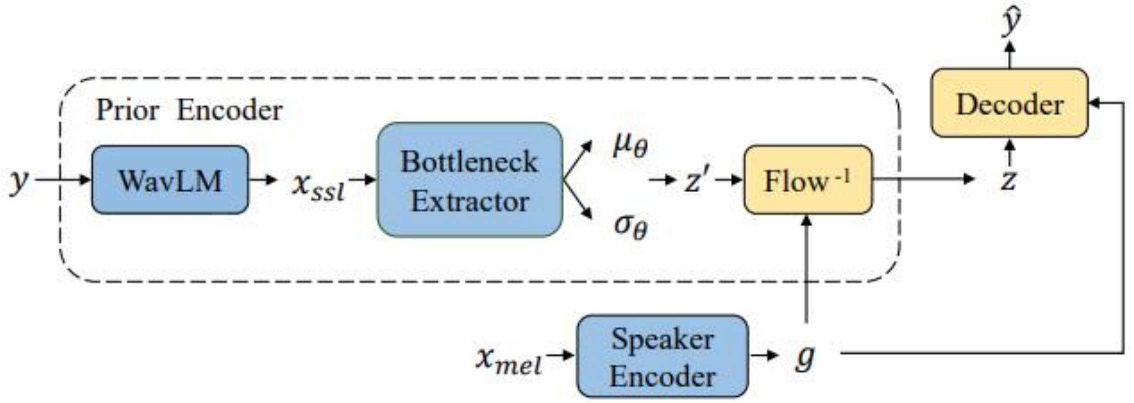

**Fig. 1**: Training and inference procedure of FreeVC. Here $y$ denotes source waveform, $y'$ denotes augmented waveform, $\hat{y}$ denotes converted waveform, $x_{mel}$ denotes mel-spectrogram, $x_{lin}$ denotes linear spectrogram, $x_{ssl}$ denotes SSL feature, and $g$ denotes speaker embedding.

# FreeVC (2)

$\mu_\theta$ and $d$-dim $\sigma_\theta$. The normalizing flow, which conditions on speaker embedding $g$, is adopted to improve the complexity of prior distribution. Following VITS, it is composed of multiple affine coupling layers [18] and is made to be volume-preserving with the Jacobian determinant $|det\frac{\partial z'}{\partial z}|$ of 1.



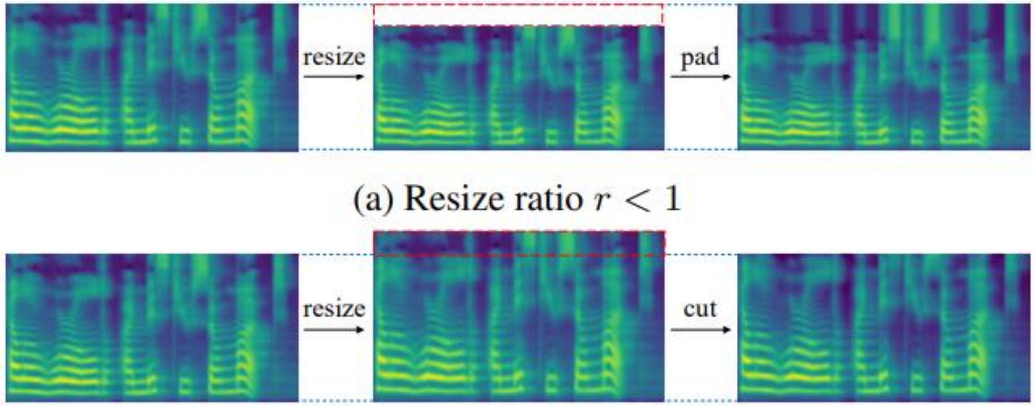

(a) Training procedure




(b) Inference procedure

**Fig. 1**: Training and inference procedure of FreeVC. Here $y$ denotes source waveform, $y'$ denotes augmented waveform, $\hat{y}$ denotes converted waveform, $x_{mel}$ denotes mel-spectrogram, $x_{lin}$ denotes linear spectrogram, $x_{ssl}$ denotes SSL feature, and $g$ denotes speaker embedding.

