음성학회
학제간 워크숍

한국전자통신연구원

초지능창의연구소, 복합지능연구실

박기영

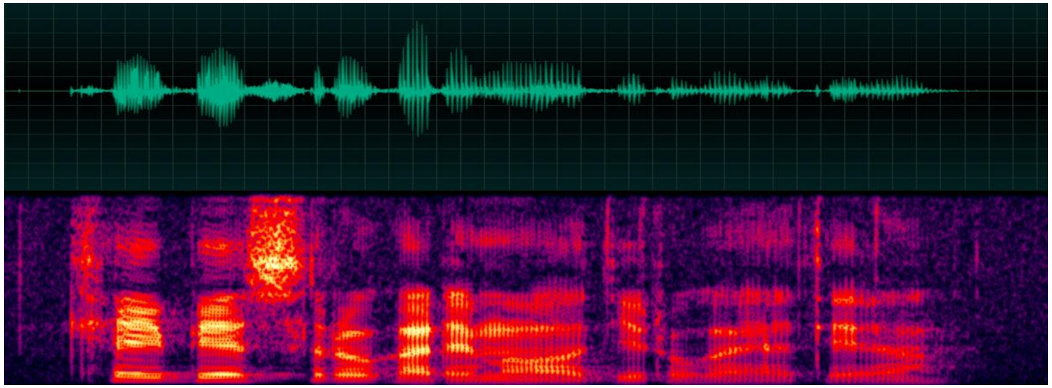
강의내용

- 음성 인식 개요
- 음성 인식의 성능 측정
- 특징 추출 방법
- 트랜스포머 기반 종단형 음성인식 기술

PART I: 음성인식 개요

What is speech recognition

- ASR(Automatic Speech Recognition), STT(Speech-to-text)



  - Isolated, Connected, Continuous, Keyword Spotting
  - Speaker Dependent/Independent
- Difference with Image/Video Classification
  - Sequence Generation Problem

Recent Landmarks in ASR

1986,
Error Backpropagation
Algorithm

Geoffrey E. Hinton

2016

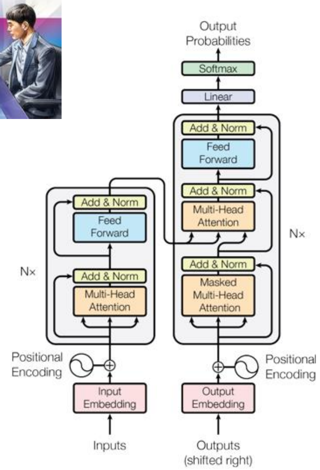
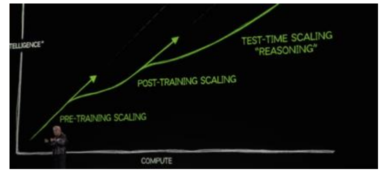
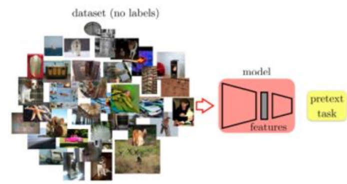
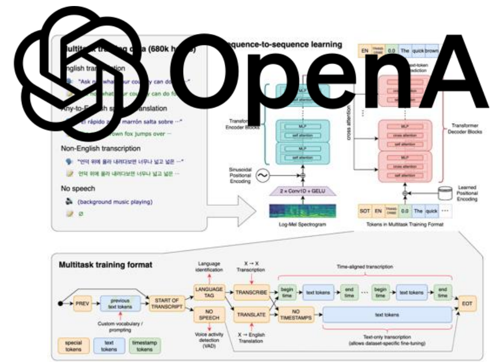


Figure 1: The Transformer - model architecture.







