Deep Learning For Audio Processing

박수철

Audio processing의 종류

Speech

- Speech Recognition
- Speech Synthesis - Tacotron2, Wavenet
- Speech Enhancement

Sound

- Acoustic Scene/Event Identification

Music

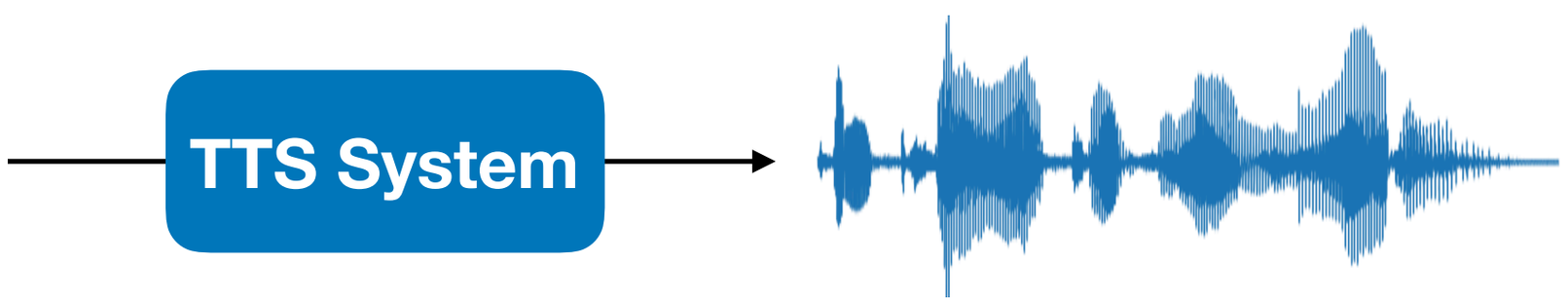
- Music Generation - Wavenet, Melnet, Music Transformer, Musenet
- Source Separation - MMDenseNet
- MIR(Music Information Retrieval)
  - pitch recognition
  - genre classification
  - tempo estimation

Speech Synthesis (TTS, Text To Speech)

안녕하세요? 반갑습니다~

Hi! Nice to meet you.

Text 입력

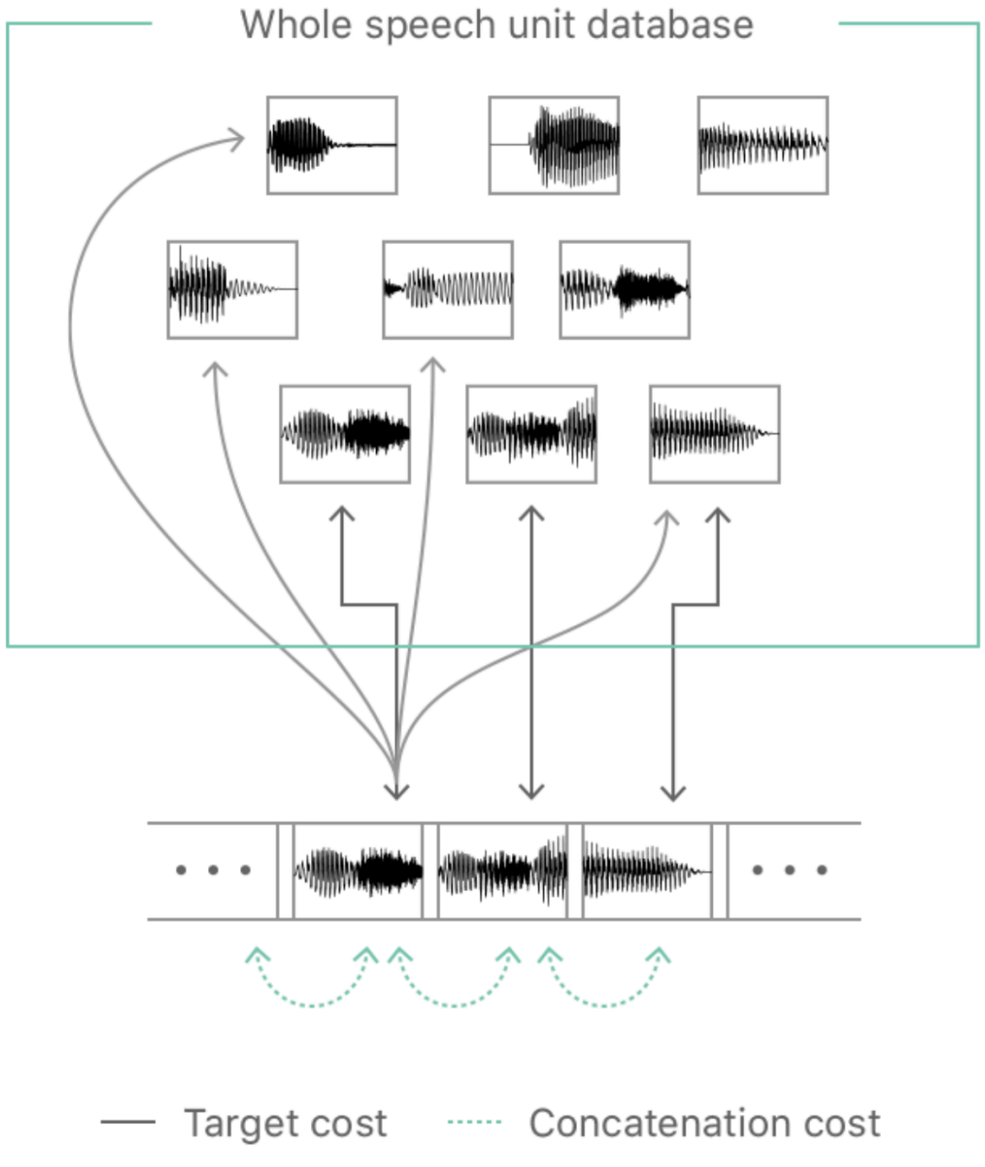


Audio 출력

Speech Synthesis (TTS, Text To Speech)

Concatenative

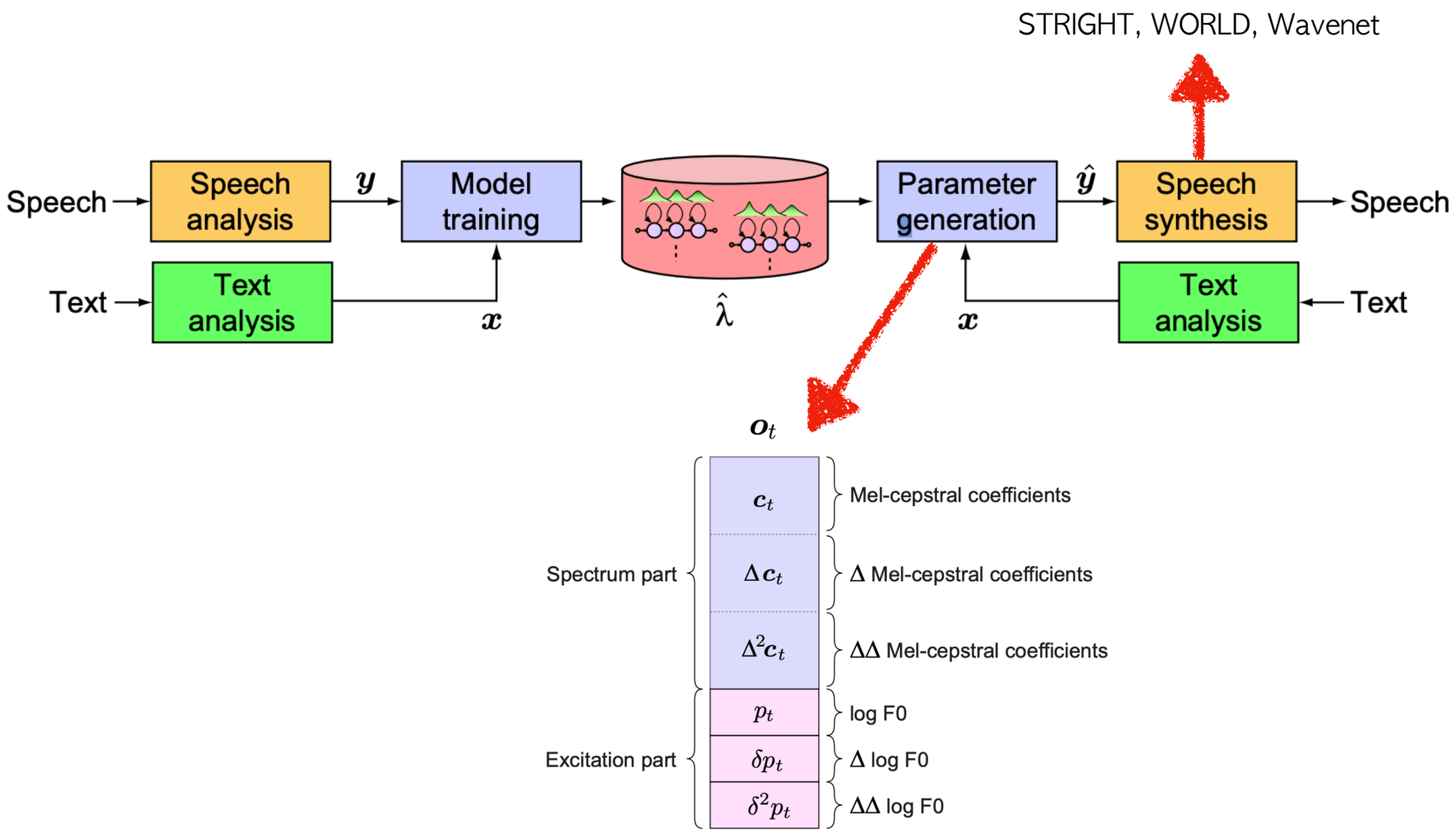
Figure 4. Illustration of the unit selection method based on target and concatenation costs.