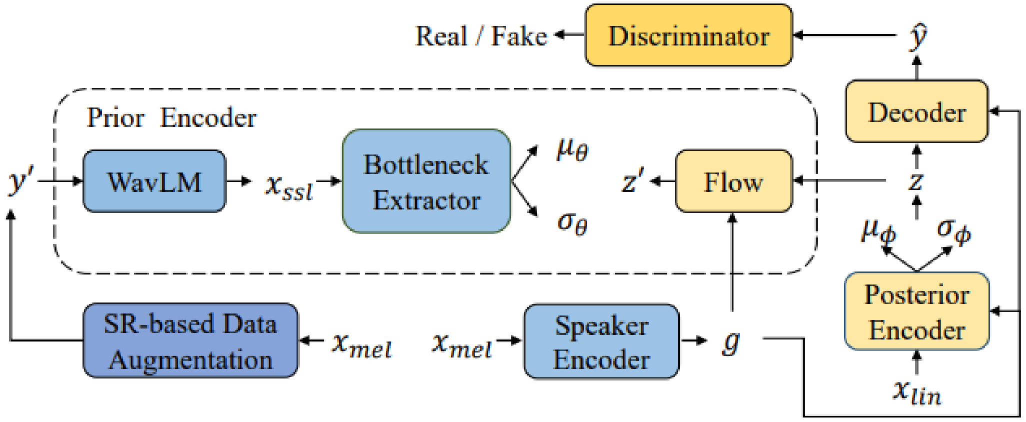
# FreeVC (3): SR-based Data Augmentation




(a) Resize ratio $r < 1$

(b) Resize ratio $r > 1$

**Fig. 2**: Vertical spectrogram-resize operation.




(a) Training procedure

$$q_\phi(z|x_{lin}) = N(z; \mu_\phi, \sigma_\phi^2),$$

$$p_\theta(z|c) = N(z'; \mu_\theta, \sigma_\theta^2)|det\frac{\partial z'}{\partial z}|.$$

CVAE GAN

$$L(G) = \boxed{L_{rec} + L_{kl}} + \boxed{L_{adv}(G) + L_{fm}(G)}, \quad (3)$$

$$L(D) = L_{adv}(D). \quad (4)$$

L_(fm) is the feature matching loss

# FreeVC (3): SR-based Data Augmentation

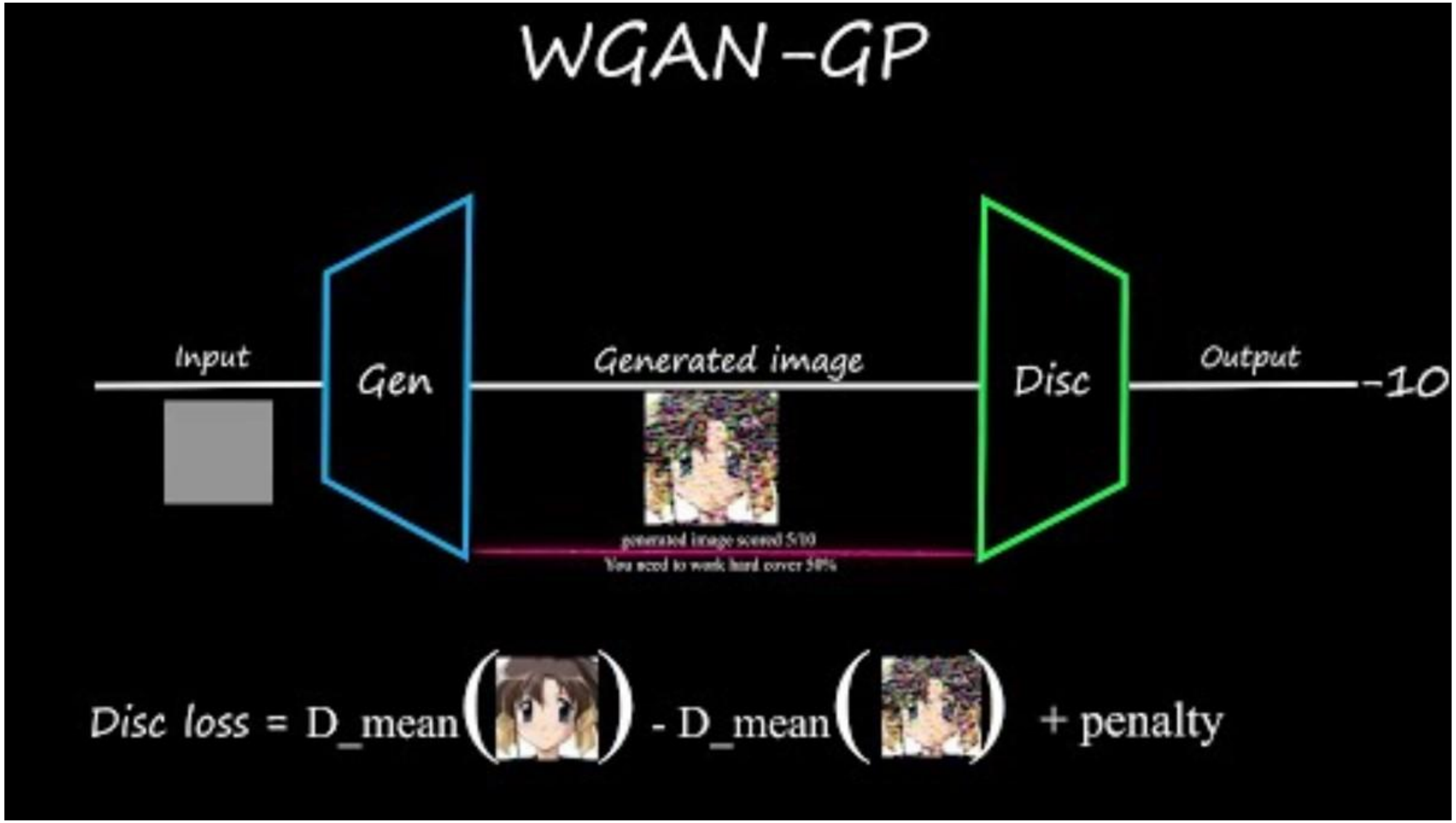
**Table 1**: Subjective evaluation results in terms of 5-scale MOS and SMOS with 95% confidence intervals under seen-to-seen, unseen-to-seen and unseen-to-unseen scenarios. For reference, we also report scores of source utterances.

