Vector Quantized Attention for Speech Enhancement

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Outline

- Speech Enhancement
- Methodology
- Problems
- Possible Solutions
- Schedule

Speech Enhancement

The real world is full of various background noises. These noises can pollute the speech signal and reduce the accuracy of ASR, hearing aids and other speech tasks.

However, when humans face these sounds disturbed by background noise, they can reduce the noise interference by adjusting their focus.

Speech Enhancement

It can even use its own language knowledge to recover damaged voice signals when understanding the content of the speaker.

Therefore, the research focus of this monograph will focus on how to use the attention mechanism and acoustic units to suppress the damage caused by noise and reconstruct clean speech.

Methodology

Incorporating Symbolic Sequential Modeling For Speech Enhancement

U-Net

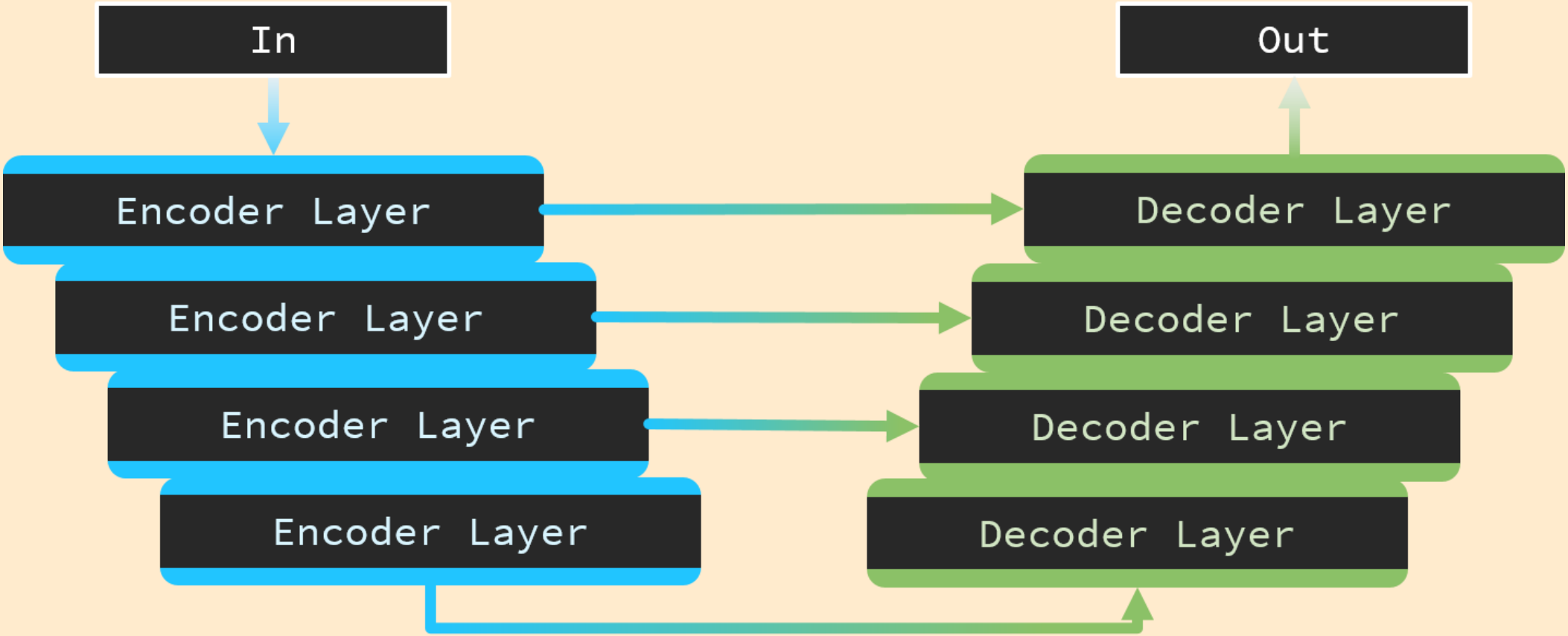
+

VQ-VAE

+

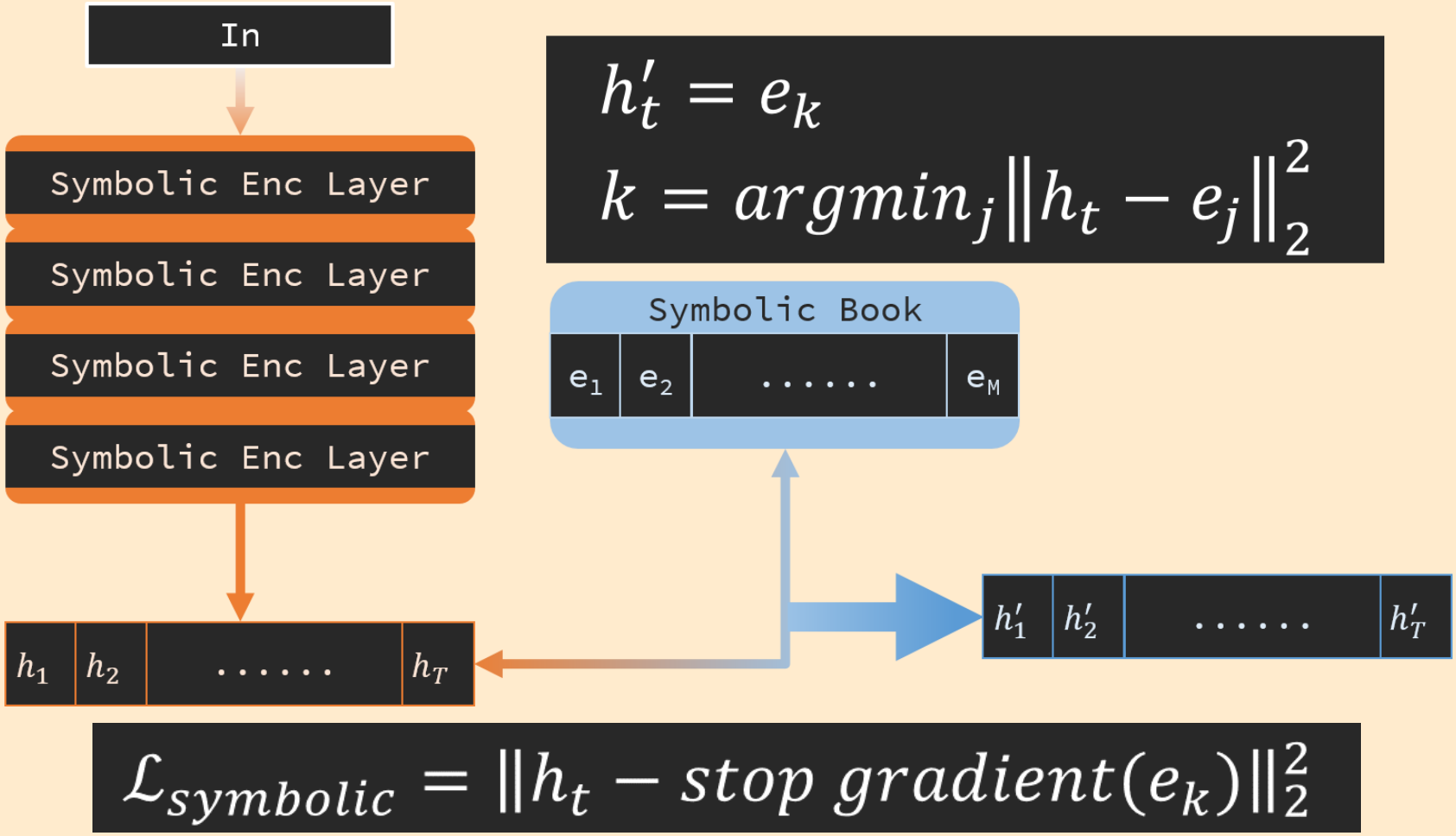
Multi Head Attention

U-Net

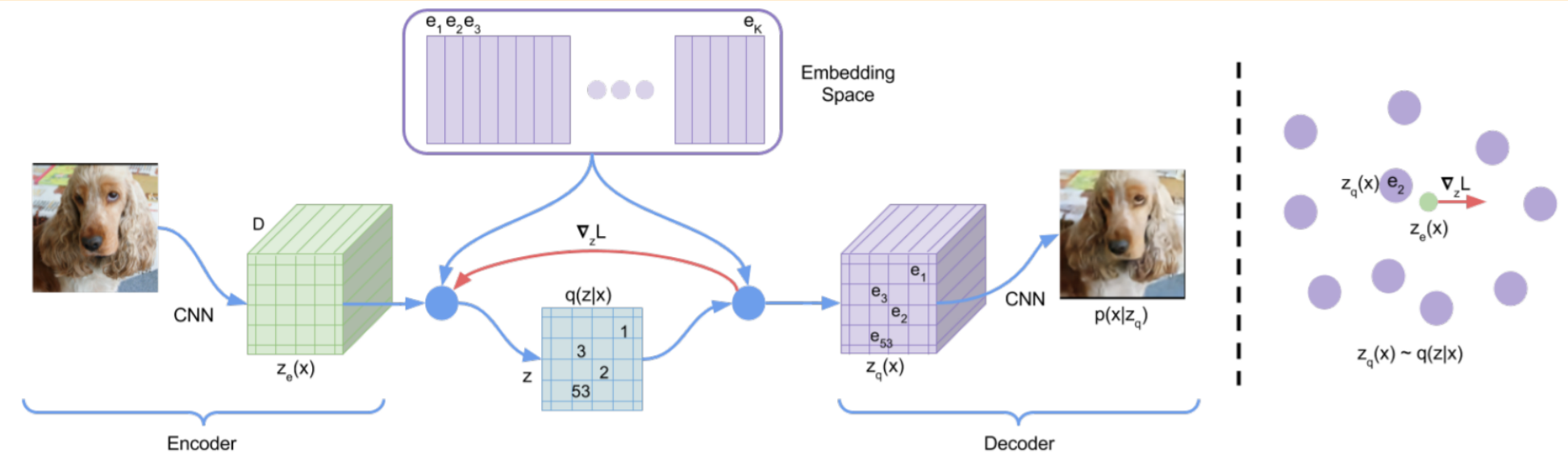


$$\mathcal{L}_{mse} = \frac{1}{N}\sum_{i=1}^{N} \left\| Dec\left(Enc(x_i)\right) - y_i \right\|_2^2$$

