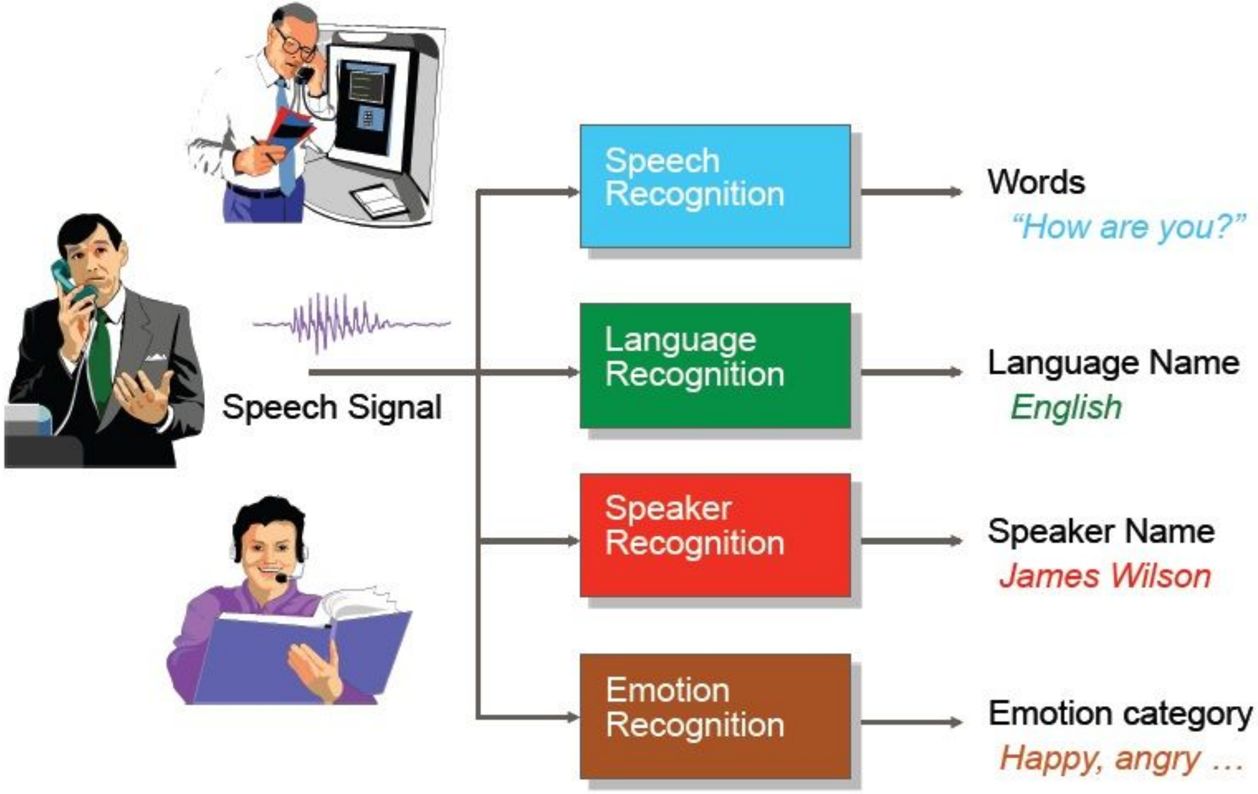
Voice Conversion

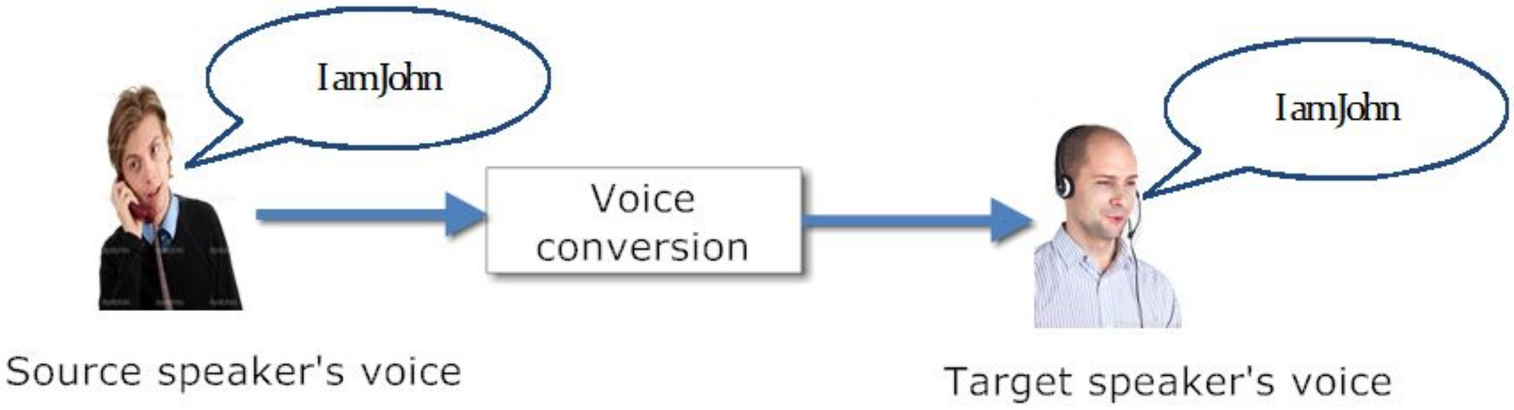
Dipjyoti Paul
University of Crete, Greece

Information in Speech

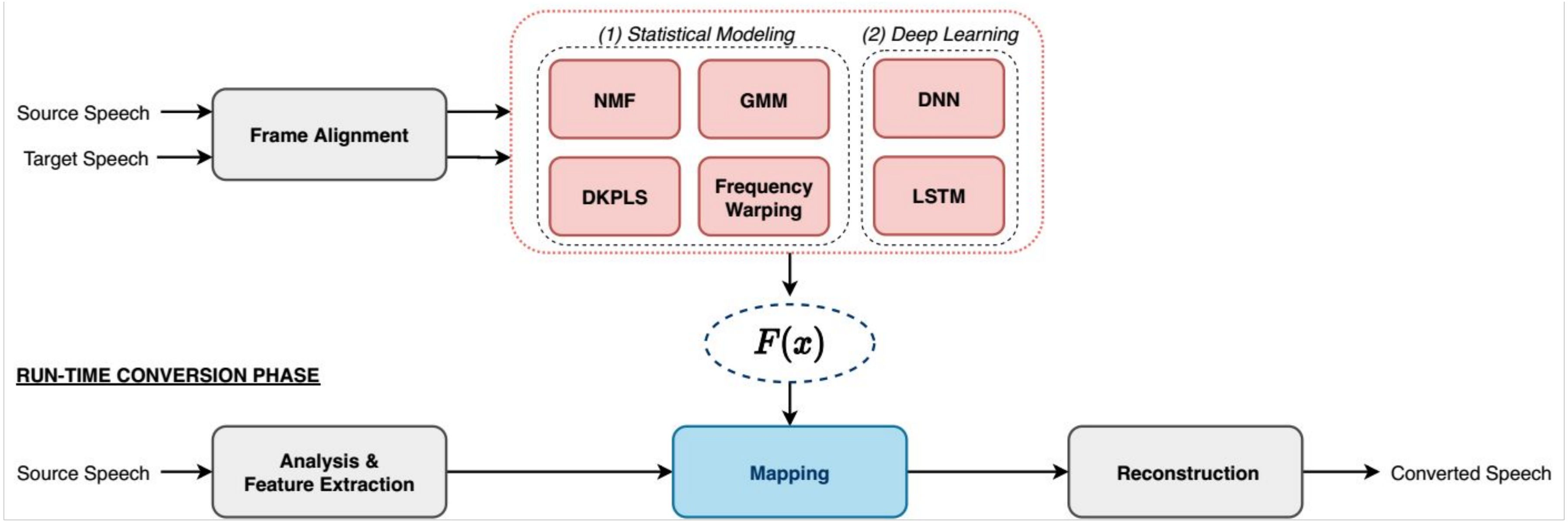


Voice Conversion (VC)

- Technique to convert the utterance of a source speaker to create the perception as if spoken by a specified target speaker.
- Only transform the speaker timbre (para-linguistic information) and keep the linguistic message in the utterance unchanged.



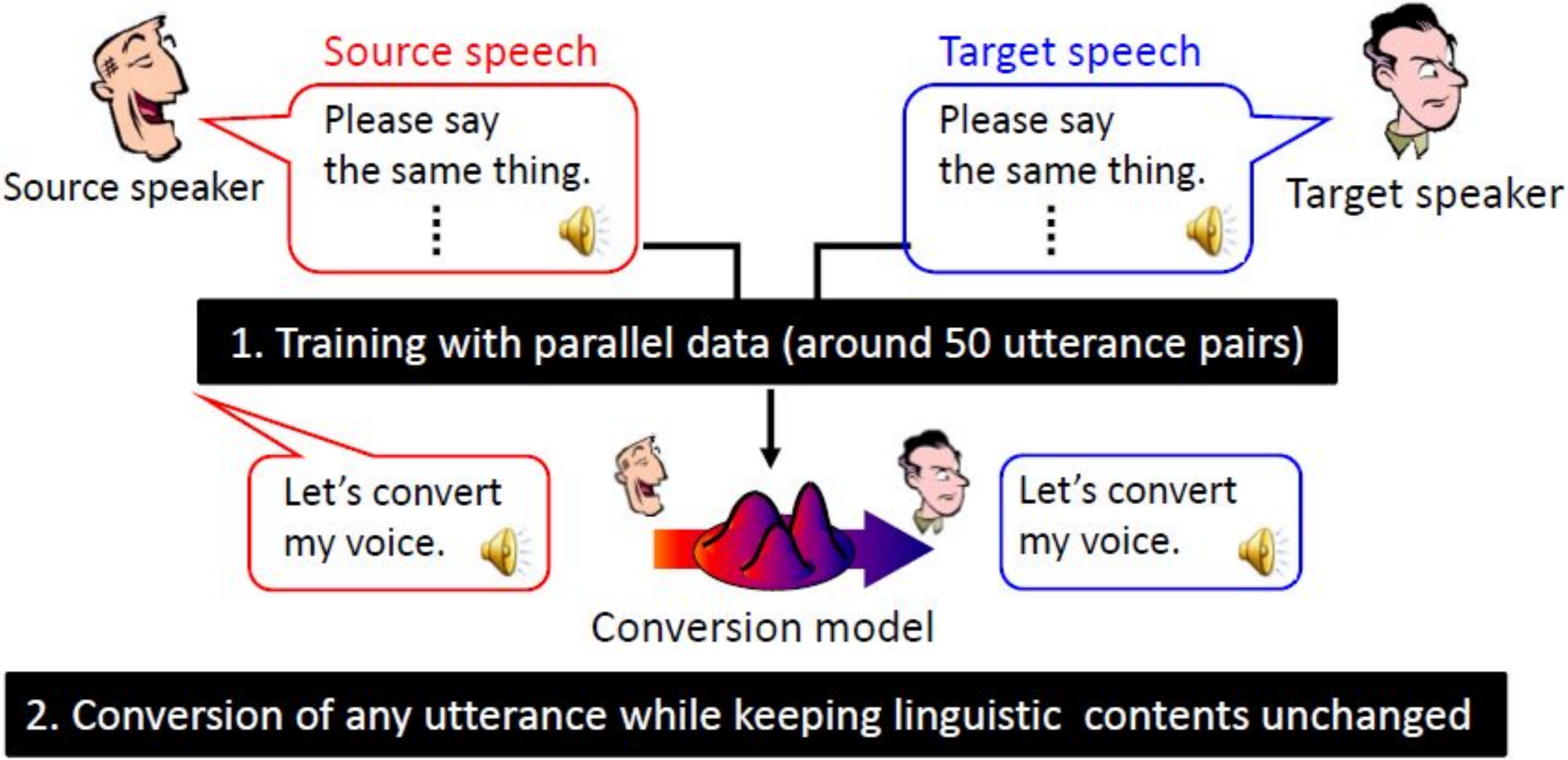
Voice Conversion



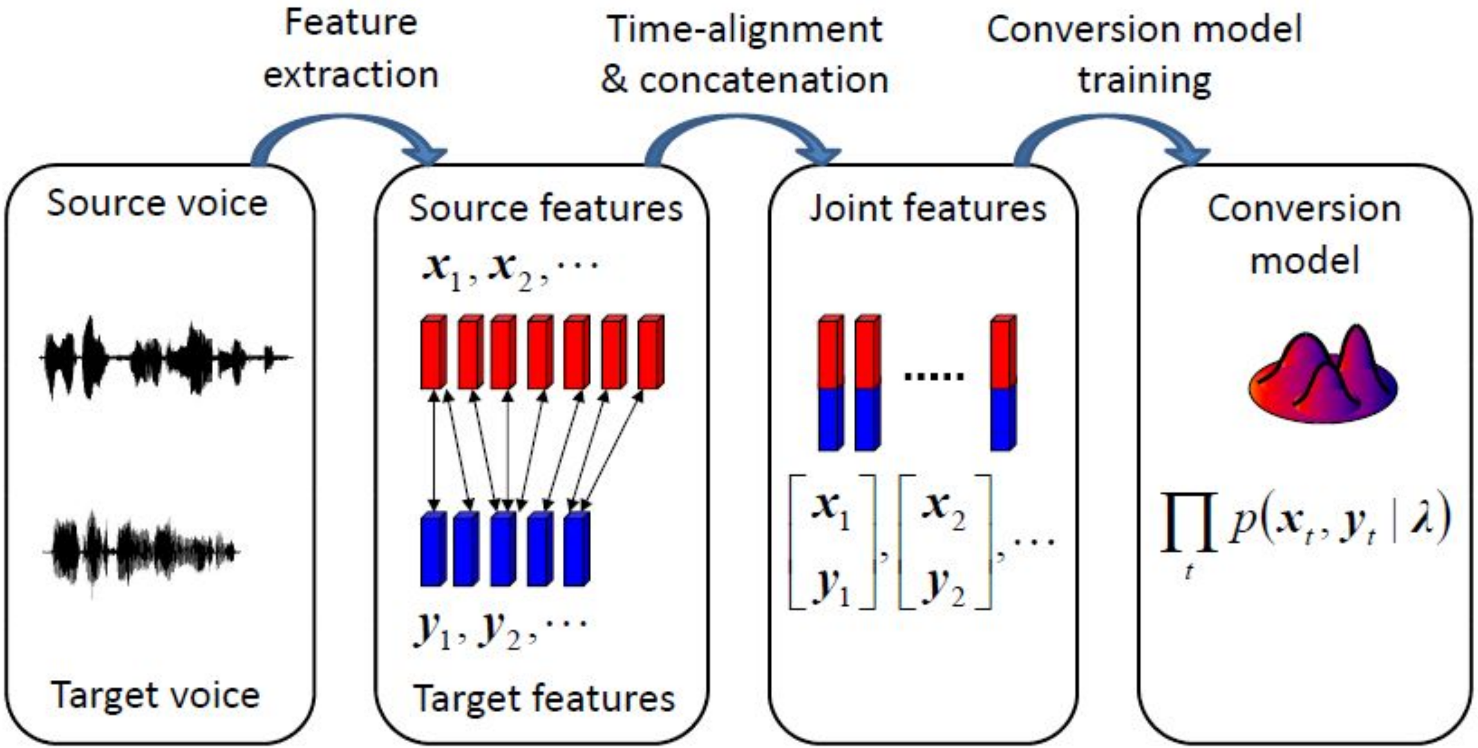
Applications

- Text-To-Speech (TTS) customization
- Film dubbing
- Design of speaking aids
- Education etc

