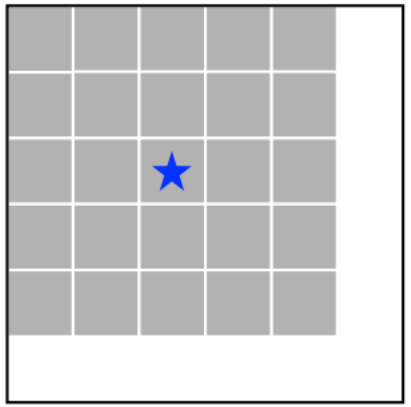
Conformer: Convolution-augmented Transformer for Speech Recognition

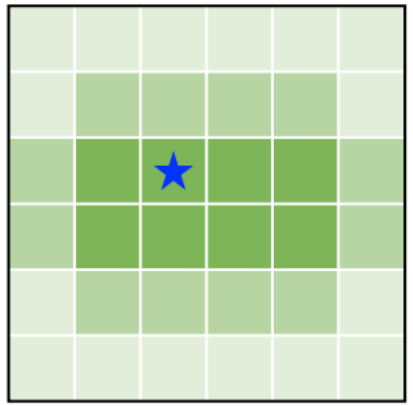
CNN vs Transformer(MHSA)

CNN



(c) large kernel

Attention



(a) global attention

Speech 영역에서 **Transformer model**은 다른 도메인과 마찬가지로 **Long range dependency**와 **training efficiency**로 성공을 거뒀다.

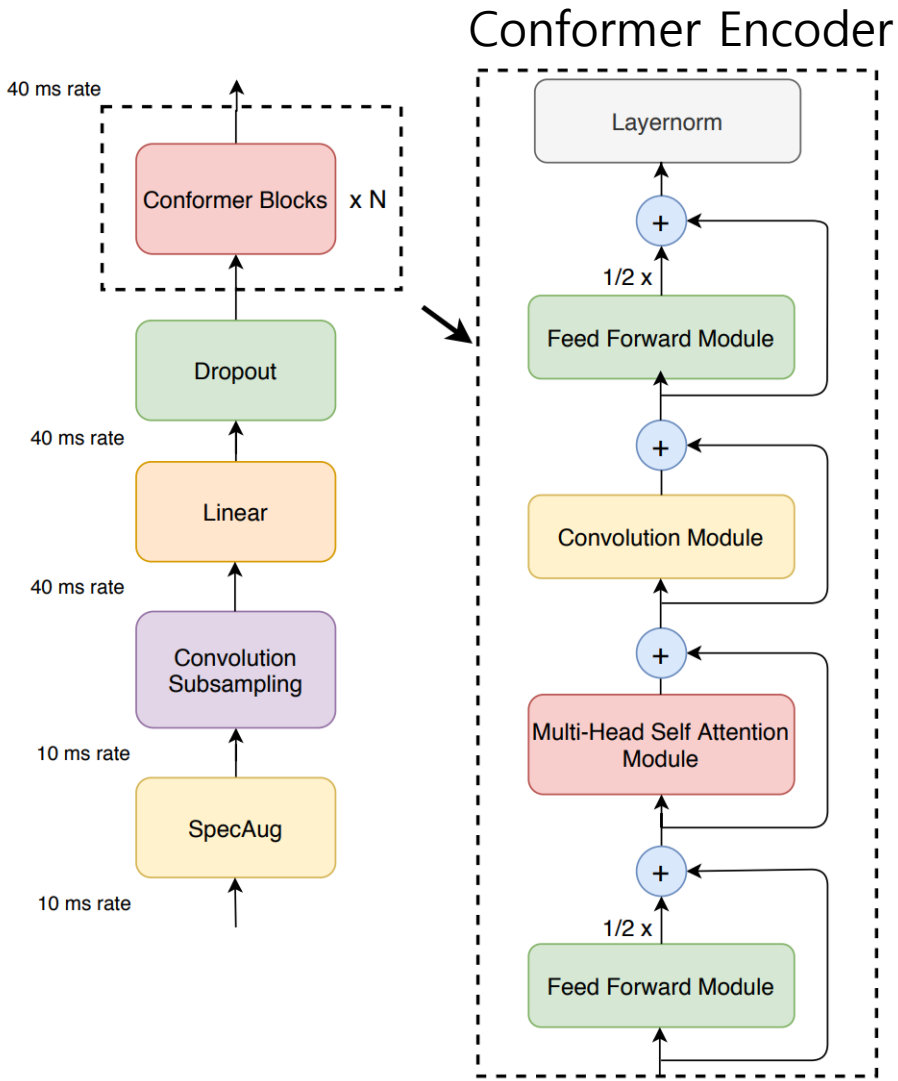
CNN역시 **local context**를 점진적으로 capture하기 때문에 ASR에서 성공을 거뒀다.

그러나 위의 두 모델은 각각의 단점이 있다.

Transformer는 **long range global context extraction**에 좋지만, **fine grained local feature patterns extraction**에는 성능이 좋지 않다.

CNN은 **local information extraction** 성능이 좋고, kernel을 사용하기 때문에 **translation equivariance**를 유지하며 **edge**나 **shape**을 뽑아낼 수 있지만, **global information**을 capture하기 위해서는 더 깊은 Layer나 parameter가 필요해진다.

Conformer

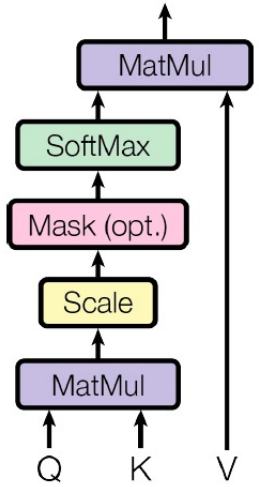


- CNN과 Transformer는 결국 각각의 문제를 가지고 있다.
- 우리는 global contex와 local context의 상호작용이 parameter efficient를 위해 중요할 것이라는 가설을 세웠다.
- 그래서 이것을 해결하기 위해 CNN과 self-attention을 섞어버렸다.