2006, A Fast Learning Algorithm for Deep Belief Nets

2009, An Efficient Learning Procedure for Deep Boltzmann Machines

2012, ImageNet Classification with Deep Convolutional Neural Networks

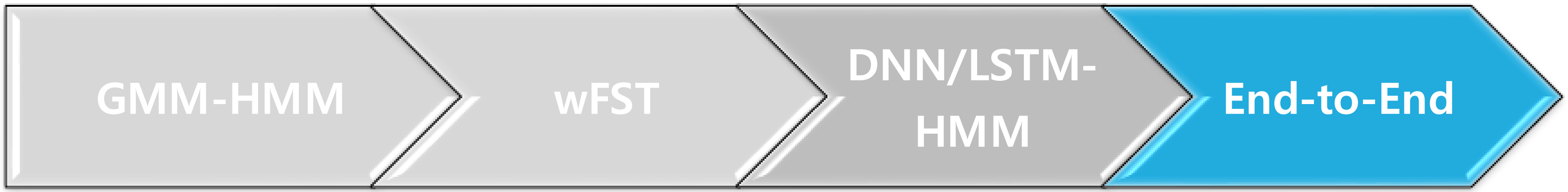
2017, Attention is all you need

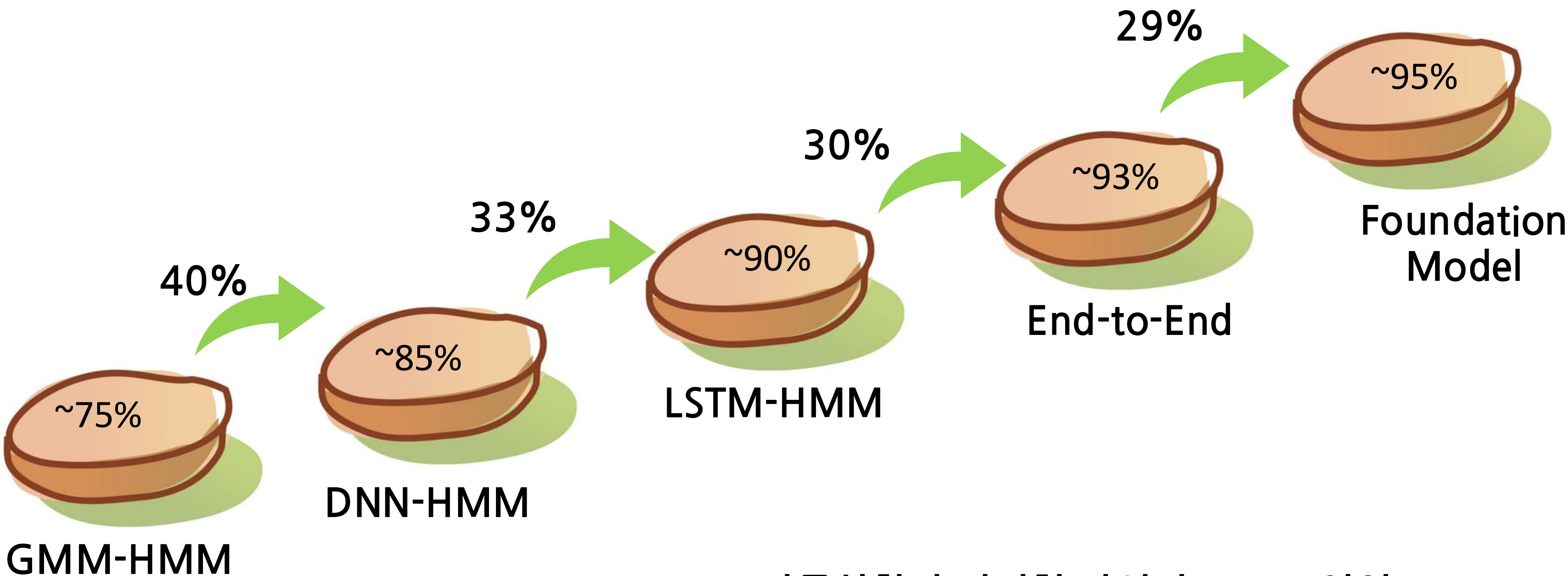
2018, BERT, GPT

2022, whisper

2023, whisper large-v3

음성인식 기술의 현재 성능





* 사무실환경 비정형 자연어 LVCSR영역
* 상대적 체감 성능

음성인식의 어려움

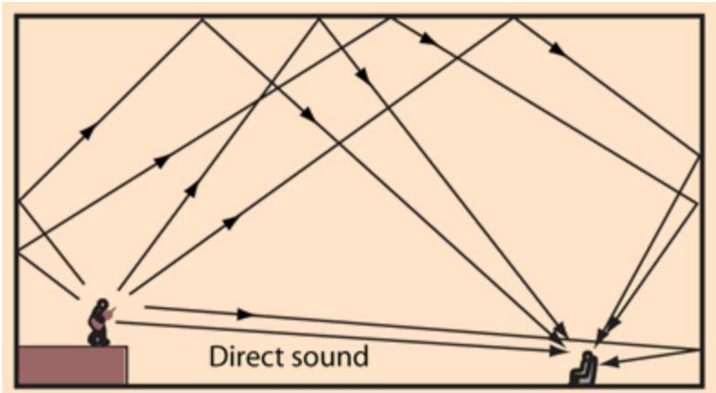
- 화자별 변이
  - Age, gender, accent, dialect
- 배경잡음 및 발화 환경
  - Noise, echo
  - Far-field (reverberation)
- 비정형 발화 & 유창성
  - 간투사(Filler words: “음”, “그러니까”, “uh”, “um”)
  - hesitations, self-corrections, repetition
  - Code-switching
- Homophones & Ambiguities
  - Words with similar sounds (e.g., “to, two, too”)
  - Context-dependent disambiguation

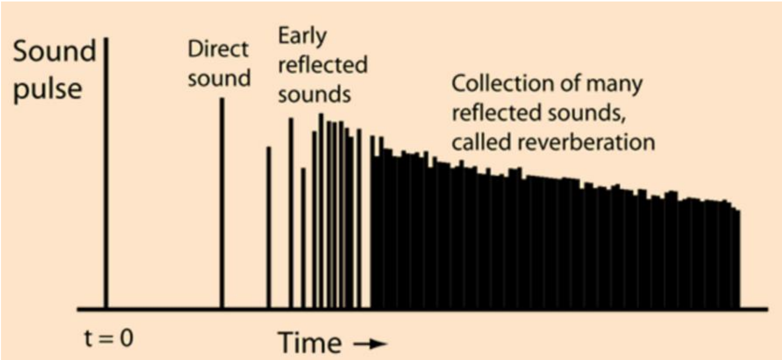
배경 잡음

- Stationary vs Non-stationary Noise
  - 자동차 엔진소리, 공조기 소리
  - 음악 잡음, 주변 사람 말소리
- 측정 Metric
  - Signal-to-noise (SNR)
  - 10*log(SignalPower/NoisePower)
  - 0dB, 10dB, -10dB
  - SDR: Signal-to-Distortion Ratio
  - SIR: Signal-to-Inteferance Ratio

발화 환경

- Closed-talk vs Distant-talk
- 반사된 소리: Reververation(반향, 잔향)



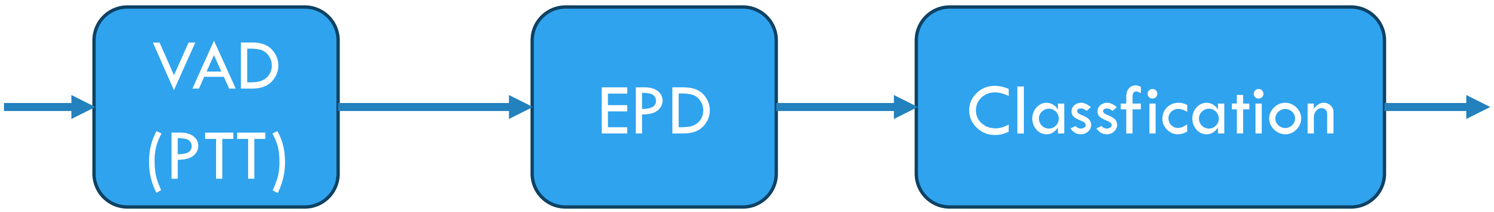


- Metric
  - rt60 (강당, 공연장: 1.5~2.5초)

