CDiffuSE:
Conditional Diffusion Probabilistic Model for Speech Enhancement

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Meta

Introduction

- We formulate a generalized conditional diffusion probabilistic model that incorporates the observed noisy data into the model.
- We derive the corresponding conditional diffusion and reverse processes as well as the evidence lower bound (ELBO) optimization criterion
- In our experiment, conditional diffusion model not only improve over the vanilla diffusion model, but also outperform other generative models.

1

Denoising Diffusion Probabilistic Model

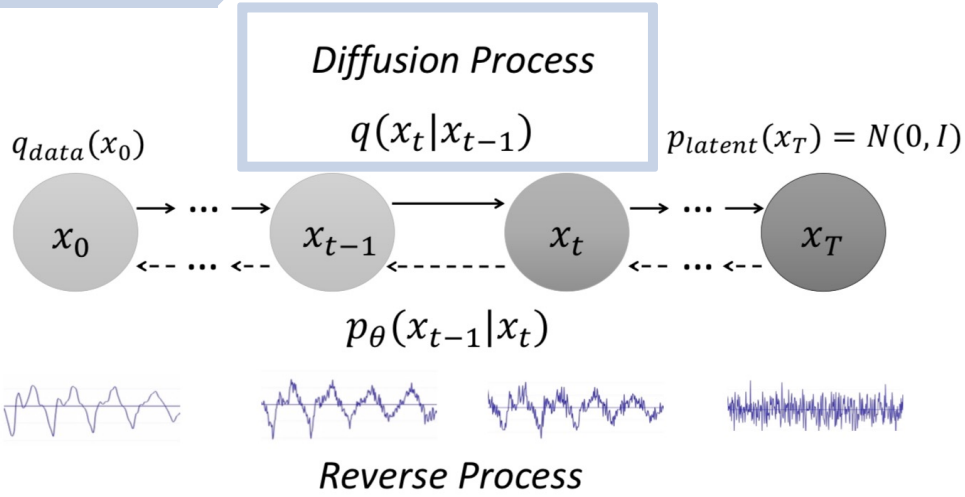
DDPM

Diffusion Probabilistic Model

Diffusion Markov process

Combines Gaussian noise into the clean speech x_0.

$$q(x_1, \cdots, x_T|x_0) = \prod_{t=1}^{T} q(x_t|x_{t-1}),$$



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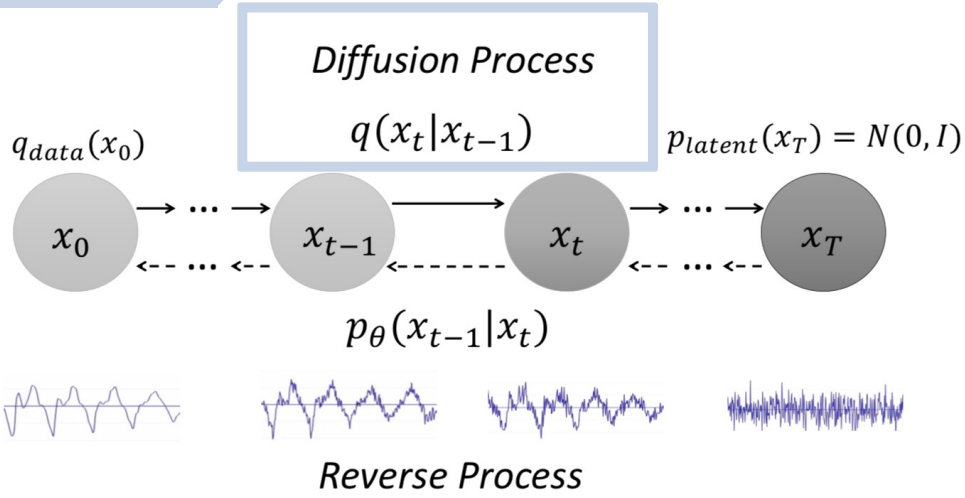
Diffusion step:

$$q(x_t|x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t I),$$



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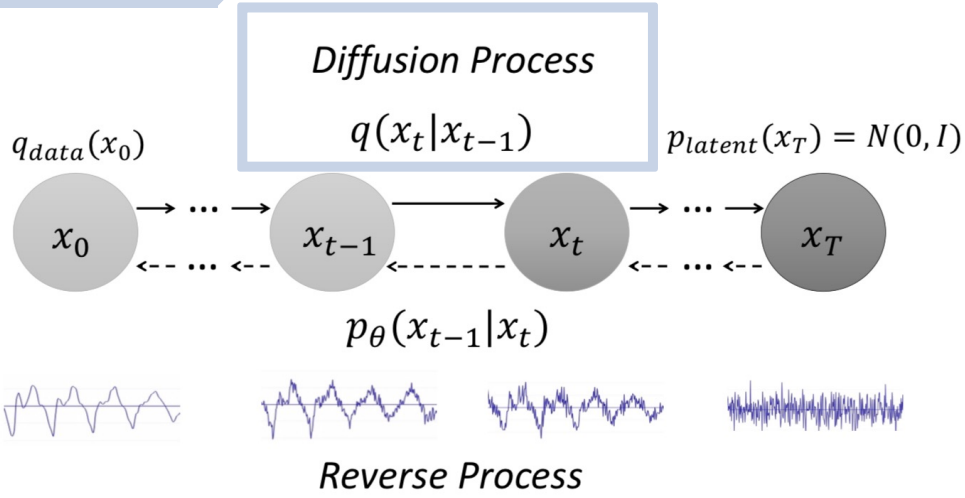


Marginalized diffusion step:

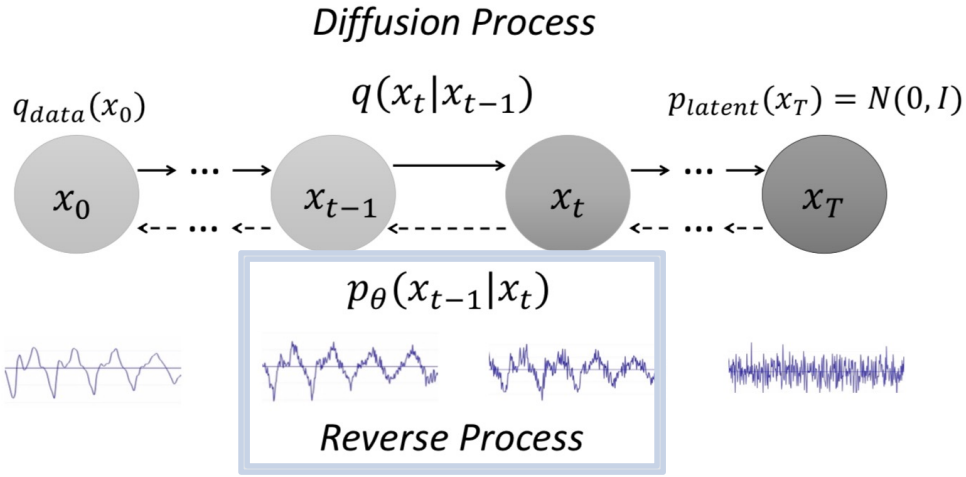
$$q(x_t|x_0) = \mathcal{N}(x_t; \sqrt{\bar{\alpha}_t}x_0, (1-\bar{\alpha}_t)I), \quad \text{where } \alpha_t = 1-\beta_t \text{ and } \bar{\alpha}_t = \prod_{s=1}^{t} \alpha_s.$$

Diffusion Probabilistic Model

Reverse Markov process

Estimates the clean speech x_0 from Gaussian noise x_T.