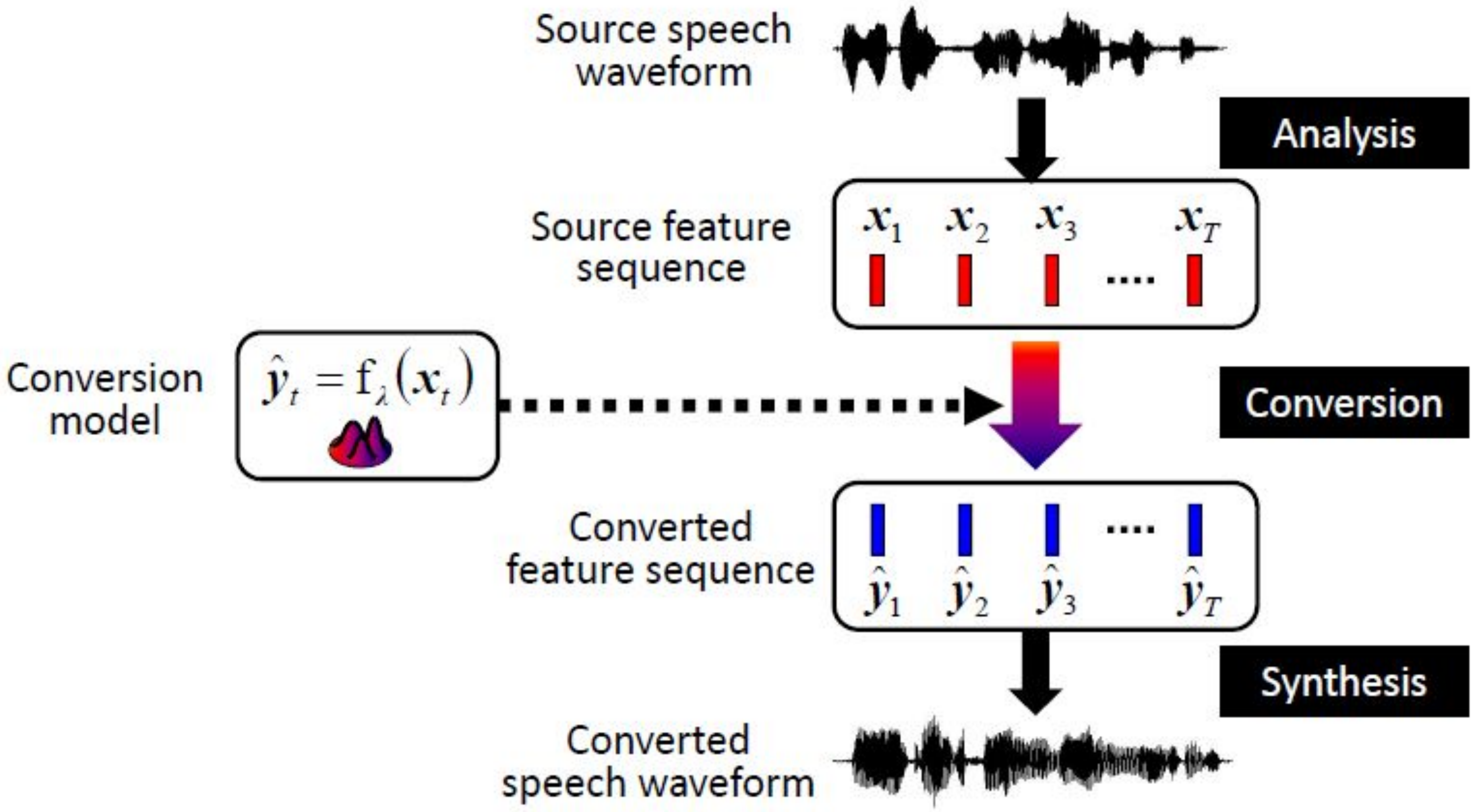
Statistical VC



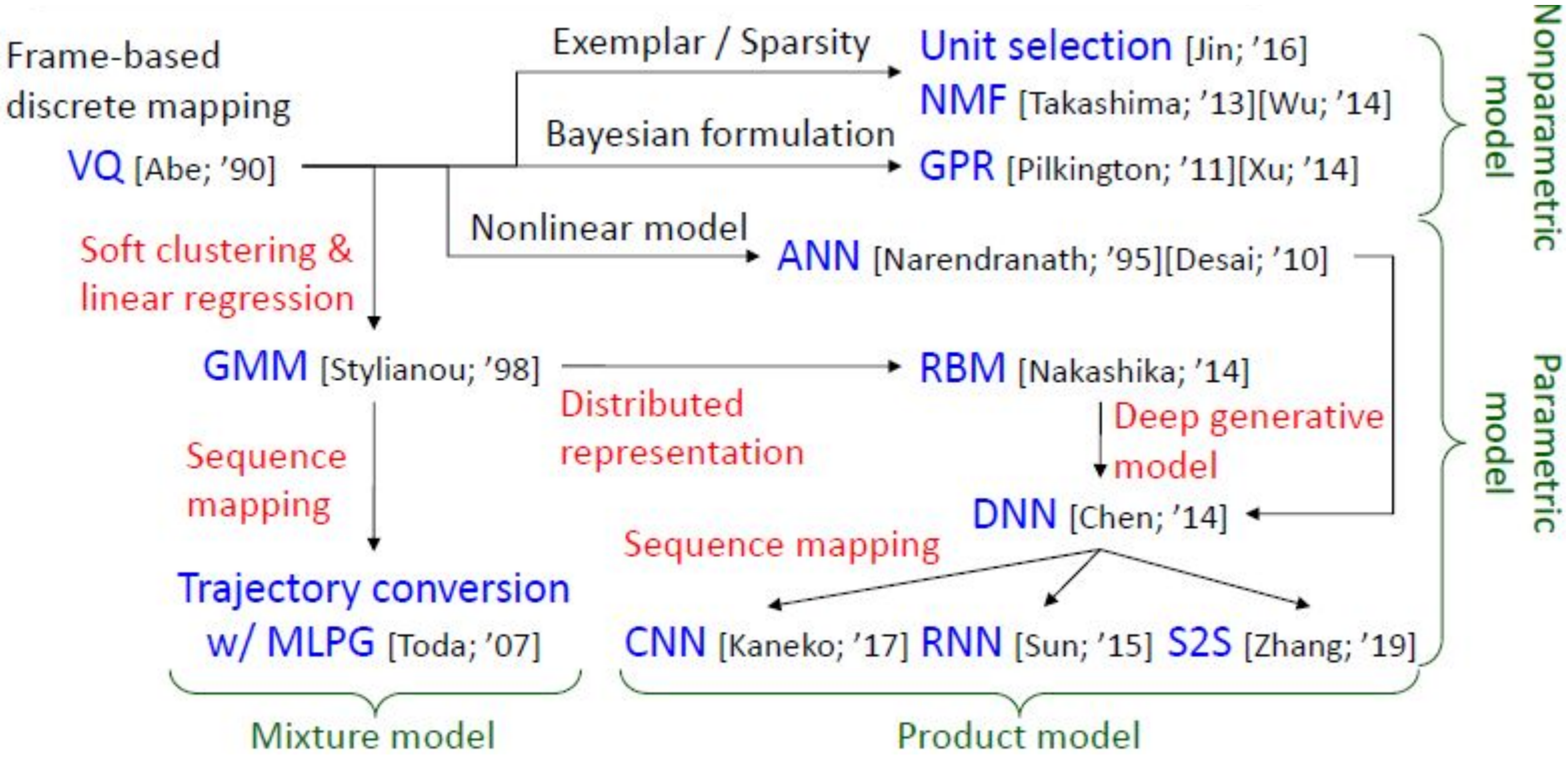
VC Training


Feature extraction
Time-alignment & concatenation
Conversion model training
Source voice
Target voice
Source features
$x_1, x_2, \cdots$
$y_1, y_2, \cdots$
Target features
Joint features
$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix}, \begin{bmatrix} x_2 \\ y_2 \end{bmatrix}, \cdots$
Conversion model
$\prod_t p(x_t, y_t \mid \lambda)$

VC Conversion



Timeline of VC Research

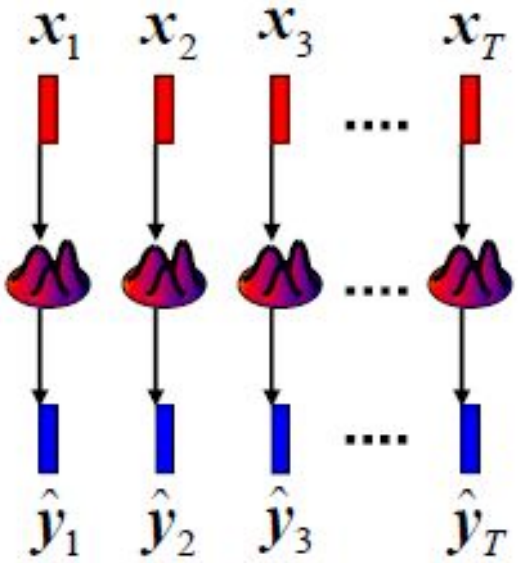


Frame-based VC

- Source feature: x
- Target feature: y
- Converted feature: ŷ

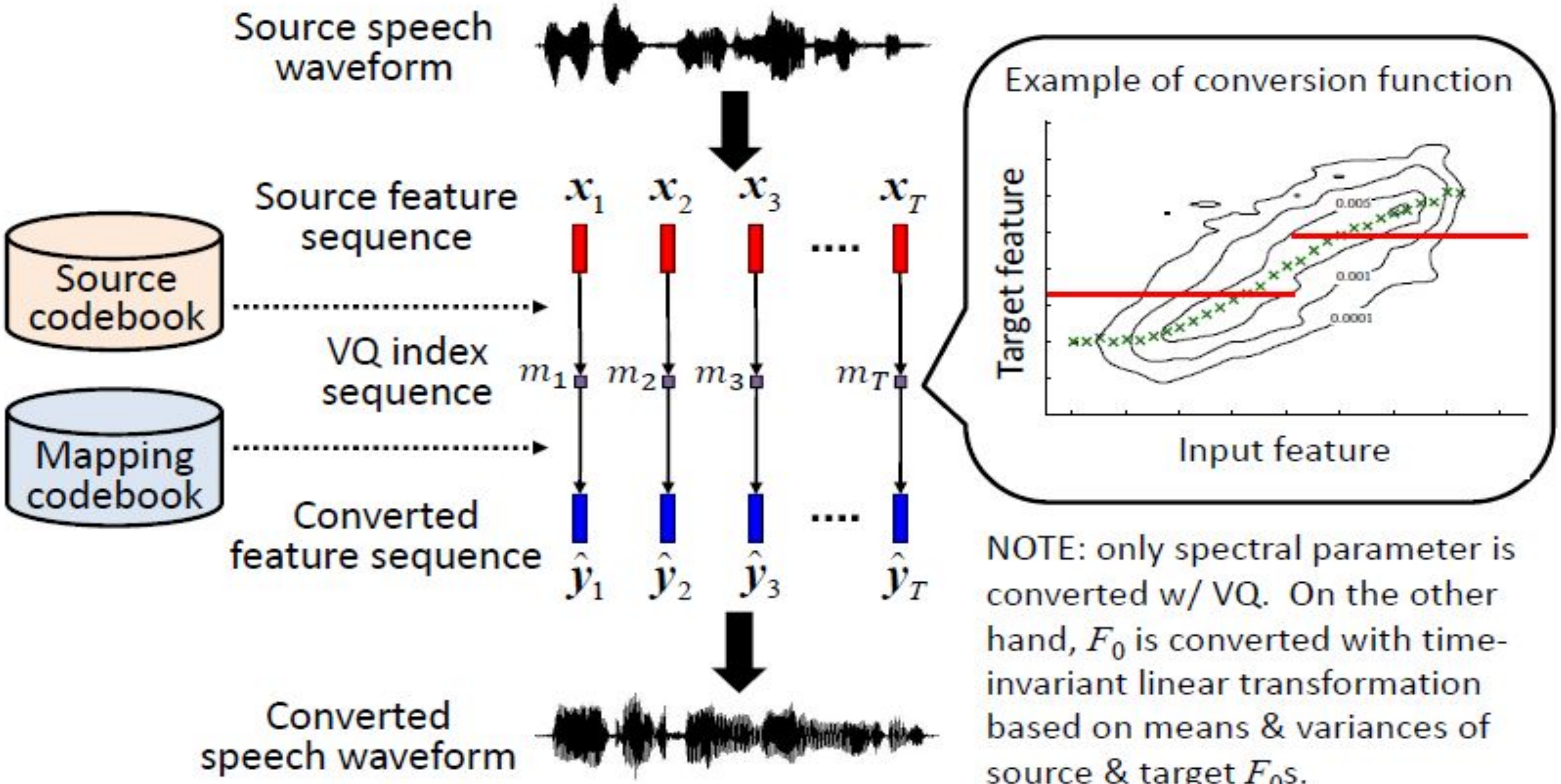
Frame-based conversion function

$$\hat{y}_t = f_\lambda(x_t)$$



Vector Quantization-based VC

[Abe et. al. 1990]

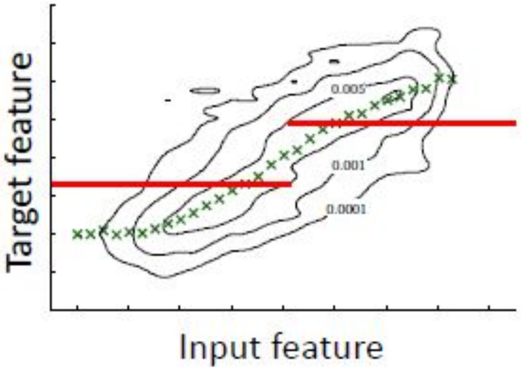


NOTE: only spectral parameter is converted w/ VQ. On the other hand, F_0 is converted with time-invariant linear transformation based on means & variances of source & target F_0s.

Discontinuous to Continuous Conversion

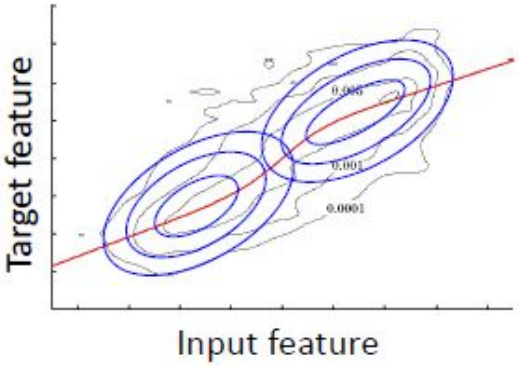
VQ-based conversion

- Discrete function w/ hard clustering
- Ignore feature correlation w/ discrete mapping

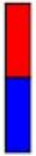


GMM-based conversion

- Continuous function w/ soft clustering
- Directly model feature correlation w/ linear regression



GMM based Conversion

Joint feature vector: $\boldsymbol{z}_t = \begin{bmatrix} \boldsymbol{x}_t \\ \boldsymbol{y}_t \end{bmatrix}$ 

<u>GMM:</u>

Joint $p.d.f.$: $P(\boldsymbol{x}_t, \boldsymbol{y}_t \mid \lambda) = \sum_{m=1}^{M} \alpha_m \mathcal{N}(\boldsymbol{z}_t ; \boldsymbol{\mu}_m^{(z)}, \boldsymbol{\Sigma}_m^{(zz)})$

Maximum likelihood training

$$\hat{\lambda} = \arg\max \prod_t P(\boldsymbol{x}_t, \boldsymbol{y}_t \mid \lambda)$$

Updated model parameters

Likelihood for all joint vectors

GMM based Conversion

[Stylianou et. al. 1998]

Training of joint *p.d.f.* (modeled by a GMM) [Kain; '98]

Parameter set

Component weight α_m

$$p(\boldsymbol{x}_t, \boldsymbol{y}_t \mid \boldsymbol{\lambda}) = \sum_{m=1}^{M} \alpha_m \mathcal{N}\left(\begin{bmatrix} \boldsymbol{x}_t \\ \boldsymbol{y}_t \end{bmatrix}; \begin{bmatrix} \boldsymbol{\mu}_m^{(x)} \\ \boldsymbol{\mu}_m^{(y)} \end{bmatrix}, \begin{bmatrix} \boldsymbol{\Sigma}_m^{(xx)} & \boldsymbol{\Sigma}_m^{(xy)} \\ \boldsymbol{\Sigma}_m^{(yx)} & \boldsymbol{\Sigma}_m^{(yy)} \end{bmatrix} \right)$$

Joint feature vector $\boldsymbol{x}_t$ $\boldsymbol{y}_t$

Mean vector $\boldsymbol{\mu}_m^{(x)}$ $\boldsymbol{\mu}_m^{(y)}$

Covariance matrix $\boldsymbol{\Sigma}_m^{(xx)}$ $\boldsymbol{\Sigma}_m^{(xy)}$ $\boldsymbol{\Sigma}_m^{(yx)}$ $\boldsymbol{\Sigma}_m^{(yy)}$

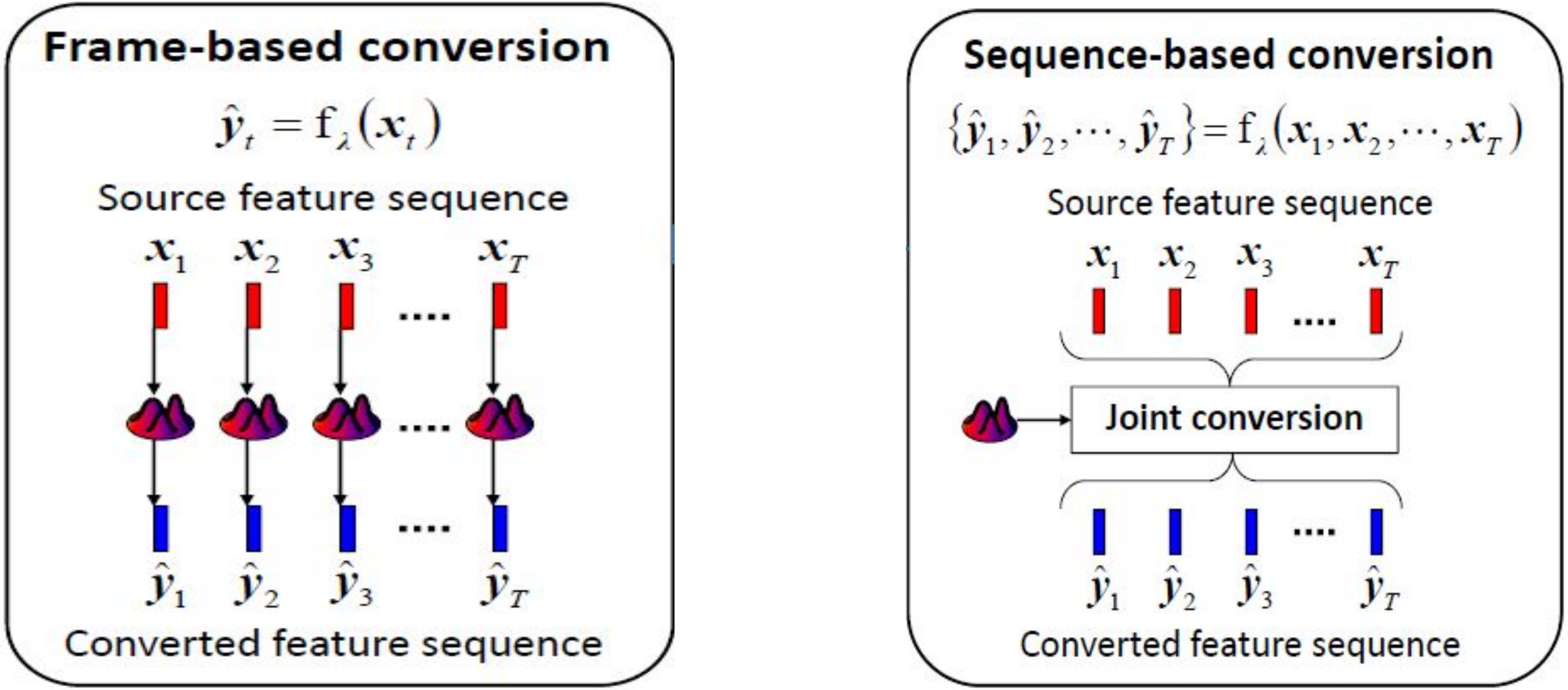
Conversion w/ conditional *p.d.f.* (also modeled by a GMM)

$$p(\boldsymbol{y}_t \mid \boldsymbol{x}_t, \boldsymbol{\lambda}) = \frac{p(\boldsymbol{x}_t, \boldsymbol{y}_t \mid \boldsymbol{\lambda})}{\int p(\boldsymbol{x}_t, \boldsymbol{y}_t \mid \boldsymbol{\lambda}) \mathrm{d}\boldsymbol{y}_t} = \sum_{m=1}^{M} p(m \mid \boldsymbol{x}_t, \boldsymbol{\lambda}) \mathcal{N}\left(\boldsymbol{y}_t; \boldsymbol{\mu}_{m,t}^{(y|x)}, \boldsymbol{\Sigma}_m^{(y|x)} \right)$$

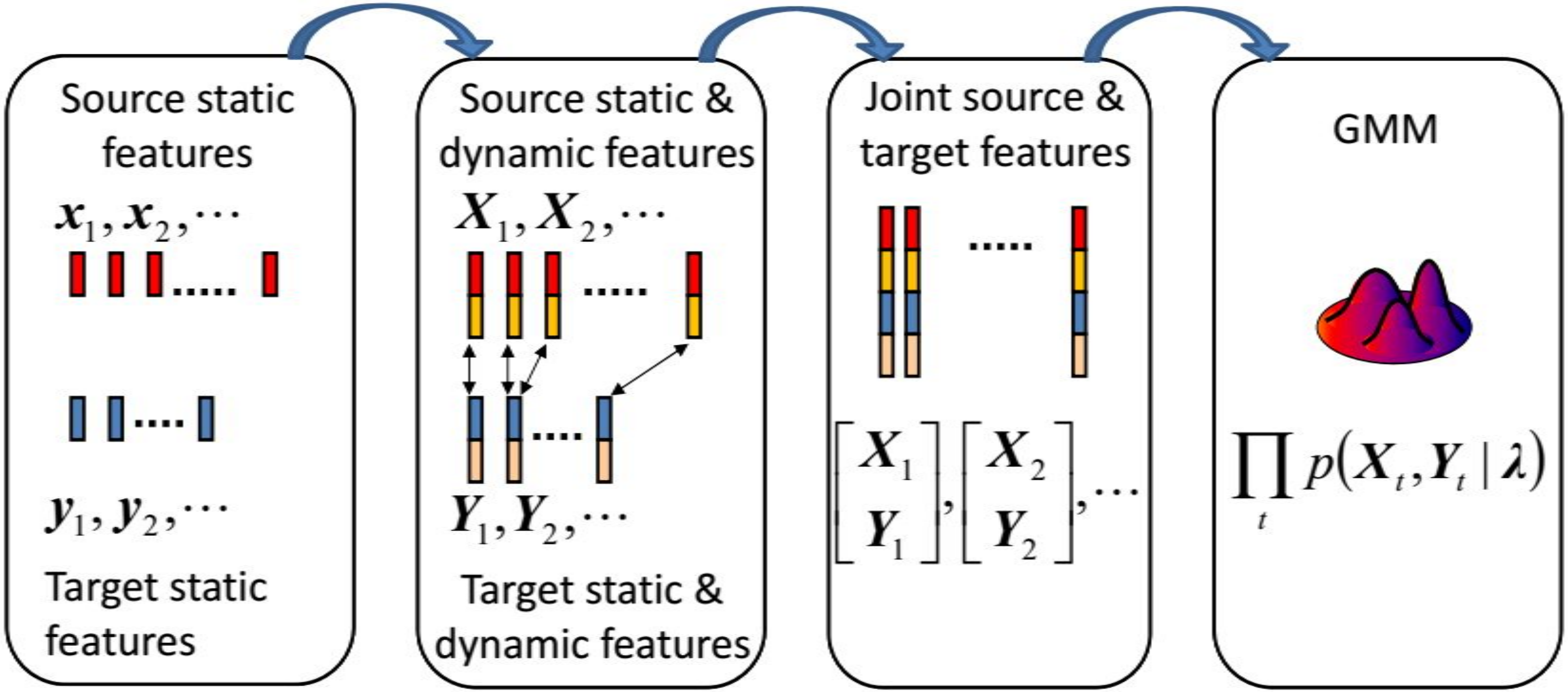
MMSE estimate: $\hat{\boldsymbol{y}}_t = \int \boldsymbol{y}_t p(\boldsymbol{y}_t \mid \boldsymbol{x}_t, \boldsymbol{\lambda}) \mathrm{d}\boldsymbol{y}_t = \sum_{m=1}^{M} p(m \mid \boldsymbol{x}_t, \boldsymbol{\lambda}) \boldsymbol{\mu}_{m,t}^{(y|x)}$