http://hyperphysics.phy-astr.gsu.edu/hbase/Acoustic/reverb.html

고립어 인식 및 Keyword Spotting

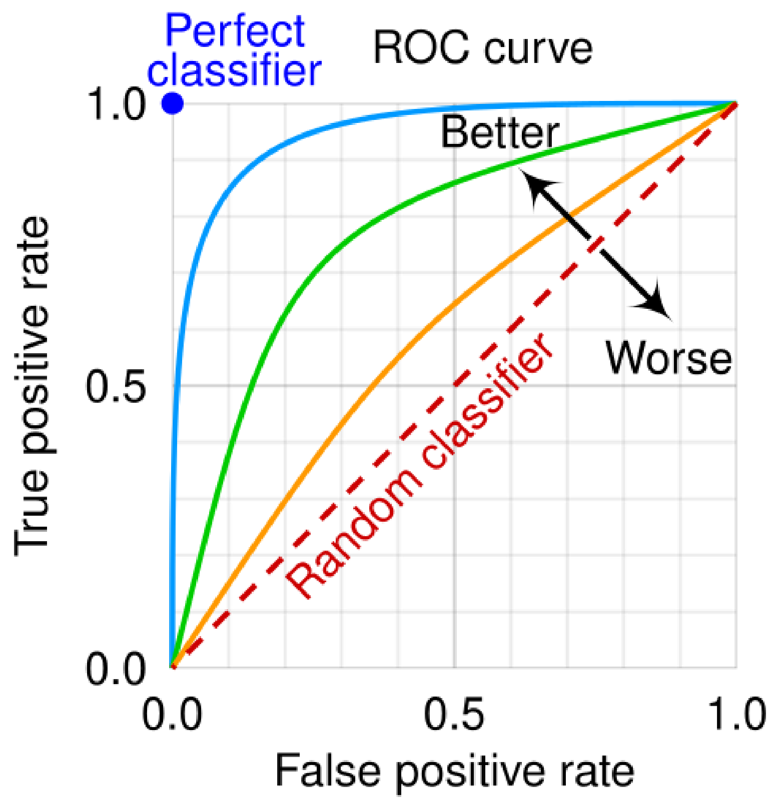
- Push-to-talk (PTT)
- Endpoint-Detection (EPD)
- VAD: Voice Activity Detection



<고립어 인식 절차>

Evaluation Metric: Classification

- keyword spotting 의 경우
  - 2class classfication problem
- Type of errors
  - False positive (false alarm)
  - False negative (false rejection)
- AUROC (Area under ROC)
- EER (Equal-error-rate)



Evaluation Metric

Accuracy $\frac{TP + TN}{TP + FP + FN + TN}$		Actual	
		Positive	Negative
Predicted	Positive	TP	FP
	Negative	FN	TN

$$\text{Precisoin} = \frac{\text{TP}}{\text{TP+FP}}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}}$$

$$\text{Sensitivity} = \text{Recall}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}}$$

연속음성인식(LVCSR)

- Large vocabulary continuous speech recognition
- Find mapping
  - X: speech/spectrogram → Y: sequence of words/tokens
- How to handle length variation
  - HMM: state transition + self-transition
  - CTC: blank symbol
  - Sequence-to-sequence model: token generation

Evaluation Metric

- Types of Error
  - Substitution
  - Deletion
  - Insertion
- Error Rate (cab be > 1)
  - (S + D + I)/N
- Accuracy (can be < 0)
  - 1-(Error Rate)
- WER/CER/SER:
  - Word/Character/Sentence Error Rate

REF : how is the weather today
REC/HYP: how was the better to day

In Words: WER = 100%, Acc=0%
- N= 5: how, is, the, weather, today
- S = 2
- D = 1
- I = 2

how is the weather today
how was the better to day

In Chars: CER = 25%, Acc=75%
- N= 20:
h,o,w,i,s,t,h,e,w,e,a,t,h,e,r,t,o,d,a,y
- S = 3
- D = 1
- I = 1

how is the weather today
how was the better to day

In Sentence: SER = 100%, Acc=0%
- N = 1
- S = 1

한국어

- REF: 오늘 서울의 날씨가 어때
- REC: 음 오눌의 날씨 가 어때
- WER=4/4 = 1.0 Acc=0.0
  - N=4, 오늘, 날씨가, 어때요
  - S = 2, D = 1, I = 2, WER=5/4
  - S = 3, I = 1, WER=4/4
- CER= 4/10 = 0.4, Acc=0.6
  - N = 10
  - S = 1
  - D = 2
  - I = 1

	오늘	서울의	날씨가		어때
음	오눌의		날씨	가	어때

오늘	서울의	날씨가		어때
음	오눌의	날씨	가	어때

	오	늘	서	울	의	날	씨	가	어	때
음	오	눌			의	날	씨	가	어	때

측정방법

- Edit distance 측정
  - 최소편집거리
  - https://en.wikipedia.org/wiki/Edit_distance
- 사용도구
  - HResults (HTK)
  - compute-wer (kaldi)
  - sclite (NIST, ESPnet)
- 예)
  - compute-wer ark:ref.txt ark:rec.txt

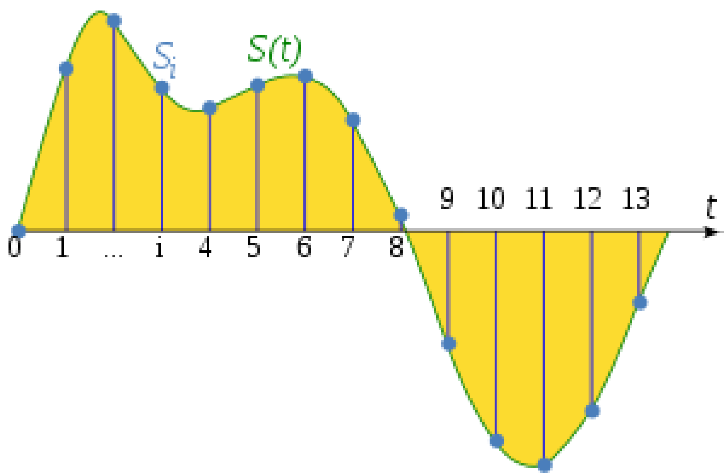
실습

- 음성인식 오유율 측정 실습
- https://colab.research.google.com/github/pkyoung/a1003/blob/main/local/wer.ipynb

PART II: 특징 추출

Sampling

- Analog to Digital Conversion (ADC)
  - Sampling



8kHz: Narrowband, 전화망
16kHz: Wideband
44.1/48kHz: High quality audio

  - Quantization
    - 16bit = 2-byte short integer -32768 < s <+32767
    - 24bit, 32bit

https://en.wikipedia.org/wiki/Sampling_(signal_processing)