Symbolic Encoder



VQ-VAE

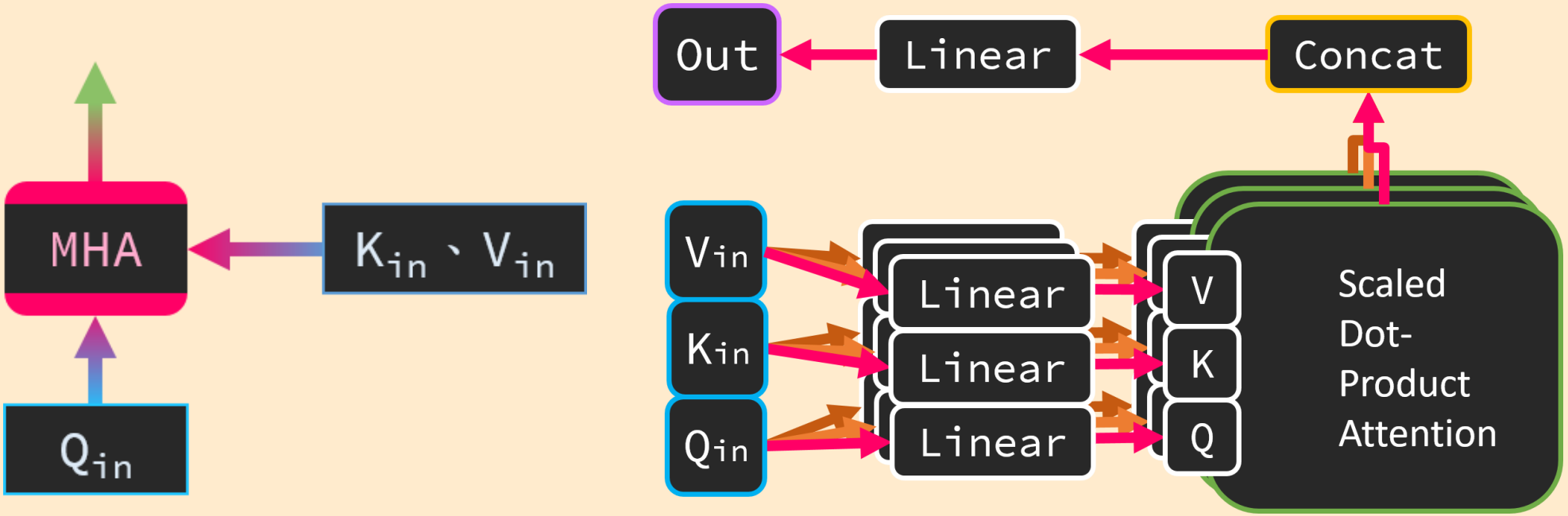


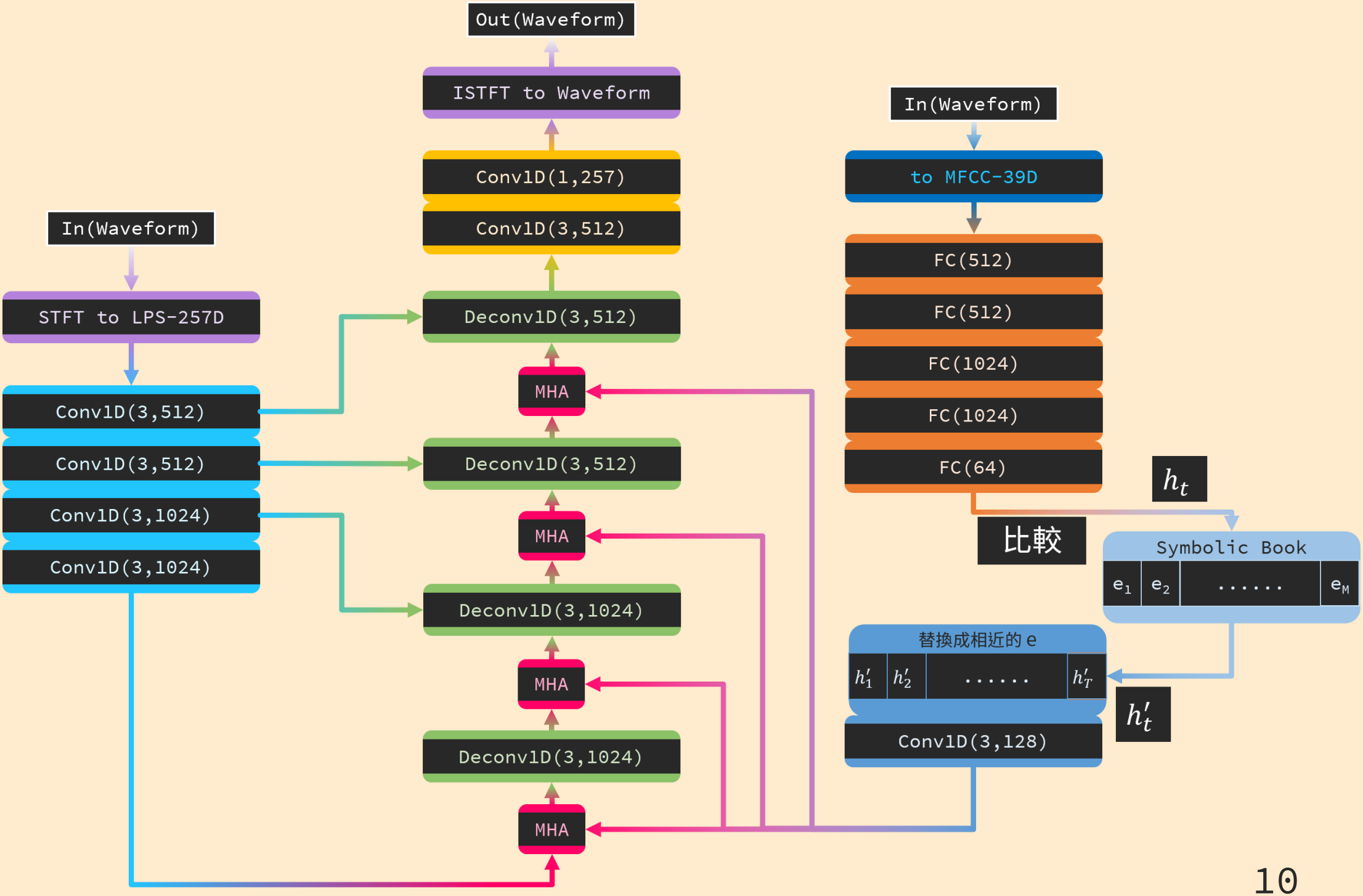
The hidden vector output by the Encoder is vector quantized before being input to the Decoder for generation.

Two-step training:

- Train Encoder-CodeBook-Decoder.
- Train Pixel CNN to generate discrete hidden variants. (Q(z|x) in the figure above)

Multi Head Attention




Out(Waveform)
ISTFT to Waveform
Conv1D(1,257)
Conv1D(3,512)
Deconv1D(3,512)
MHA
Deconv1D(3,512)
MHA
Deconv1D(3,1024)
MHA
Deconv1D(3,1024)
MHA
In(Waveform)
STFT to LPS-257D
Conv1D(3,512)
Conv1D(3,512)
Conv1D(3,1024)
Conv1D(3,1024)
In(Waveform)
to MFCC-39D
FC(512)
FC(512)
FC(1024)
FC(1024)
FC(64)
h_t
比較
Symbolic Book
e_1 e_2 ..... e_M
替換成相近的 e
h'_1 h'_2 ..... h'_T
h'_t
Conv1D(3,128)