Sequence-based VC

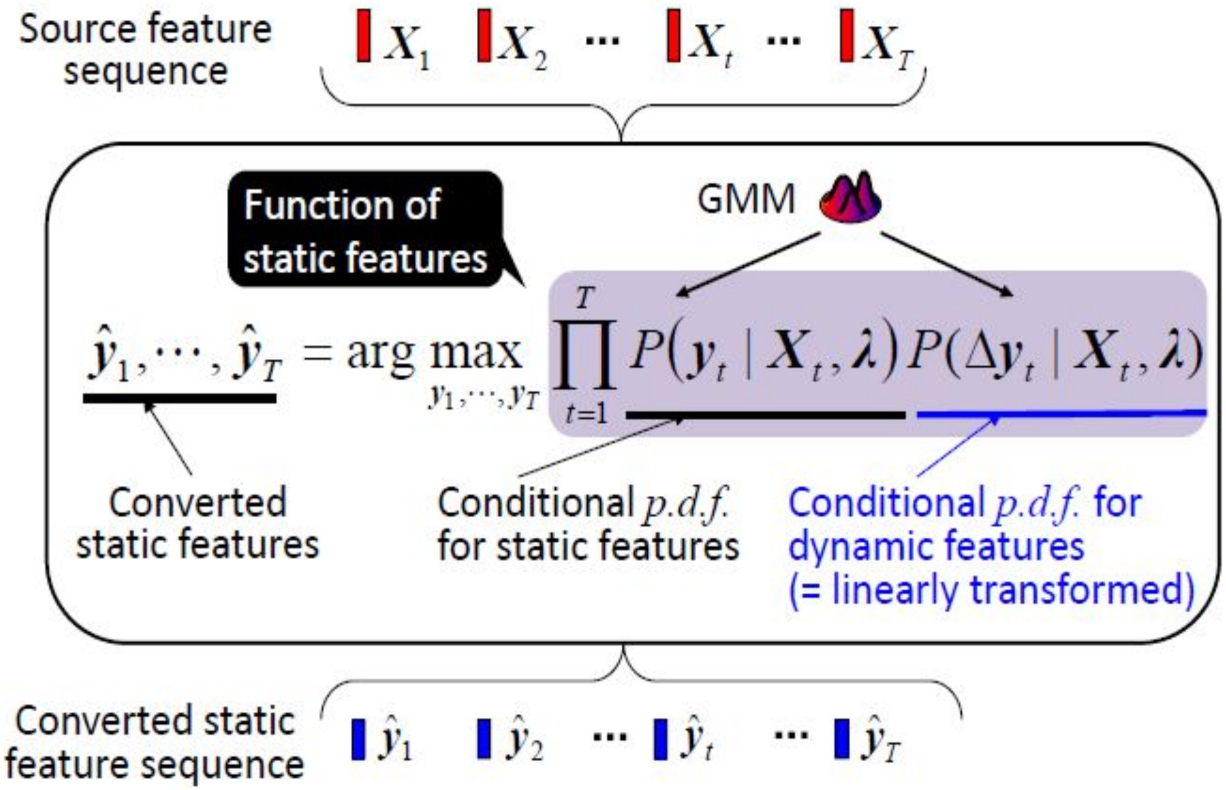
[Toda et. al. 2007]



Sequence-based VC



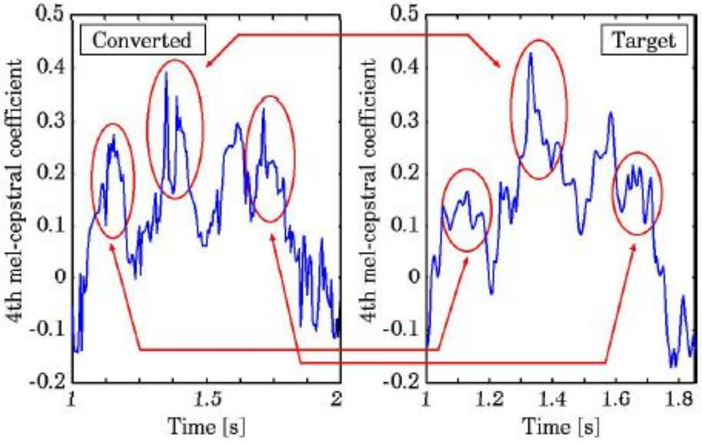
Sequence-based VC



Limitations of JD-GMM

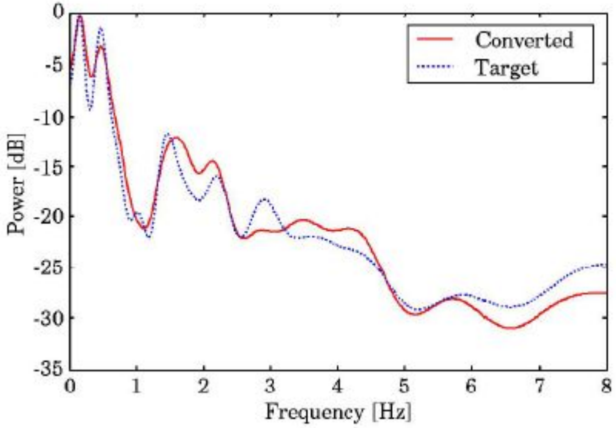
Discontinuous transitions

- Ignoring inter-frame correlation...



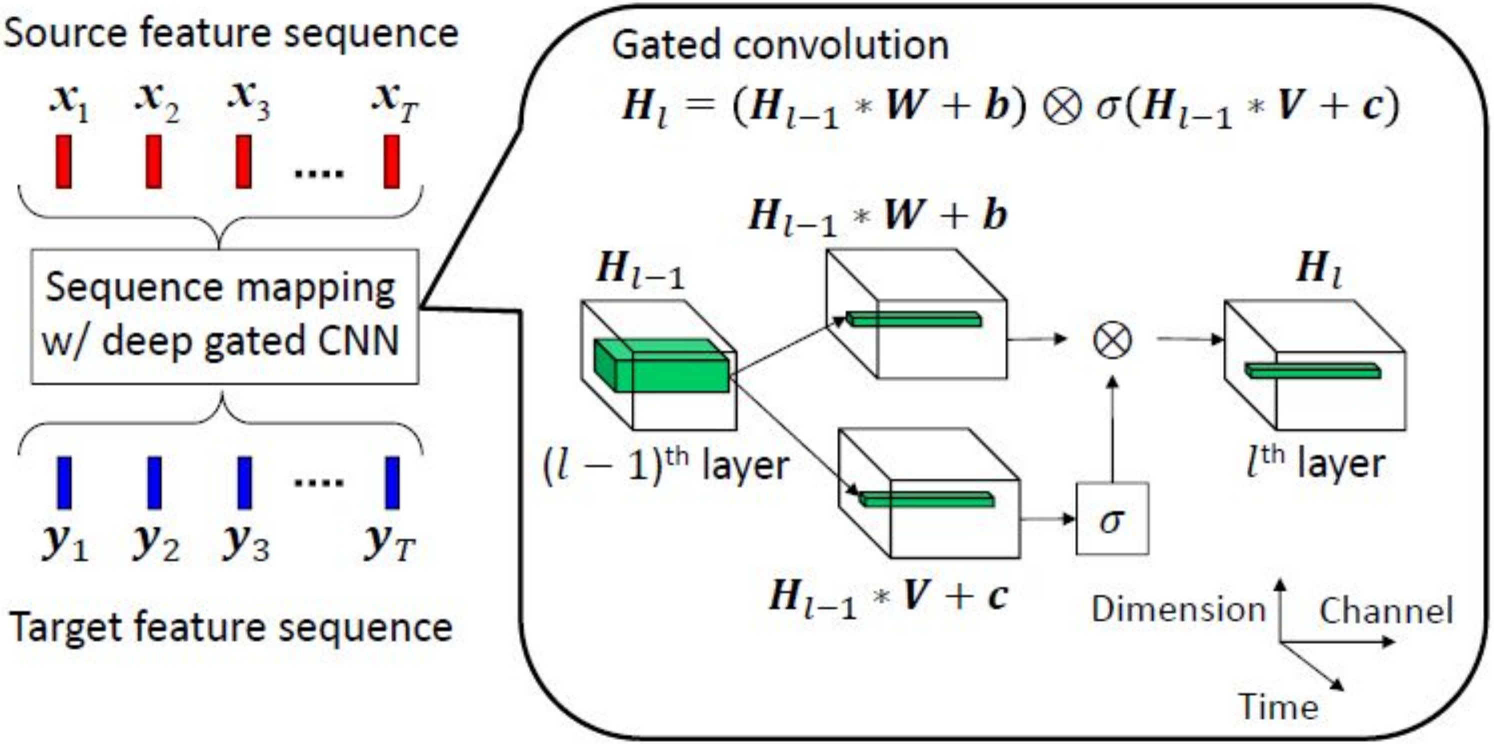
Over-smoothing effect

- Missing some characteristics not well modeled by GMM...



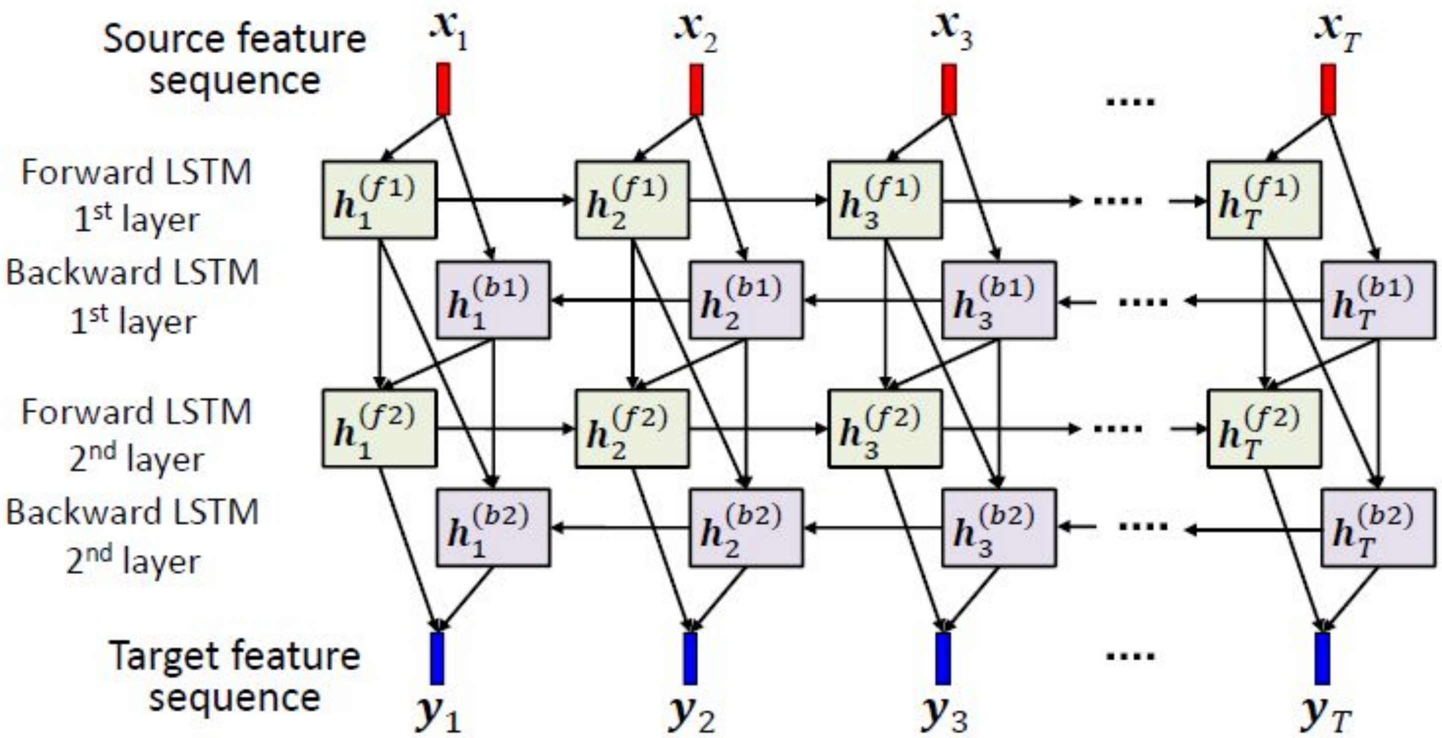
VC based on Deep Neural Networks

Sequence-based VC



[Kaneko et. al. 2017]

Sequence-based VC



[Sun et. al. 2015]

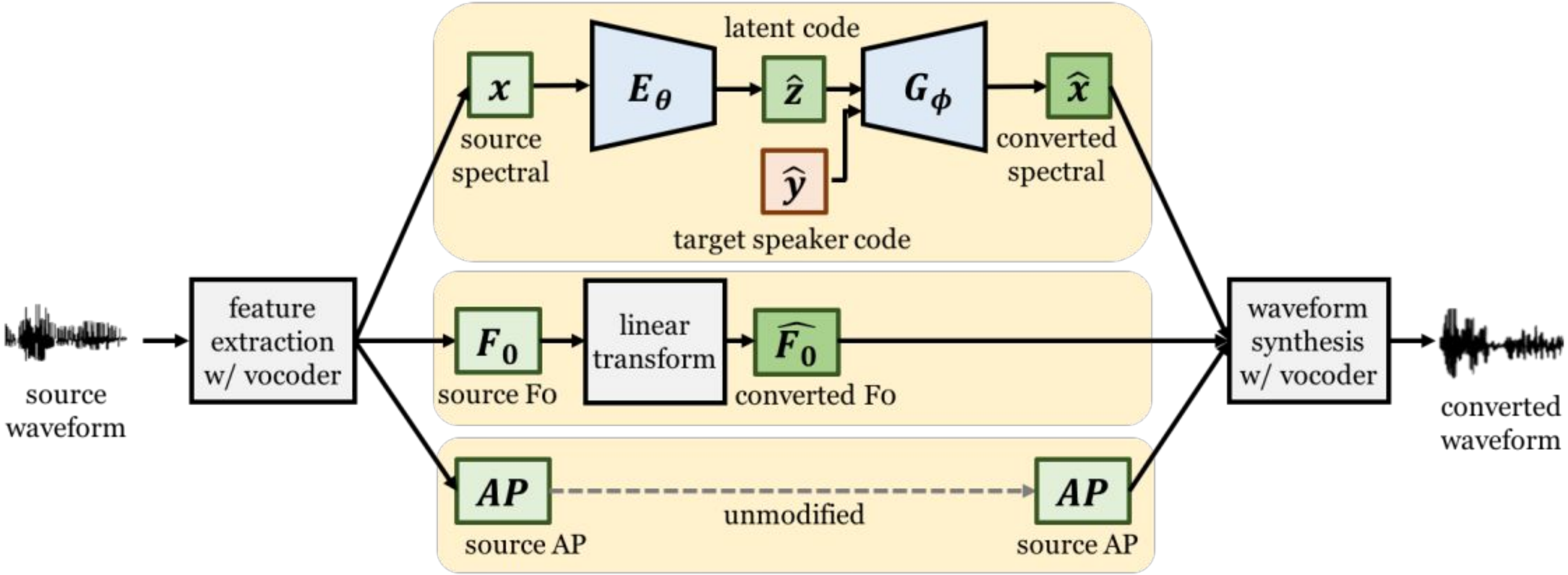
Variational Autoencoder (VAE)-VC

- The core of VAE-VC is an encoder-decoder network.
- During training, given an observed (source or target) spectral frame $\boldsymbol{x}$, a speaker-independent encoder $\boldsymbol{E_\theta}$ with parameter set $\boldsymbol{\theta}$ encodes $\boldsymbol{x}$ into a latent code: $\bar{\boldsymbol{z}} = E_\theta(\boldsymbol{x})$.
- The speaker code $\boldsymbol{y}$ of the input frame is then concatenated with the latent code, and passed to a conditional decoder $\boldsymbol{G_\phi}$ with parameter set $\boldsymbol{\phi}$ to reconstruct the input.

$$\bar{\boldsymbol{x}} = G_\phi(\bar{\boldsymbol{z}}, \boldsymbol{y}) = G_\phi(E_\theta(\boldsymbol{x}), \boldsymbol{y})$$

[Hsu et al, 16]

VAE-VC



latent code
x
E_θ
$\hat{z}$
G_ϕ
$\hat{x}$
source spectral
converted spectral
$\hat{y}$
target speaker code
source waveform
feature extraction w/ vocoder
F_0
linear transform
$\widehat{F_0}$
source Fo
converted Fo
waveform synthesis w/ vocoder
converted waveform
AP
unmodified
AP
source AP
source AP

VAE-VC

- The model parameters can be obtained by maximizing the variational lower bound:

$$
\begin{aligned}
\mathcal{L}_{vae}(\theta, \phi; \boldsymbol{x}, \boldsymbol{y}) &= \mathcal{L}_{recon}(\boldsymbol{x}, \boldsymbol{y}) + \mathcal{L}_{lat}(\boldsymbol{x}), \\
\mathcal{L}_{recon}(\boldsymbol{x}, \boldsymbol{y}) &= \mathbb{E}_{\boldsymbol{z} \sim q_\theta(\bar{\boldsymbol{z}}|\boldsymbol{x})}\left[\log p_\phi(\bar{\boldsymbol{x}}|\boldsymbol{z}, \boldsymbol{y})\right], \\
\mathcal{L}_{lat}(\boldsymbol{x}) &= -D_{KL}(q_\theta(\bar{\boldsymbol{z}}|\boldsymbol{x}) \| p(\boldsymbol{z})),
\end{aligned}
$$

$q_\theta(\bar{\boldsymbol{z}}|\boldsymbol{x})$: approximate posterior.

$p_\phi(\bar{\boldsymbol{x}}|\boldsymbol{z}, \boldsymbol{y})$: data likelihood.