| | seen-to-seen | | unseen-to-seen | | unseen-to-unseen | |
|---|---|---|---|---|---|---|
| | MOS | SMOS | MOS | SMOS | MOS | SMOS |
| VQMIVC | $2.31 \pm 0.09$ | $2.10 \pm 0.08$ | $1.50 \pm 0.08$ | $1.71 \pm 0.08$ | $1.49 \pm 0.08$ | $1.29 \pm 0.05$ |
| BNE-PPG-VC | $2.80 \pm 0.12$ | $2.95 \pm 0.12$ | $2.89 \pm 0.10$ | $2.83 \pm 0.10$ | $3.44 \pm 0.08$ | $2.63 \pm 0.10$ |
| YourTTS | $3.46 \pm 0.10$ | $3.25 \pm 0.09$ | $2.54 \pm 0.10$ | $2.50 \pm 0.10$ | $2.87 \pm 0.09$ | $1.97 \pm 0.09$ |
| FreeVC | $3.99 \pm 0.09$ | **$3.80 \pm 0.09$** | $4.06 \pm 0.08$ | **$3.77 \pm 0.09$** | **$4.06 \pm 0.08$** | **$2.83 \pm 0.08$** |
| FreeVC (w/o SR) | $3.85 \pm 0.10$ | $3.50 \pm 0.10$ | $3.88 \pm 0.08$ | $3.58 \pm 0.08$ | $3.97 \pm 0.09$ | $2.80 \pm 0.09$ |
| FreeVC-s | **$4.01 \pm 0.09$** | $3.75 \pm 0.09$ | **$4.08 \pm 0.08$** | $3.68 \pm 0.09$ | $4.02 \pm 0.09$ | $2.78 \pm 0.09$ |
| Source | $4.32 \pm 0.08$ | - | $4.11 \pm 0.10$ | - | $4.17 \pm 0.09$ | - |

The mean opinion score(MOS) test, which is used to evaluate the quality of converted speech.

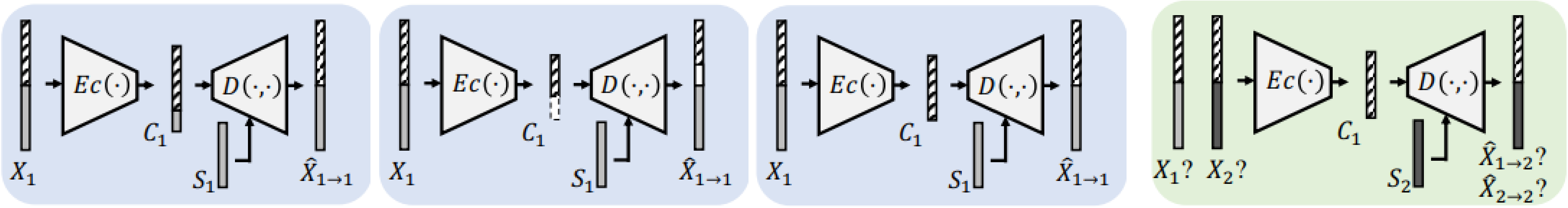
The Sage Instruments Mean Opinion Score (SMOS) test line provides an accurate assessment of how telephone users perceive speech quality.