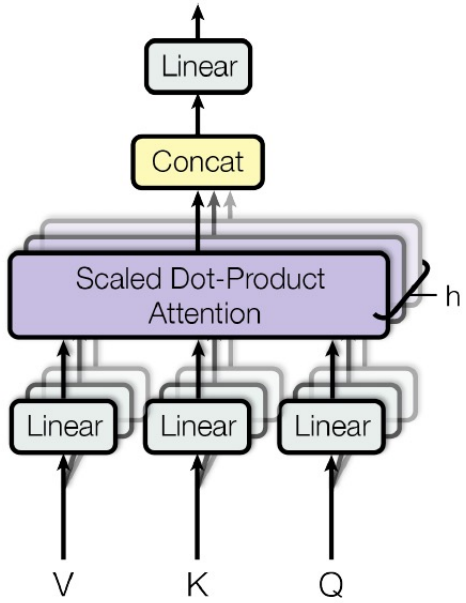
Conformer Encoder

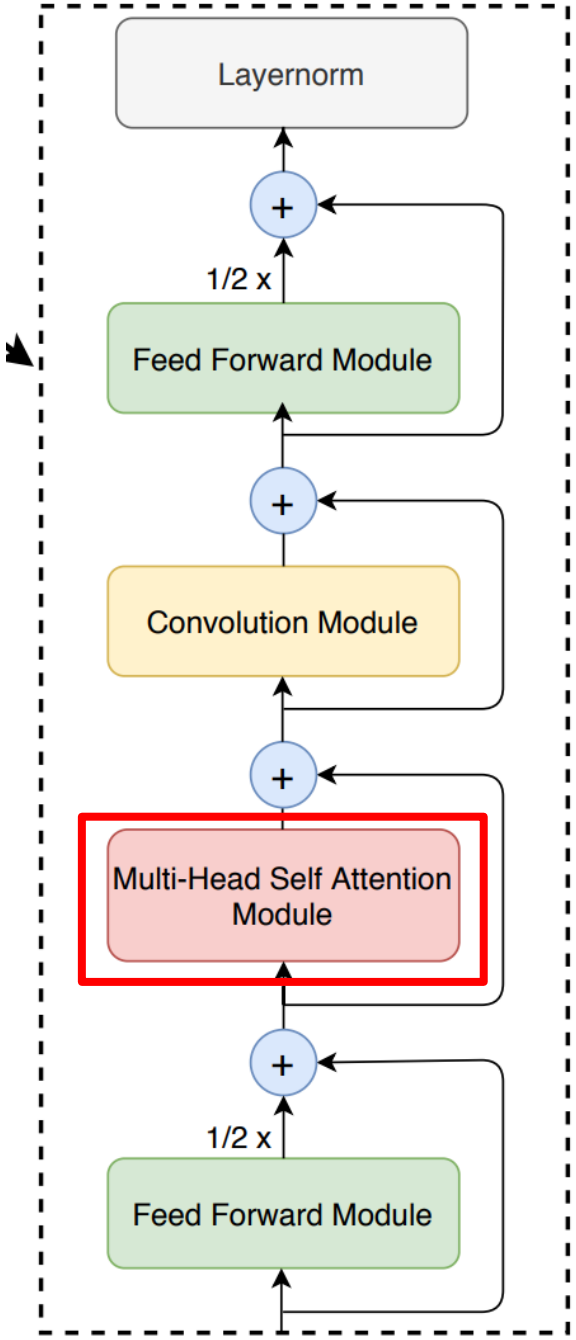
1. Multi-Head Self-Attention Module

Scaled Dot-Product Attention



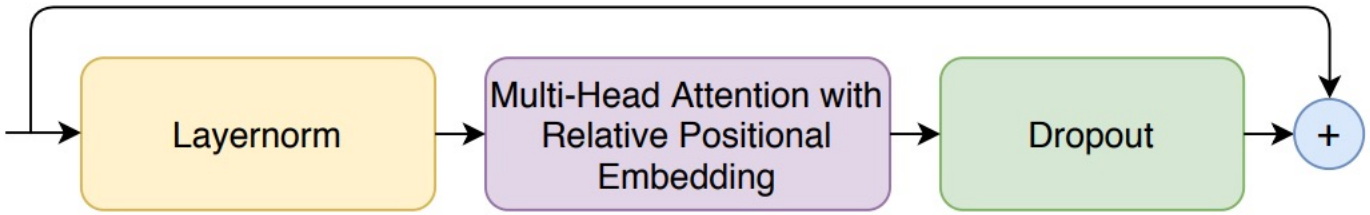
Multi-Head Attention





Conformer Encoder

1. Multi-Head Self-Attention Module



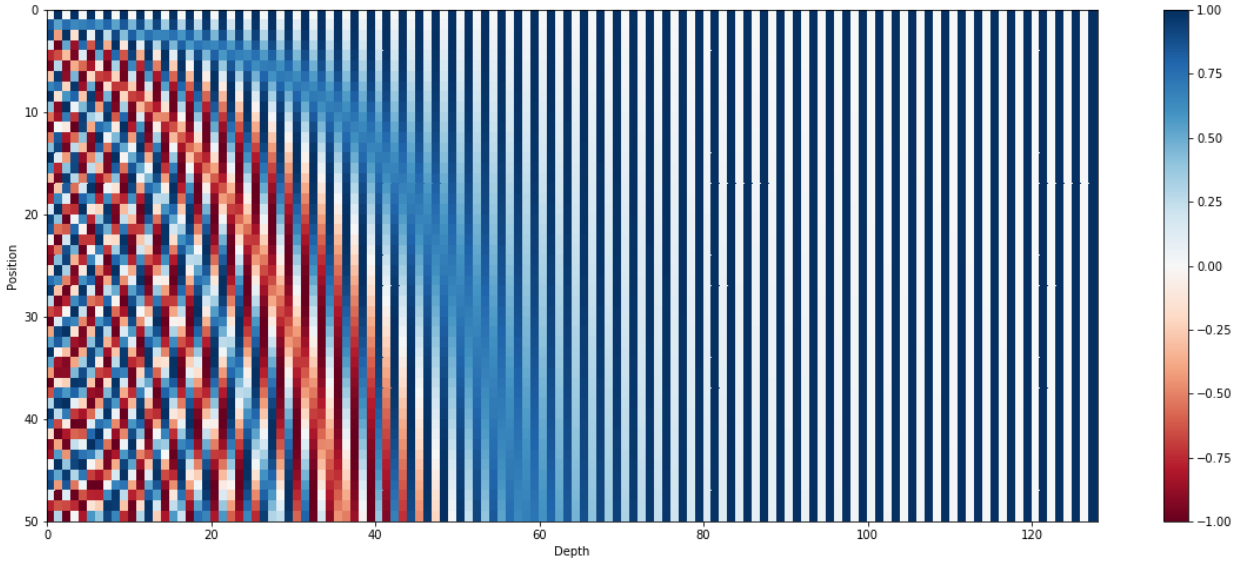
연산 전에 norm을 사용하는 pre-norm을 이용했고,
relative positional encoding을 통해서 length가 다른 Input에도 general하게 작용할 수 있게 했다.

Conformer Encoder

1-1. 기존 Positional Encoding

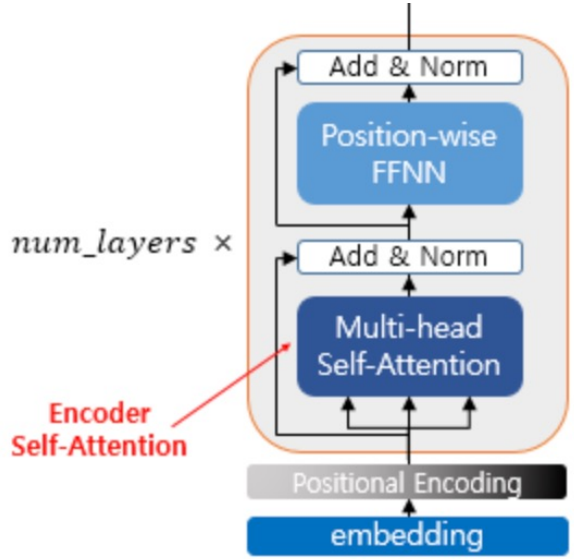
$$\overrightarrow{p_t}^{(i)} = f(t)^{(i)} := \begin{cases} \sin(\omega_k . t), & \text{if } i = 2k \\ \cos(\omega_k . t), & \text{if } i = 2k+1 \end{cases}$$

$$\omega_k = \frac{1}{10000^{2k/d}}$$

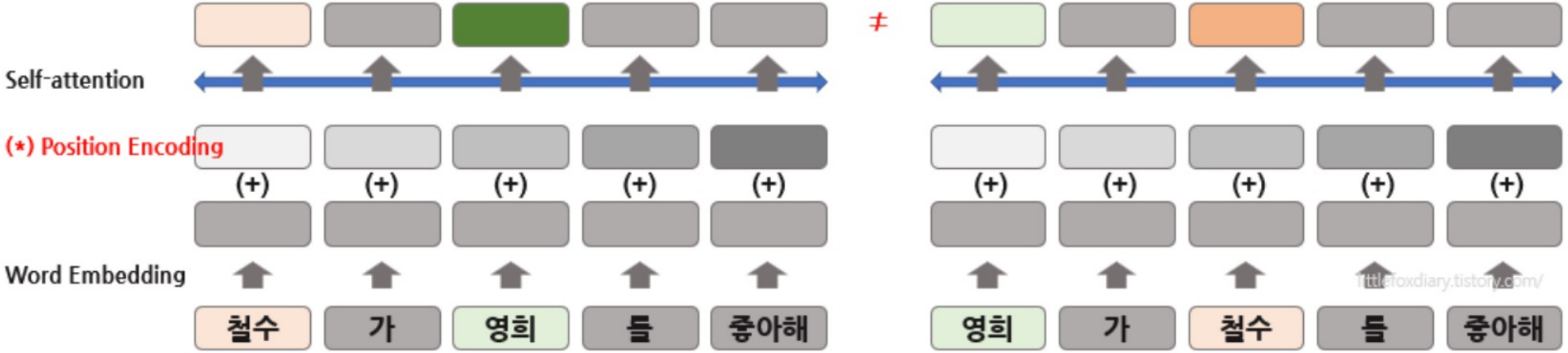


Conformer Encoder

1-1. 기존 Positional Encoding



(b) 위치 인코딩을 더해줌으로써 단어 시퀀스 정보를 줄 수 있고, 아래의 두 문장은 다른 representation을 가짐



Conformer Encoder

1-2. Relative Positional Encoding

인풋 시퀀스 512인 문장에 대해 Self-attention 상황을 가정하면, relative position은 다음과 같이 구할 수 있다.