https://machinelearning.apple.com/2017/08/06/siri-voices.html

Speech Synthesis (TTS, Text To Speech)

Parametric

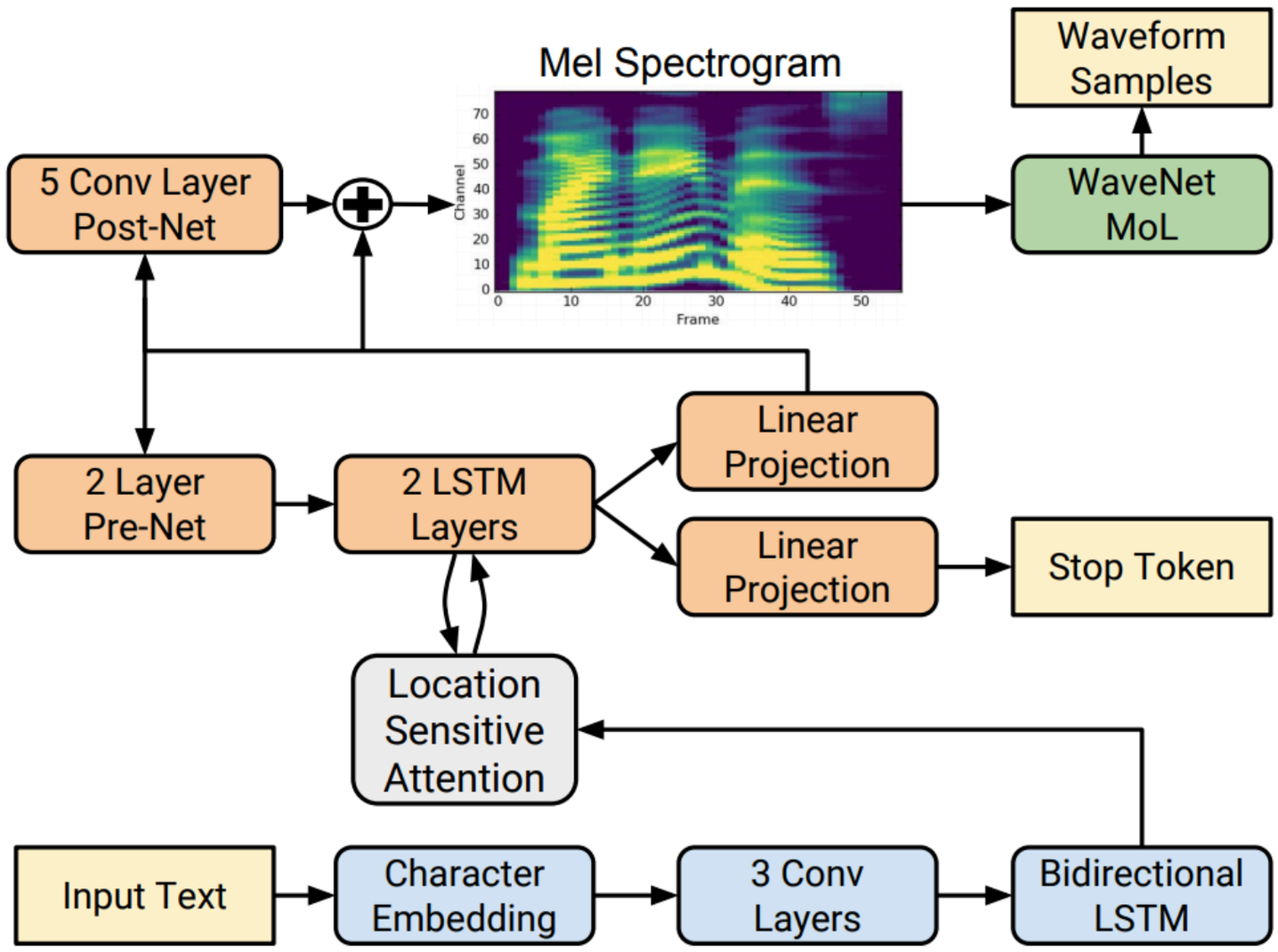


Heiga Zen, Statistical Parametric Speech Synthesis
https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/42624.pdf

Speech Synthesis (TTS, Text To Speech)

End-to-end

Audio Samples
https://google.github.io/tacotron/publications/tacotron2/index.html