Fourier Series / Transform

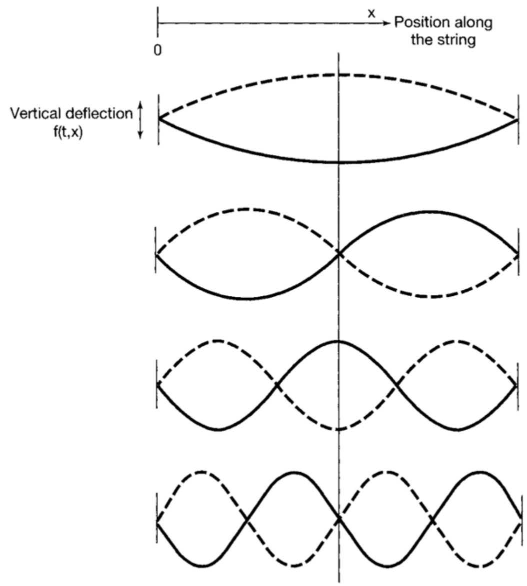
- Jean Baptiste Joseph Fourier(1768-1830)
- Claimed "any" periodic signal can be represented by series of harmonically related sinusoids

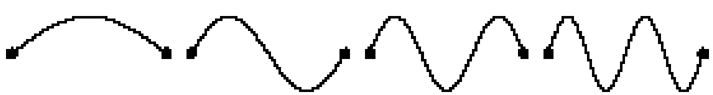
$$x[n] = \sum_{k=\langle N\rangle} a_k e^{jk\omega_0 n} = \sum_{k=\langle N\rangle} a_k e^{jk(2\pi/N)n},$$

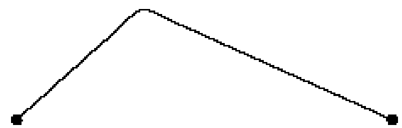
$$a_k = \frac{1}{N} \sum_{n=\langle N\rangle} x[n] e^{-jk\omega_0 n} = \frac{1}{N} \sum_{n=\langle N\rangle} x[n] e^{-jk(2\pi/N)n}.$$