# Wasserstein GAN (Take a break)




https://www.youtube.com/watch?v=QJOEmwvnmTM

# Is there perfect disentanglement?




(a) Bottleneck too wide

(b) Bottleneck too narrow

Content is damaged! Already bad

(c) Bottleneck just right

Did not see the perfect conversion in real life.

(d) Conversion

1. Perfect reconstruction is achieved.

2. The content embedding $C_1$ does not contain any information about the source speaker $U_1$, which we refer to as *speaker disentanglement*.

We will now show by contradiction how these two properties imply an ideal conversion. Suppose when AUTOVC is

# A Research Problem

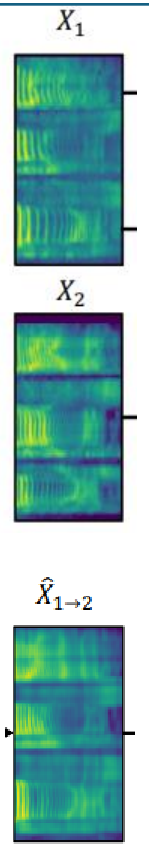
- It is widely recognized that the content encoder may encode partial speaker identity-related information.

- Reverse Engineering the VC Model: the **disentangle-based** ones.

- Given the converted voice, how to know the voice conversion model?
- How to get the source voice to provide more powerful evidence than the classification scores?

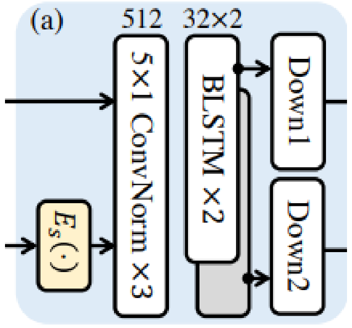
# VC Model Stealing Attack

First, can we steal the real model?