첫 번째 토큰을 기준으로 마지막 토큰은 511만큼 뒤에 있음

```
tensor([[   0,    1,    2,    3,    4,  ...,  507,  508,  509,  510,  511],
        [  -1,    0,    1,    2,    3,  ...,  506,  507,  508,  509,  510],
        [  -2,   -1,    0,    1,    2,  ...,  505,  506,  507,  508,  509],
        [  -3,   -2,   -1,    0,    1,  ...,  504,  505,  506,  507,  508],
        [  -4,   -3,   -2,   -1,    0,  ...,  503,  504,  505,  506,  507],
        ...,
        [-507, -506, -505, -504, -503,  ...,    0,    1,    2,    3,    4],
        [-508, -507, -506, -505, -504,  ...,   -1,    0,    1,    2,    3],
        [-509, -508, -507, -506, -505,  ...,   -2,   -1,    0,    1,    2],
        [-510, -509, -508, -507, -506,  ...,   -3,   -2,   -1,    0,    1],
        [-511, -510, -509, -508, -507,  ...,   -4,   -3,   -2,   -1,    0]])
```

마지막 토큰을 기준으로 첫 번째 토큰은 511만큼 앞에 있음

자기 자신과의 거리는 0

Conformer Encoder

1-2. Relative Positional Encoding

이제 이 relative position을 _relative_position_bucket에 대입하면 **상대적인 거리에 따른 버킷** 값을 얻을 수 있다.

Conformer Encoder

1-2. Relative Positional Encoding

기존 Self-Attetnion
Positional Encoding은 사전에 더해짐

$$z_i = \sum_{j=1}^{n} \alpha_{ij}(x_j W^V)$$

input and output

$$\alpha_{ij} = \frac{\exp e_{ij}}{\sum_{k=1}^{n} \exp e_{ik}}$$

softmax function

$$e_{ij} = \frac{(x_i W^Q)(x_j W^K)^T}{\sqrt{d_z}}$$

attention score

Relative positional encoding은
Attention 계산에 직접 encoding 반영
(a_ij)

$$z_i = \sum_{j=1}^{n} \alpha_{ij}(x_j W^V + a_{ij}^V)$$

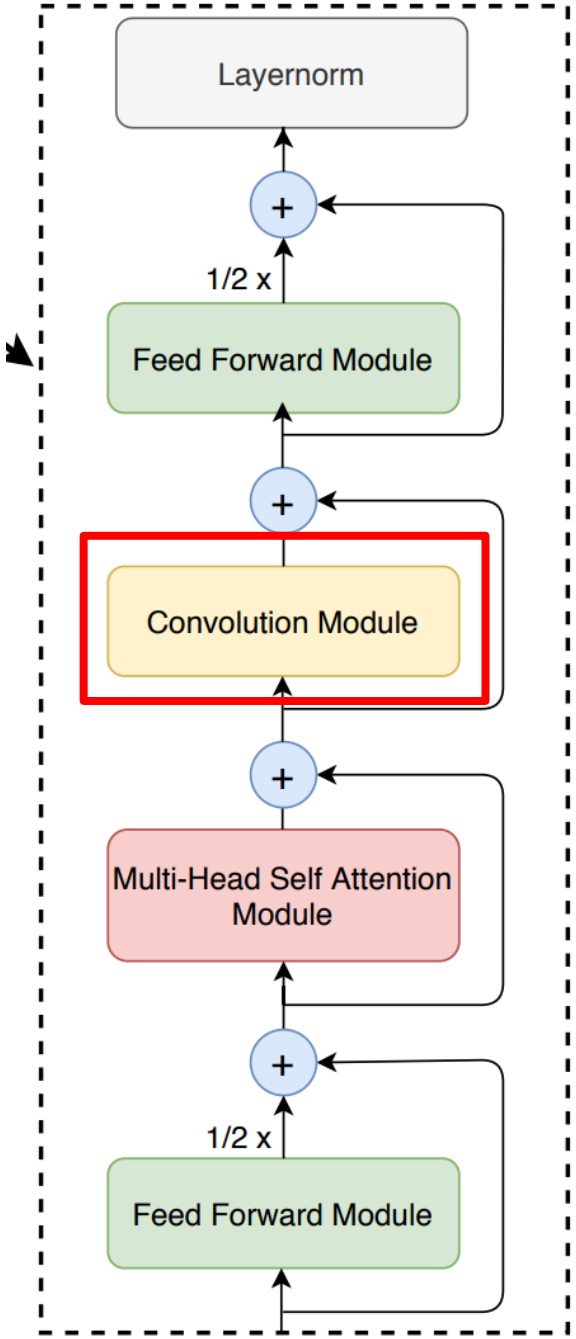
new input and output

$$e_{ij} = \frac{x_i W^Q (x_j W^K + a_{ij}^K)^T}{\sqrt{d_z}}$$

new attention score

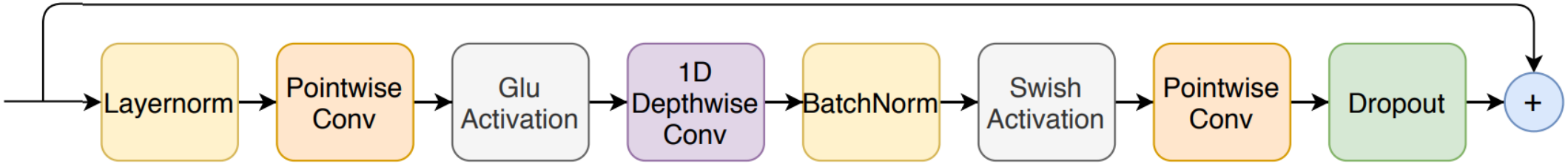
Conformer Encoder

2. Convolution Module



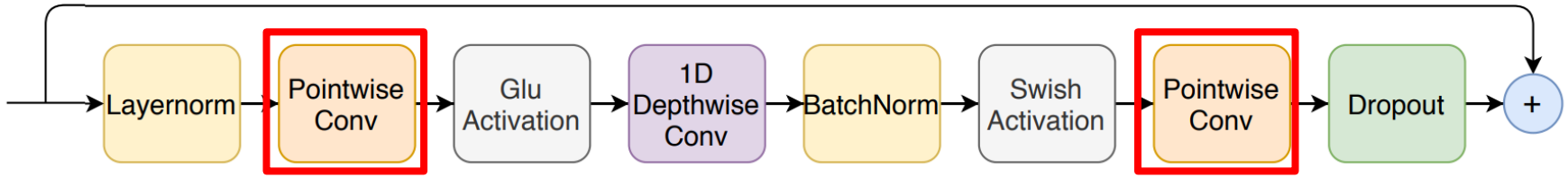
Conformer Encoder

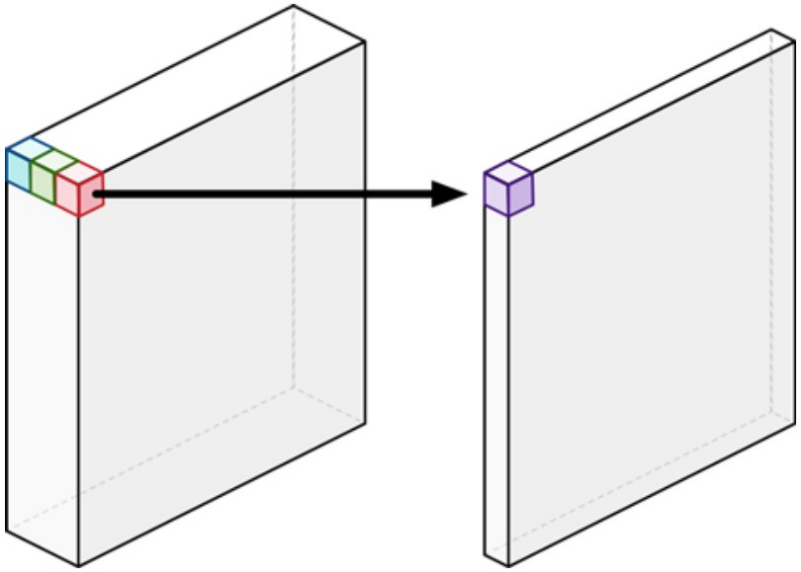
2. Convolution Module



Conformer Encoder

2. Convolution Module





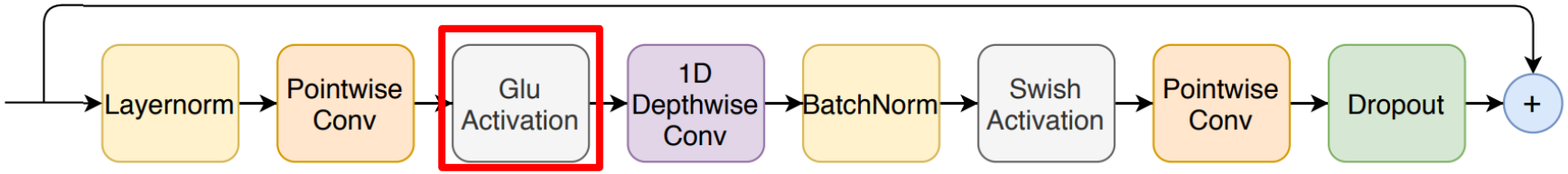
Filter 수 조절 가능

Bottleneck 구조로 연산 효율화 가능

Filter수를 줄이고 연산 후 다시 Filter 늘리기

Conformer Encoder

2. Convolution Module



Gated Linear Unit

It is used in natural language processing architectures, for example the Gated CNN, because here b is the gate that control what information from a is passed up to the following layer. Intuitively, for a language modeling task, the gating mechanism allows selection of words or features that are important for predicting the next word. The GLU also has non-linear capabilities, but has a linear path for the gradient so diminishes the vanishing gradient problem.