Loss

$$\mathcal{L}_{mse} = \frac{1}{N}\sum_{i=1}^{N}\left\|Dec\left(Enc(x_i)\right) - y_i\right\|_2^2$$

$$\mathcal{L}_{symbolic} = \|h_t - stop\ gradient(e_k)\|_2^2$$

$$\mathcal{L}_{total} = \mathcal{L}_{mse} + \lambda \cdot \mathcal{L}_{symbolic}$$

Experiments

SNR	Noisy		U-Net		U-Net-MOL		Proposed (64)		Oracle	
	PESQ	STOI	PESQ	STOI	PESQ	STOI	PESQ	STOI	PESQ	STOI
-6	1.213	0.532	1.685	0.602	1.800	0.619	**1.828**	**0.624**	1.961	0.703
-3	1.353	0.598	1.880	0.669	1.974	0.681	**2.045**	**0.693**	2.140	0.741
0	1.517	0.669	2.071	0.725	2.140	0.736	**2.240**	**0.750**	2.306	0.776
3	1.702	0.739	2.237	0.770	2.290	0.779	**2.416**	**0.794**	2.456	0.806
6	1.902	0.823	2.387	0.805	2.424	0.813	**2.581**	**0.830**	2.592	0.831
Avg.	1.537	0.669	2.052	0.714	2.126	0.725	**2.222**	**0.738**	2.291	0.771

Problems

1. The experiment did not reach the desired result on the evaluation criteria of PESQ and STOI.

2. Even if the correct acoustic information is given to the Oracle model, there is not much improvement compared with the Proposed model.

Possible Solutions

- Change the current Encoder-Decoder :
  Even if the correct acoustic information is used, it cannot bring significant improvement.
  Indicates that the current Encoder-Decoder may not be able to extract important information.

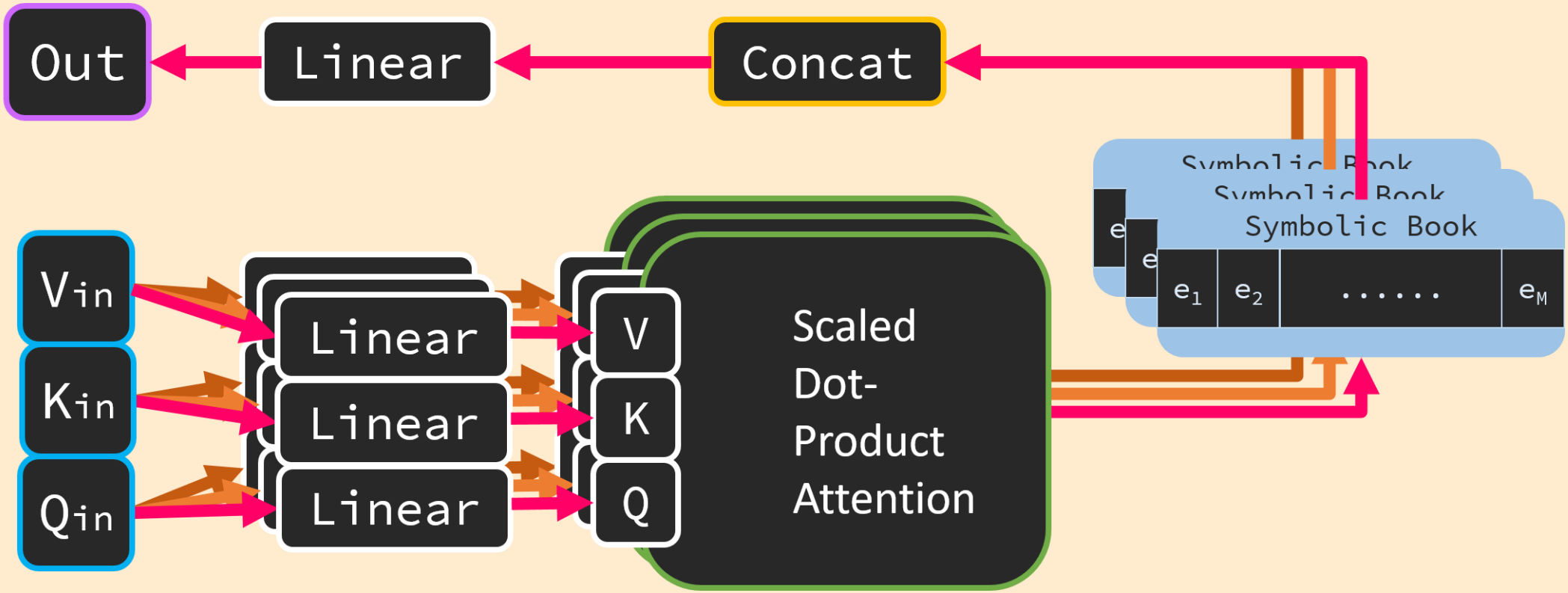
Possible Solutions

- Use the multi-layer (multi-resolution) of VQ-VAE 2 to try to preserve the sound characteristics of different fineness.