$$p_\theta(x_0, \cdots, x_{T-1}|x_T) = \prod_{t=1}^{T} p_\theta(x_{t-1}|x_t),$$



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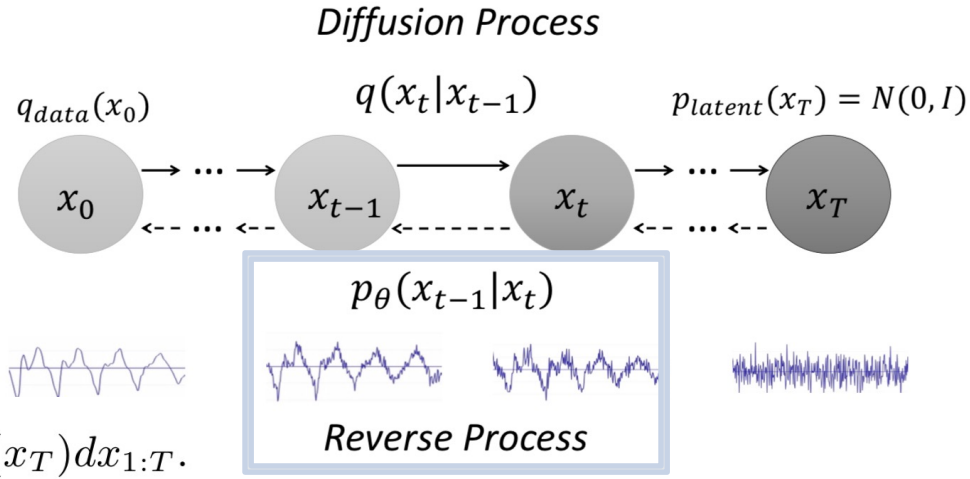
Intractable marginal likelihood:

$$p_\theta(x_0) = \int p_\theta(x_0, \cdots, x_{T-1}|x_T) \cdot p_{\text{latent}}(x_T) dx_{1:T}.$$



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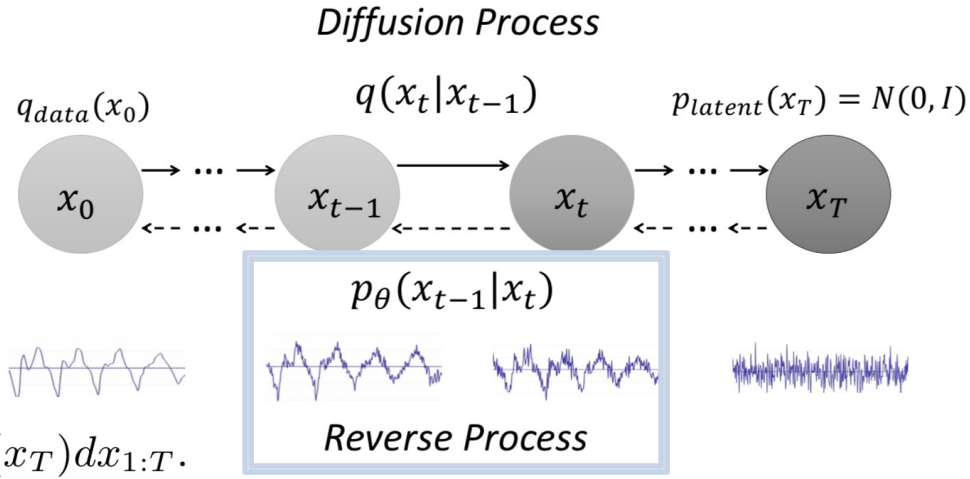
ELBO as Optimization target:

$$-\mathbb{E}_q \left(\text{KL}\left(q(x_T|x_0) \| p_{\text{latent}}(x_T)\right) + \sum_{t=2}^{T} \text{KL}\left(q(x_{t-1}|x_t, x_0) \| p_\theta(x_{t-1}|x_t)\right) - \log p_\theta(x_0|x_1) \right)$$



Diffusion Probabilistic Model

Diffusion Process (Training)

Training neural network to reduce the loss from ELBO

$$c + \sum_{t=1}^{T} \kappa_t \mathbb{E}_{x_0,\epsilon} \parallel \epsilon - \epsilon_\theta(\sqrt{\bar{\alpha}_t} x_0 + \sqrt{1-\bar{\alpha}_t}\epsilon, t) \parallel_2^2,$$