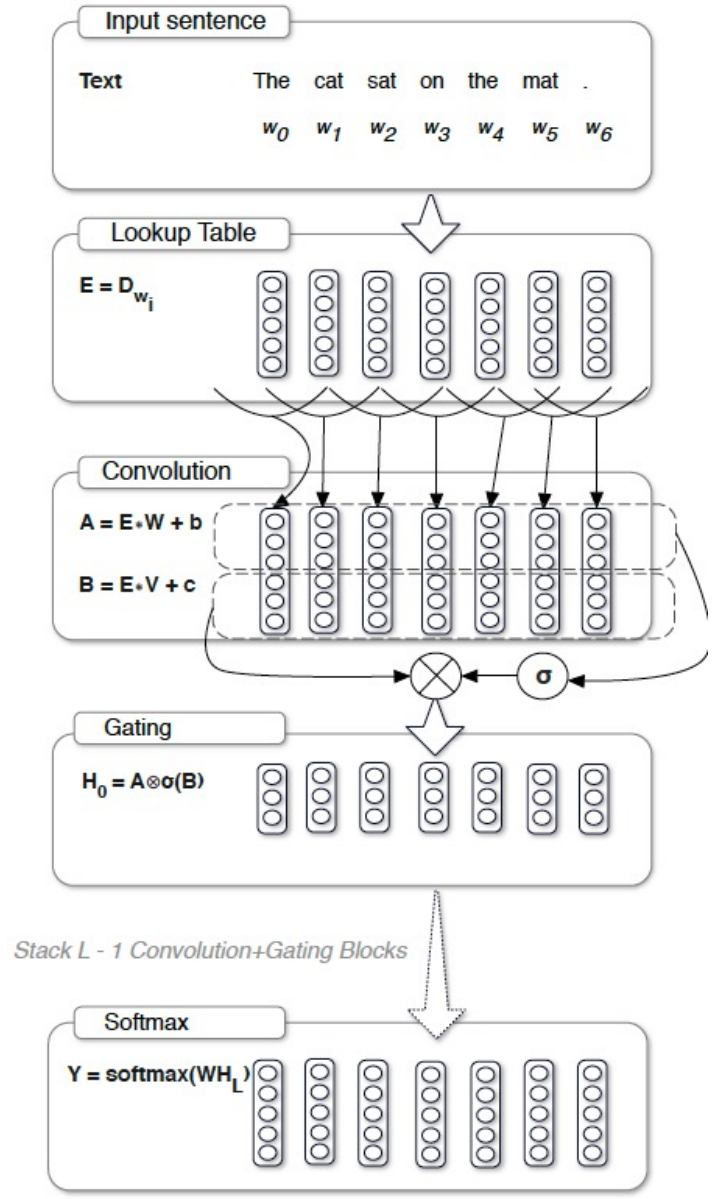
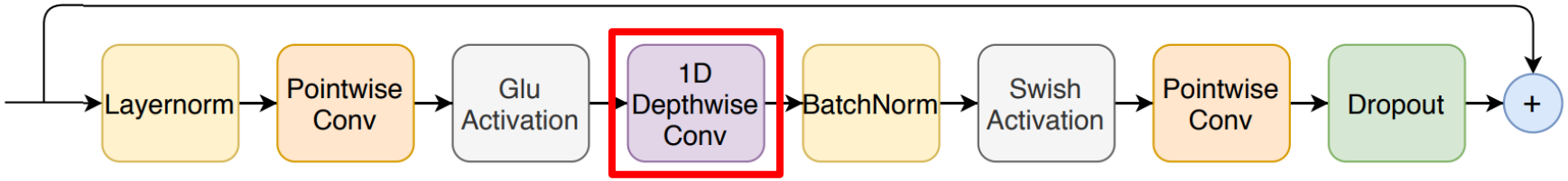
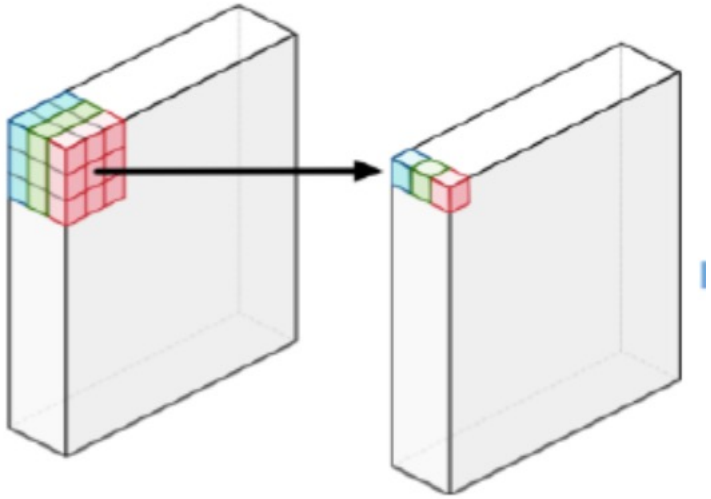


Figure 1. Architecture of the gated convolutional network for language modeling.

Conformer Encoder

2. Convolution Module



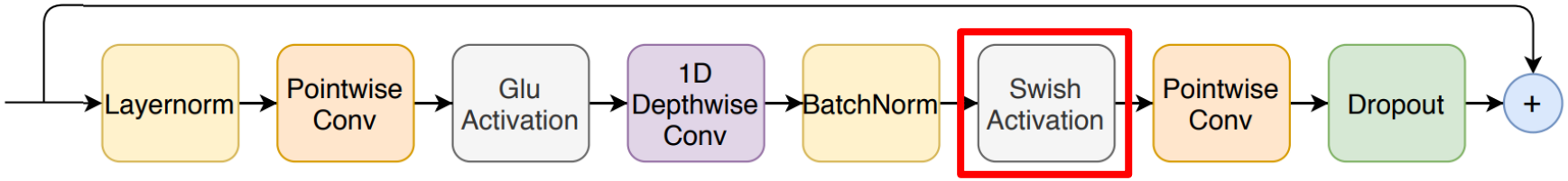


Channel별 convolution

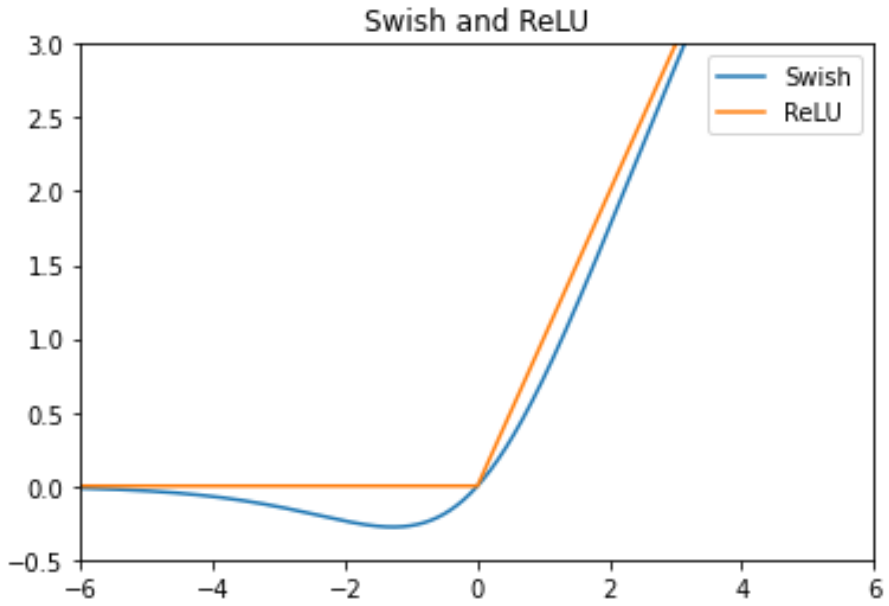
원래 Depthwise Conv -> Pointwise Conv 순으로 쓰임