Challenge

- Calculate from Time Domain.
- Use Phase information.

MVQHA


Out
Linear
Concat
Symbolic Book
Symbolic Book
Symbolic Book
e
e
e1
e2
.....
eM
Vin
Kin
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Linear
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Scaled
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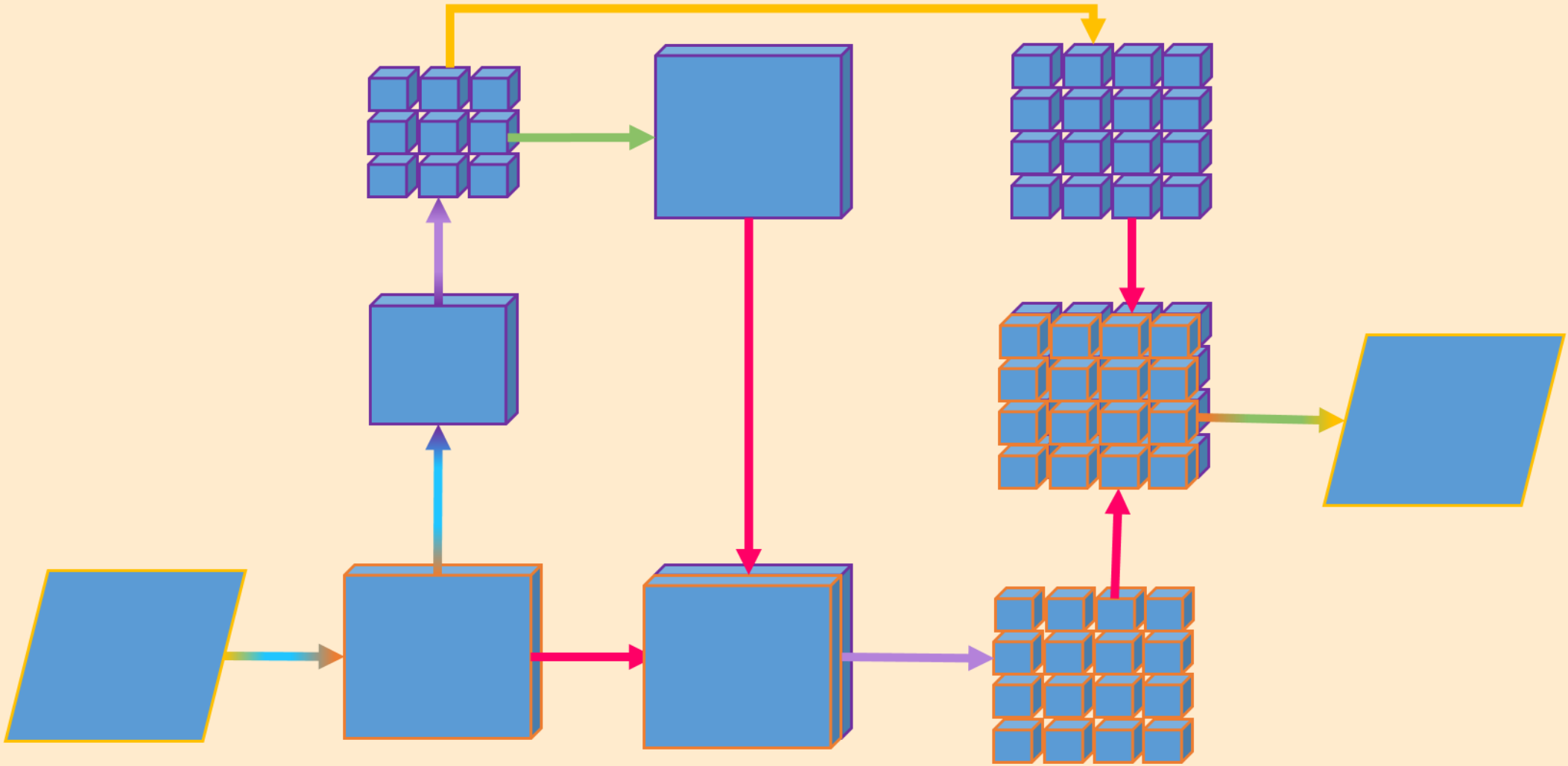
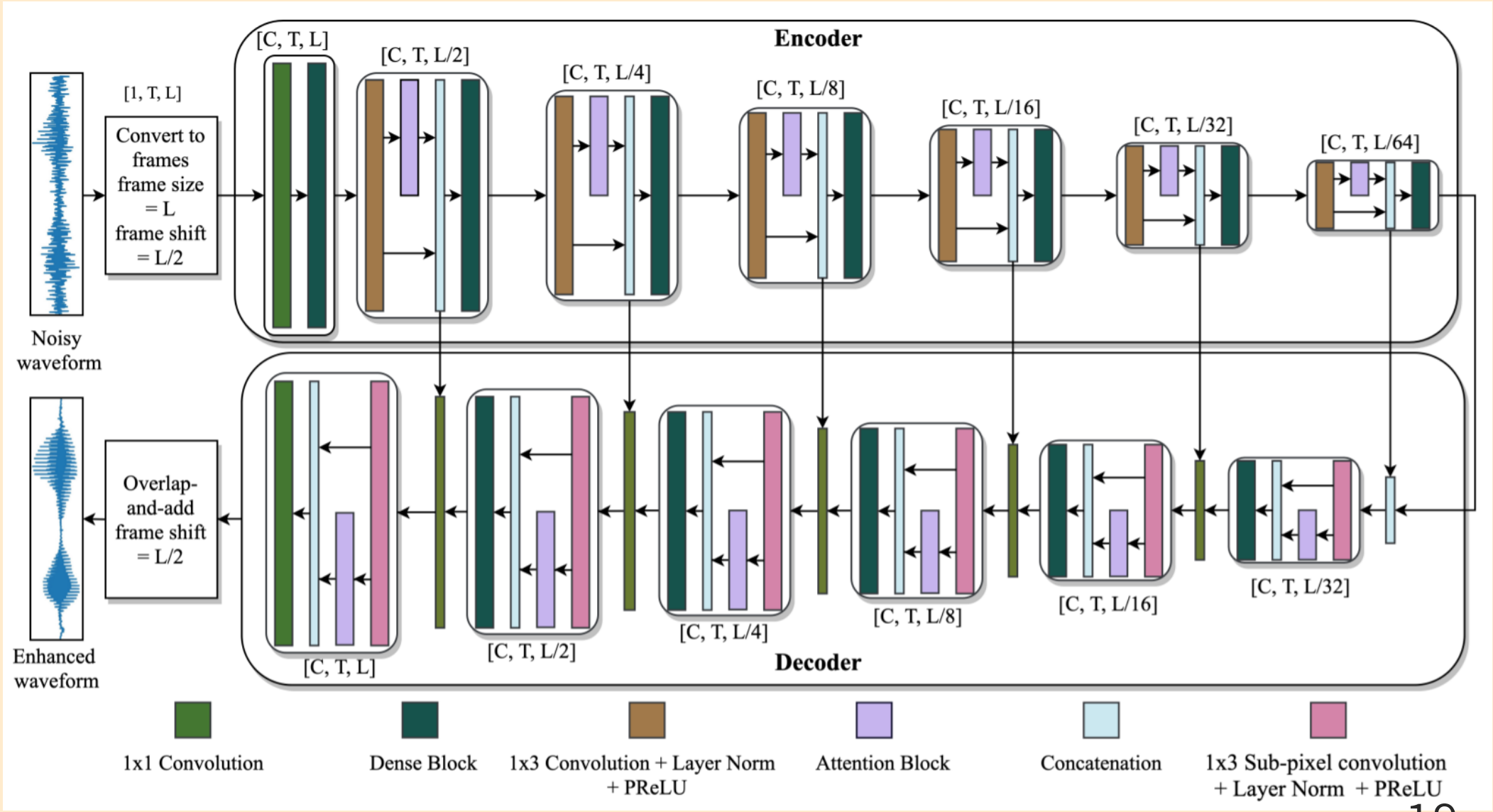
Product
Attention