Neural Network

Model ε_θ takes x_t and t as input to estimate noise ε in x_t.

c and κ_t: constants

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Reverse Process (Sampling)

Predict μ_θ, mean of the previous distribution x_{t-1} by removing ε_θ from the x_t sample.

$$p_\theta(x_{t-1}|x_t) = \mathcal{N}(x_{t-1}; \mu_\theta(x_t, t), \tilde{\beta}_t I),$$

$$\mu_\theta(x_t, t) = \frac{1}{\sqrt{\alpha_t}}(x_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon_\theta(x_t, t)).$$

θ:the parameters of the neural network.
$\tilde{\beta}_t$: the variance of $q(x_{t-1}|x_t, x_0)$

2

Conditional Diffusion Probabilistic Model

CDPM

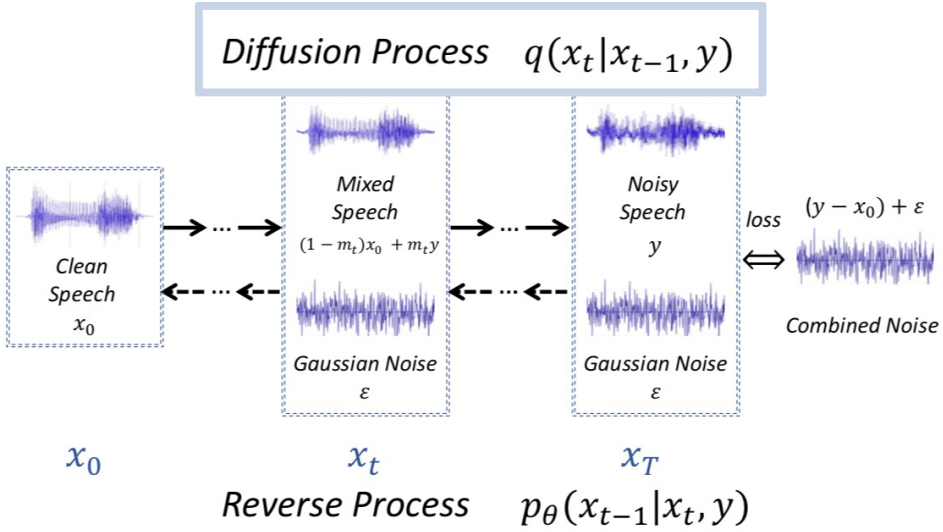
Conditional Diffusion Probabilistic Model

- Vanilla diffusion probabilistic model generates clean speech signal x_0 from Gaussian noise ε.
- Generalized conditional diffusion probabilistic model incorporates the observed noisy data into the model.
- Generate speech signal x_0 from the mixture of Gaussian noise ε and noisy speech y.

Conditional Diffusion Probabilistic Model

Conditional Diffusion Process

Starts from clean speech x_0 and gradually becomes a combination of noisy speech y and Gaussian noise ε.



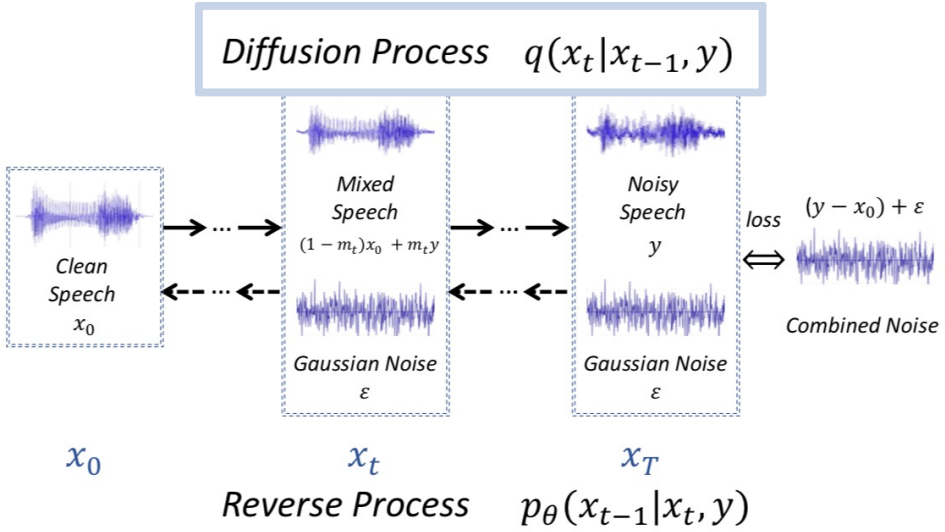
Conditional Diffusion Probabilistic Model