Conformer Encoder

2. Convolution Module



$$f(x) = x \cdot \sigma(x),$$



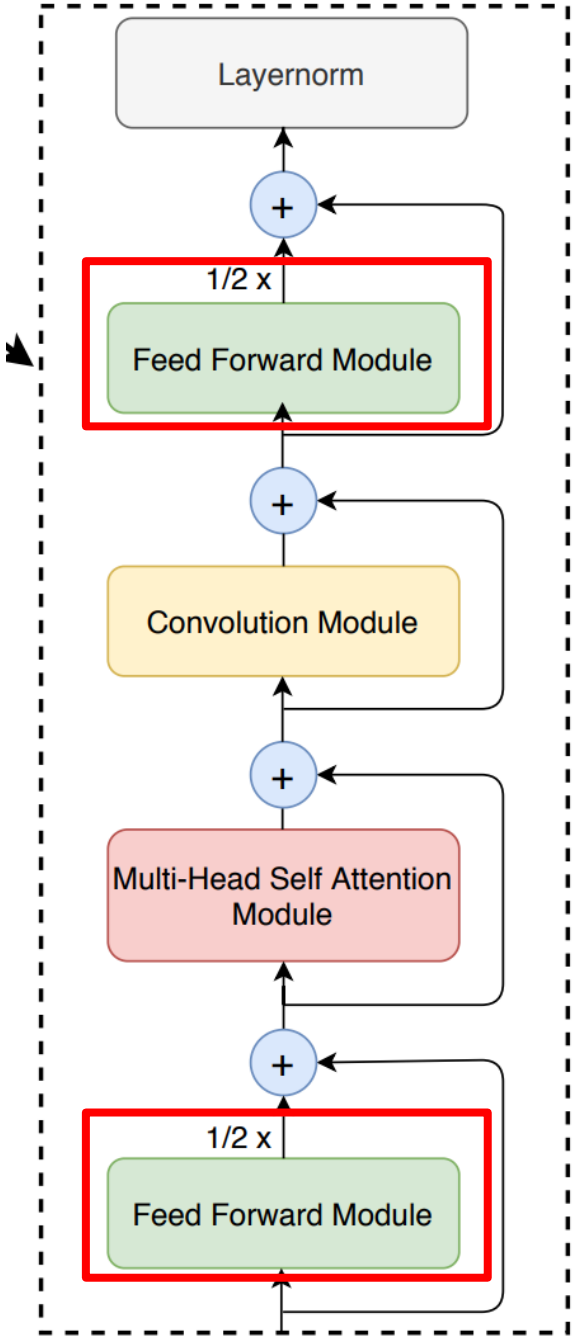
Sigmoid Activation Function에 x를 곱해준 단순한 형태

Sigmoid(B*x)로 B를 학습 가능한 파라미터로 넣기도 한다.