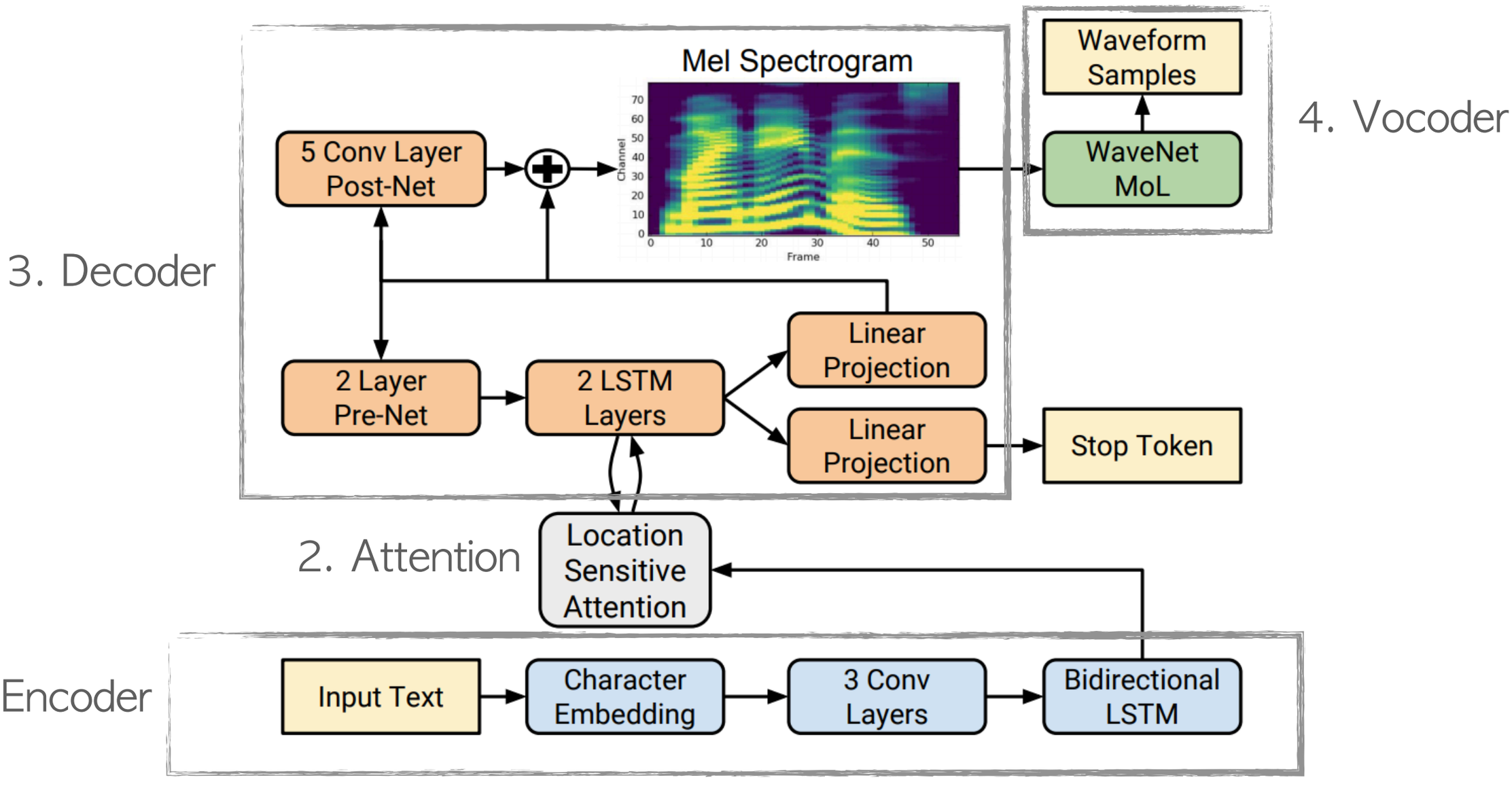


Natural TTS synthesis by conditioning wavenet on mel spectrogram predictions
arXiv preprint arXiv:1712.05884

Speech Synthesis (TTS, Text To Speech)

End-to-end: Tacotron2

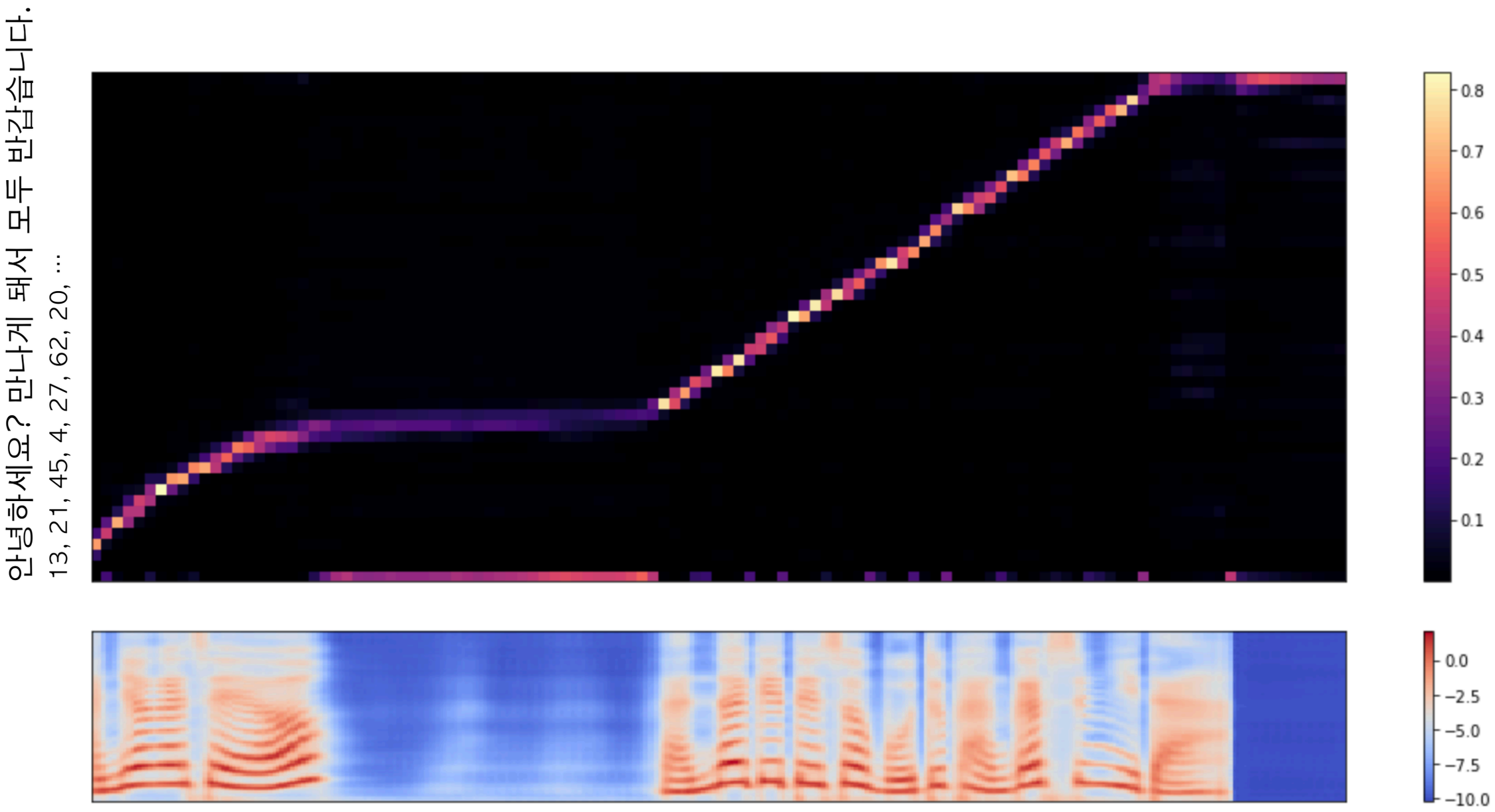
Audio Samples
https://google.github.io/tacotron/publications/tacotron2/index.html



Natural TTS synthesis by conditioning wavenet on mel spectrogram predictions
arXiv preprint arXiv:1712.05884

Speech Synthesis (TTS, Text To Speech)

End-to-end: Attention



Speech Synthesis (TTS, Text To Speech)