Conditional Diffusion Process

Starts from clean speech x_0 and gradually becomes a combination of noisy speech y and Gaussian noise ε.

$$q_{\text{cdiff}}(x_t|x_0, \text{y}) =$$

$$\mathcal{N}\left(x_t; (1-m_t)\sqrt{\bar{\alpha}_t}x_0 + m_t\sqrt{\bar{\alpha}_t}y, \delta_t I\right),$$



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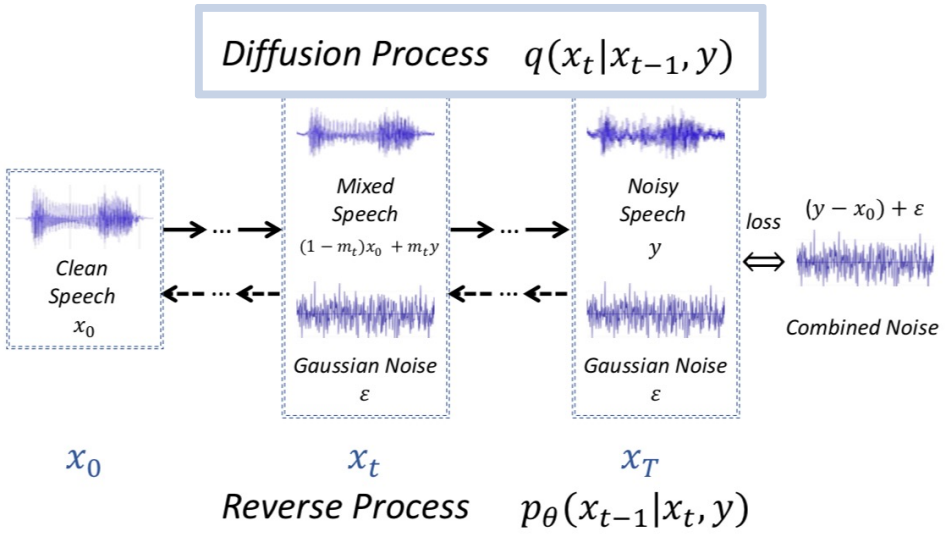
Interpolation



δ_t: the variance of x_t given x_0 and y.

m_t starts from $m_0 = 0$ and is gradually increased to $m_T \approx 1$

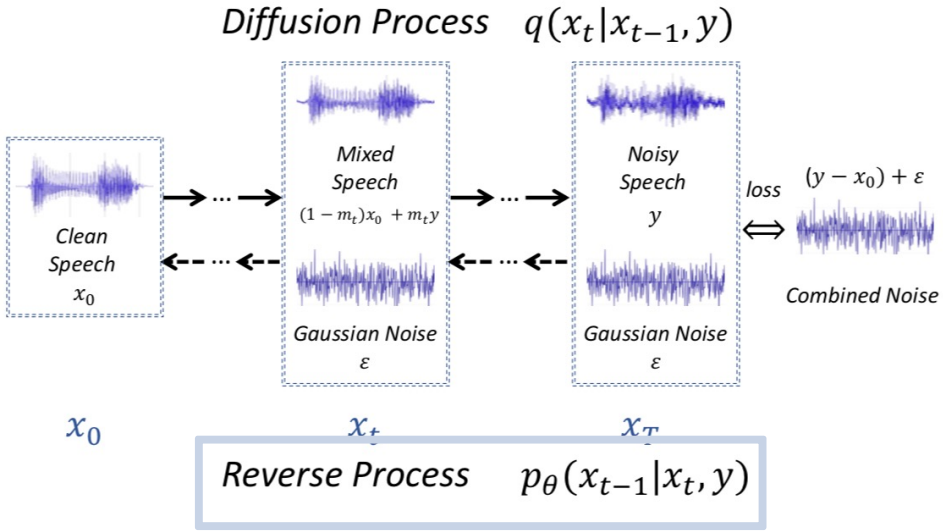
x_t starts from x_0 (clean speech) and gradually turns into $\mathcal{N}(x_T; \sqrt{\bar{\alpha}_T}y, \delta_T I)$