SiLU라고도 불림

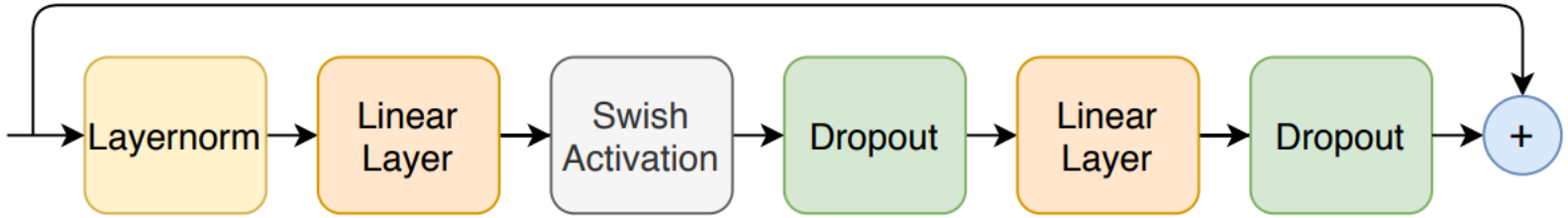
Conformer Encoder

3. FeedForward Module



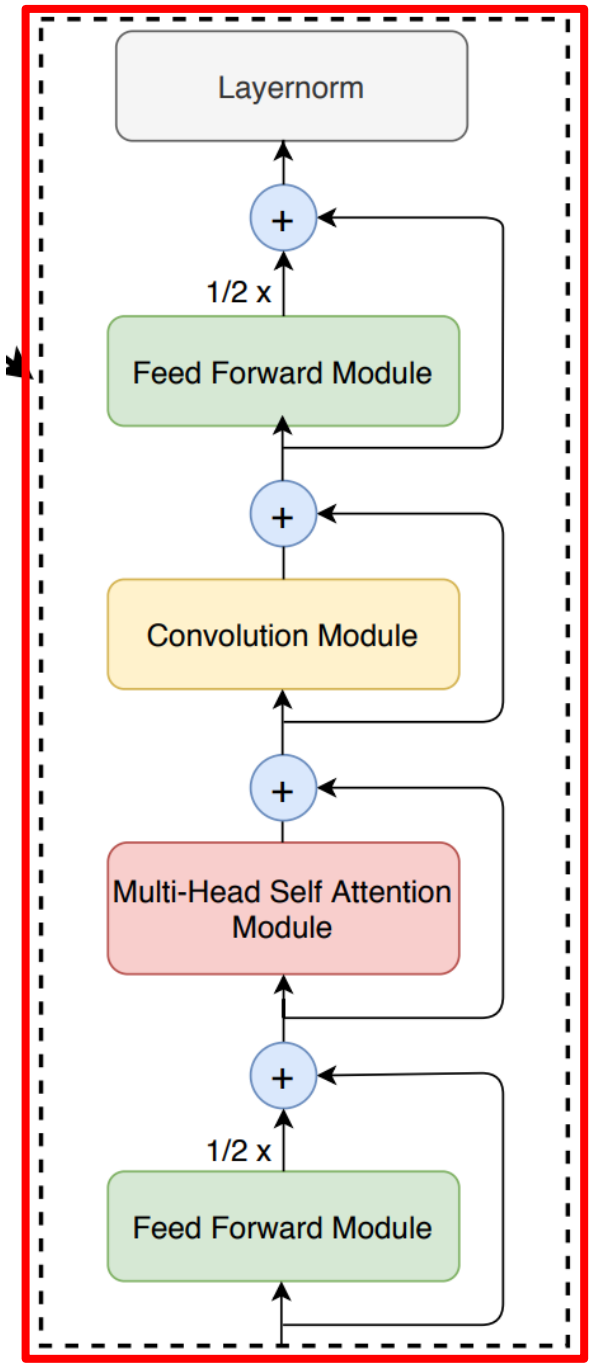
Conformer Encoder

3. FeedForward Module



Conformer Encoder

4. Encoder Block



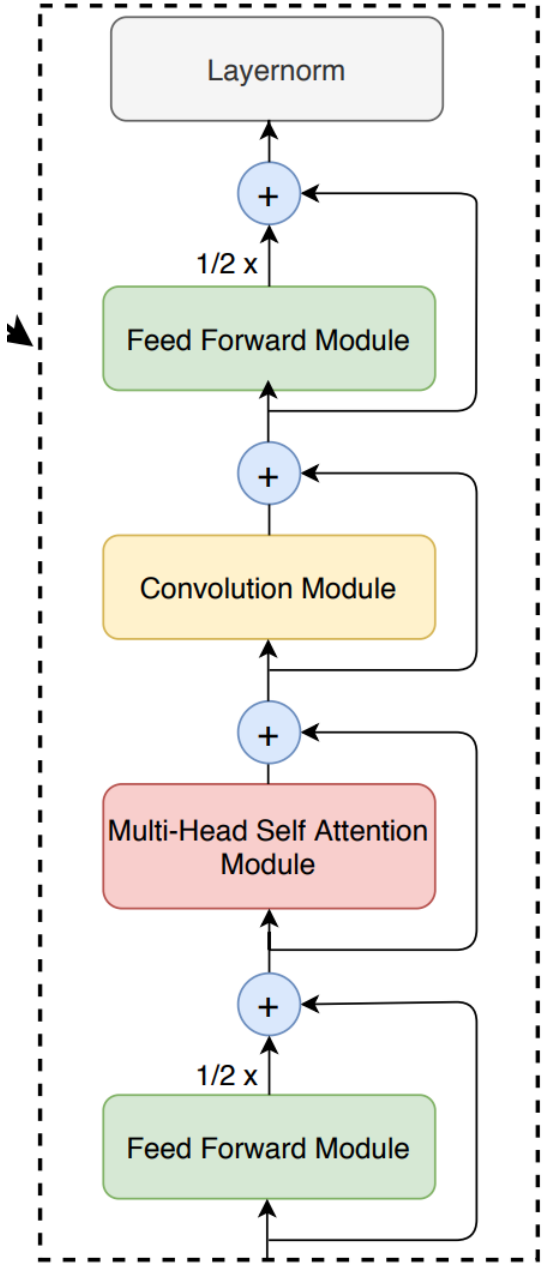
Conformer Encoder

4. Encoder Block

Macaron-Net에서 영감을 받아 sandwich structure를 고안

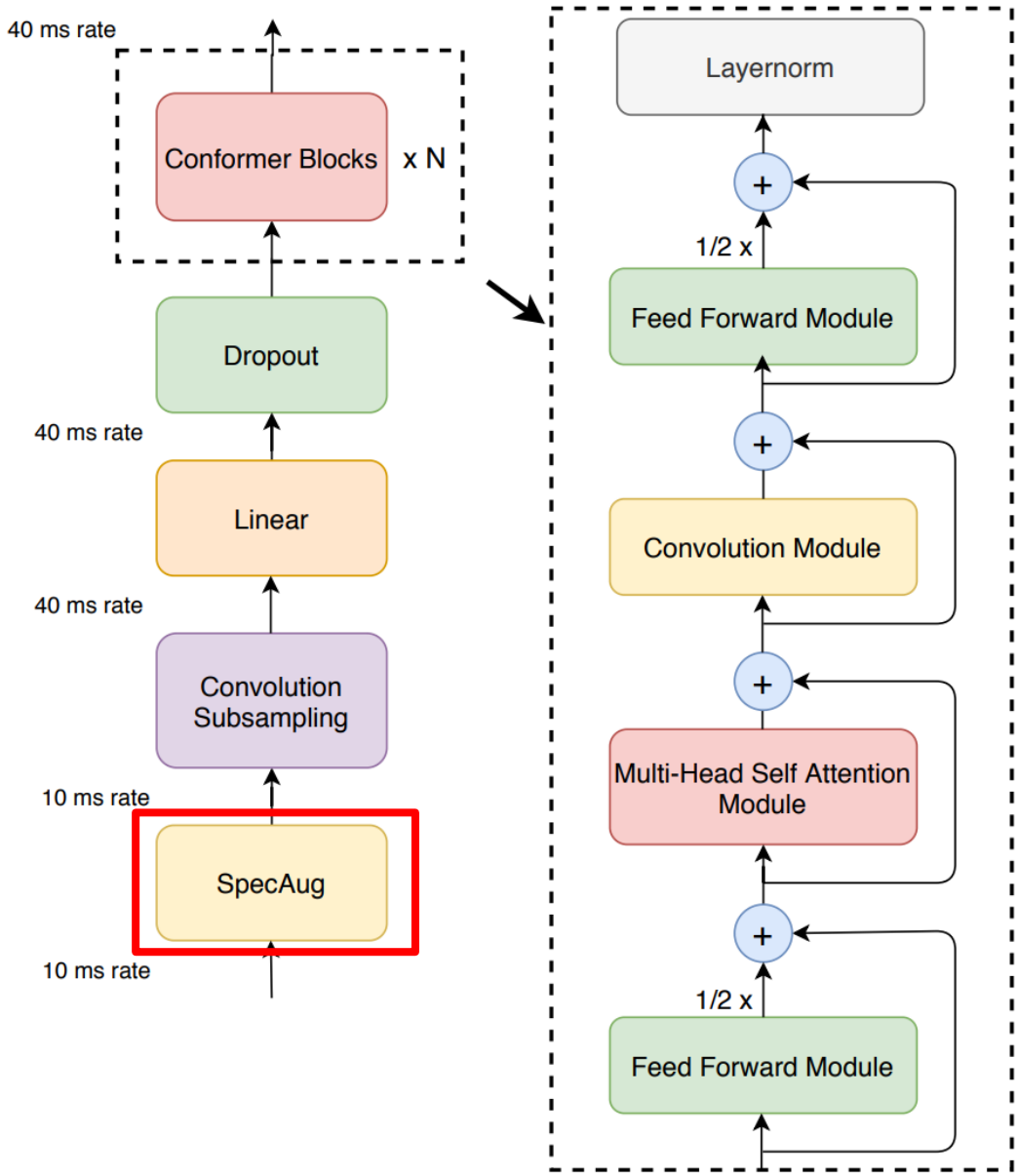
FFNN을 2-half-step FFNN으로 변경

$$\tilde{x}_i = x_i + \frac{1}{2}\mathrm{FFN}(x_i)$$
$$x'_i = \tilde{x}_i + \mathrm{MHSA}(\tilde{x}_i)$$
$$x''_i = x'_i + \mathrm{Conv}(x'_i)$$
$$y_i = \mathrm{Layernorm}(x''_i + \frac{1}{2}\mathrm{FFN}(x''_i))$$