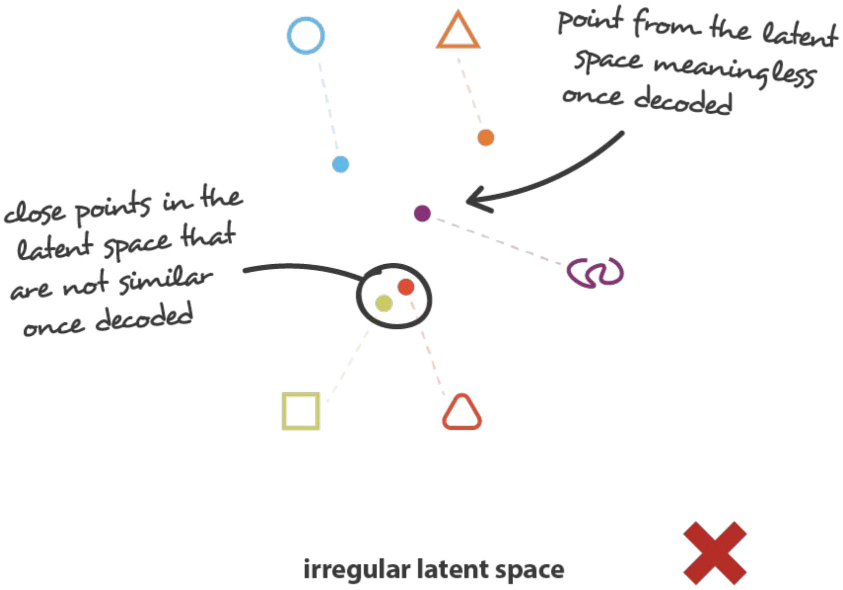
$p(\boldsymbol{z})$: prior distribution of the latent space.

- Conversion phase:

$$\hat{\boldsymbol{x}} = f(\boldsymbol{x}, \hat{\boldsymbol{y}}) = G_\phi(\hat{\boldsymbol{z}}, \hat{\boldsymbol{y}}) = G_\phi(E_\theta(\boldsymbol{x}), \hat{\boldsymbol{y}})$$

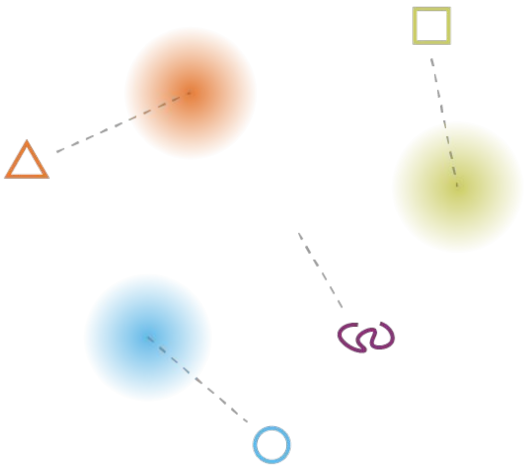
[Hsu et al, 16]

Intuitions about Regularization

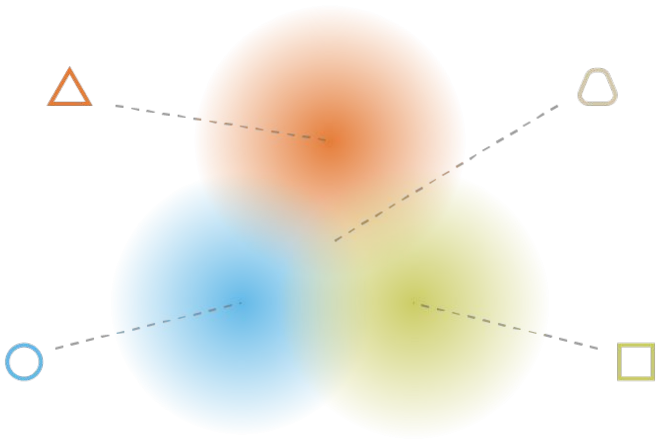


irregular latent space

regular latent space



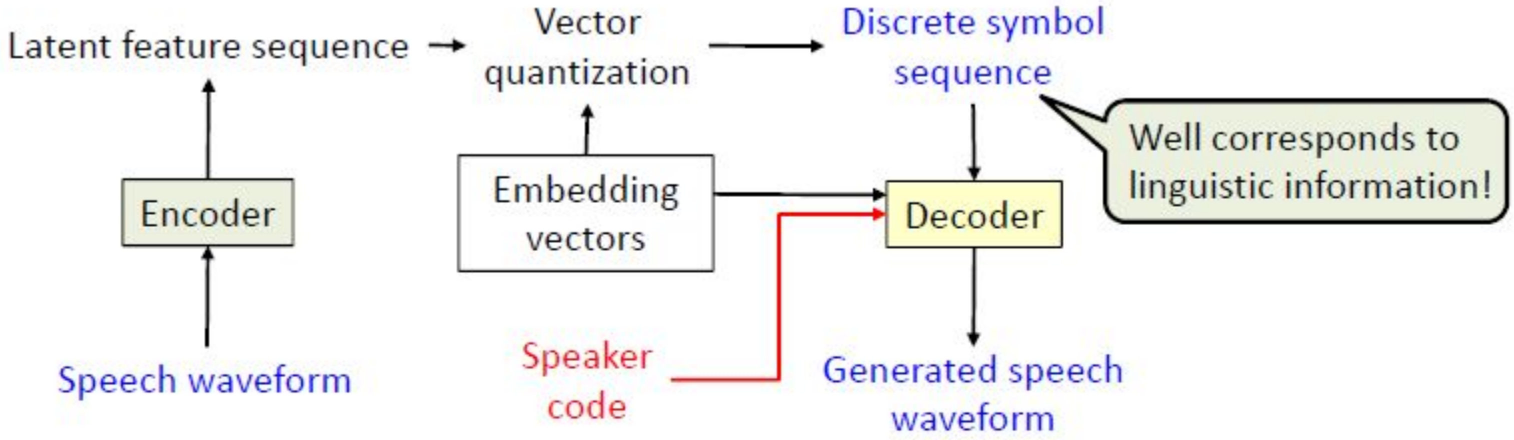
what can happen without regularisation



what we want to obtain with regularisation

Vector Quantization VAE (VQ-VAE)

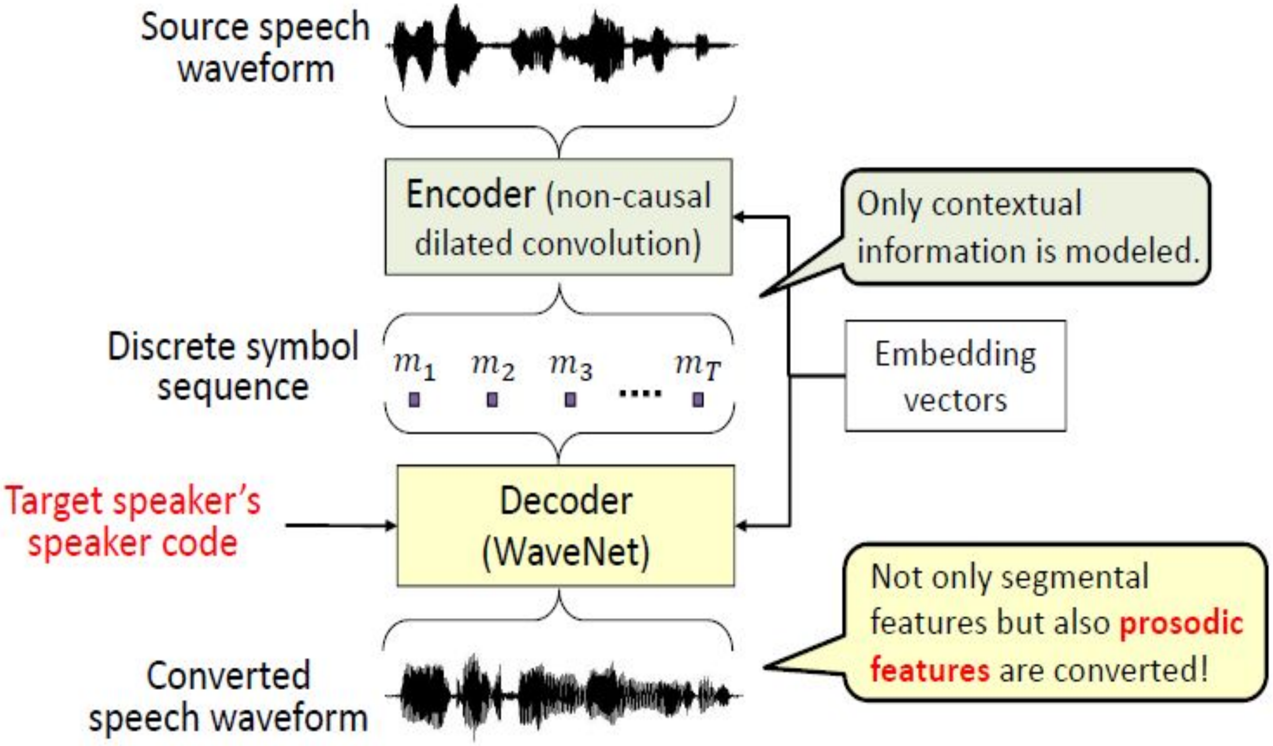
- Directly encode speech waveform into a discrete symbol sequence capturing long-term dependencies (including prosodic features!) by using a dilated convolution network



[van den Oord; '17]

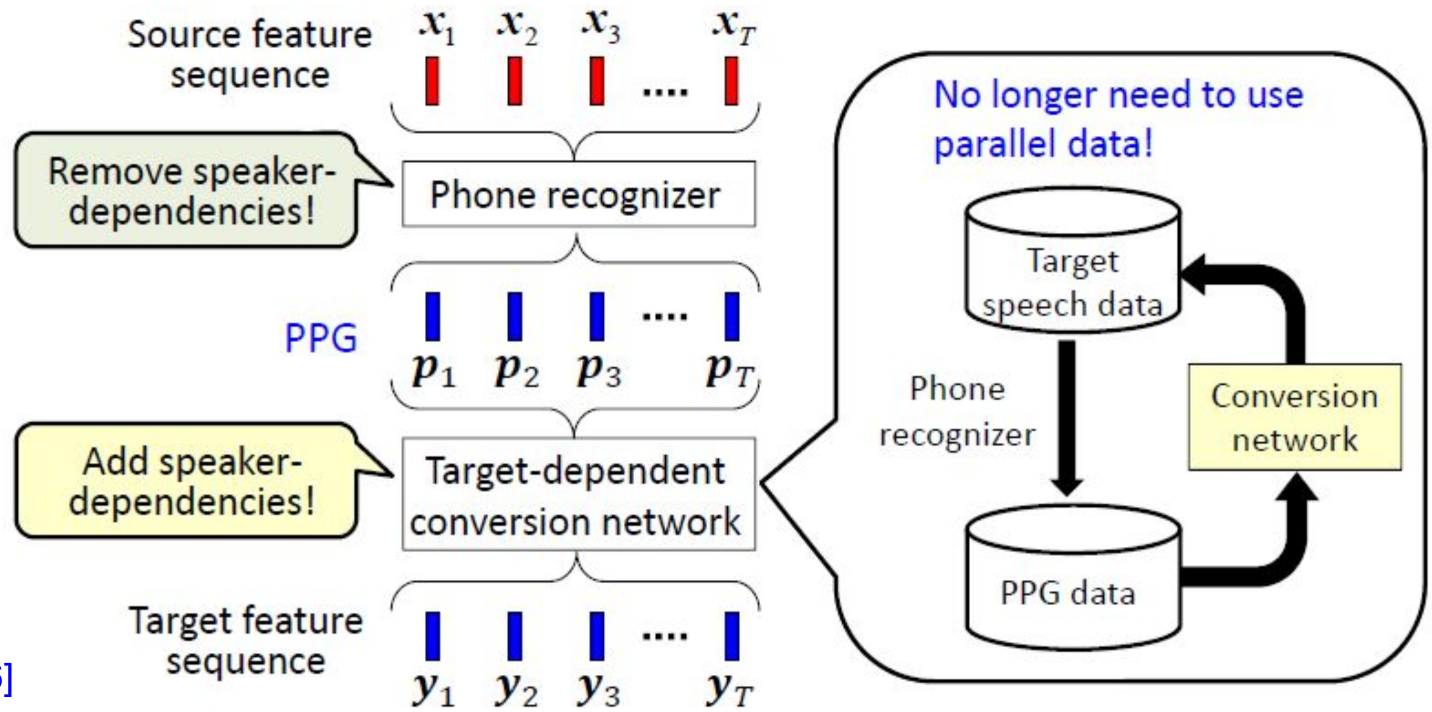
VC based on VQ-VAE

- Extract phoneme posteriorgram (PPG) as speaker-independent contextual features.



Phoneme Posteriogram VC

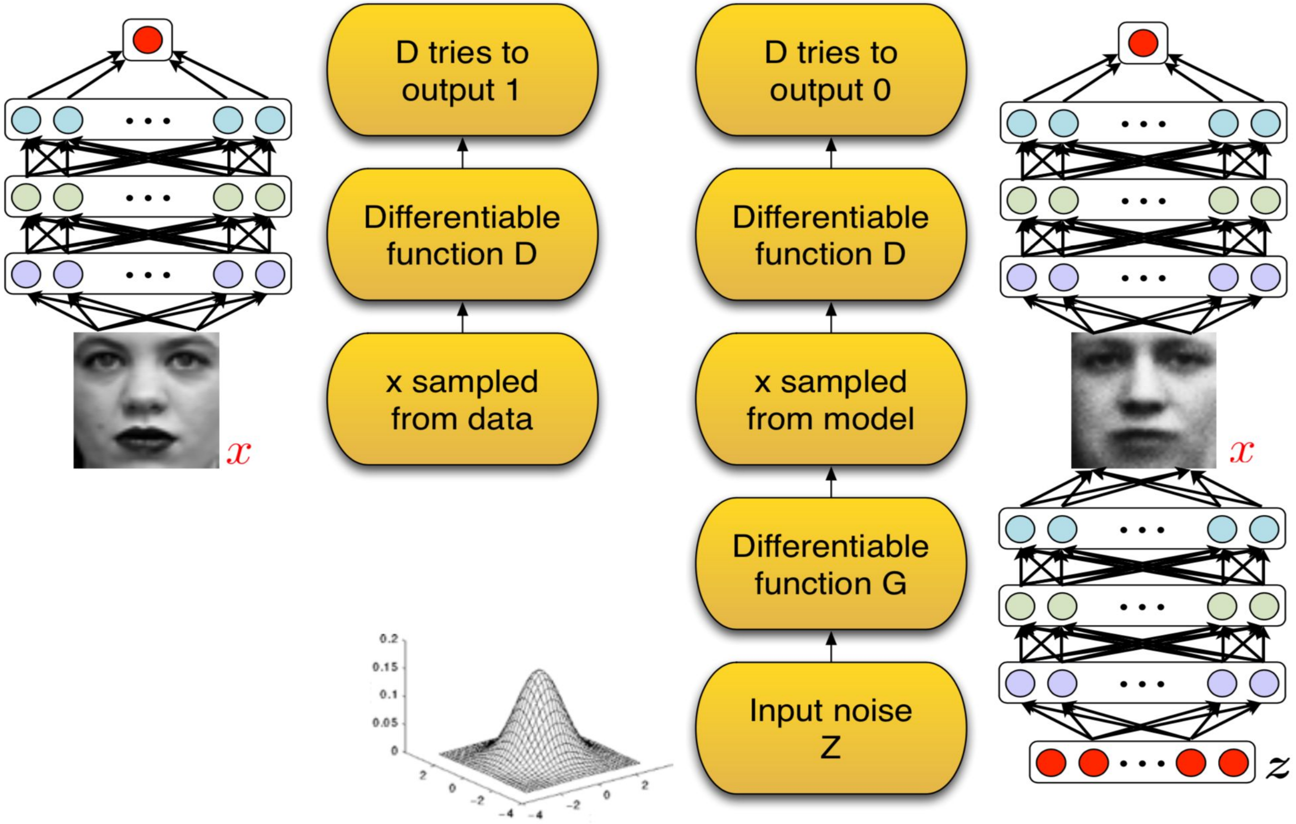
- Extract phoneme posteriorgram (PPG) as speaker-independent contextual features and use them as input of the conversion network.



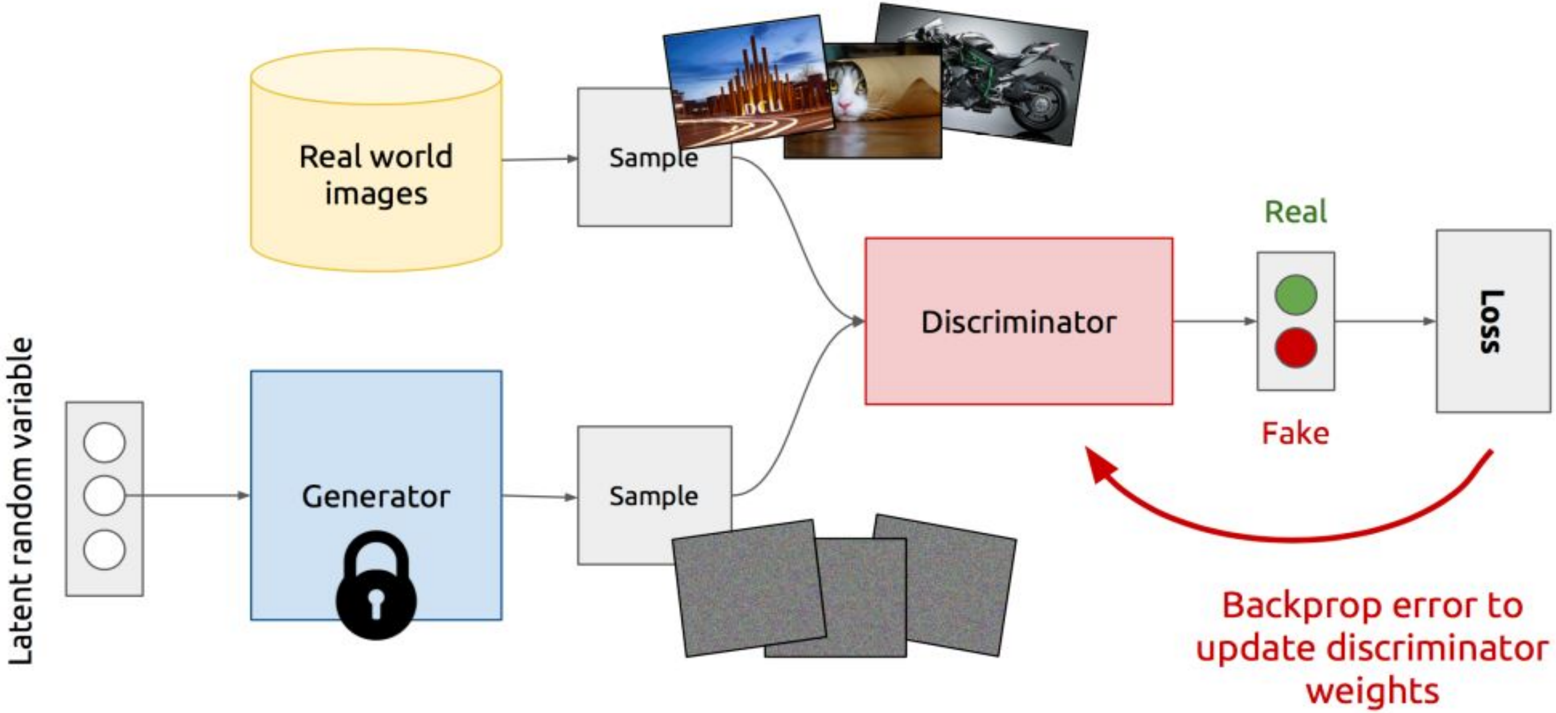
[Sun et. al. 16]