Conditional Diffusion Probabilistic Model

Conditional Reverse Process

Estimates x_0 from x_T, noisy speech y with variance δ_T:

$$p_{\text{cdiff}}(x_T|\text{y}) = \mathcal{N}\left(x_T; \sqrt{\bar{\alpha}_T}y, \delta_T I\right).$$



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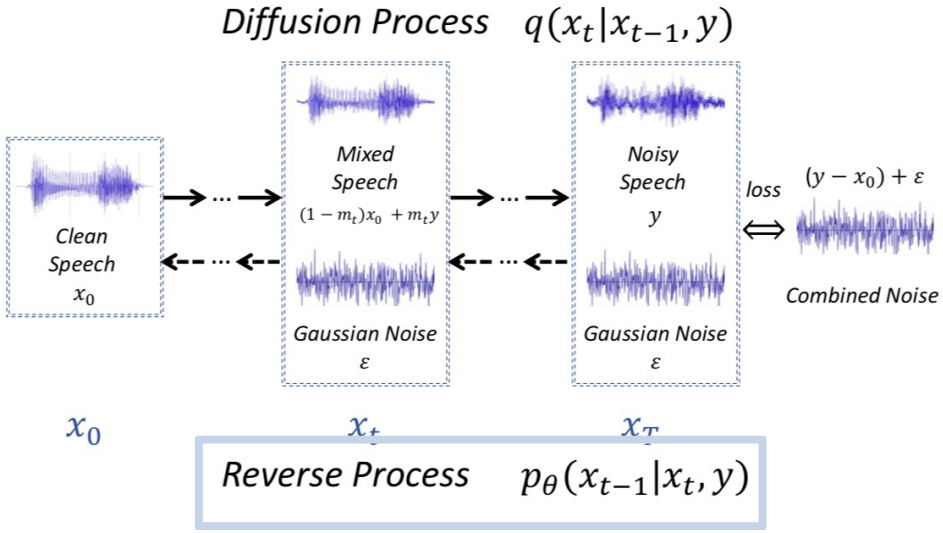
Estimates the mean of x_{t-1} from x_t, noisy speech y, and predicted noise ε_θ.

$$p_{\text{cdiff}}(x_{t-1}|x_t, \text{y}) = \mathcal{N}(x_{t-1}; c_{xt}x_t + c_{yt}y - c_{\varepsilon t}\varepsilon_\theta(x_t, y, t), \tilde{\delta}_t I)$$