Conformer

5. SpecAug

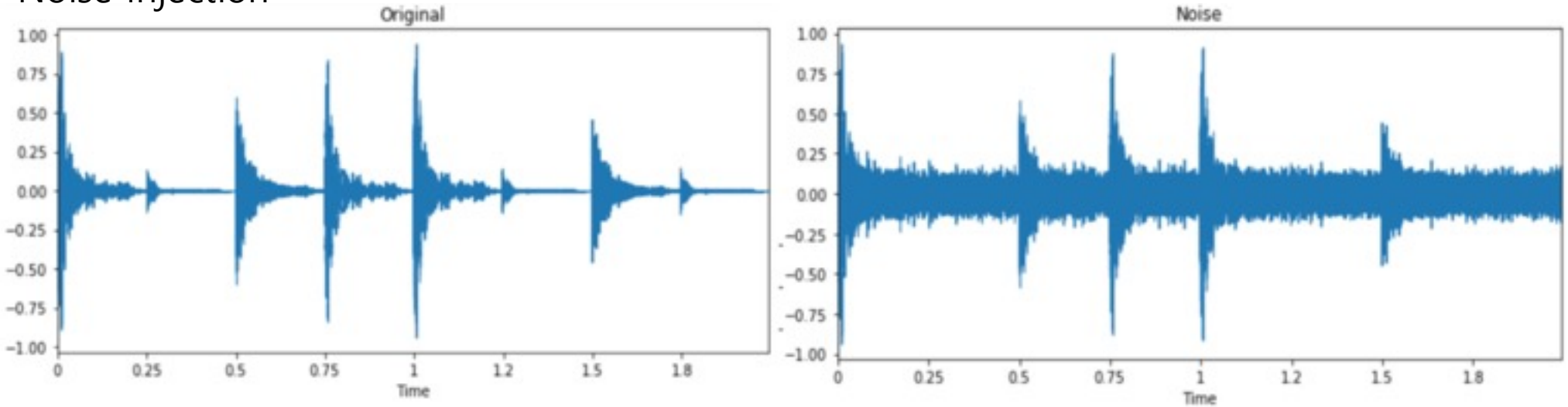


Conformer

5. SpecAugment

기본적인(옛날에 쓰던) Speech Augmentation

Noise Injection



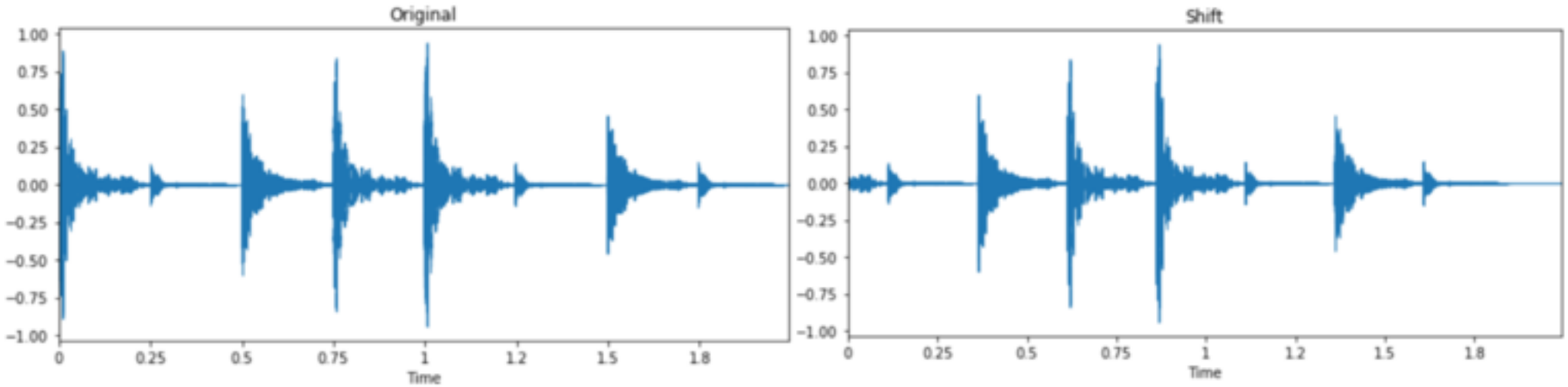
Raw audio에 임의의 난수를 더하여 Noise 추가

Conformer

5. SpecAugment

기본적인(옛날에 쓰던) Speech Augmentation

Shifting Time



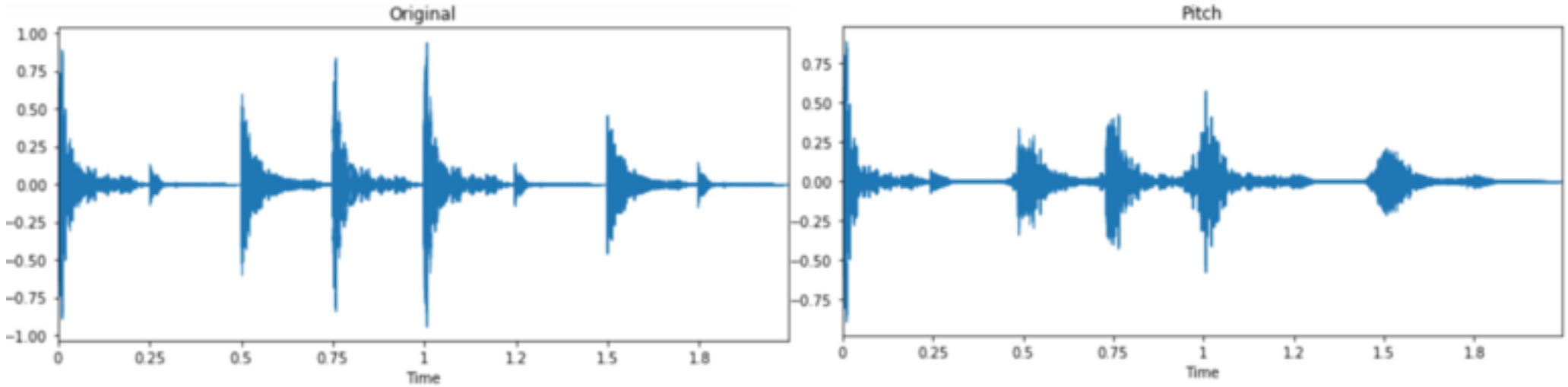
Raw audio를 한 방향으로 밀고 빈 공간 0으로

Conformer

5. SpecAugment

기본적인(옛날에 쓰던) Speech Augmentation

Changing Pitch



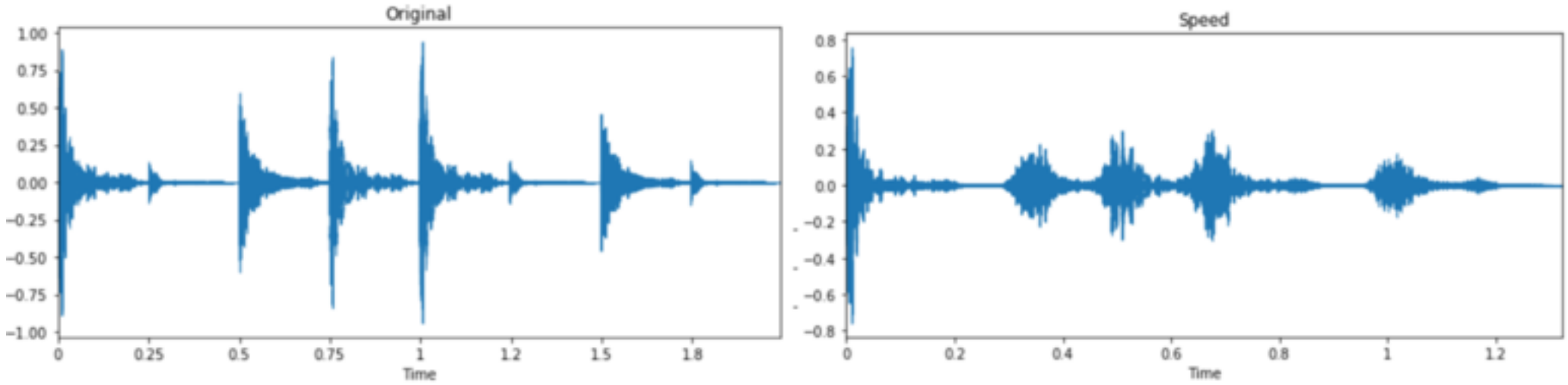
Raw audio의 Pitch(음높이 or 주파수)를 조정

Conformer

5. SpecAugment

기본적인(옛날에 쓰던) Speech Augmentation

Changing Speed



Raw audio의 속도를 바꿔줌

Conformer

5. SpecAugment

본 논문에서는 굳이 Raw Audio를 바꿀 필요가 없다고 주장

MFCC / Log Mel-spectrogram을 사용하는데, 여기서 augmentation을 하자!

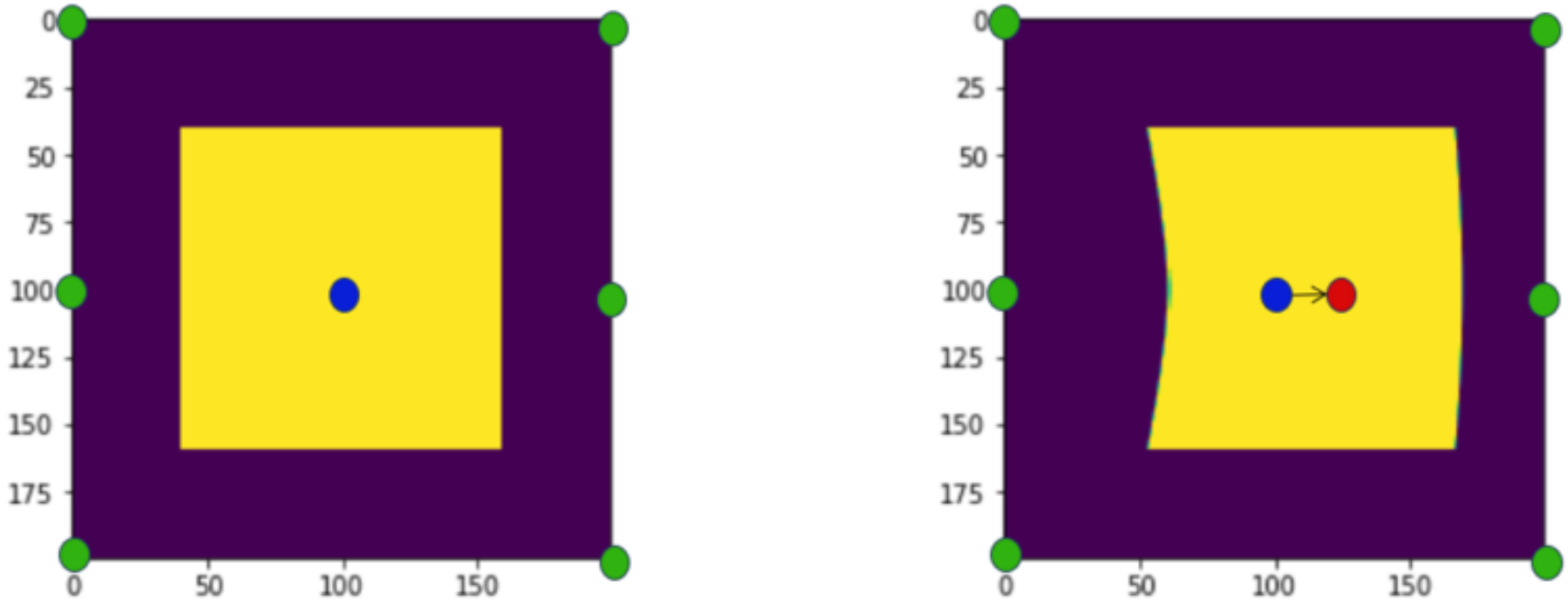
MFCC / Log Mel-spectrogram을 이미지와 비슷하게 생각하고 Augmentation기법 3가지를 제시