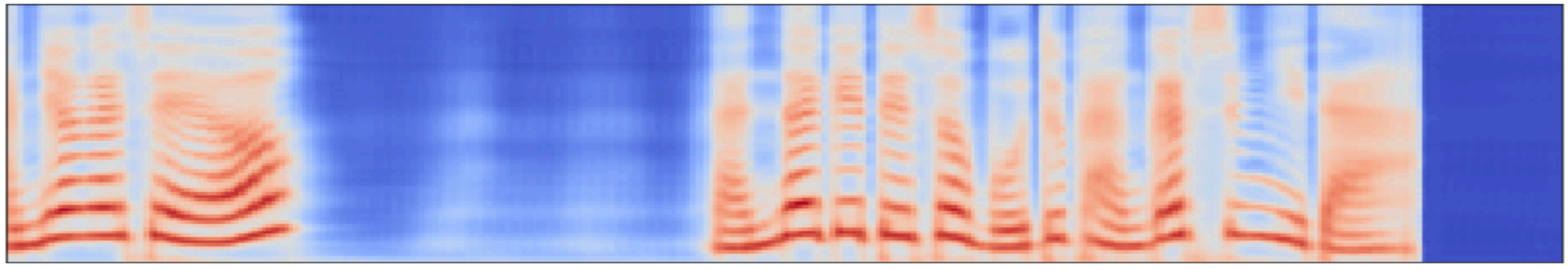
Wavenet

1. Unconditional Wavenet $p(\mathbf{x}) = \prod_{t=1}^{T} p(x_t \mid x_1, \ldots, x_{t-1})$

waveform

2. Conditional Wavenet $p(\mathbf{x} \mid \mathbf{h}) = \prod_{t=1}^{T} p(x_t \mid x_1, \ldots, x_{t-1}, \mathbf{h})$

MelSpectrogram
Condition



Vocoding

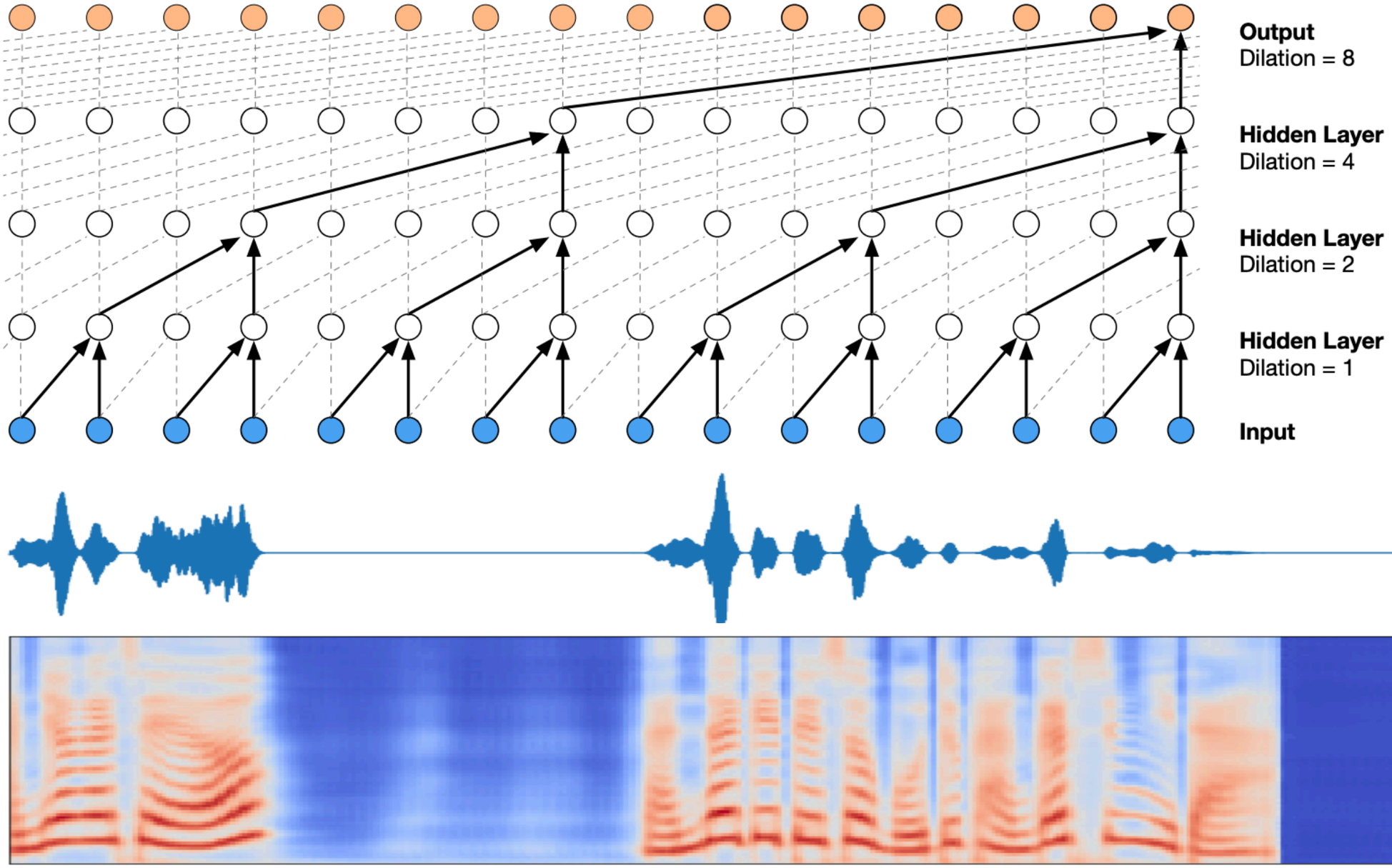
waveform

Audio Samples
https://deepmind.com/blog/wavenet-generative-model-raw-audio

"Wavenet: A generative model for raw audio," arXiv:1609.03499, 2016.

Speech Synthesis (TTS, Text To Speech)

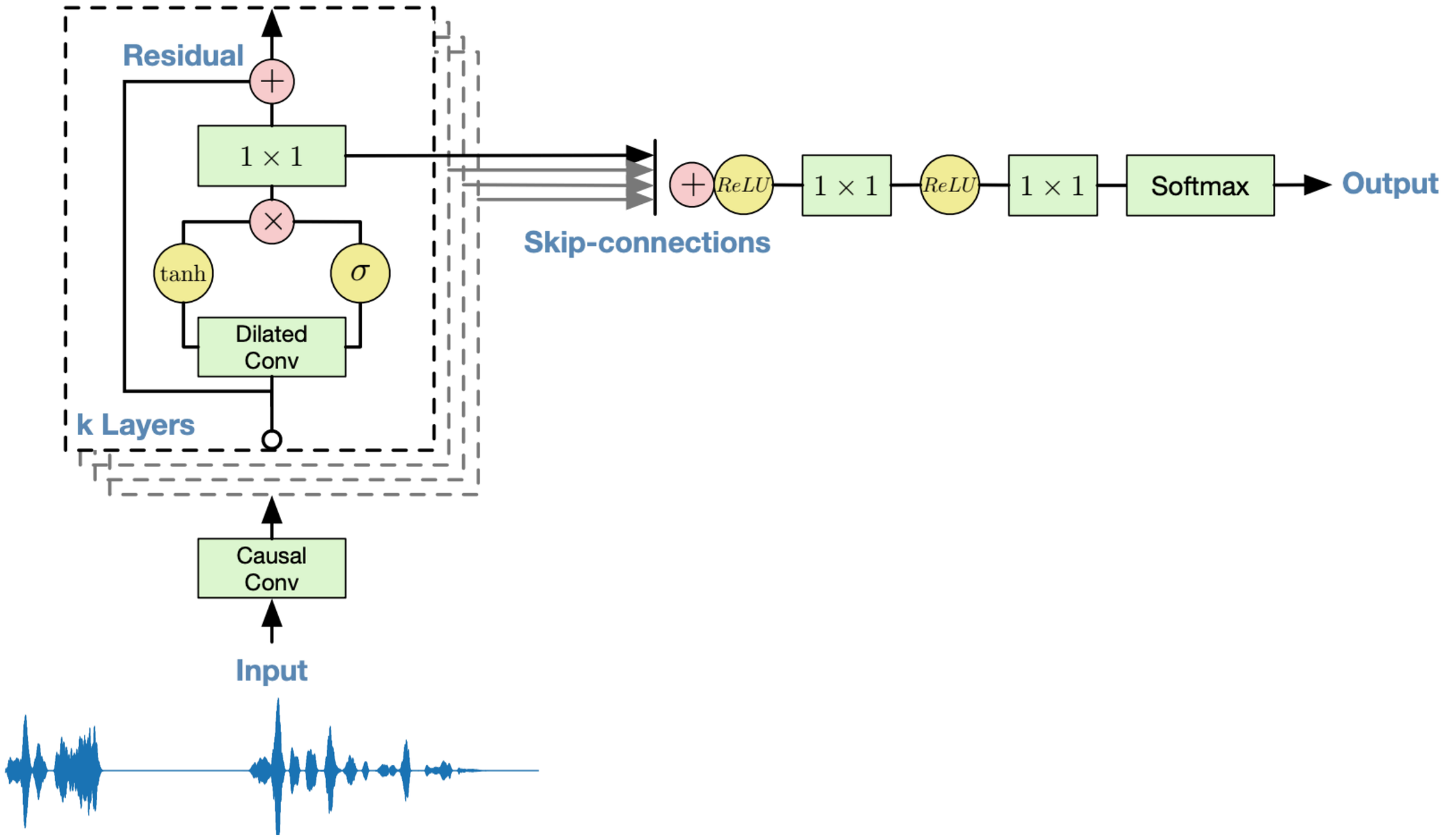
Conditional Wavenet



"Wavenet: A generative model for raw audio," arXiv:1609.03499, 2016.

Speech Synthesis (TTS, Text To Speech)

Wavenet entire architecture



"Wavenet: A generative model for raw audio," arXiv:1609.03499, 2016.