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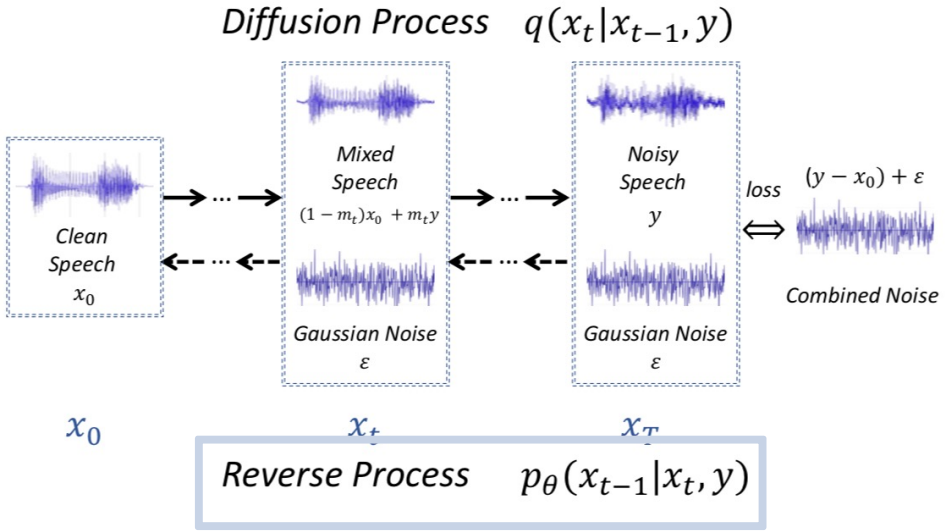

To find the c_{xt}, c_{yt}, and $c_{\epsilon t}$, which bring to the lowest ELBO for the conditional diffusion probabilistic model.

Conditional Diffusion Probabilistic Model

Optimization

To optimize the likelihood of $p_\theta(x_0)$

$$ELBO = -\mathbb{E}_q\Big(D_{\mathrm{KL}}(q_{\mathrm{cdiff}}(x_T|x_0,y)||p_{\mathrm{latent}}(x_T|y)) + \sum_{t=2}^{T} D_{\mathrm{KL}}(q_{\mathrm{cdiff}}(x_{t-1}|x_t,x_0,y)||p_\theta(x_{t-1}|x_t,y)) - \log p_\theta(x_0|x_1,y)\Big).$$

$p_\theta(x_{t-1}|x_t,y)$: Sampling Process

$q_{\mathrm{cdiff}}(x_{t-1}|x_t,x_0,y)$: Diffusion Process (opposite direction)

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$p_\theta(x_{t-1}|x_t,y)$: Sampling Process

$q_{\mathrm{cdiff}}(x_{t-1}|x_t,x_0,y)$: Diffusion Process (opposite direction)

Bayes' theorem:

$$q_{\mathrm{cdiff}}(x_{t-1}|x_t,x_0,y) = \frac{q_{\mathrm{cdiff}}(x_t|x_{t-1},x_0,y)\times q_{\mathrm{cdiff}}(x_{t-1}|x_0,y)}{q_{\mathrm{cdiff}}(x_t|x_0,y)}$$

Conditional Diffusion Probabilistic Model

Conditional Diffusion Process

Training neural network to reduce the loss from ELBO

Difference between signals **Gaussian noise**

$$c' + \sum_{t=1}^{T} \kappa_t' \mathbb{E}_{x_0,\epsilon,y} \parallel \left(\frac{m_t\sqrt{\bar{\alpha}_t}}{\sqrt{1-\bar{\alpha}_t}}(y - x_0) + \frac{\sqrt{\delta_t}}{\sqrt{1-\bar{\alpha}_t}}\epsilon\right) - \epsilon_\theta(x_t, y, t) \parallel_2^2$$

Model ε_θ estimates the combination of the signal difference $(y - x_0)$ and Gaussian noise ε in x_t mixture.

Conditional Diffusion Probabilistic Model

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Training neural network to reduce the loss from ELBO

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c' and κ_t': constants

$\widetilde{\delta_t}$: the variance of $q_{\text{cdiff}}(x_{t-1}|x_t, x_0, y)$

Conditional Reverse Process

Predict the mean of previous distribution x_{t-1} by combining y and removing ε_θ from the x_t sample.