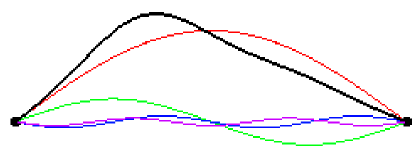
Vibrating Strings

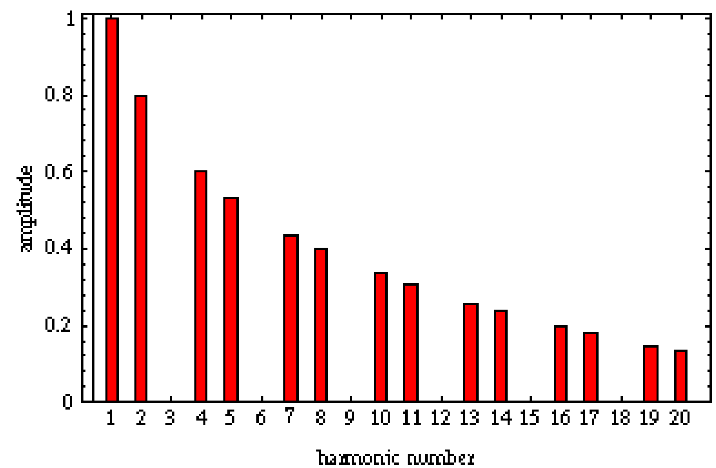
- Vibration of fixed-fixed string





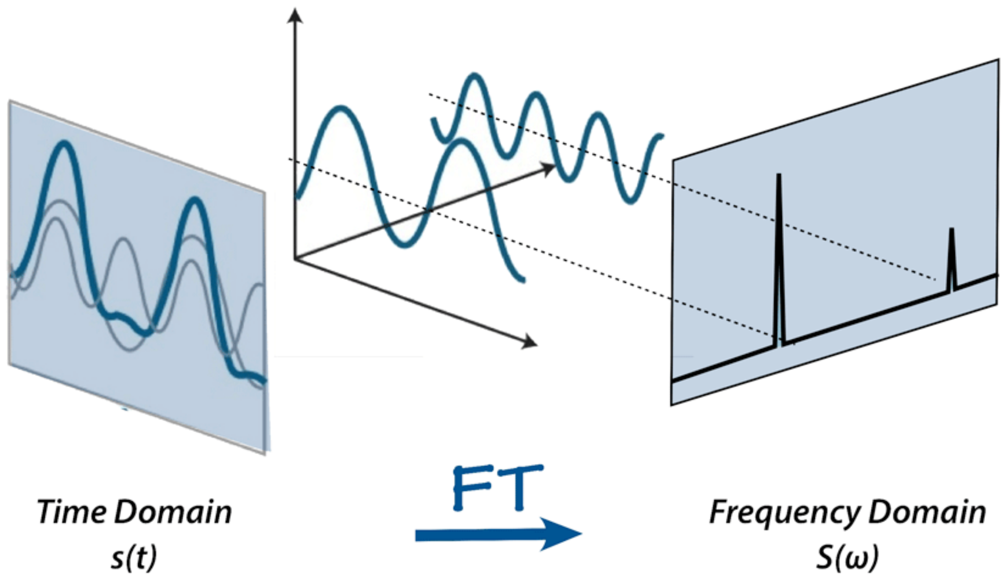






https://www.acs.psu.edu/drussell/demos/string/fixed.html

Spectrum



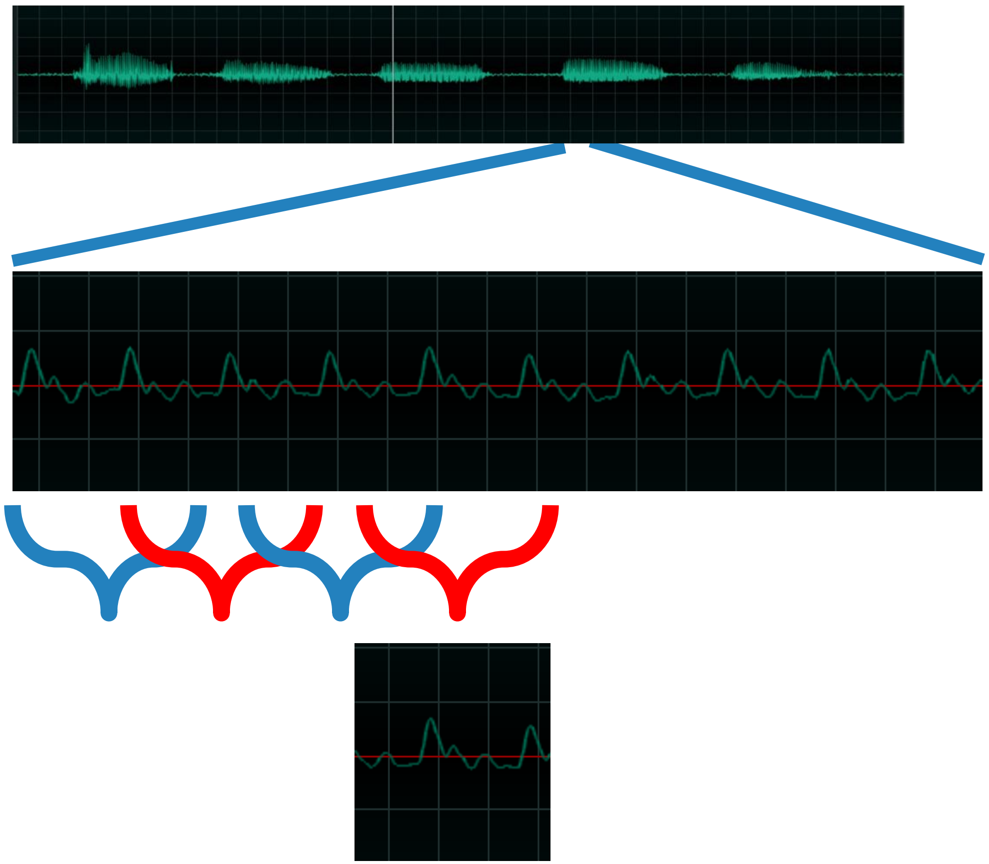
https://towardsdatascience.com/understanding-audio-data-fourier-transform-fft-spectrogram-and-speech-recognition-a4072d228520