Speech Synthesis (TTS, Text To Speech)

```python
def naive_wavenet(X, dilations, name='naive_wavenet', channels=256, embedding_dim=256, hidden_dim=256):
    with tf.variable_scope(name):
        '''
        For Training
        '''
        # X : [Batch, Length]

        # [channels, embedding_dim]
        embedding_table = tf.get_variable('embedding_table', [channels, embedding_dim])
        # [Batch, Length, embedding_dim]
        X_embedded = tf.gather(embedding_table, X)

        # [Batch, Length, hidden_dim]
        outputs = tf.layers.conv1d(X_embedded, filters=hidden_dim, kernel_size=1)

        skips = []
        for dilation in dilations:
            layer_inputs = outputs
            # [Batch, dilation+Length, hidden_dim]
            layer_inputs_padded = tf.pad(layer_inputs, [[0, 0], [dilation, 0], [0, 0]])

            # [Batch, Length, hidden_dim]
            filter_outputs = tf.layers.conv1d(layer_inputs_padded,
                                              filters=hidden_dim, kernel_size=2, dilation_rate=dilation)
            # [Batch, Length, hidden_dim]
            gate_outputs = tf.layers.conv1d(layer_inputs_padded,
                                            filters=hidden_dim, kernel_size=2, dilation_rate=dilation)

            layer_outputs = tf.nn.tanh(filter_outputs) + tf.nn.sigmoid(gate_outputs)

            # [Batch, Length, hidden_dim]
            skip_outputs = tf.layers.conv1d(layer_outputs, filters=hidden_dim, kernel_size=1)
            skips.append(skip_outputs)

            outputs = layer_inputs + skip_outputs

    # [Batch, Length, hidden_dim]
    outputs = sum(skips)
    outputs = tf.nn.relu(outputs)
    outputs = tf.layers.conv1d(outputs, filters=channels, kernel_size=1)
    outputs = tf.nn.relu(outputs)
    logits = tf.layers.conv1d(outputs, filters=channels, kernel_size=1)

    return logits
```

Embedding

Causal Conv.

Padding for causality

Gated Unit

Skip Connection

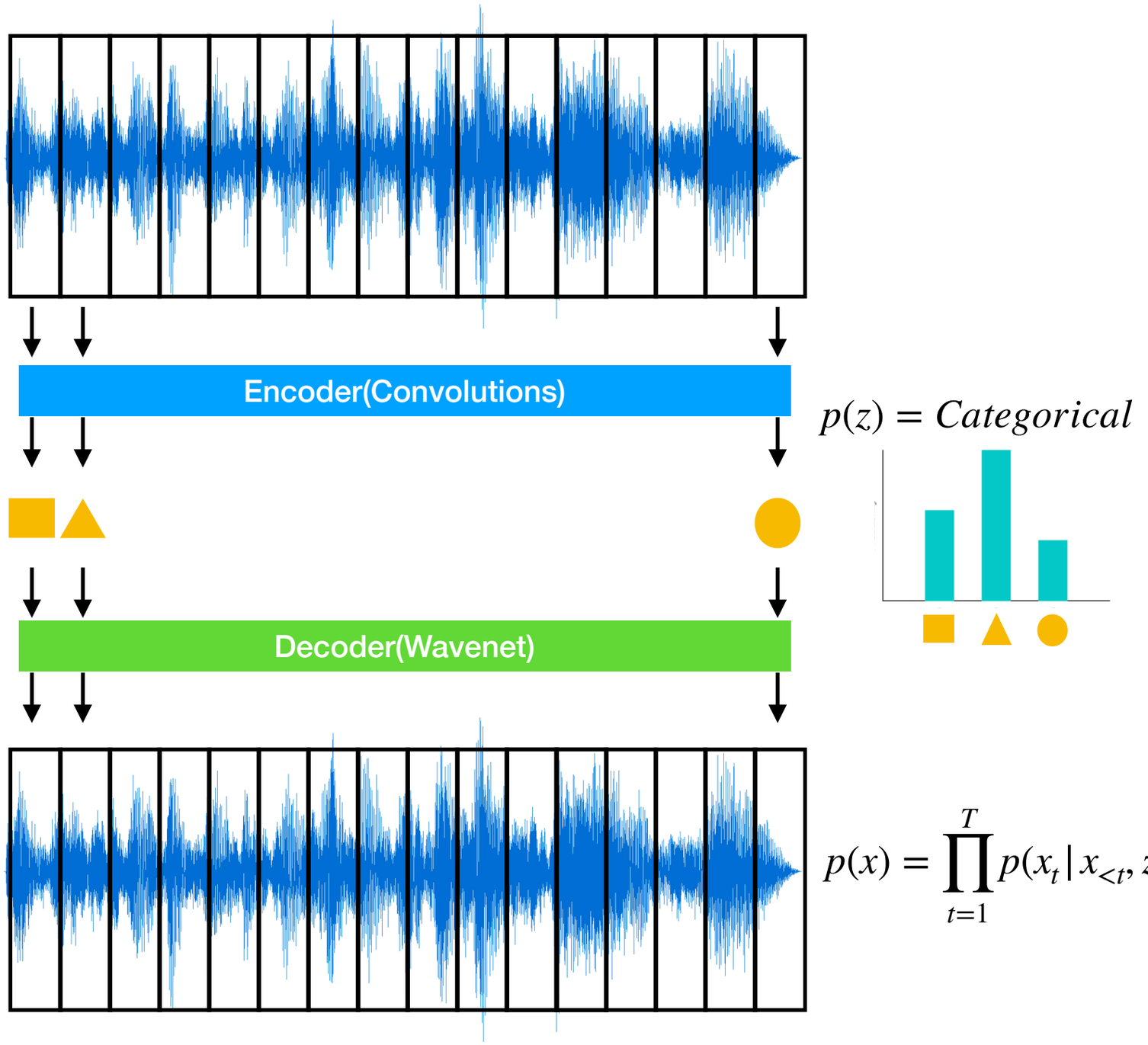
Residual Connection

Logits for softmax regression

https://github.com/scpark20/audio-preprocessing-practice/blob/master/Naive%20wavenet%20model.ipynb

Music Generation

Wavenet (VQ-VAE, AMAE)



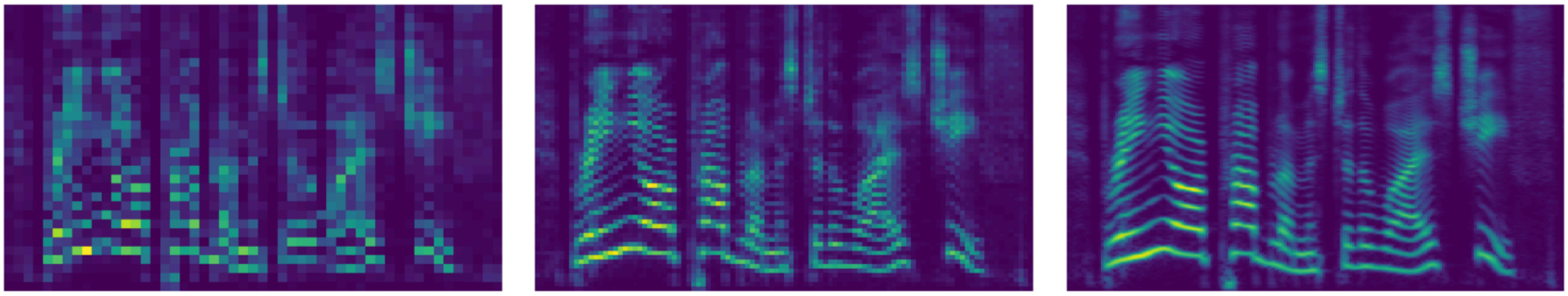
관련 논문

Neural Discrete Representation Learning. https://arxiv.org/pdf/1711.00937.pdf

The challenge of realistic music generation: modelling raw audio at scale. https://arxiv.org/pdf/1806.10474.pdf

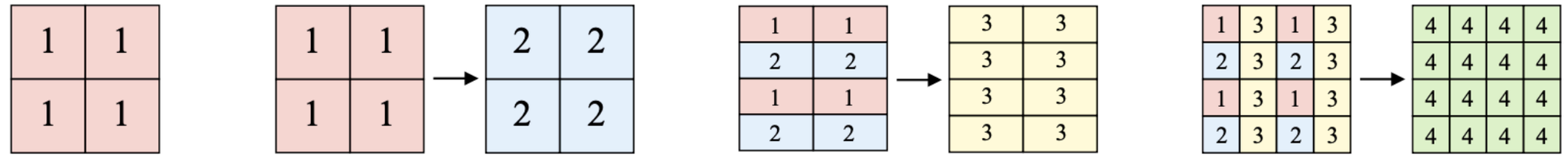
Music Generation

Wavenet (Melnet)



(a) Tier 1 (32×50) (b) Tiers 1–3 (64×100) (c) Tiers 1–6 (256×200)

Figure 5. A sampled spectrogram viewed at different stages of the multiscale generation procedure. The initial tier dictates high-level structure and subsequent tiers add fine-grained details. Each upsampling tier doubles the resolution of the spectrogram, resulting in the initial tier being upsampled by a factor of 32.