위의 방법으로 SOTA달성

Conformer

5. SpecAugment

(1) Time Warping

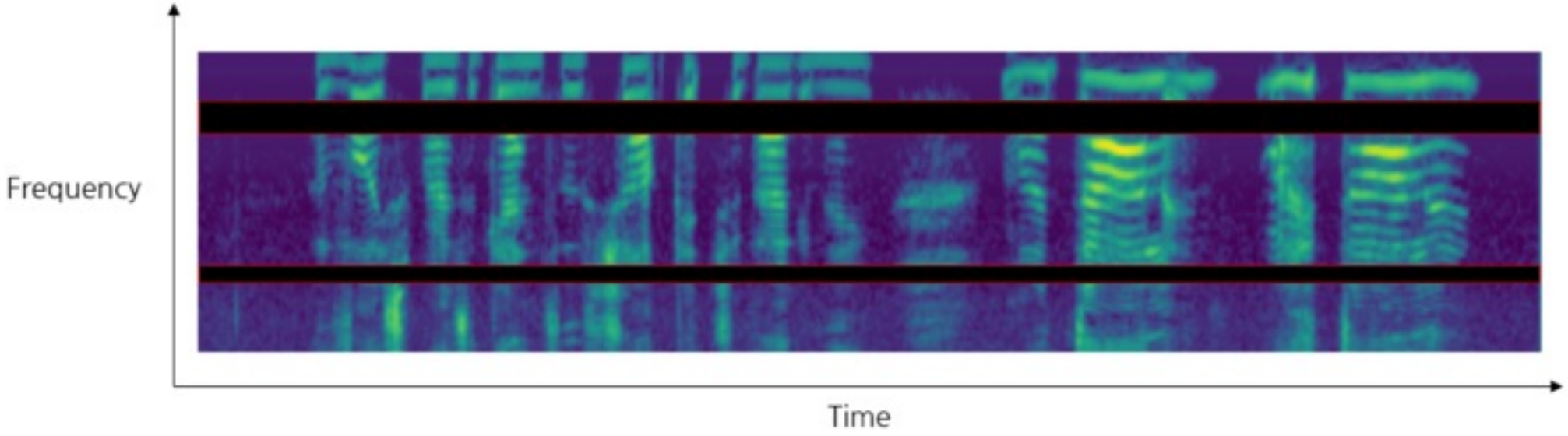


MFCC / log mel-spectrogram 를 이미지처럼 보고 Warping을 수행

Conformer

5. SpecAugment

(2) Frequency Masking

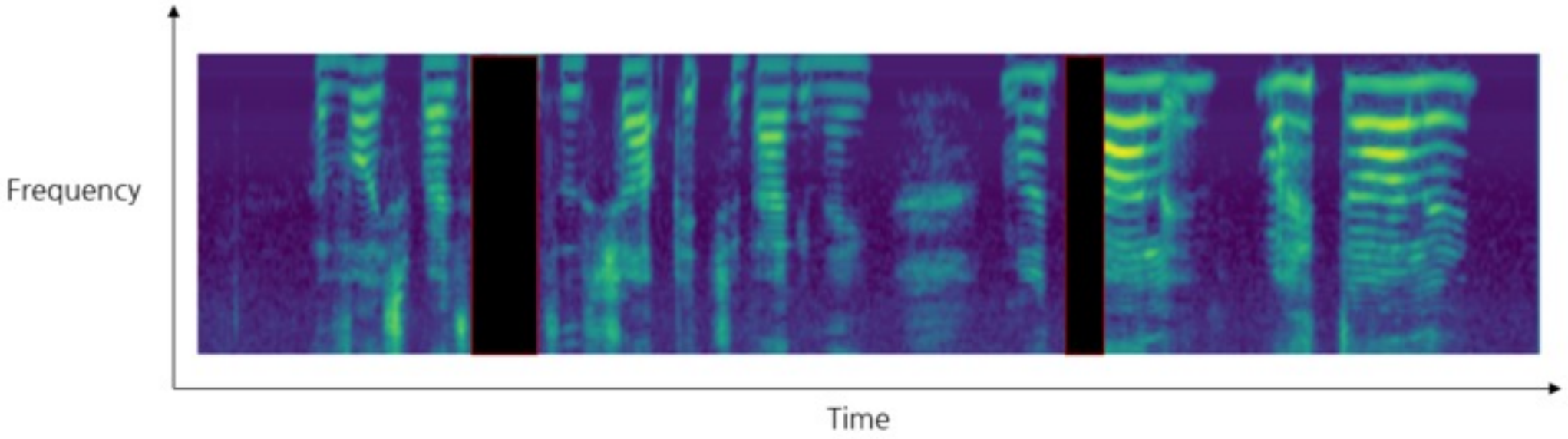


MFCC / log mel-spectrogram의 Frequency축을 그냥 간단하게 mask해버림

Conformer

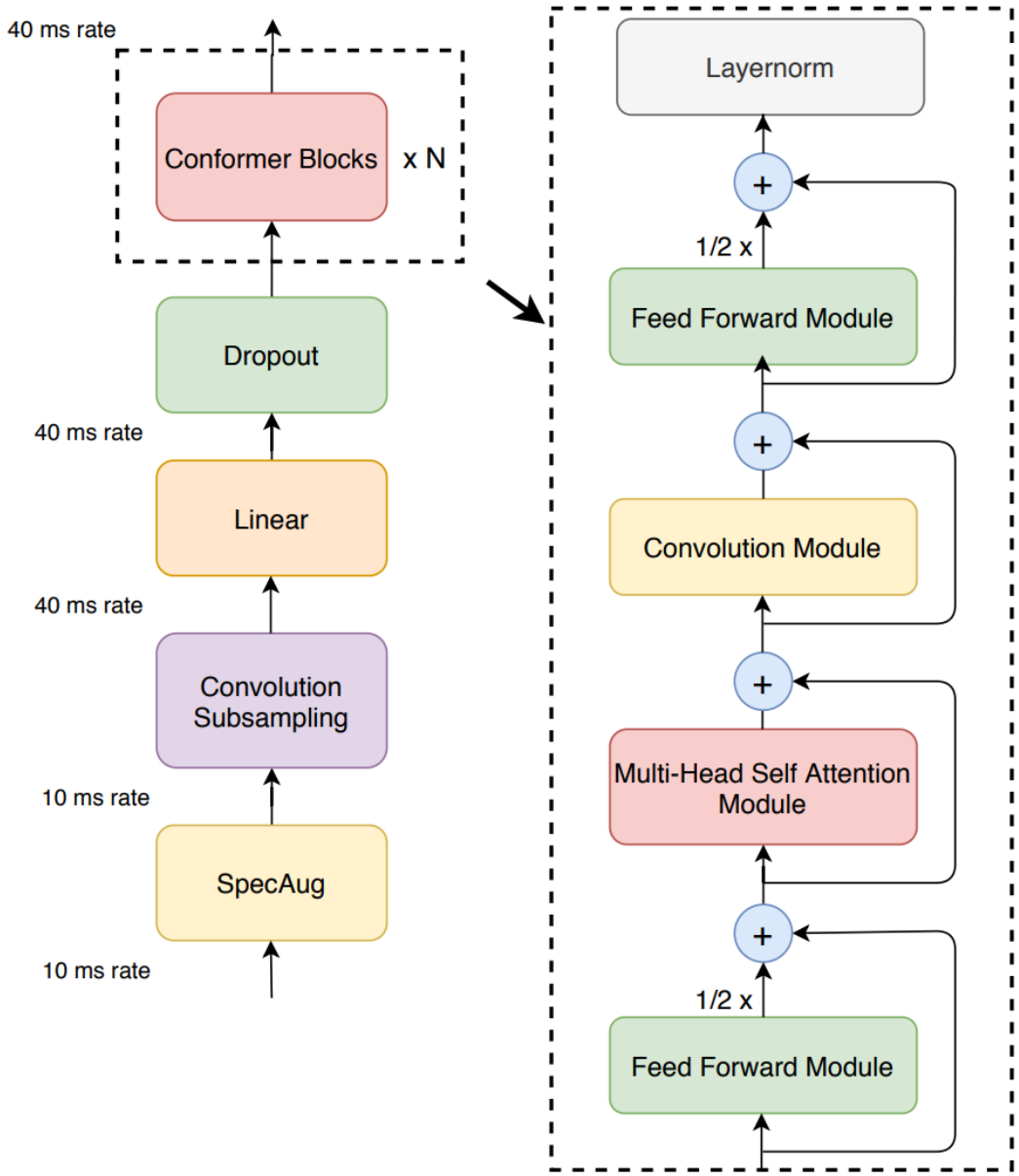
5. SpecAugment

(3) Time Masking



MFCC / log mel-spectrogram의 Time축을 그냥 간단하게 mask해버림

Conformer


40 ms rate
Conformer Blocks
x N
Dropout
40 ms rate
Linear
40 ms rate
Convolution Subsampling
10 ms rate
SpecAug
10 ms rate
Layernorm
+
1/2 x
Feed Forward Module
+
Convolution Module
+
Multi-Head Self Attention Module
+
1/2 x
Feed Forward Module