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$$\mu_\theta(x_t, y, t) = c_{xt}x_t + c_{yt}y - c_{\epsilon t}\epsilon_\theta(x_t, y, t),$$

where

$$c_{xt} = \frac{1-m_t}{1-m_{t-1}}\frac{\delta_{t-1}}{\delta_t}\sqrt{\alpha_t} + (1-m_{t-1})\frac{\delta_{t|t-1}}{\delta_t}\frac{1}{\sqrt{\alpha_t}},$$

$$c_{yt} = (m_{t-1}\delta_t - \frac{m_t(1-m_t)}{1-m_{t-1}}\alpha_t\delta_{t-1})\frac{\sqrt{\bar{\alpha}_{t-1}}}{\delta_t},$$

$$c_{\epsilon t} = (1-m_{t-1})\frac{\delta_{t|t-1}}{\delta_t}\frac{\sqrt{1-\bar{\alpha}_t}}{\sqrt{\alpha_t}}.$$

3

Experiment Results

Matched and Mismatched Condition

Experiment Results

Table 1. Results of DiffuSE and CDiffuSE on VoiceBank.

Method	PESQ	CSIG	CBAK	COVL
Unprocessed	1.97	3.35	2.44	2.63
DiffuSE (Base) [25]	2.41	3.61	2.81	2.99
CDiffuSE (Base)	**2.44**	**3.66**	**2.83**	**3.03**
DiffuSE (Large) [25]	2.43	3.63	2.81	3.01
CDiffuSE (Large)	**2.52**	**3.72**	**2.91**	**3.10**

- CDiffuSE shows improved performance on all the metrics over the diffusion probabilistic model baseline DiffuSE.

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Table 2. Performance comparison of CDiffuSE and time-domain generative models on VoiceBank.

Method	PESQ	CSIG	CBAK	COVL
Unprocessed	1.97	3.35	2.44	2.63
SEGAN [11]	2.16	3.48	2.94	2.80
DSEGAN [32]	2.39	3.46	**3.11**	2.90
SE-Flow [15]	2.28	3.70	3.03	2.97
CDiffuSE (Base)	**2.44**	3.66	2.83	**3.03**
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- CDiffuSE shows improved performance on all the metrics over the diffusion probabilistic model baseline DiffuSE.
- CDiffuSE outperforms its competitors on all metrics with the exception of CBAK and achieves a particularly significant improvement in PESQ

Experiment Results

Table 3. Comparison of CDiffuSE and discriminative models.

(a) Trained and tested on VoiceBank (**matched** condition).

Method	PESQ	CSIG	CBAK	COVL
Unprocessed	1.97	3.35	2.44	2.63
WaveCRN [33]	2.63	3.95	3.06	3.29
Demucs* [16]	2.65/3.07	**3.99**/4.31	**3.33**/3.40	**3.32**/3.63
Conv-TasNet [34]	**2.84**	2.33	2.62	2.51
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(b) Trained on VoiceBank, tested on CHiME-4 (**mismatched** condition).

Method	PESQ	CSIG	CBAK	COVL
Unprocessed	1.27	2.61	1.93	1.88
WaveCRN [33]	1.43	2.53	2.03	1.91
Demucs* [16]	1.38	2.50	2.08	1.88
Conv-TasNet [34]	1.63	1.70	1.82	1.54
CDiffuSE (Large)	**1.66**	**2.98**	**2.19**	**2.27**

*We directly used the default setup from https://github.com/facebook-researh/denoiser to test performance, and we also copied the Demucs results in [16] to the right-side of "/" in Table 3(a).

- Generative speech enhancement models are still lagging behind the performance of their regressive counterparts.
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- Generative speech enhancement models are still lagging behind the performance of their regressive counterparts.
- Given a domain shift in test data, regression based approaches suffer from a significant drop in performance.
- CDiffuSE degrades to a much smaller degree than its regressive competitors, demonstrates its high robustness to variation in noise characteristics.

Conclusions

- We proposed conditional diffusion probabilistic model that can explore noise characteristics from the noisy input signal explicitly in real-world speech enhancement problems.
- We showed that our model is a strict generalization of the original diffusion probabilistic model and achieves state of the art results compared to other generative speech enhancement approaches.
- Our method has great generalization capabilities to speech data with noise characteristics not observed in the training data.

GitHub: https://github.com/neillu23/CDiffuSE