(a) $p(x^1;\ \psi^1)$ (b) $p(x^2 \mid x^1;\ \psi^2)$ (c) $p(x^3 \mid x^1, x^2;\ \psi^3)$ (d) $p(x^4 \mid x^1, x^2, x^3;\ \psi^4)$

Figure 6. Schematic showing how tiers of the multiscale model are interleaved and used to condition the distribution for the subsequent tier. a) The initial tier is generated unconditionally. b) The second tier is generated conditionally given the the initial tier. c) The outputs of tiers 1 and 2 are interleaved along the frequency axis and used to condition the generation of tier 3. d) Tier 3 is interleaved along the time axis with all preceding tiers and used to condition the generation of tier 4.

Audio Samples sjvasquez.github.io/blog/melnet/
관련 논문 MelNet: A Generative Model for Audio in the Frequency Domain. arxiv.org/abs/1906.01083

Music Generation

Music Transformer

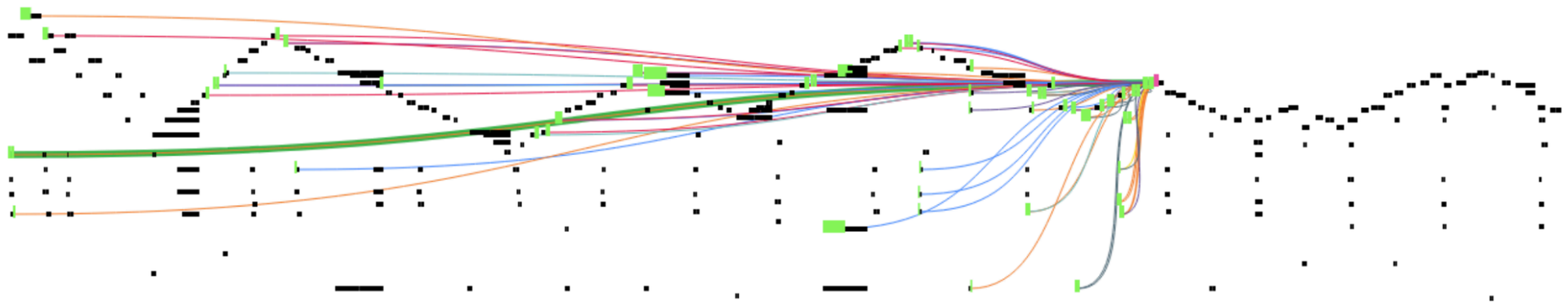


Figure 8: This piece has a recurring triangular contour. The query is at one of the latter peaks and it attends to all of the previous high notes on the peak, all the way to beginning of the piece.

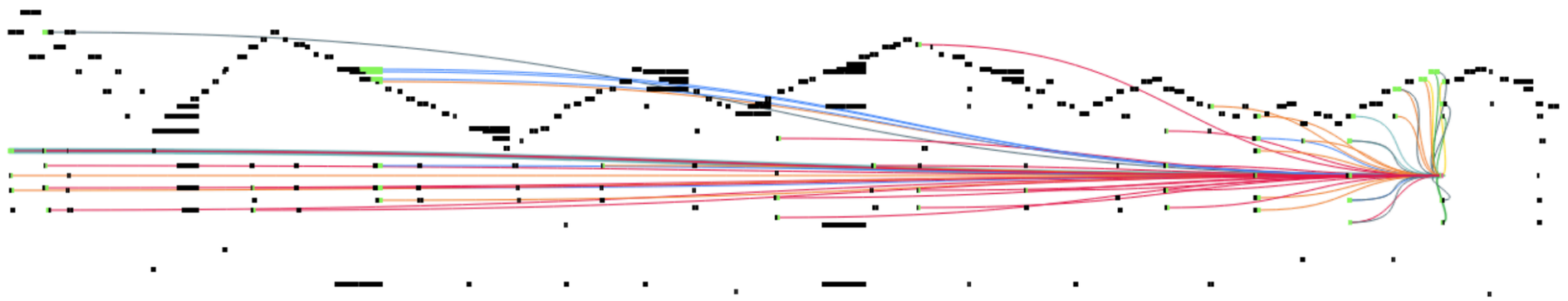
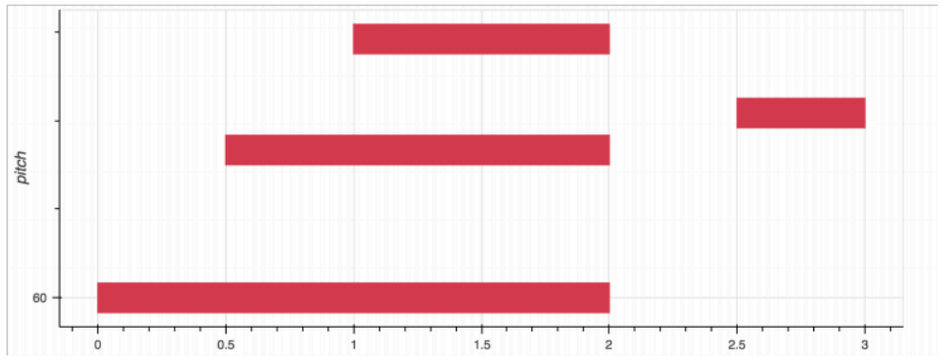


Figure 9: The query a note in the left-hand, and it attends to its immediate past neighbors and mostly to the earlier left hand chords, with most attention lines distributed in the lower half of the pianoroll.

Blog
https://magenta.tensorflow.org/music-transformer
관련 논문
Attention Is All You Need. arxiv.org/abs/1706.03762
Music Transformer. arxiv.org/abs/1809.04281

Music Generation

Music Transformer -MIDI Representation




```
SET_VELOCITY<80>, NOTE_ON<60>
TIME_SHIFT<500>, NOTE_ON<64>
TIME_SHIFT<500>, NOTE_ON<67>
TIME_SHIFT<1000>, NOTE_OFF<60>, NOTE_OFF<64>,
NOTE_OFF<67>
TIME_SHIFT<500>, SET_VELOCITY<100>, NOTE_ON<65>
TIME_SHIFT<500>, NOTE_OFF<65>
```

Next, the MIDI note events are converted into a sequence from the following set of vocabulary: 128 `NOTE_ON` events for starting a note of with one of the 128 MIDI pitches, 128 `NOTE_OFF` events for ending a note with one of the 128 MIDI pitches, 100 `TIME_SHIFT` events representing forward time shifts in 10ms increments from 10ms to 1s, and 32 `SET_VELOCITY` events representing the velocity for future `NOTE_ON` events in the form of the 128 possible MIDI velocities quantized into 32 bins. An example performance encoding is illustrated in Figure 7.