VC based on Generative Adversarial Networks

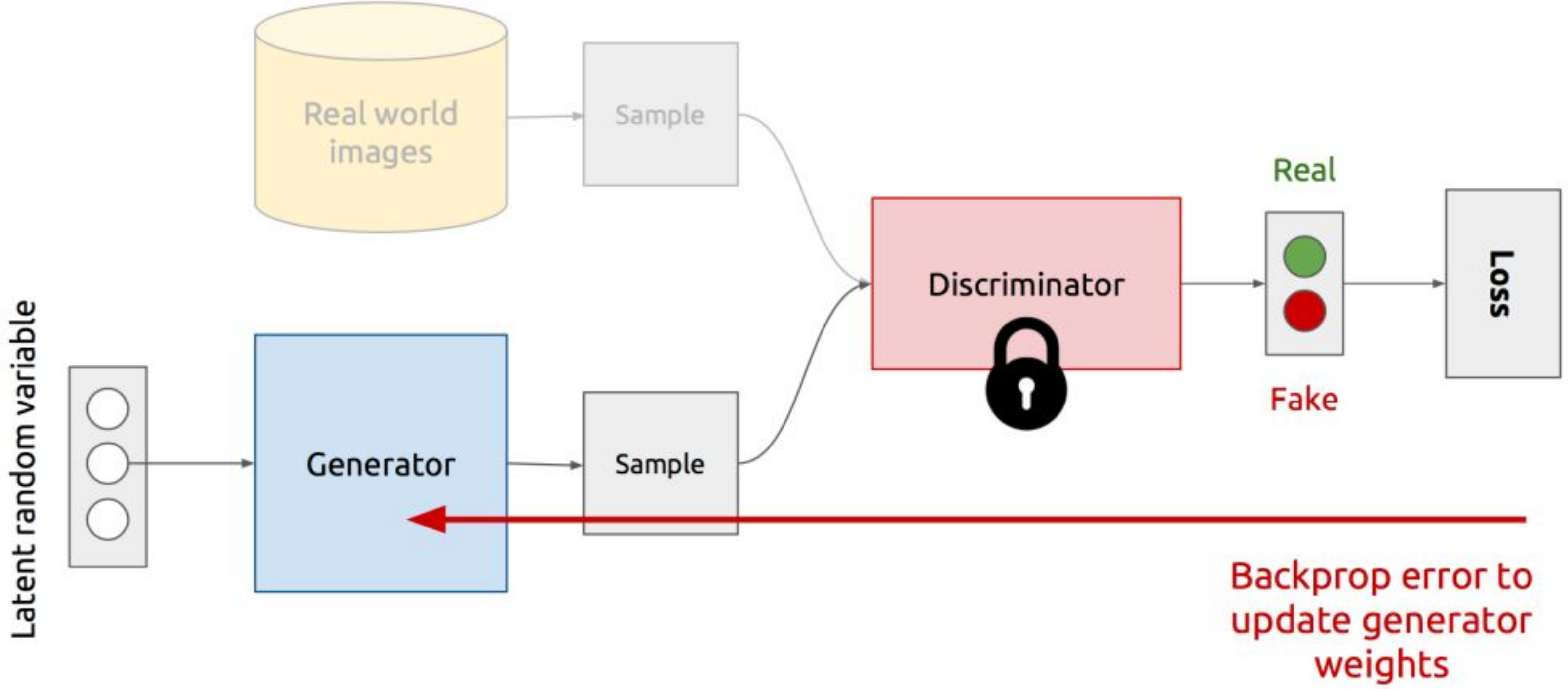
GAN Formulation



Discriminator Training



Generator Training



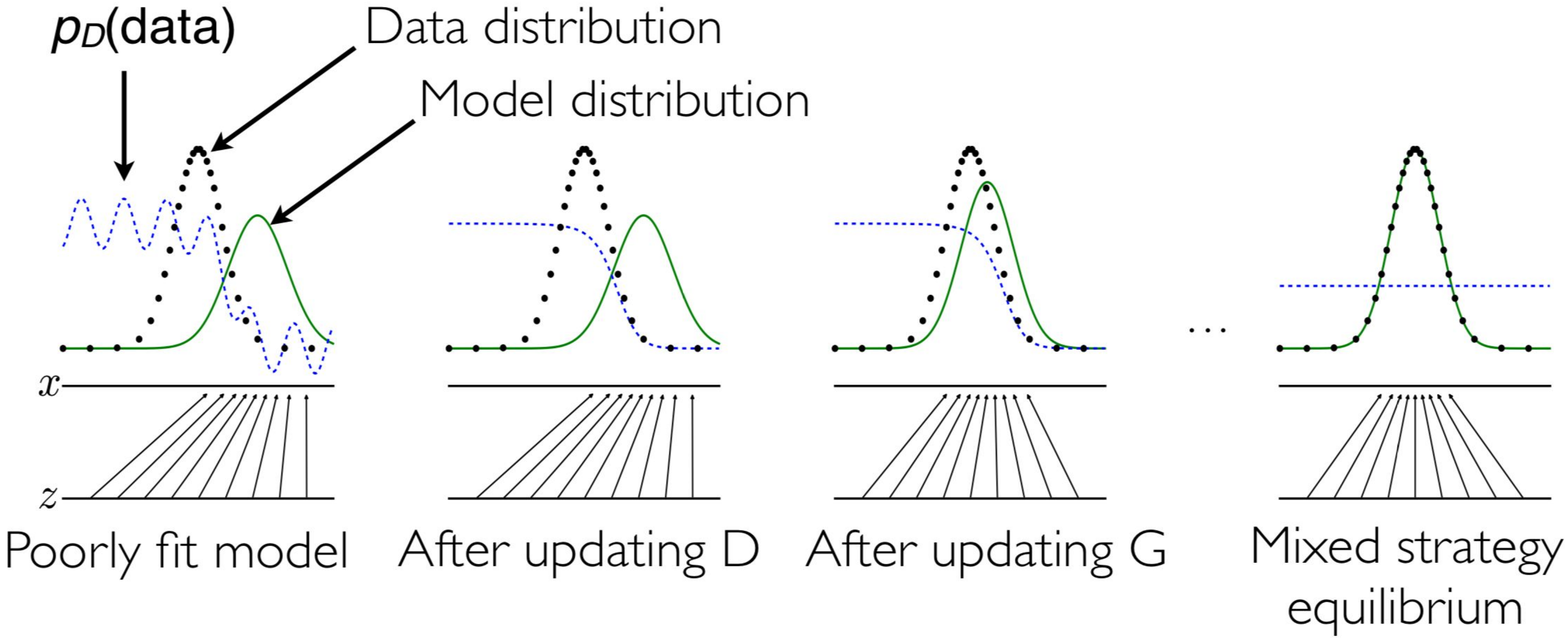
Mathematical Notations

Value of Expectation prob. of D(real) prob. of D(fake)

$$\min_{G} \max_{D} V(D, G) = \mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z} \sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]$$

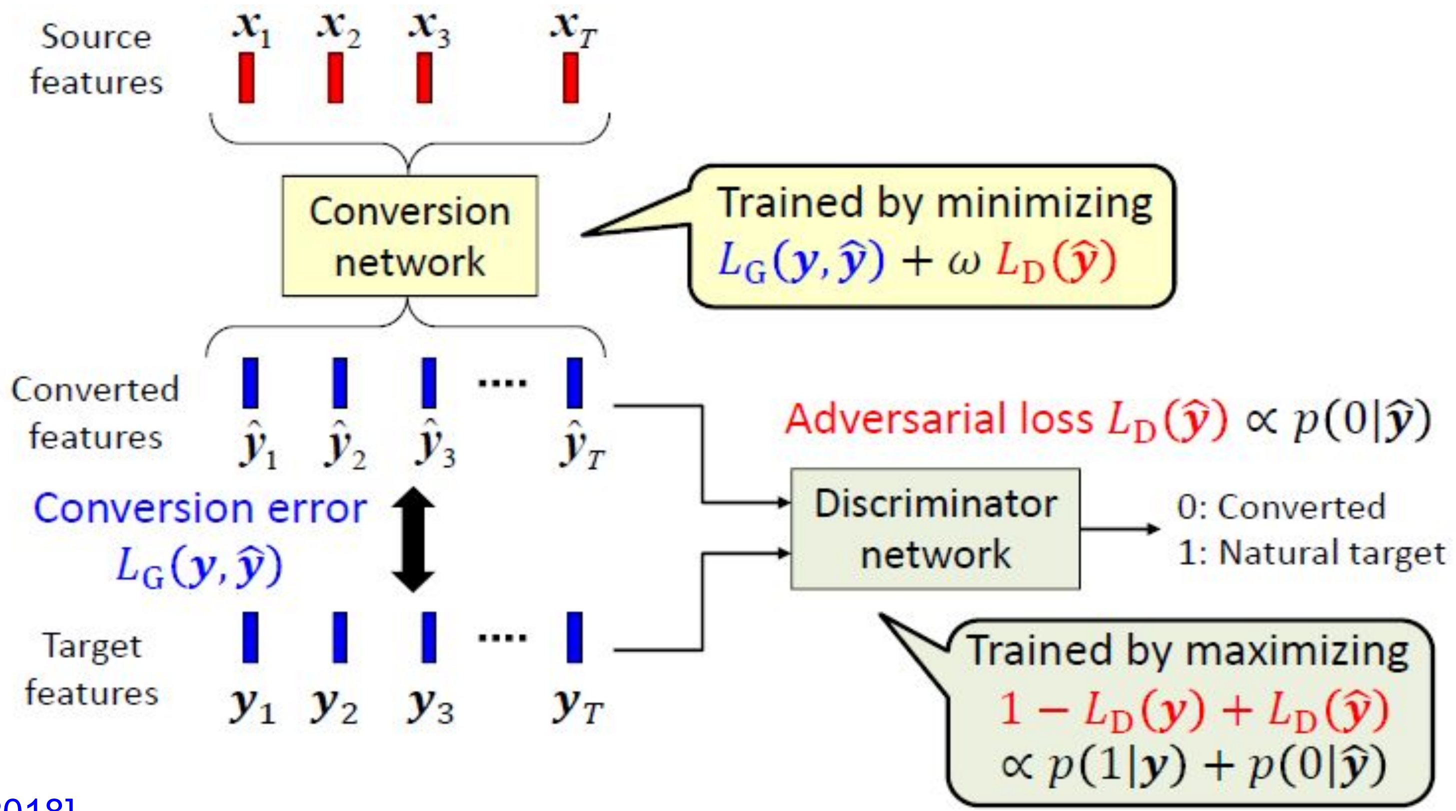
Minimize G Maximize D x is sampled from real data z is sampled from N(0, I) fake

Learning GANs



[Goodfellow et al., 2017]

GAN-based VC



[Saito et. al. 2018]

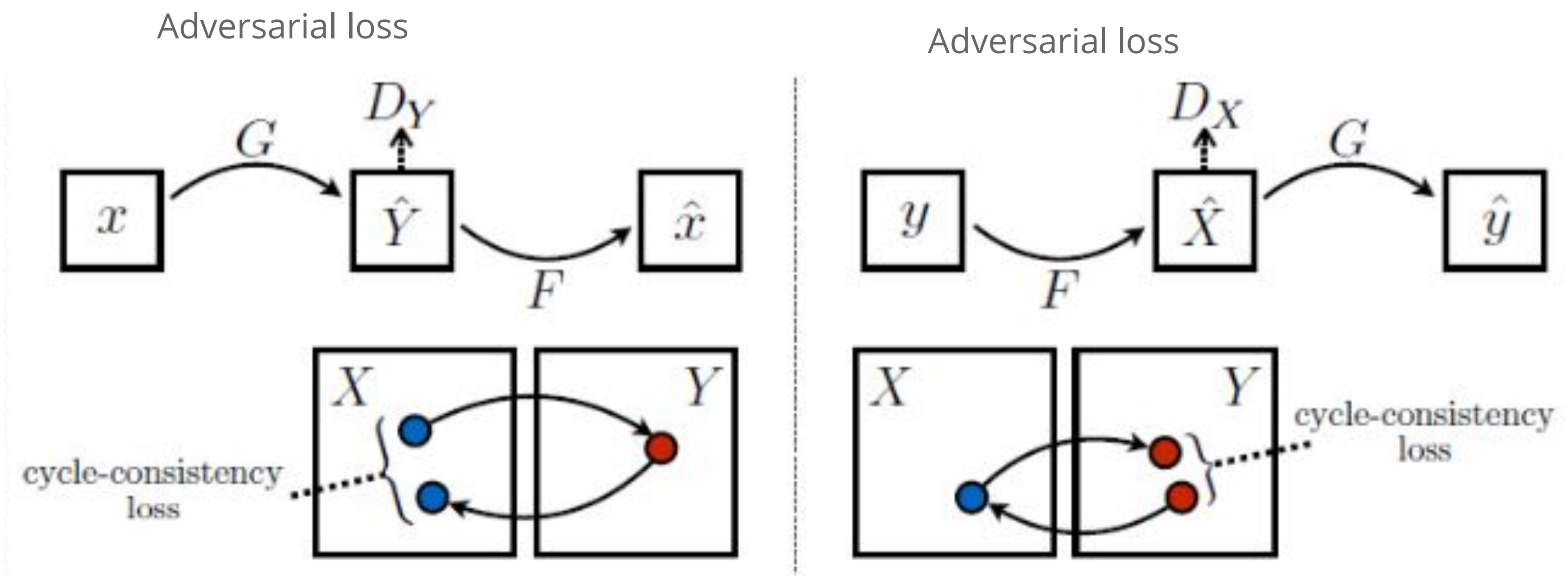
CycleGAN Voice Conversion

- A non-parallel voice-conversion (VC) method that can learn a mapping from source to target speech without relying on parallel data.

- In a CycleGAN, forward and inverse mappings are simultaneously learned using an adversarial loss and cycle-consistency loss.

- Two important losses are introduced:
  - Adversarial loss
  - cycle-consistency loss
  - identity-mapping loss

CycleGAN losses



[Kaneko et. al. 2018]

CycleGAN losses

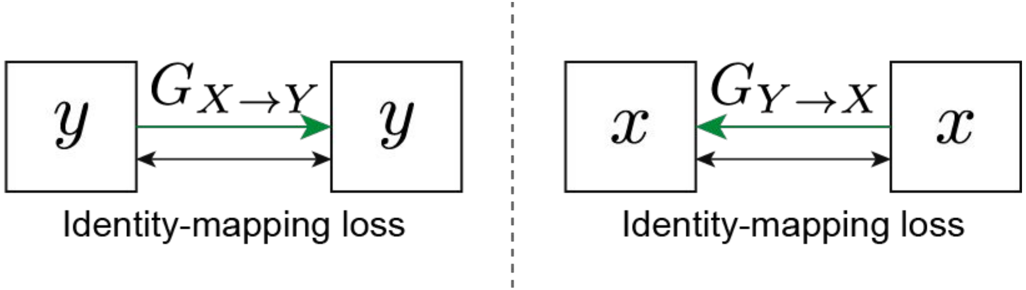
- Two mapping function (Adversarial loss): *G* and *F*. $G : X \rightarrow Y$ and $F : Y \rightarrow X$
- Cycle-consistency loss:
  - Forward: $x \rightarrow G(x) \rightarrow F(G(x)) \approx x$
  - Backward: $y \rightarrow F(y) \rightarrow G(F(y)) \approx y$

- Adversarial loss + cycle-consistency loss:

$$\mathcal{L}_{adv}(G_{X\rightarrow Y}, D_Y) + \mathcal{L}_{adv}(G_{Y\rightarrow X}, D_X) + \lambda_{cyc}\mathcal{L}_{cyc}(G_{X\rightarrow Y}, G_{Y\rightarrow X})$$

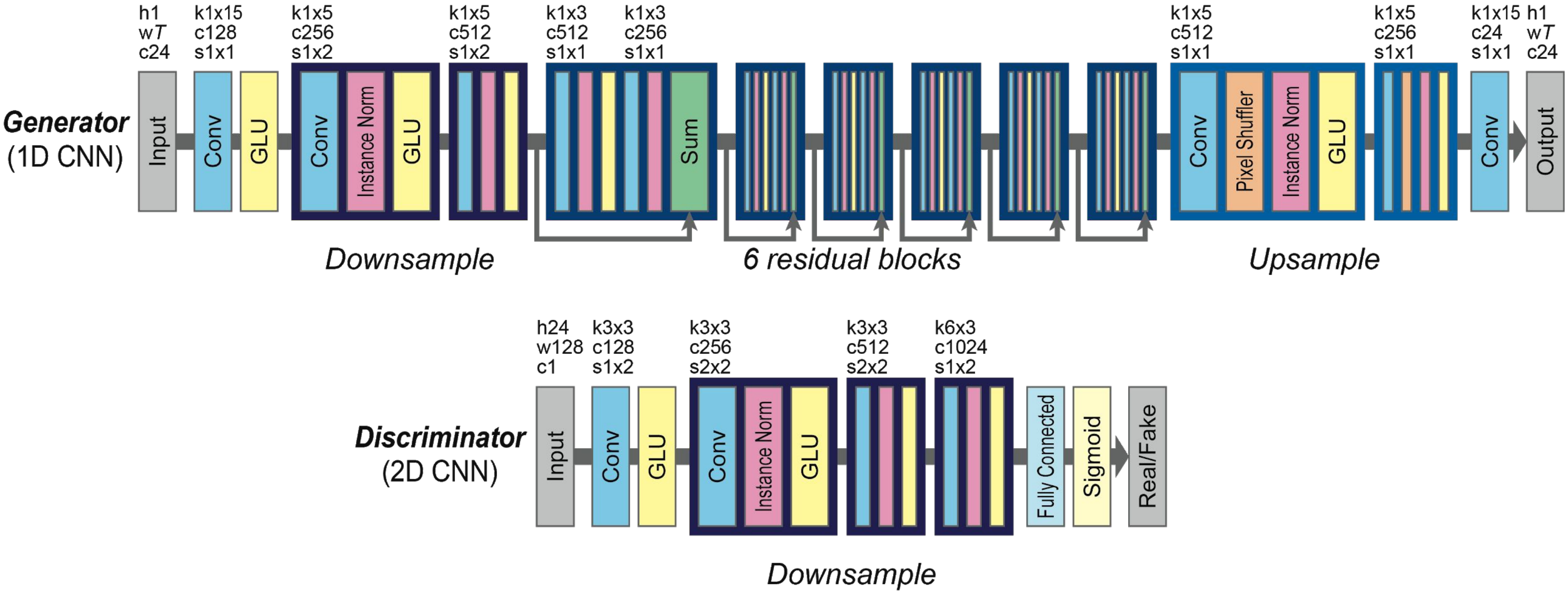
Identity-mapping loss

- To encourage linguistic-information preservation, an identity-mapping loss is implemented.
- It encourages the generator to find the mapping that preserves composition between the input and output.



$$\mathcal{L}_{id}(G_{X\to Y}, G_{Y\to X}) = \mathbb{E}_{y\sim P_{\text{Data}}(y)}[||G_{X\to Y}(y) - y||_1] + \mathbb{E}_{x\sim P_{\text{Data}}(x)}[||G_{Y\to X}(x) - x||_1],$$

CycleGAN Architecture



Sound Samples

http://www.kecl.ntt.co.jp/people/kaneko.takuhiro/projects/cyclegan-vc/

StarGAN Voice Conversion

- A non-parallel many-to-many voice conversion (VC) by using a variant of a genitive adversarial network called StarGAN.