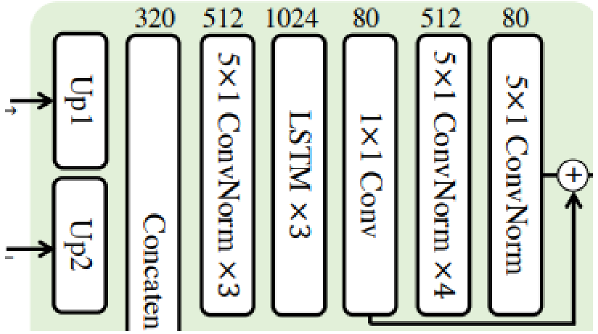



Suppose we know

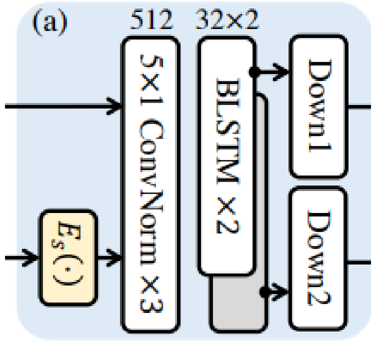
Encoder

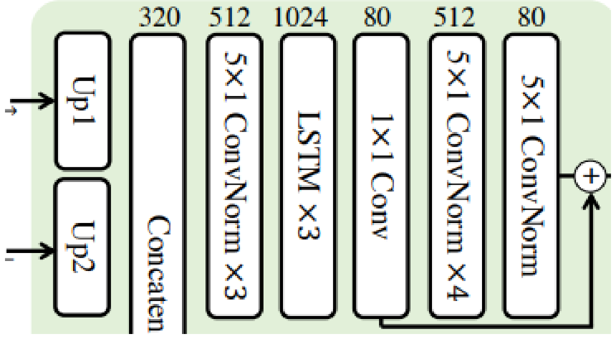



Decoder



# VC Source Voice Recovery



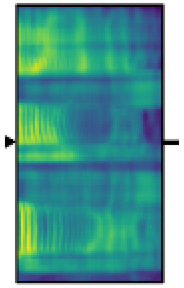




Encoder

Decoder

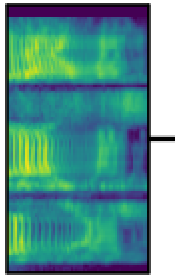
Output

$\hat{X}_{1\to2}$



Target

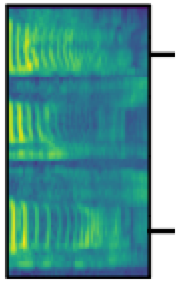
$X_2$



Suppose we know

## Can we get the Input?

$X_1$



X(hat) = Decoder{X_2 (speaker) + X_1 (content+ weak speaker)}

Can we get an Encoder to achieve:

Encoder (X(hat)) = [X_2 (speaker)+X_1(weak Speaker)] + X_1 (content)?

Suppose we directly train an Encoder to do the reverse engineering… contrastive loss?

# VC Source Voice Recovery

Table 7: Voice conversion dataset.

| Method | Dataset† | Alias | Lang. | #Speaker | #Sample |
|---|---|---|---|---|---|
| VQVC | *train-clean-100* | VQ-Train | English | 251 | 62,750 |
| | *train-clean-360* | | | 921 | 276,300 |
| | *train-other-500* | | | 1,166 | 349,800 |
| | VoxCeleb1 | | | 1,251 | 375,300 |
| | VoxCeleb2 | | | 5,994 | 599,400 |
| | *test-clean* | VQ-Test | English | 40 | 31,200 |
| VQVC+ | *train-clean-100* | V+-Train | English | 251 | 62,750 |
| | *train-clean-360* | | | 921 | 276,300 |
| | *train-other-500* | | | 1,166 | 349,800 |
| | VoxCeleb1 | | | 1,251 | 375,300 |
| | VoxCeleb2 | | | 5,994 | 599,400 |
| | *test-clean* | V+-Test | English | 40 | 31,200 |
| AGAIN | *train-clean-100* | AG-Train | English | 251 | 62,750 |
| | *train-clean-360* | | | 921 | 276,300 |
| | *train-other-500* | | | 1,166 | 349,800 |
| | VoxCeleb1 | | | 1,251 | 375,300 |
| | VoxCeleb2 | | | 5,994 | 599,400 |
| | *test-clean* | AG-Test | English | 40 | 31,200 |
| BNE | *train-clean-100* | BN-Train | English | 251 | 62,750 |
| | *train-clean-360* | | | 921 | 276,300 |
| | *train-other-500* | | | 1,166 | 349,800 |
| | VoxCeleb1 | | | 1,251 | 375,300 |
| | VoxCeleb2 | | | 5,994 | 599,400 |
| | *test-clean* | BN-Test | English | 40 | 31,200 |
| BNE | MLS German | BN-GE | German | 30 | 17,400 |
| | MLS French | BN-FR | French | 18 | 6,120 |
| | MLS Spanish | BN-SP | Spanish | 20 | 7,600 |

† *train-clean-100*, *train-clean-360* and *train-other-500* are training sets in LibriSpeech [40]. We use the test sets in German, French, and Spanish of Multilingual LibriSpeech (MLS) [44] for evaluation.

Voice conversion models and datasets.

1. Get trained voice conversion models;
2. Convert large scale voice data: obtain converted voice, target voice, and source voice
3. Given converted voice and target voice, synthesize the source voice;
    1. Using GAN to get the distribution of source voice;
    2. Generated new voice to match the original voice conversion process.

# Related: GAN-based Model Inversion Attack

Inferring Sensitive Features (e.g., face image):

Rather than reconstructing private training data from scratch, we leverage partial public information, to **learn a distributional prior** via generative adversarial networks (GANs) and use it to guide the inversion process.