Music Generation

Transformer

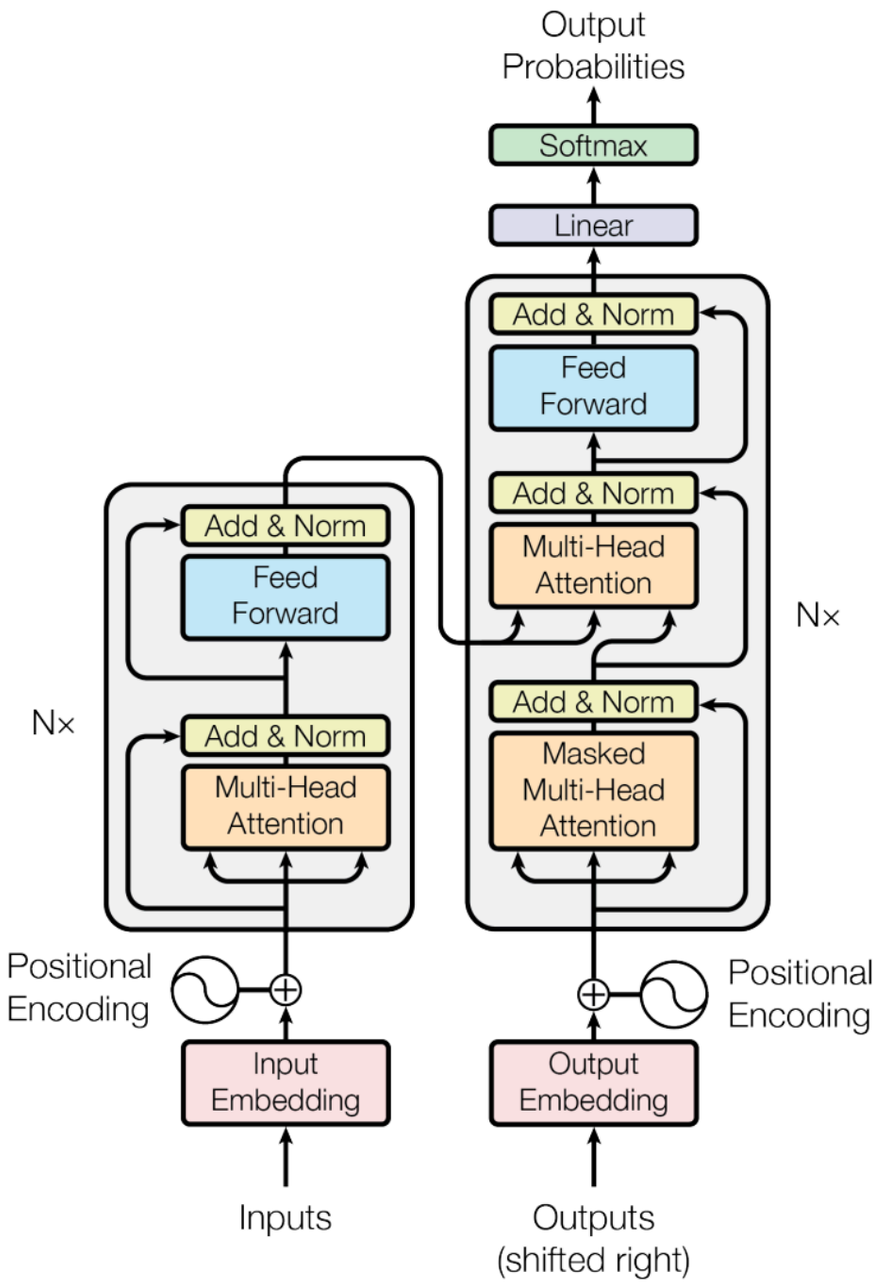
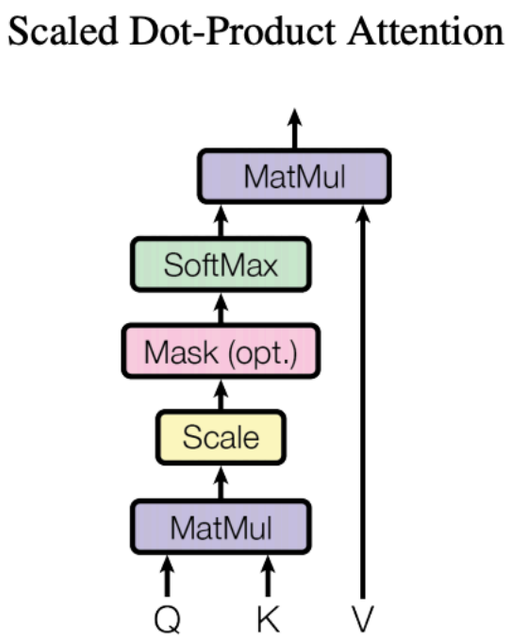


Figure 1: The Transformer - model architecture.



Absolute Position Attention

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Relative Position Attention(Music Transformer)

$$\textbf{RelativeAttention} = \textbf{Softmax}\left(\frac{QK^\top + S^{rel}}{\sqrt{D_h}}\right)V.$$

Music Generation

GPT-2

```
def model(hparams, X, past=None, scope='model', reuse=False):
    with tf.variable_scope(scope, reuse=reuse):
        results = {}
        batch, sequence = shape_list(X)

        wpe = tf.get_variable('wpe', [hparams.n_ctx, hparams.n_embd],
                              initializer=tf.random_normal_initializer(stddev=0.01))
        wte = tf.get_variable('wte', [hparams.n_vocab, hparams.n_embd],
                              initializer=tf.random_normal_initializer(stddev=0.02))
        past_length = 0 if past is None else tf.shape(past)[-2]
        h = tf.gather(wte, X) + tf.gather(wpe, positions_for(X, past_length))
```

Embedding

```
        # Transformer
        presents = []
        pasts = tf.unstack(past, axis=1) if past is not None else [None] * hparams.n_layer
        assert len(pasts) == hparams.n_layer
        for layer, past in enumerate(pasts):
            h, present = block(h, 'h%d' % layer, past=past, hparams=hparams)
            presents.append(present)
        results['present'] = tf.stack(presents, axis=1)
        h = norm(h, 'ln_f')

        # Language model loss.  Do tokens <n predict token n?
        h_flat = tf.reshape(h, [batch*sequence, hparams.n_embd])
        logits = tf.matmul(h_flat, wte, transpose_b=True)
        logits = tf.reshape(logits, [batch, sequence, hparams.n_vocab])
        results['logits'] = logits
        return results
```

Block repeats

Logit outputs

https://github.com/openai/gpt-2/blob/master/src/model.py

Music Generation

```
def block(x, scope, *, past, hparams):
    with tf.variable_scope(scope):
        nx = x.shape[-1].value
        a, present = attn(norm(x, 'ln_1'), 'attn', nx, past=past, hparams=hparams)
        x = x + a
        m = mlp(norm(x, 'ln_2'), 'mlp', nx*4, hparams=hparams)
        x = x + m
        return x, present
```

Attention & Residual Connection

```
def attn(x, scope, n_state, *, past, hparams):
    def multihead_attn(q, k, v):
        # q, k, v have shape [batch, heads, sequence, features]
        w = tf.matmul(q, k, transpose_b=True)
        w = w * tf.rsqrt(tf.cast(v.shape[-1].value, w.dtype))

        w = mask_attn_weights(w)
        w = softmax(w)
        a = tf.matmul(w, v)
        return a
```

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

```
    with tf.variable_scope(scope):
        c = conv1d(x, 'c_attn', n_state*3)
        q, k, v = map(split_heads, tf.split(c, 3, axis=2))
        present = tf.stack([k, v], axis=1)
        if past is not None:
            pk, pv = tf.unstack(past, axis=1)
            k = tf.concat([pk, k], axis=-2)
            v = tf.concat([pv, v], axis=-2)
        a = multihead_attn(q, k, v)
        a = merge_heads(a)
        a = conv1d(a, 'c_proj', n_state)
        return a, present
```