Frame-wise Processing

4 sec

0.1 sec

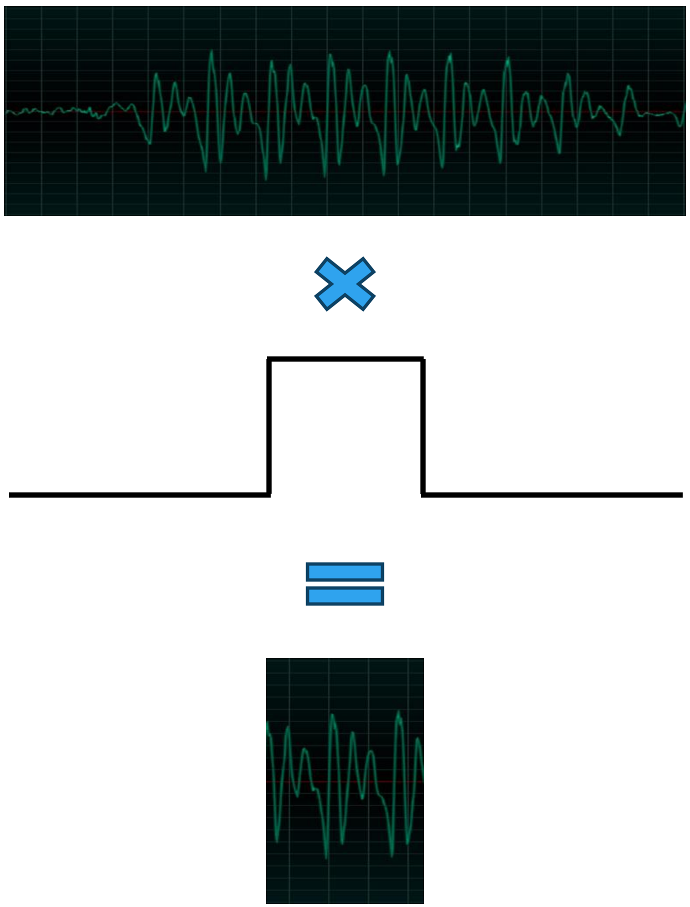
0.02 sec



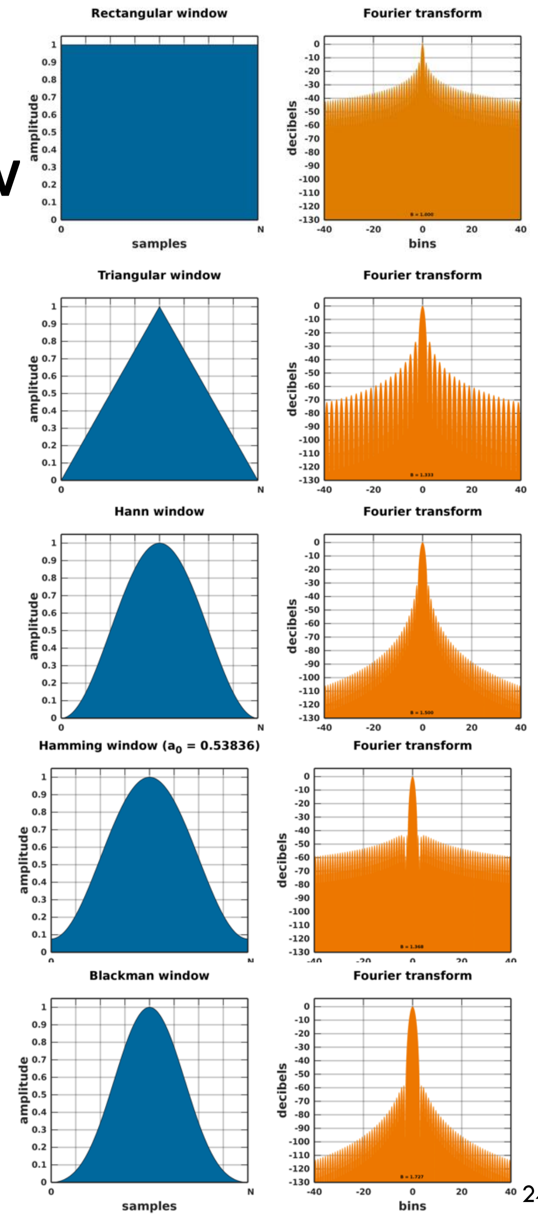
Window length,
Hop size

Windowing

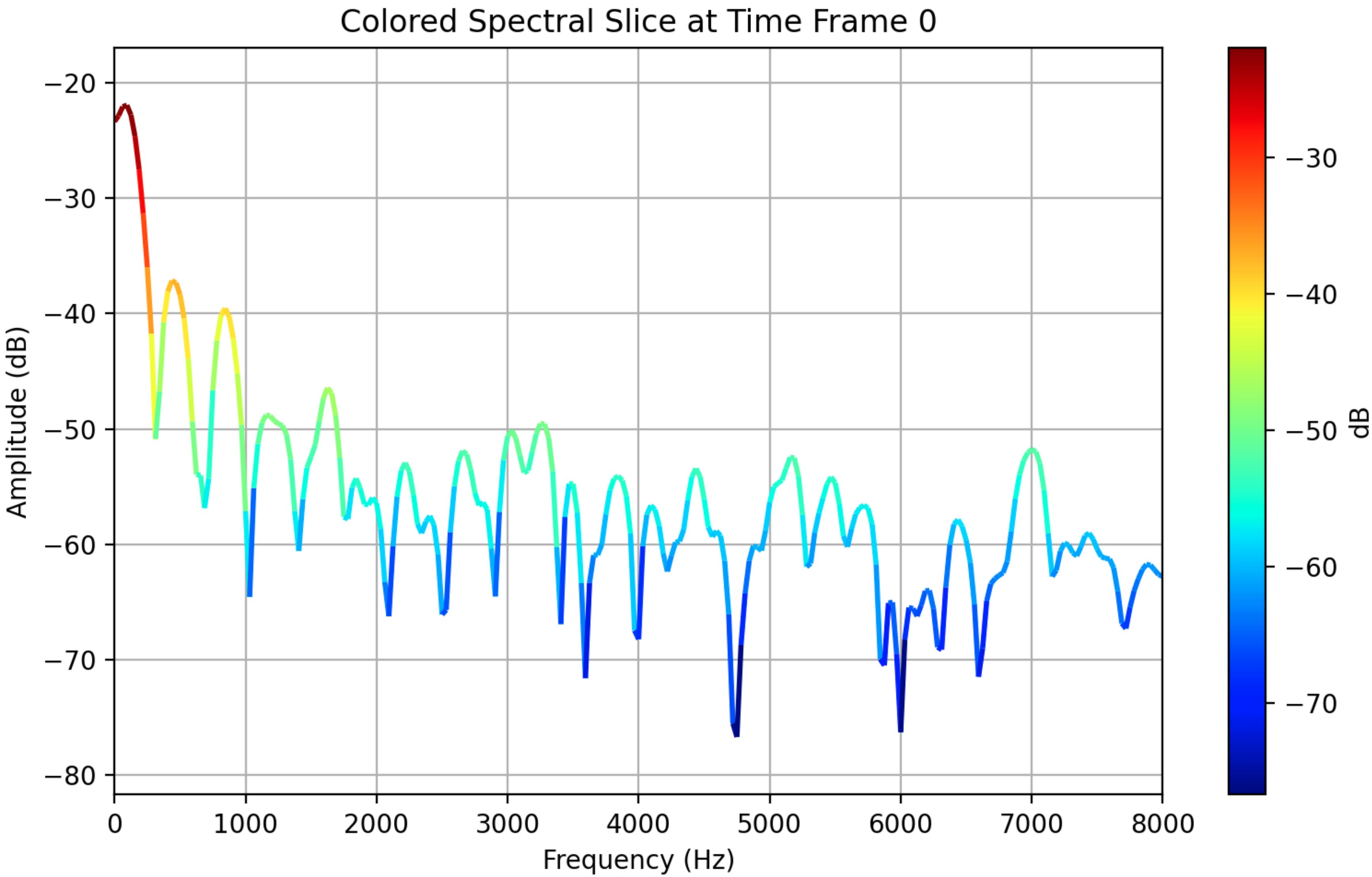
- Windowing = Framing
  - Element-wise multiplication with window