VQ-VAE2



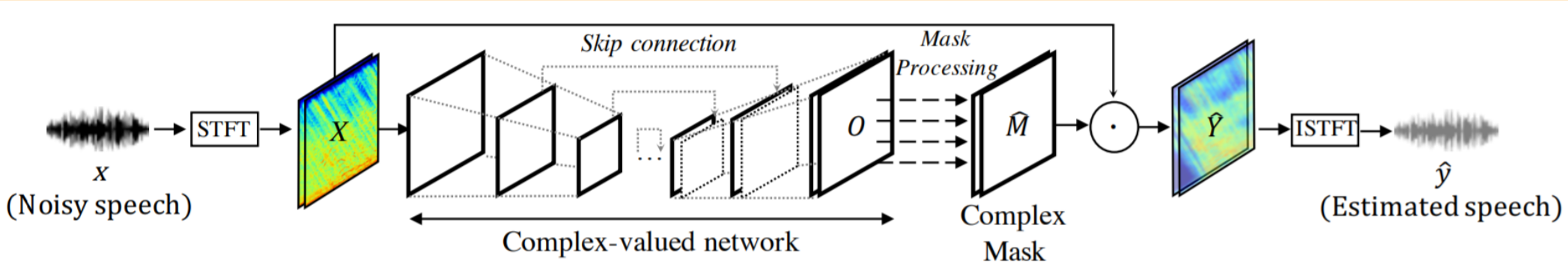
Possible Solutions

Dense CNN

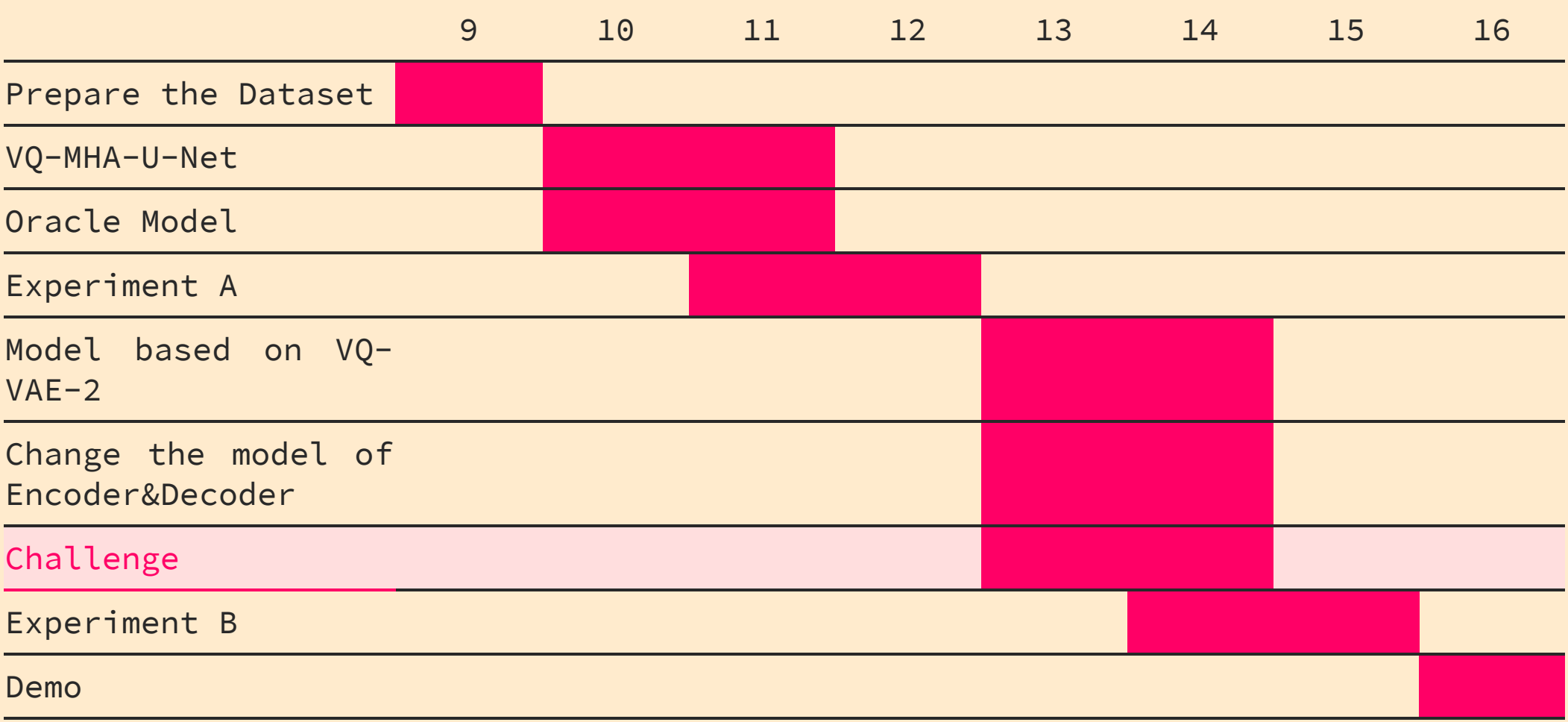


Deep Complex U-Net

Phase-Aware Speech Enhancement with Deep Complex U-Net



Schedule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Prepare the Dataset
VQ-MHA-U-Net
Oracle Model
Experiment A
Model based on VQ-VAE-2
Change the model of Encoder&Decoder
Challenge
Experiment B
Demo