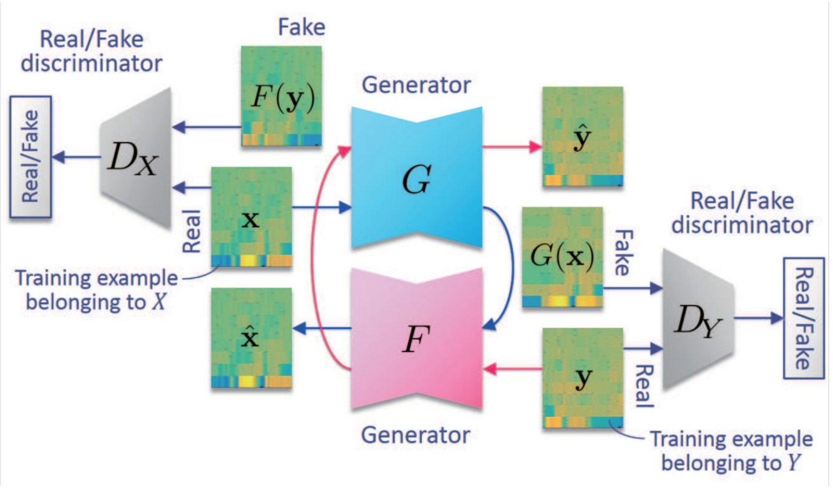
- Generator (G) takes an acoustic feature with an attribute c as the inputs and generates an acoustic feature sequence $y' = G(x, c)$.

- Discriminator (D) is designed to produce a probability $D(y, c)$ that an input y is a real speech feature.

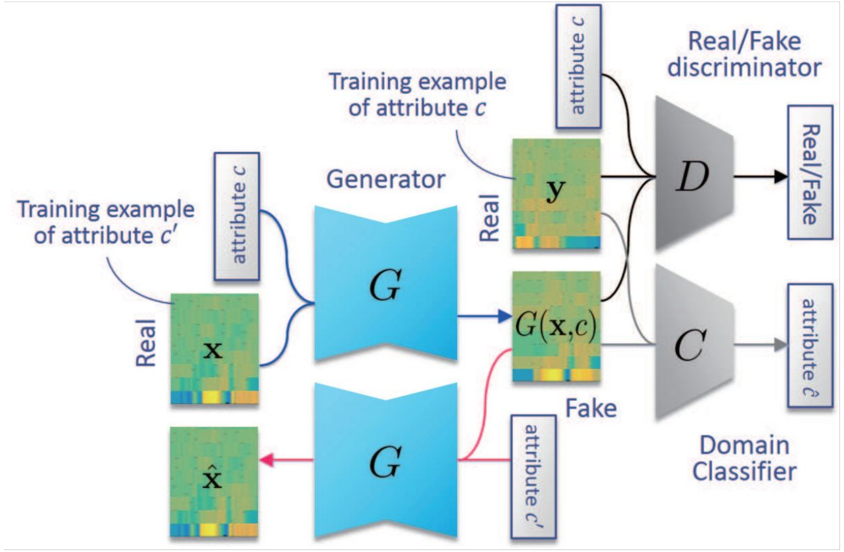
- A domain classifier (C) predicts classes of the input.

StarGAN training

CycleGAN



StarGAN



[Kameoka et. al. 2018]

StarGAN training losses

Adversarial loss:

- Adversarial losses for discriminator *D* and generator *G*, respectively, where y denotes a training example of an acoustic feature sequence of real speech with attribute *c* and *x* denotes that with an arbitrary attribute.

$$\mathcal{L}_{\mathrm{adv}}^{D}(D) = -\,\mathbb{E}_{c\sim p(c),\mathbf{y}\sim p(\mathbf{y}|c)}[\log D(\mathbf{y},c)] \\ -\,\mathbb{E}_{\mathbf{x}\sim p(\mathbf{x}),c\sim p(c)}[\log(1 - D(G(\mathbf{x},c),c))],$$

$$\mathcal{L}_{\mathrm{adv}}^{G}(G) = -\,\mathbb{E}_{\mathbf{x}\sim p(\mathbf{x}),c\sim p(c)}[\log D(G(\mathbf{x},c),c)],$$

StarGAN training losses

Domain Classification loss:

- Domain classification losses for classifier C and generator G is described.

$$\mathcal{L}_{\text{cls}}^{C}(C) = -\,\mathbb{E}_{c\sim p(c),\mathbf{y}\sim p(\mathbf{y}|c)}[\log p_C(c|\mathbf{y})],$$
$$\mathcal{L}_{\text{cls}}^{G}(G) = -\,\mathbb{E}_{\mathbf{x}\sim p(\mathbf{x}),c\sim p(c)}[\log p_C(c|G(\mathbf{x},c))],$$

StarGAN training losses

Cycle Consistency Loss:

- To encourage *G(x, c)* to be a bijection, a cycle consistency loss is implemented, where x denotes an acoustic feature sequence of real speech with attribute *c*′.

$$\mathcal{L}_{\text{cyc}}(G) = \mathbb{E}_{c'\sim p(c),\mathbf{x}\sim p(\mathbf{x}|c'),c\sim p(c)}[\|G(G(\mathbf{x},c),c') - \mathbf{x}\|_\rho],$$

StarGAN training losses

Identity mapping loss:

- Ensure that an input into *G* will remain unchanged when the input already belongs to the target attribute *c′*.

$$\mathcal{L}_{\mathrm{id}}(G) = \mathbb{E}_{c' \sim p(c), \mathbf{x} \sim p(\mathbf{x}|c')}[||G(\mathbf{x}, c') - \mathbf{x}||_{\rho}],$$

StarGAN Objective Function

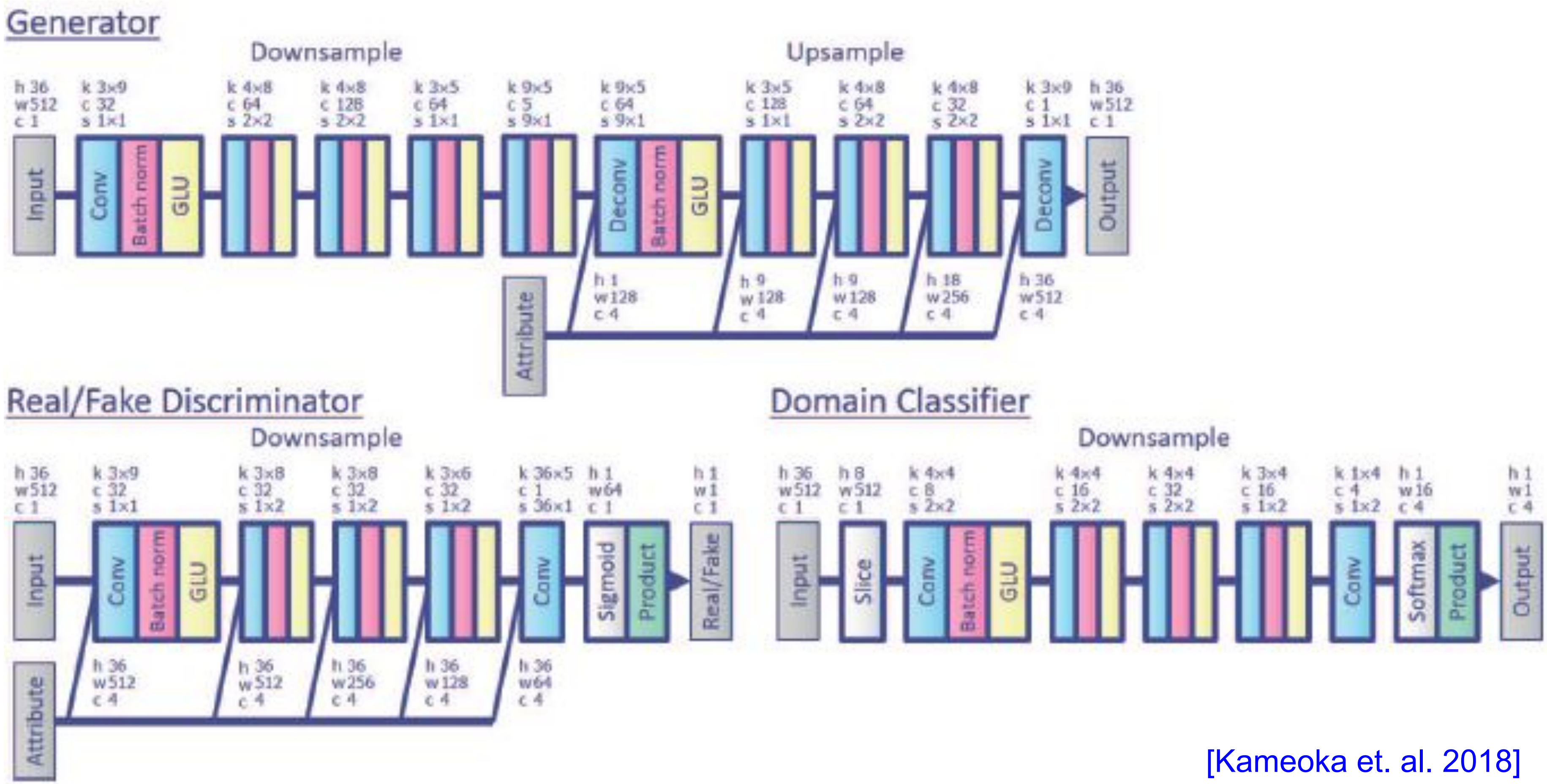
Objective function :

- The full objectives of StarGAN-VC to be minimized with respect to *G*, *D* and *C* are

$$\mathcal{I}_G(G) = \mathcal{L}_{\mathrm{adv}}^G(G) + \lambda_{\mathrm{cls}}\mathcal{L}_{\mathrm{cls}}^G(G) + \lambda_{\mathrm{cyc}}\mathcal{L}_{\mathrm{cyc}}(G) + \lambda_{\mathrm{id}}\mathcal{L}_{\mathrm{id}}(G)$$

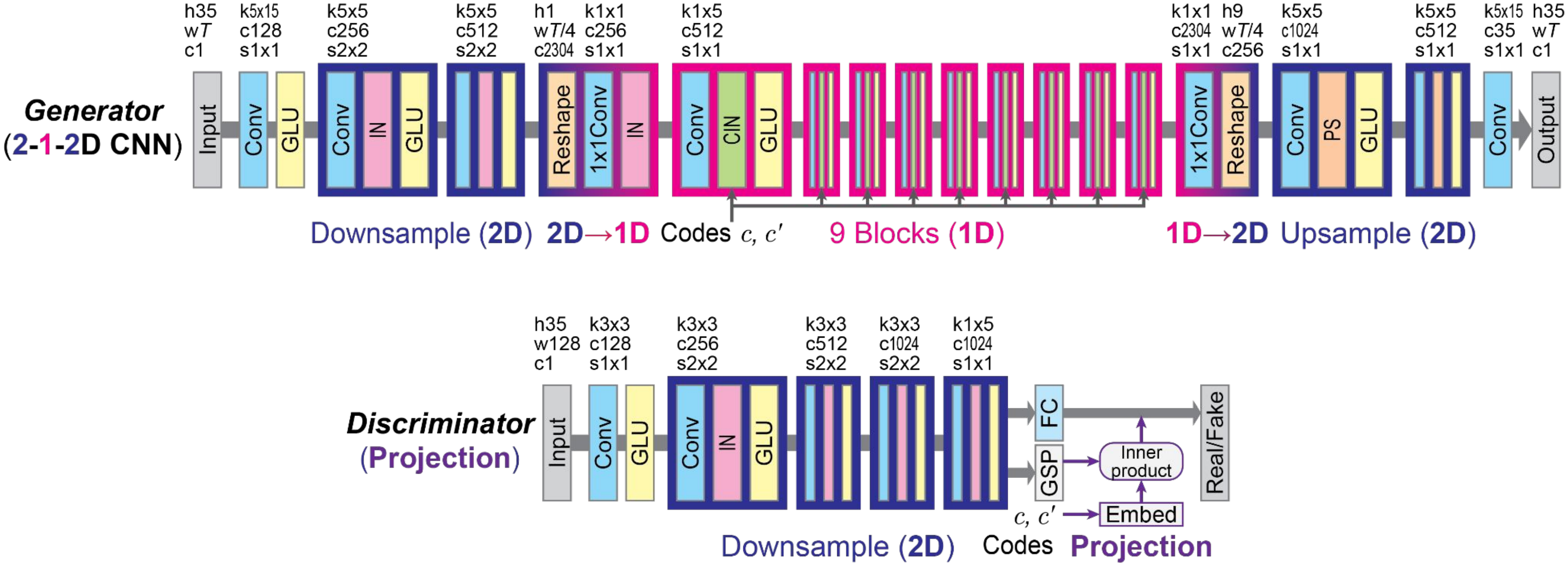
$$\mathcal{I}_D(D) = \mathcal{L}_{\mathrm{adv}}^D(D),$$

$$\mathcal{I}_C(C) = \mathcal{L}_{\mathrm{cls}}^C(C),$$



[Kameoka et. al. 2018]

Modified StarGAN



[Kaneko et. al. 2019]

Rethinking Conditional Methods

- source-and-target conditional adversarial loss defined as

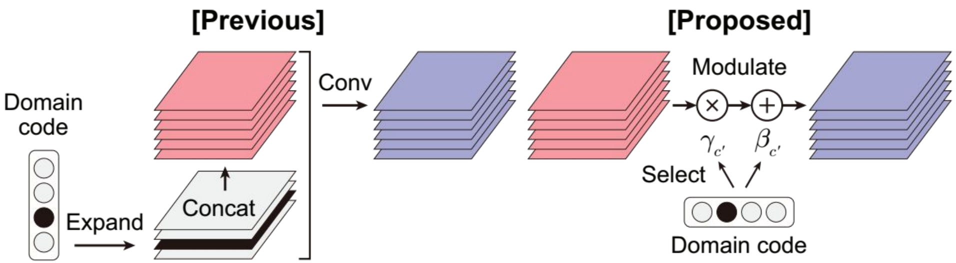
$$\mathcal{L}_{st\text{-}adv} = \mathbb{E}_{(\boldsymbol{x},c)\sim P(\boldsymbol{x},c),c'\sim P(c')}[\log D(\boldsymbol{x},c',c)] + \mathbb{E}_{(\boldsymbol{x},c)\sim P(\boldsymbol{x},c),c'\sim P(c')}[\log D(G(\boldsymbol{x},c,c'),c,c')],$$

Rethinking Conditional Methods

- Given the feature ***f***, conditional instance normalization (CIN) conducts the following procedure:

$$\mathrm{CIN}(\boldsymbol{f}; c') = \gamma_{c'} \left(\frac{\boldsymbol{f} - \mu(\boldsymbol{f})}{\sigma(\boldsymbol{f})} \right) + \beta_{c'},$$

where μ(***f***) and σ(***f***) are the average and standard deviation of ***f*** that are calculated over for each instance. γc' and βc' are domain-specific scale and bias parameters that allow the modulation to be transformed in a domain-specific manner.



(a) Channel-wise (b) Modulation-based

[Kaneko et. al. 2019]

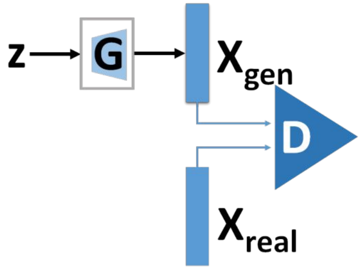
Sound Samples

http://www.kecl.ntt.co.jp/people/kameoka.hirokazu/Demos/stargan-vc/

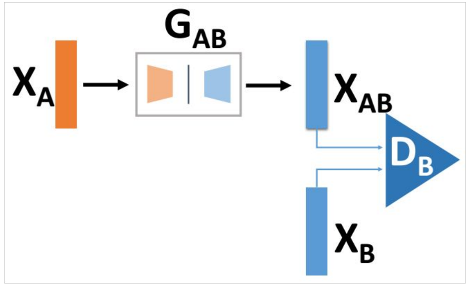
http://www.kecl.ntt.co.jp/people/kaneko.takuhiro/projects/stargan-vc2/index.html

Style Conversion (VoiceGAN)

- Voice style impersonation, where one person attempts to mimic the voice of another to sound like the other person, is a complex phenomenon.



The original GAN model



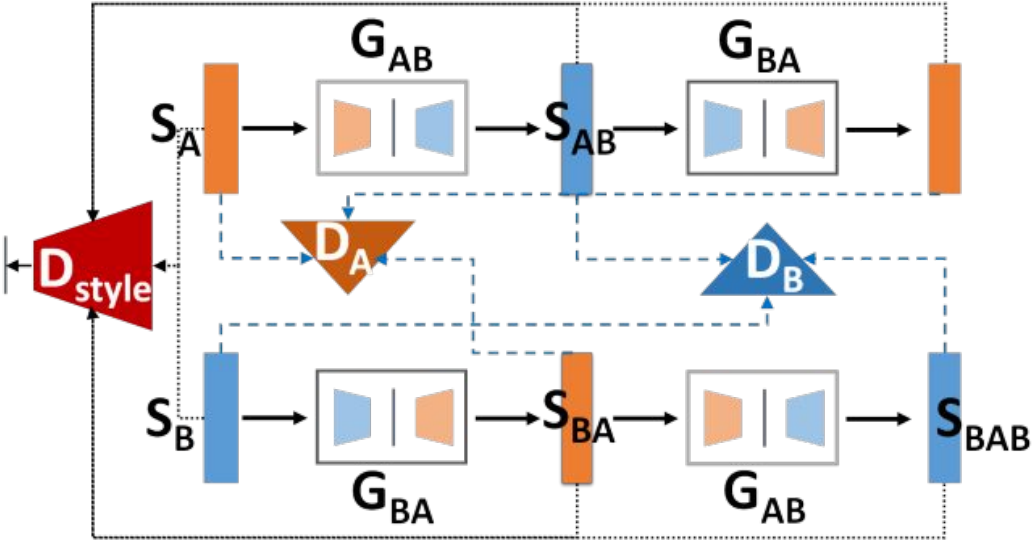
Style transfer by GAN

Mathematical notations:

$$L_G = E_{x_A \sim P_A}[\log(1 - D_B(x_{AB}))]$$
$$L_D = -E_{x_B \sim P_B}[\log D_B(x_B)] - E_{x_A \sim P_A}[\log(1 - D_B(x_{AB}))]$$

[Gao et al., 2018]

Style Conversion (VoiceGAN)



- D_A and D_B discriminate between real and fake data.
- G_{AB} transforms for style A to style B, where as G_{BA} is the opposite.
- The discriminator D_{style} determines if the original and transformed signals match the desired style.