Rectagular
Triangular
Hann
Hamming
Blackman



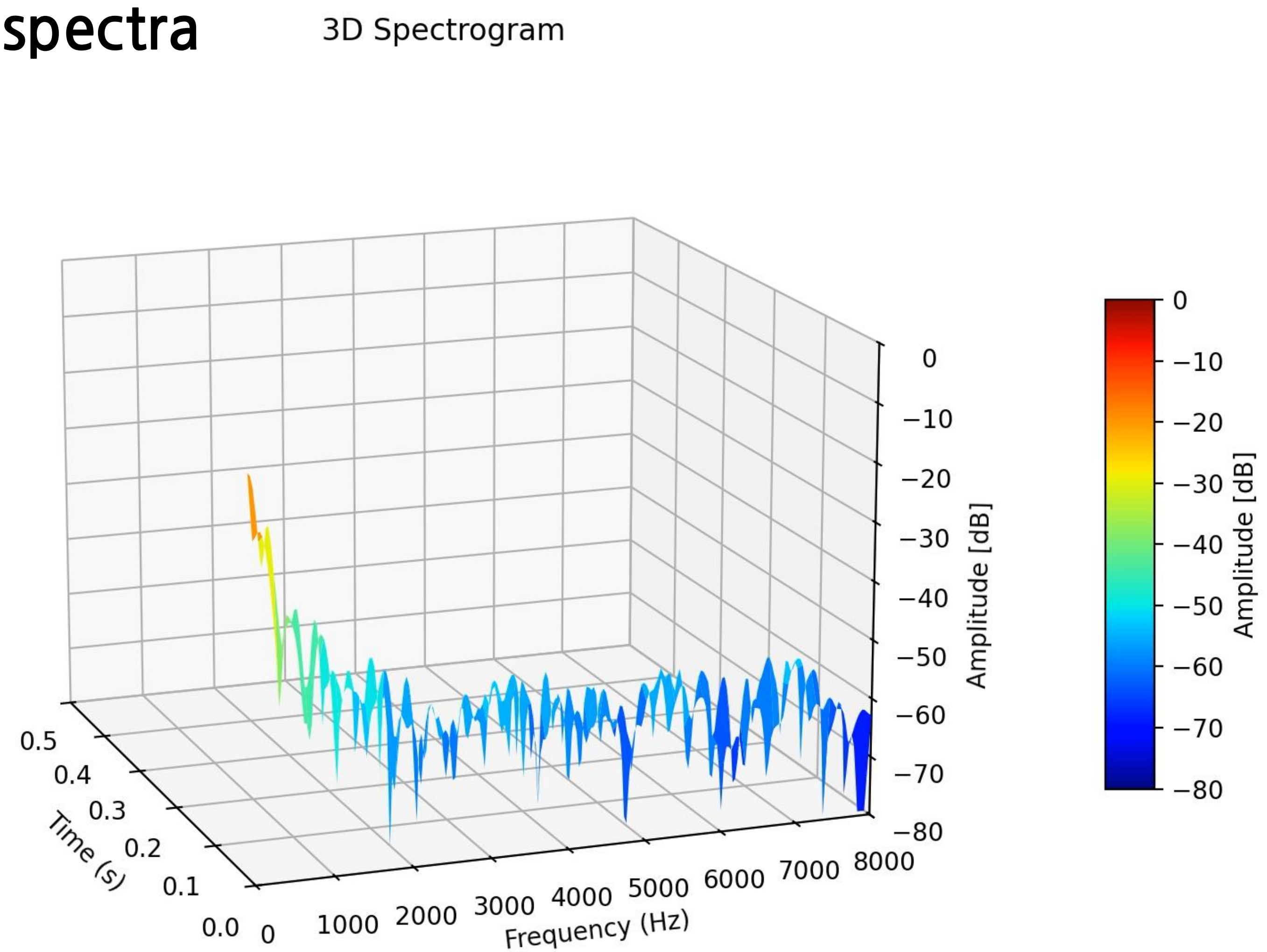
Spectrum



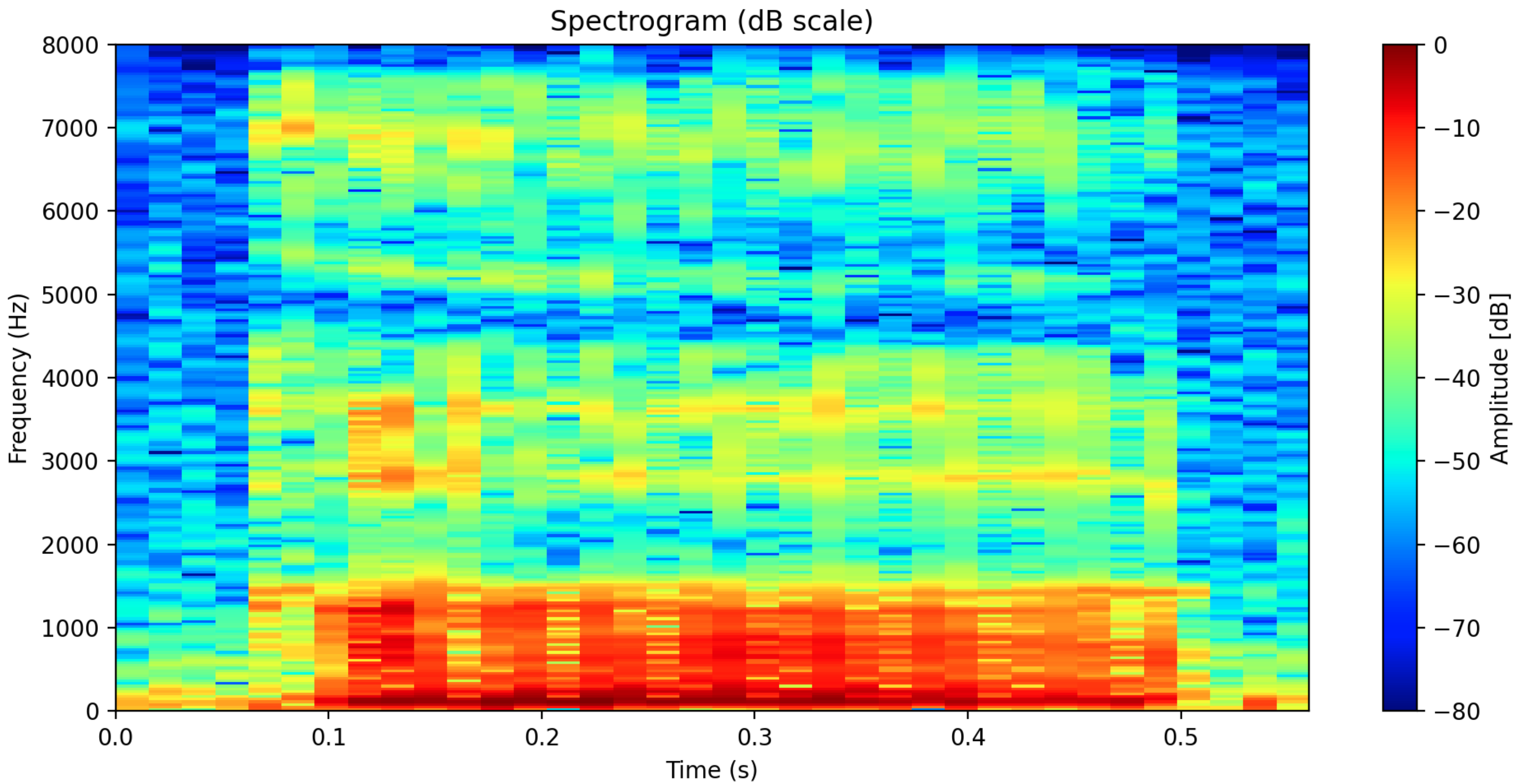
Colored Spectral Slice at Time Frame 0
Amplitude (dB)
Frequency (Hz)
dB
−20
−30
−40
−50
−60
−70
−80
0
1000
2000
3000
4000
5000
6000
7000
8000