Blurred or corrupted version of the private image

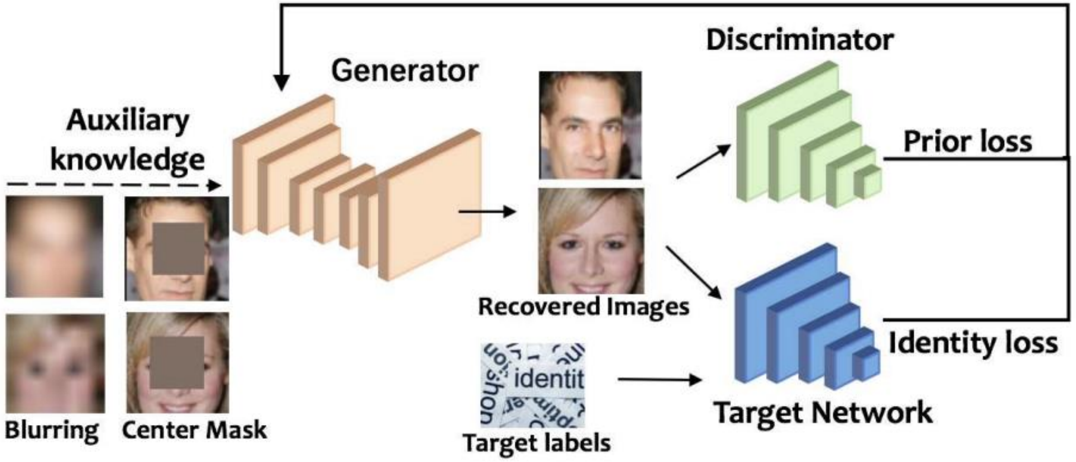



Figure 1: Overview of the proposed GMI attack method.

The Secret Revealer: Generative Model-Inversion Attacks Against Deep Neural Networks. CVPR'20 Yuheng Zhang, Ruoxi Jia , Hengzhi Pei1, Wenxiao Wang , Bo Li , and Dawn Song

# Related: GAN-based Model Inversion Attack

Stage 1: Train the generator and the discriminators on public datasets in order to encourage the generator to generate realistic-looking images.

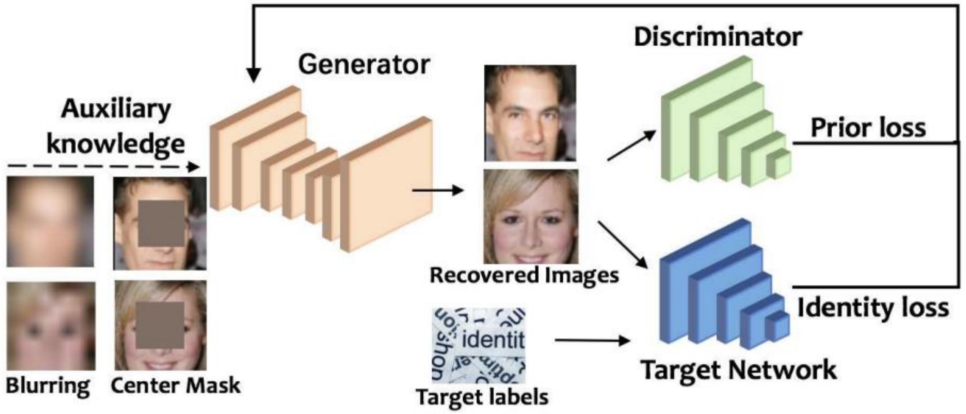



Figure 1: Overview of the proposed GMI attack method.

$$\min_G \max_D L_{\text{wgan}}(G, D) = E_x[D(x)] - E_z[D(G(z))]$$

$$\max_G L_{\text{div}}(G) = E_{\mathbf{z}_1, \mathbf{z}_2}\left[\frac{\|F(G(\mathbf{z}_1)) - F(G(\mathbf{z}_2))\|}{\|\mathbf{z}_1 - \mathbf{z}_2\|}\right]$$

Stage 2: Find the latent vector that generates an image achieving the maximum likelihood under the target network while remaining realistic

$$\hat{z} = \arg\min_z L_{\text{prior}}(z) + \lambda_i L_{\text{id}}(z)$$

$$L_{\text{prior}}(z) = -D(G(z)) \quad L_{\text{id}}(z) = -\log[C(G(z))]$$

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# References


- One-shot Voice Conversion by Separating Speaker and Content Representations with Instance Normalization (InterSpeech’2019)
- AGAIN-VC: A one-shot voice conversion using activation guidance and adaptive instance normalization. (ICASSP’2021)

- VQVC+: one-shot voice conversion by vector quantization and U-Net architecture. (ICSA’2020)
- AVQVC: One-shot voice conversion by vector quantization with applying contrastive learning.  (ICASSP’2022)

- FREEVC: Towards High-quality Text-Free **One-Shot** Voice Conversion (ICASSP’2023)