Style Conversion (VoiceGAN)

- Training objectives to be minimized for the generator and discriminator are represented by L_G and L_D respectively as follows:

$$L_G = L_{GAN_{AB}} + L_{GAN_{BA}} = L_{G_B} + L_{CONST_A} + L_{G_A} + L_{CONST_B}$$

$$L_D = L_{D_A} + L_{D_B} + L_{D_{STYLE}}$$

- Reconstruction loss:

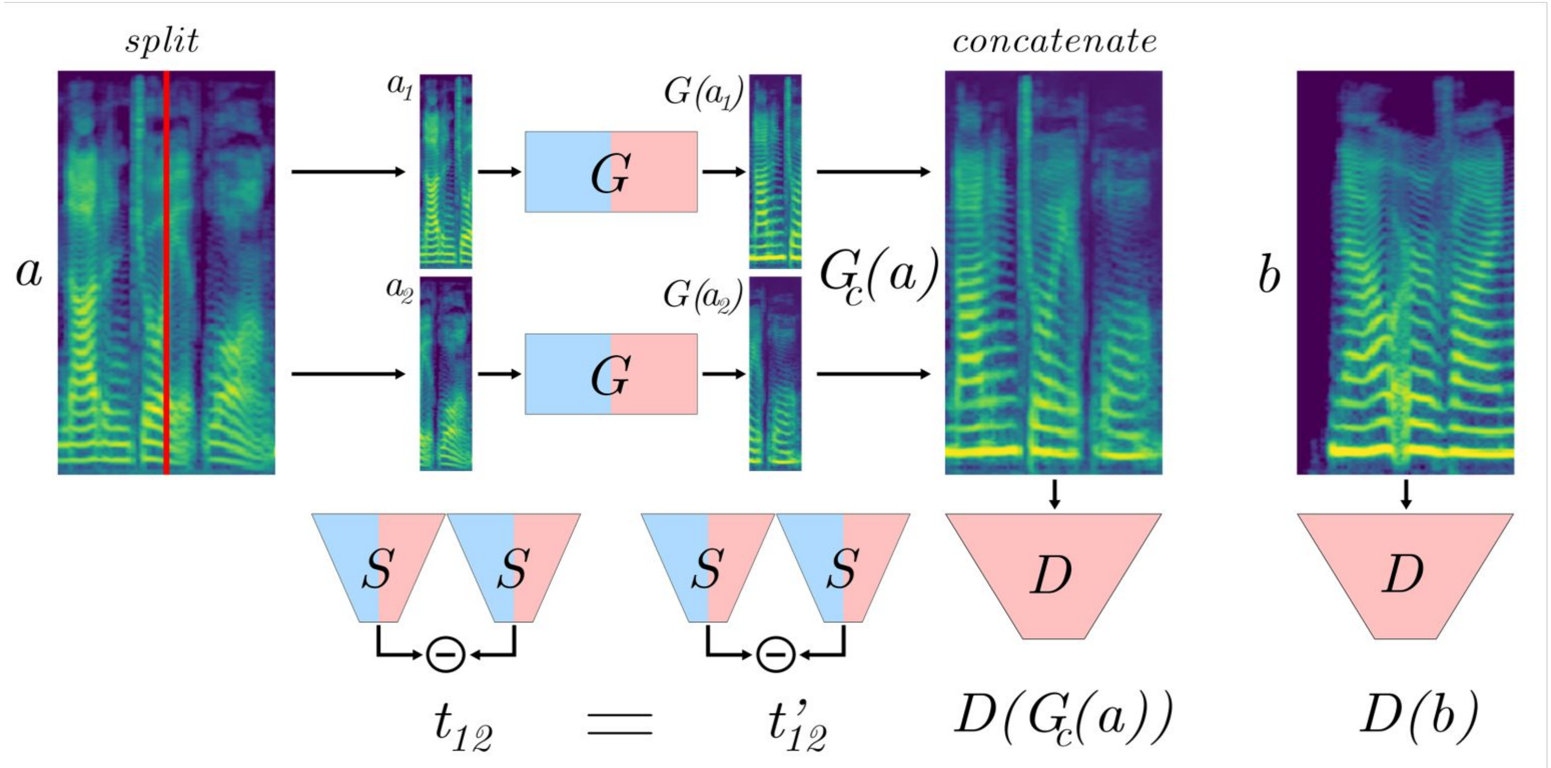
$$L_{CONST_A} = d(G_{BA}(G_{AB}(x_A)), x_A)$$

- The discriminator D_S determines if the original and transformed signals match the desired style:

$$L_{D_{STYLE}} = L_{D_{STYLE-A}} + L_{D_{STYLE-B}}$$

$$L_{D_{STYLE-A}} = d(D_S(x_A), label_A) + d(D_S(x_{AB}), label_B) + d(D_S(x_{ABA}), label_A)$$

MelGAN VC

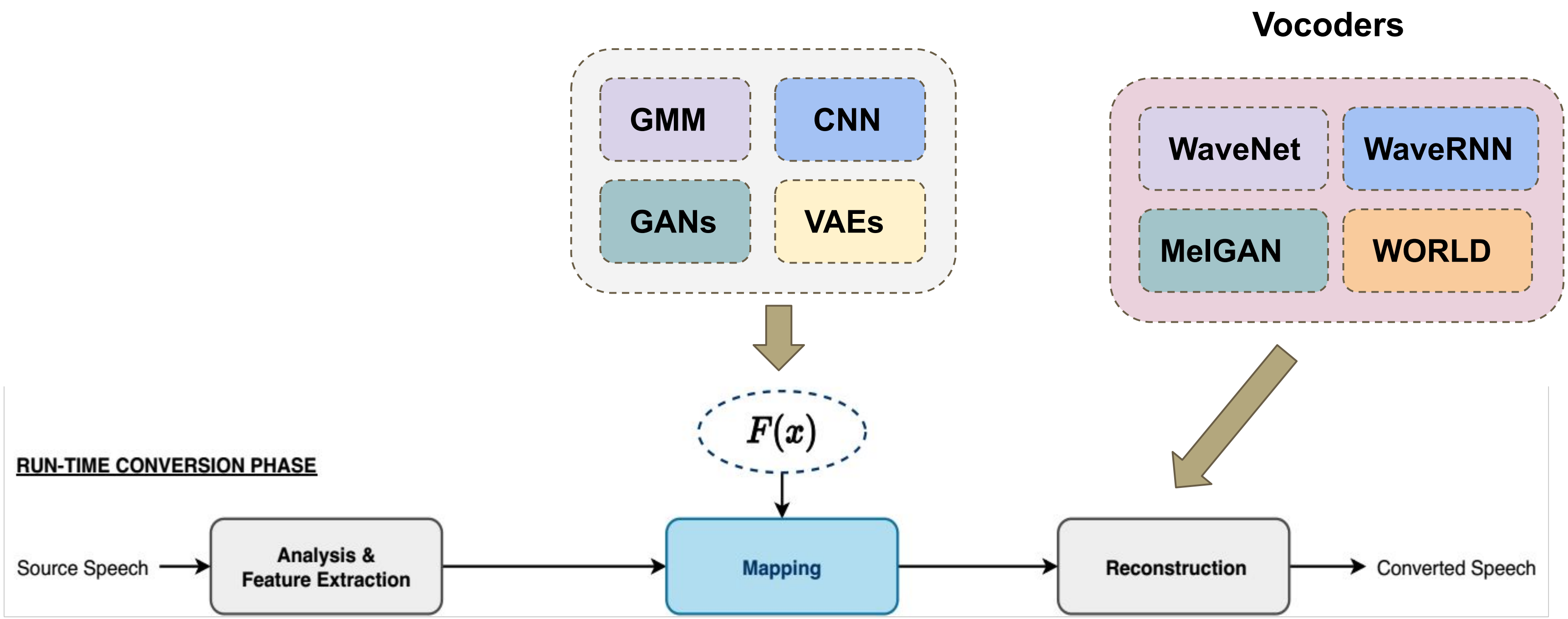


TraVeL (Transformation Vector Learning loss) loss

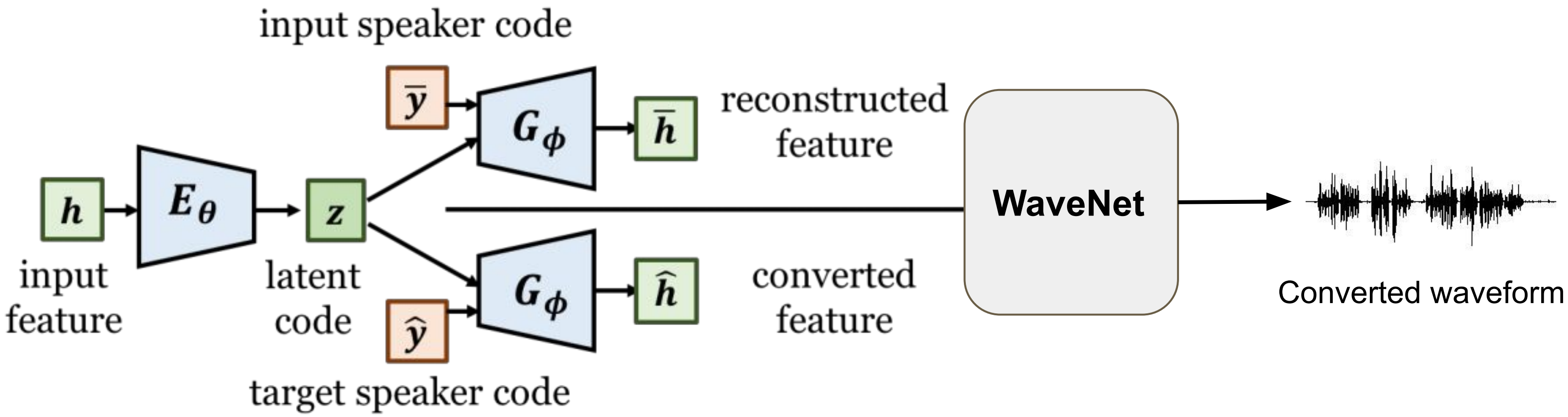
[Pasini 2020]

Various Vocoders in VC

General Framework



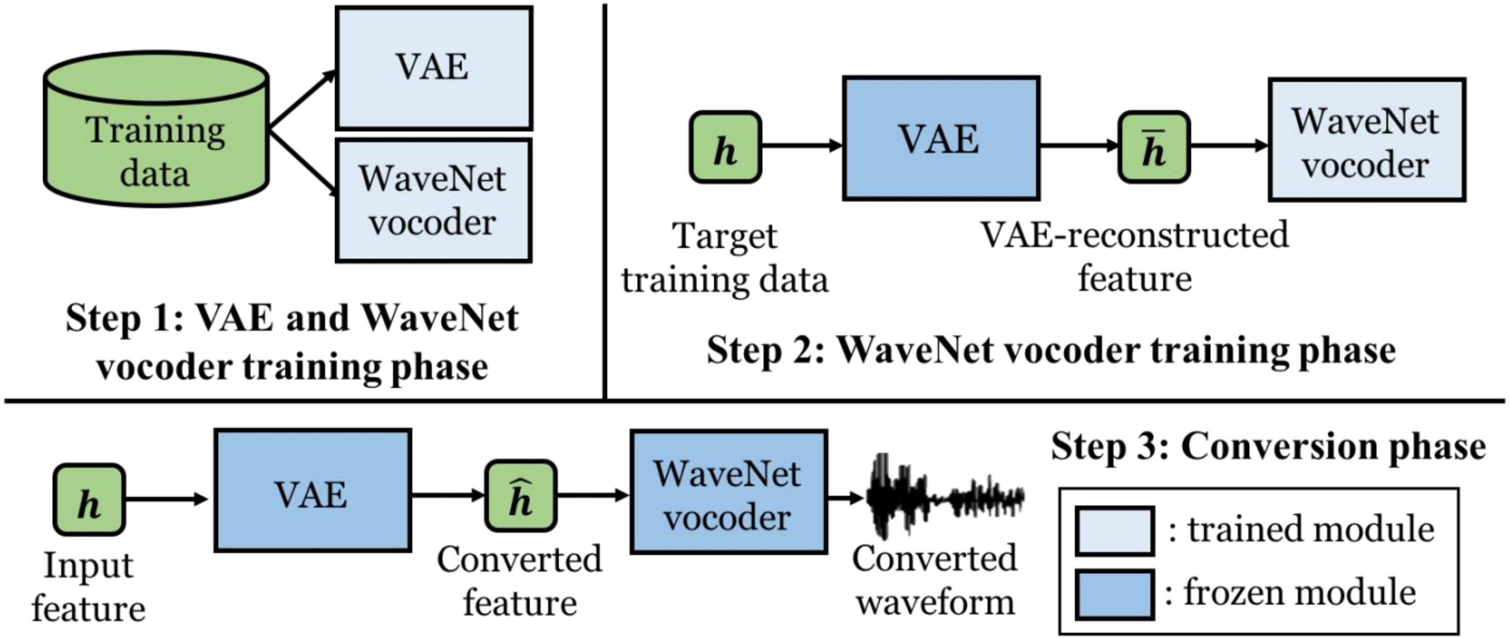
WaveNet Vocoder in VAE-VC



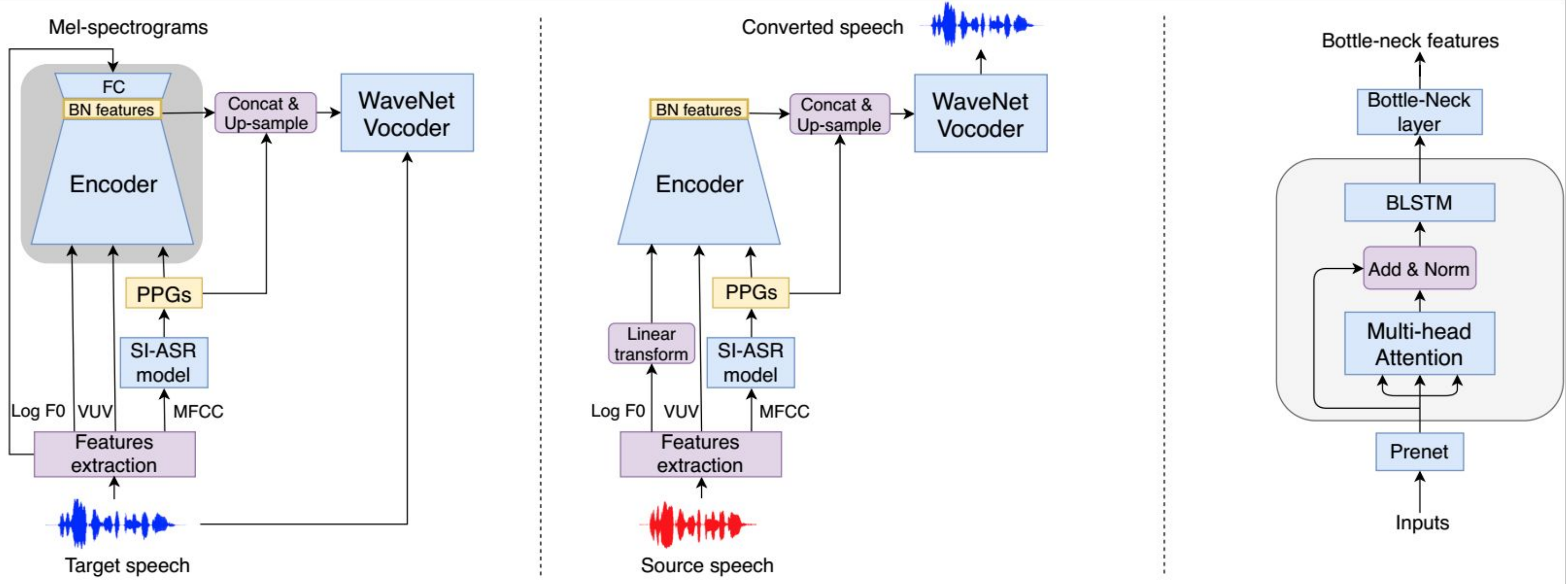
A general framework of WaveNet vocoder in voice conversion.

[Huang et. al. 2019]

Training Protocol



Jointly Trained Conversion Model and Vocoder

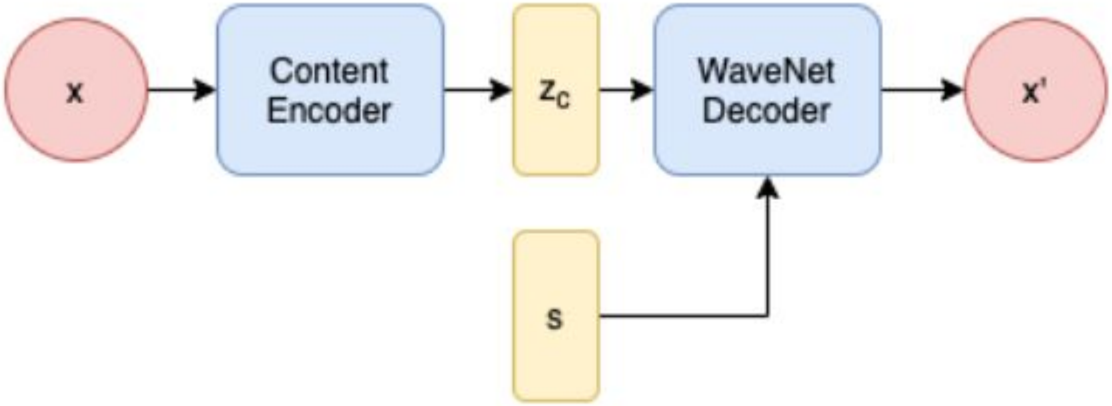


(a) Training stage (b) Conversion stage (c) Encoder module

[Liu et. al. 2019]

WaveNet Auto-encoders

- WaveNet is used as the decoder and to generate waveform data directly from the latent representation.



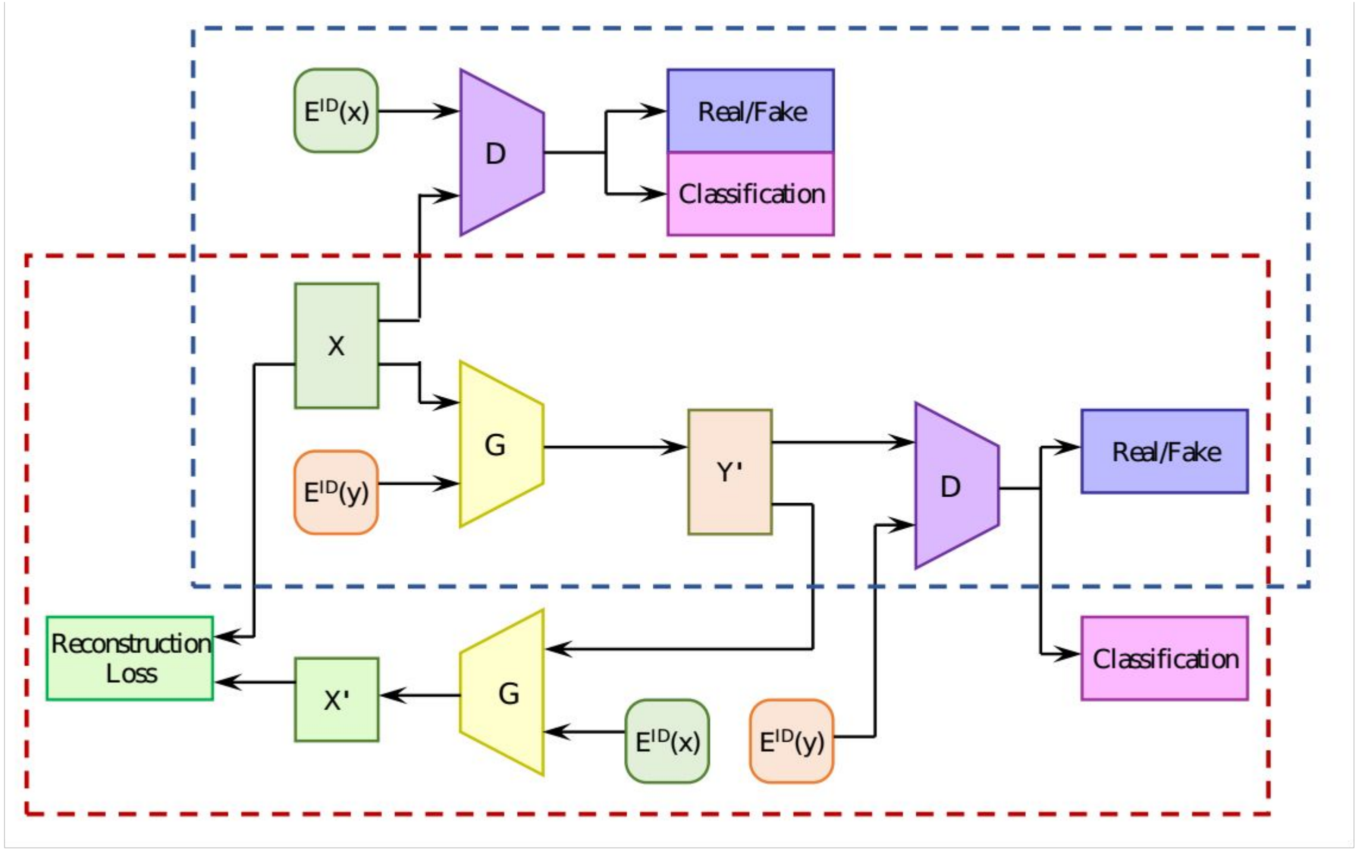
[Chen et. al. 2020]

One-shot Voice Conversion

One-shot VC

- The target speaker is unseen in training dataset or both source and target speakers are unseen in the training dataset.
- An universal embedding vector is used to represent speaker ID.
- The idea is to represent any arbitrary unseen speaker ID with an embedding vector.
- Such embedding vector represents unseen speaker’s timbre would be a weighted combination of the timbres the speakers seen in the dataset.