Query, Key, Value

Concat past data

Merge multi-heads & output projection

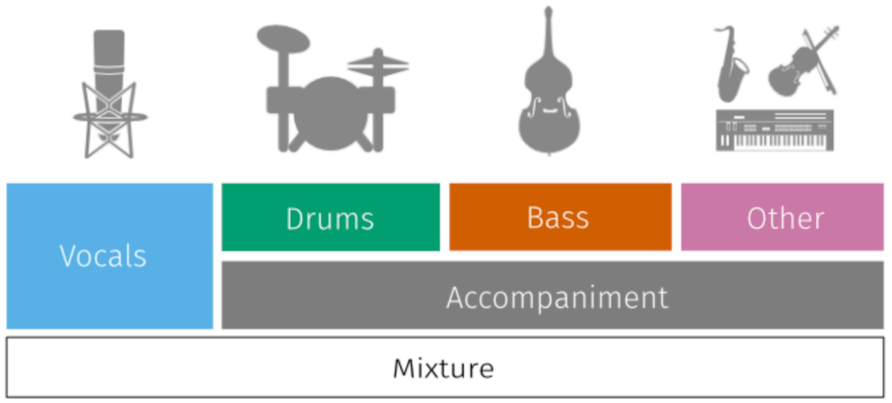
Music Generation

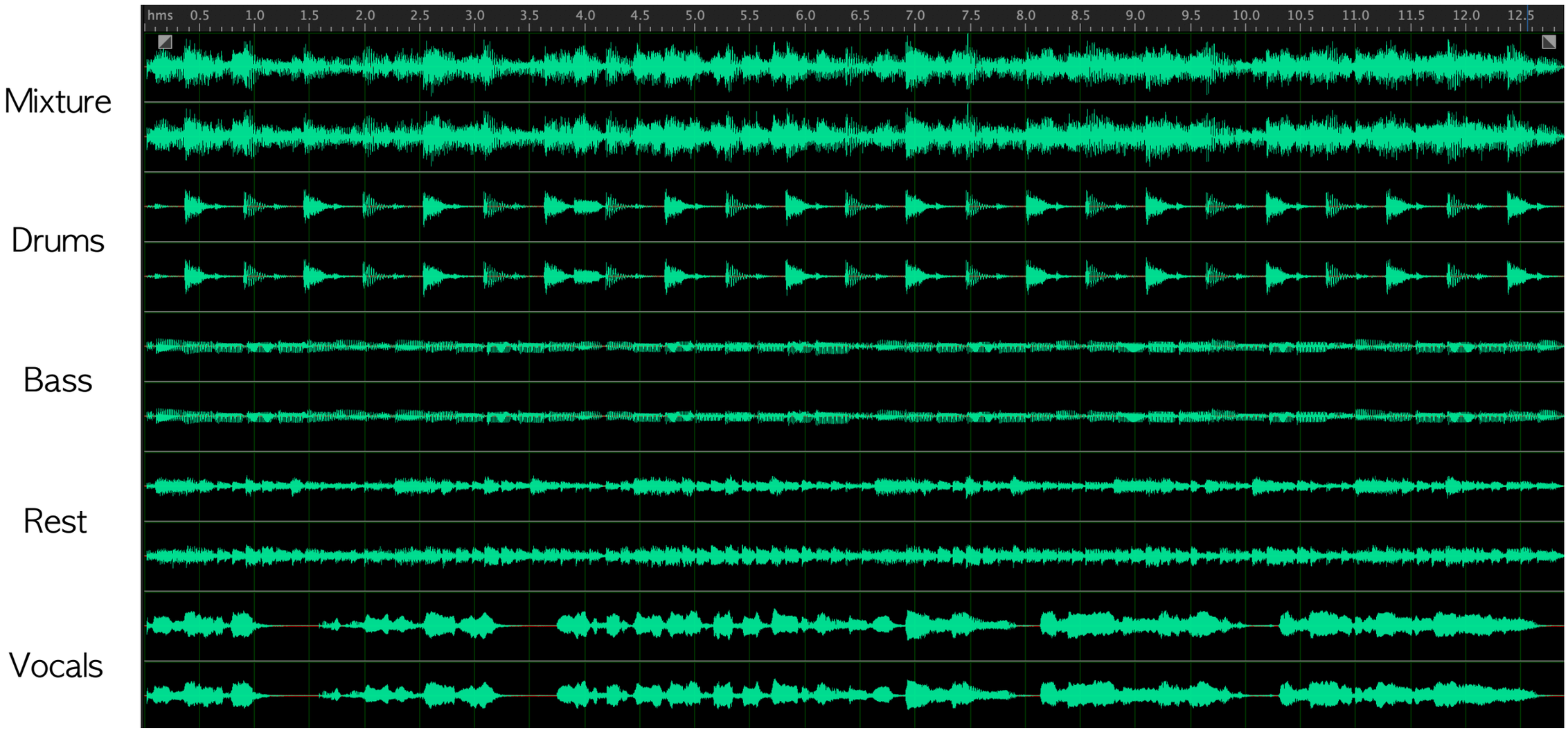
Musenet

Blog
https://openai.com/blog/musenet

Source Separation

Dataset





sigsep.github.io/datasets/musdb.html

Source Separation

MMDenseLSTM

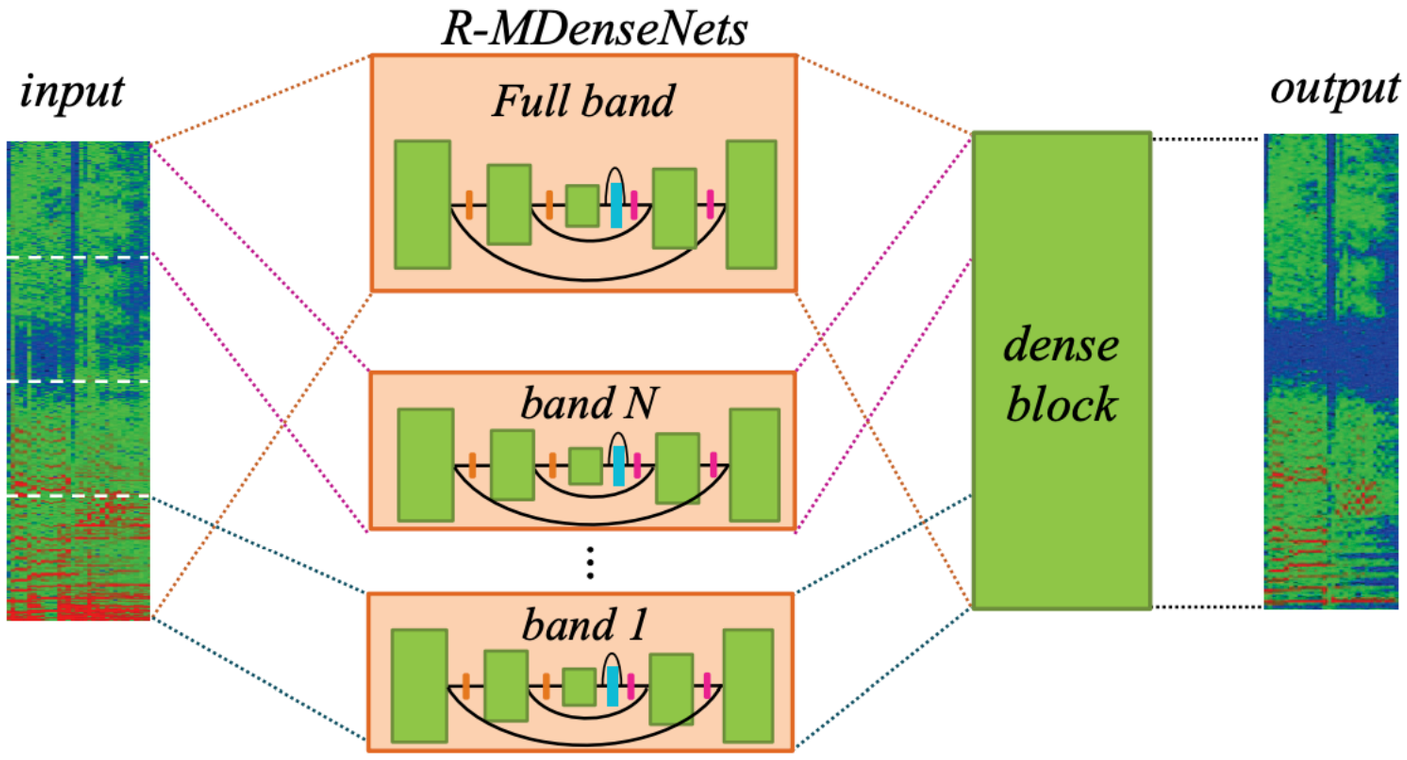


Fig. 3. MMDenseLSTM architecture. Outputs of MDenseLSTM dedicated to different frequency band including the full band are concatenated and the final dense block integrates features from these bands to create the final output.

SiSEC 2018 website
sisec18.unmix.app
관련 논문
MMDenseLSTM: An efficient combination of convolutional and recurrent neural networks for audio source separation
https://arxiv.org/abs/1805.02410