One-shot StarGAN VC

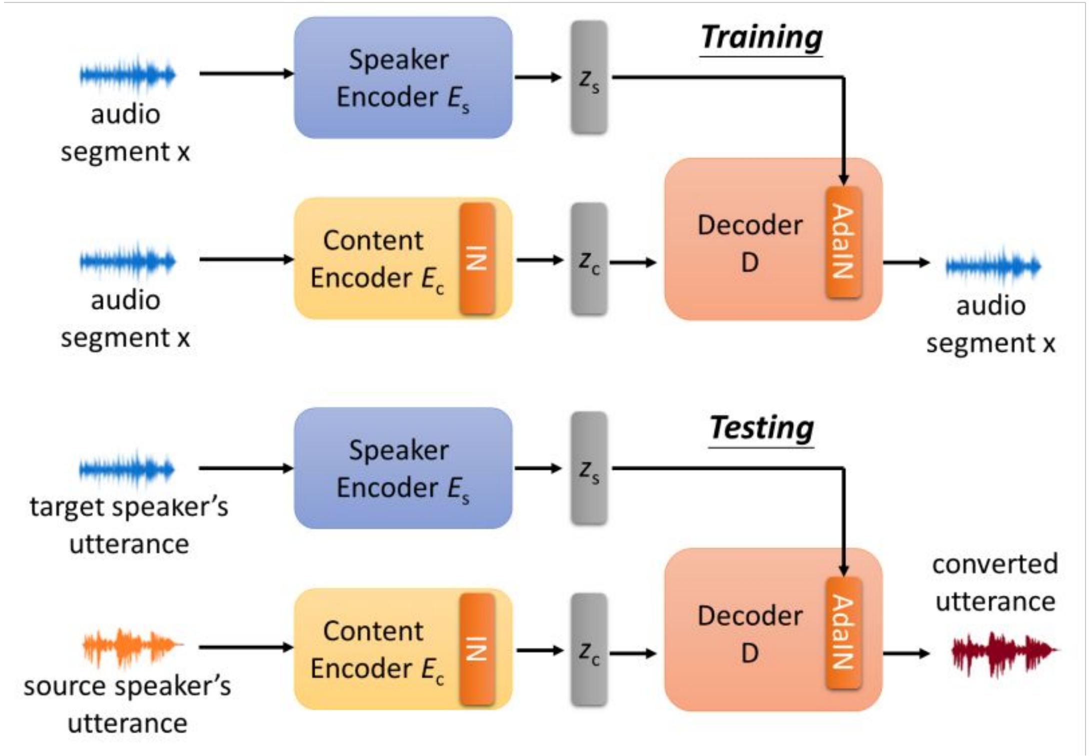


[Wang et. al. 2020]

Representations Learning

- An utterance can be factorized into a speaker plus a content representation.
- To disentangle speaker and content representation, three components is employed : a speaker encoder, a content encoder and a decoder
- The speaker encoder is trained to encode the speaker information.
- The content encoder is trained to encode only the linguistic information.
- The task of the decoder is to synthesize the voice back by combining these two representations.

Representations Learning



- *Es* is speaker encoder
- *Ec* is content encoder
- *D* is decoder.
- *IN* is instance normalization
- *AdaIN* represents adaptive instance normalization layer.

[Chou et. al. 2019]

Representations Learning

- The objective function for VAE training

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

- The reconstruction loss is given as

$$L_{rec}(\theta_{E_s},\theta_{E_c},\theta_D) = \mathop{\mathbb{E}}_{x\sim p(x),z_c\sim p(z_c|x)}[\| \mathrm{D}(\mathrm{E_s}(x), z_c) - x\|_1^1].$$

- The divergence term is given as in

$$L_{kl}(\theta_{E_c}) = \mathop{\mathbb{E}}_{x\sim p(x)}[\|\mathrm{E_c}(x)^2\|_2^2].$$

Bibliography

- I. Goodfellow et al. “Generative adversarial nets,” in Proc. NIPS, 2014.
- Arjovsky et al. “Wasserstein GAN,” arXiv preprint arXiv:1701.07875, 2017.
- I. Gulrajani et al., “Improved training of Wasserstein GANs,” in Advances in Neural Information Processing Systems, 2017, pp. 5767–5777.
- Hung-yi Lee, and Yu Tsao. ”Generative Adversarial Network and its Applications to Speech Signal and Natural Language Processing.” tutorial in ICASSP, 2018.
- Hsu, Chin-Cheng, Hsin-Te Hwang, Yi-Chiao Wu, Yu Tsao, and Hsin-Min Wang. "Voice conversion from non-parallel corpora using variational auto-encoder." In *2016 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA)*, pp. 1-6. IEEE, 2016.
- A. Kain and M. W. Macon. Spectral voice conversion for text-to-speech synthesis. Proc. IEEE ICASSP, pp. 285–288, 1998.
- T. Kaneko, H. Kameoka. CycleGAN-VC: non-parallel voice conversion using cycle-consistent adversarial networks. Proc. EUSIPCO, pp. 2114–2118, 2018.
- H. Kameoka, T. Kaneko, K. Tanaka, N. Hojo. StarGAN-VC: non-parallel many-to-many voice conversion using star generative adversarial networks. Proc. IEEE SLT, pp. 266–272, 2018.
- Kaneko, T., Kameoka, H., Tanaka, K. and Hojo, N., 2019. StarGAN-VC2: Rethinking Conditional Methods for StarGAN-Based Voice Conversion}}. Proc. Interspeech 2019, pp. 679-683.

Bibliography

- Gao, Yang, Rita Singh, and Bhiksha Raj. "Voice impersonation using generative adversarial networks." In *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 2506-2510. IEEE, 2018.
- Huang, Wen-Chin, Yi-Chiao Wu, Hsin-Te Hwang, Patrick Lumban Tobing, Tomoki Hayashi, Kazuhiro Kobayashi, Tomoki Toda, Yu Tsao, and Hsin-Min Wang. "Refined wavenet vocoder for variational autoencoder based voice conversion." In *2019 27th European Signal Processing Conference (EUSIPCO)*, pp. 1-5. IEEE, 2019.
- Liu, Songxiang, Yuewen Cao, Xixin Wu, Lifa Sun, Xunying Liu, and Helen Meng. "Jointly Trained Conversion Model and WaveNet Vocoder for Non-Parallel Voice Conversion Using Mel-Spectrograms and Phonetic Posteriorgrams." In *INTERSPEECH*, pp. 714-718. 2019.
- Pasini, Marco. "Melgan-vc: Voice conversion and audio style transfer on arbitrarily long samples using spectrograms." *arXiv preprint arXiv:1910.03713* (2020).
- Chen, Mingjie, and Thomas Hain. "Unsupervised acoustic unit representation learning for voice conversion using wavenet auto-encoders." *arXiv preprint arXiv:2008.06892* (2020).
- Wang, Ruobai, Yu Ding, Lincheng Li, and Changjie Fan. "One-Shot Voice Conversion Using Star-Gan." In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 7729-7733. IEEE, 2020.
- Chou, Ju-chieh, and Hung-Yi Lee. "One-Shot Voice Conversion by Separating Speaker and Content Representations with Instance Normalization}}." *Proc. Interspeech 2019* (2019): 664-668.

Bibliography

- M. Abe, S. Nakamura, K. Shikano, H. Kuwabara. Voice conversion through vector quantization. J. Acoust. Soc. Jpn (E), Vol. 11, No. 2, pp. 71–76, 1990.
- Y. Stylianou, O. Cappe, E. Moulines. Continuous probabilistic transform for voice conversion. IEEE Trans. Speech & Audio Process., Vol. 6, No. 2, pp. 131–142, 1998.
- L. Sun, K. Li, H. Wang, S. Kang, H.M. Meng. Phonetic posteriorgrams for many-to-one voice conversion without parallel data training. Proc. IEEE ICME, 6 pages, 2016.
- T. Toda, A.W. Black, K. Tokuda. Voice conversion based on maximum likelihood estimation of spectral parameter trajectory. IEEE Trans. Audio, Speech & Lang. Process., Vol. 15, No. 8, pp. 2222–2235, 2007.
- http://spcc.csd.uoc.gr/SPCC2019/Lectures/SPCC2019_VC_Lecture_TomokiTODA.pdf
- Pantazis et al. , ” https://www.csd.uoc.gr/~spcc/ ”


Спасибо
Gracias
شكرا
Obrigado
Спасибо
Dank U
Grazie
Ευχαριστώ
Ευχαριστώ
Danke
Merci
Ngiyabonga
Dank U
Diolch
Obrigado
Ngiyabonga
Thank You
Merci
Ευχαριστώ
Tack
Dzięki
Danke
Grazie
תודה
謝謝
Dzięki
Merci
Dank
Terima Kasih
U
Diolch
Merci
Grazie
Tack
Ευχαριστώ
Tack
감사합니다
Diolch

Speech Intelligibility Enhancement

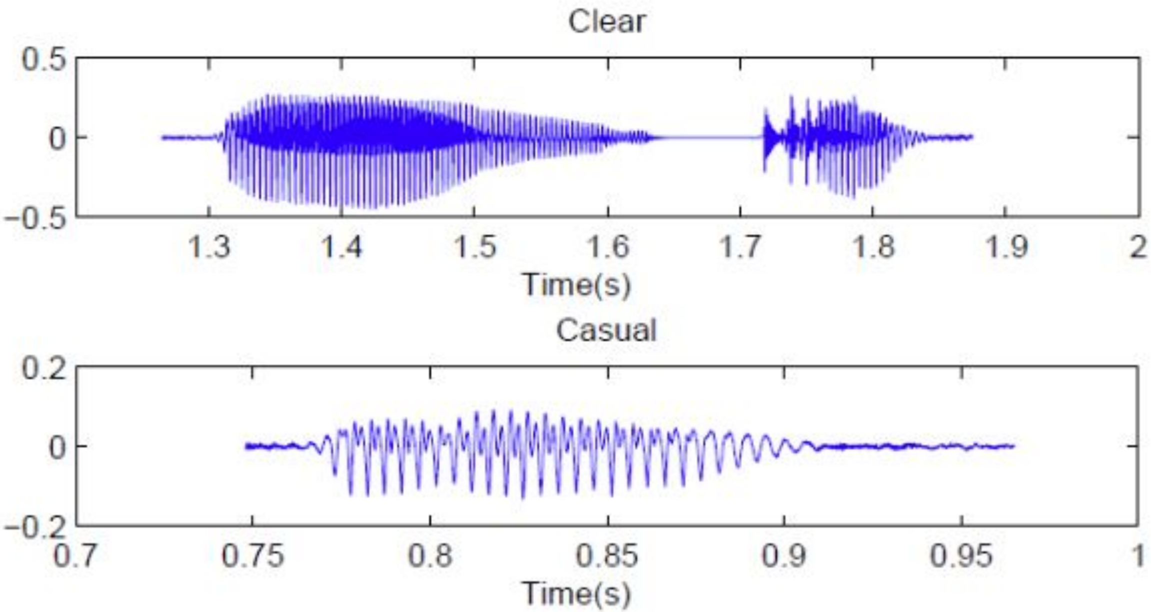
From Casual to Clear Speech

Clear and Conversational speech

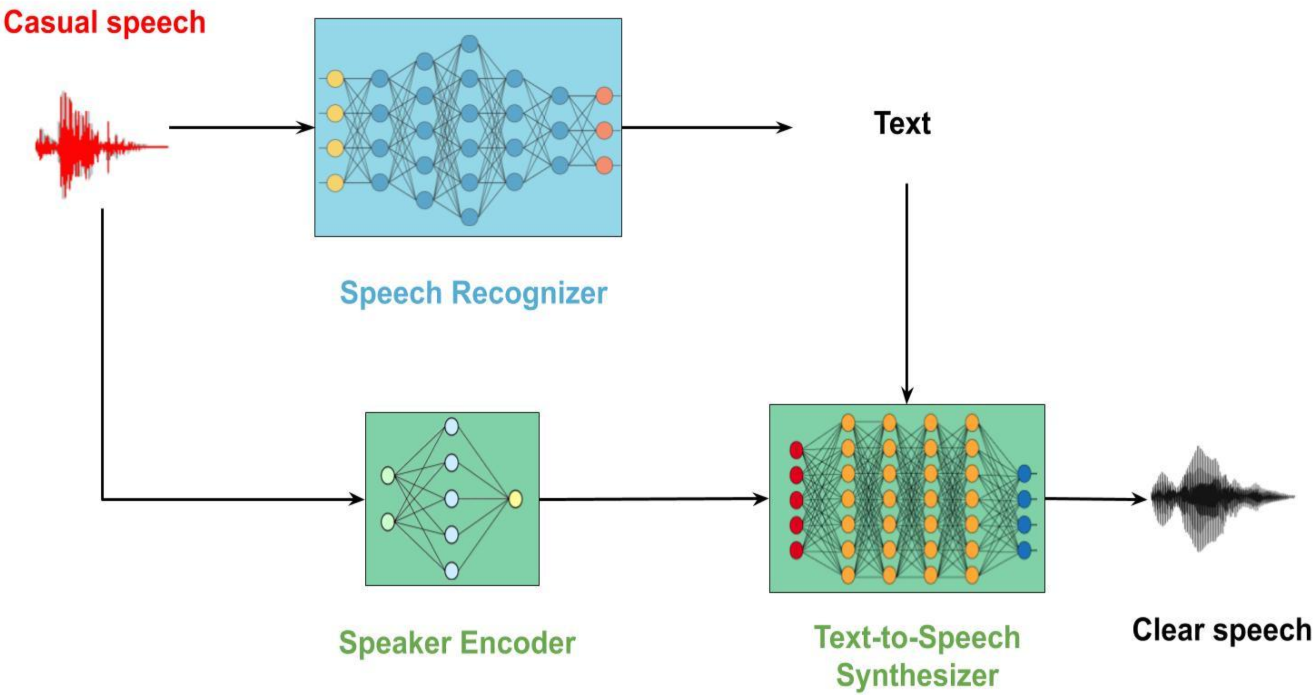
- Clear speech is a speaking style adopted by speakers in an attempt to maximize the clarity of their speech.
- Conversational speech is produced under casual or typical circumstances when no special speaking effort is made.
- However, in the presence of a communication difficulty, humans adopt different speaking styles.

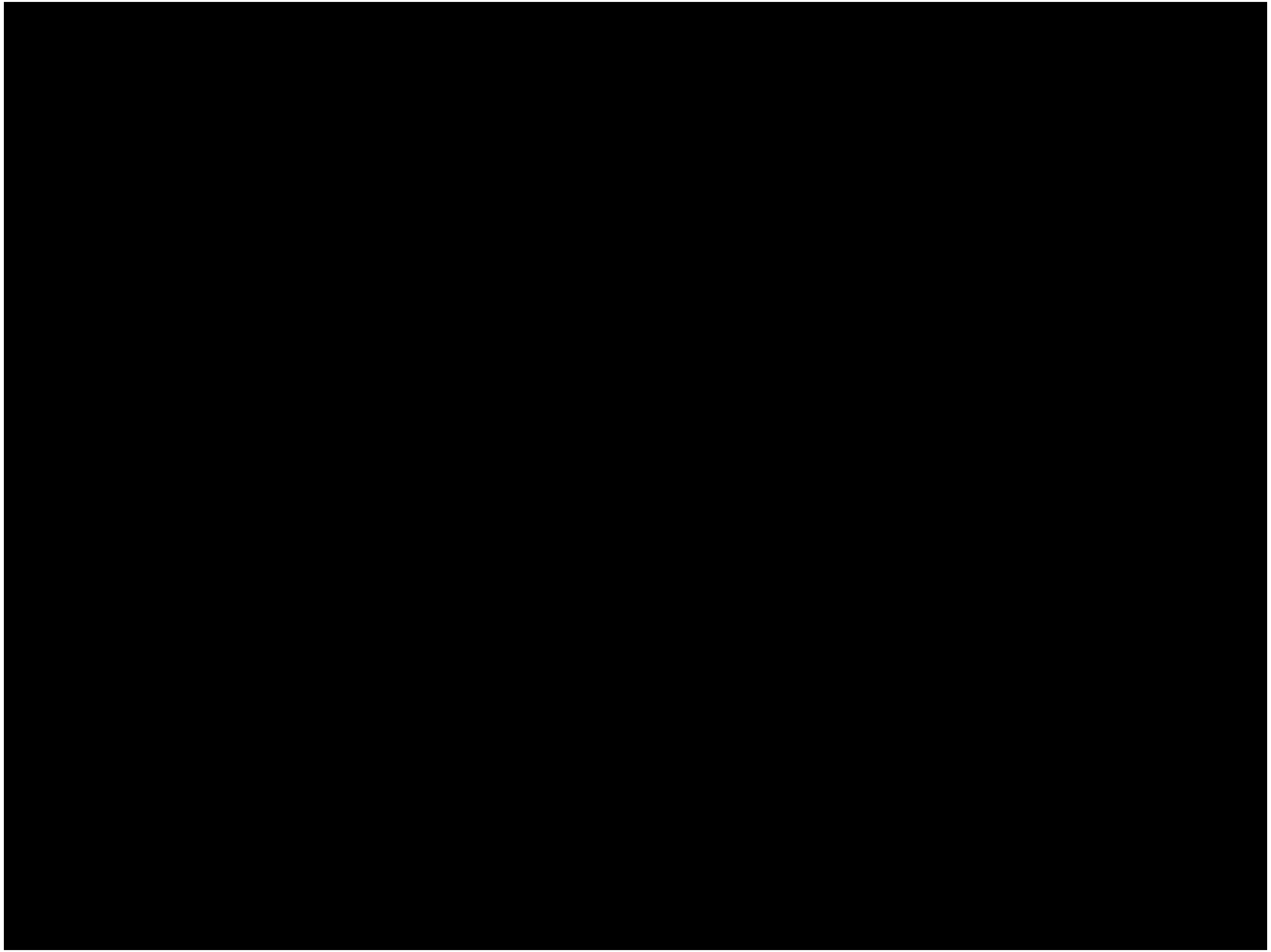
Clear and Conversational speech

- The speaking style they adopt depends mostly on the communication barrier they want to overcome in order to communicate.



System Design





Sound Samples

http://ixion.csd.uoc.gr/shifaspv/listest/index.php?n=Main.Icassp-show-tell