Spectrogram: 3D

- 3D plot of spectra

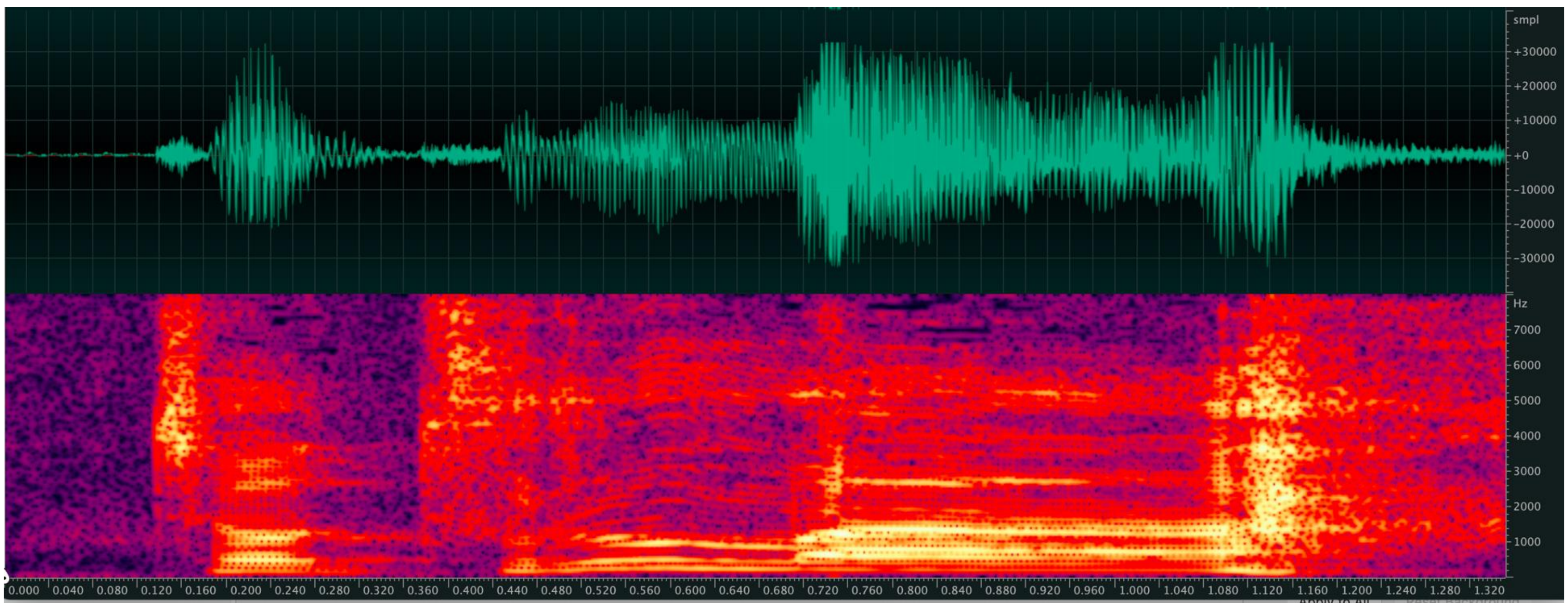


Spectrogram: 2D

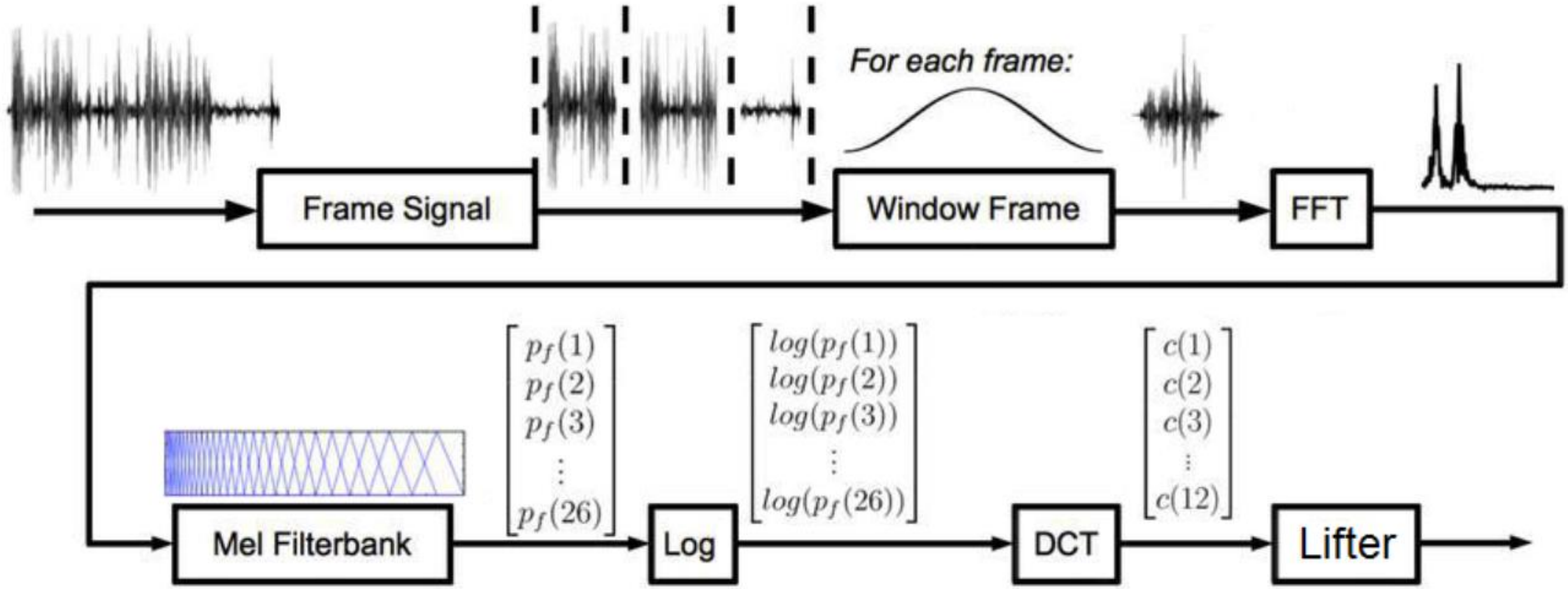


Spectrogram

- Matlab, Python, Adobe Audition, Audacity, …
- Frame Shift, Overlap, Window Length, Windowing, FFT points

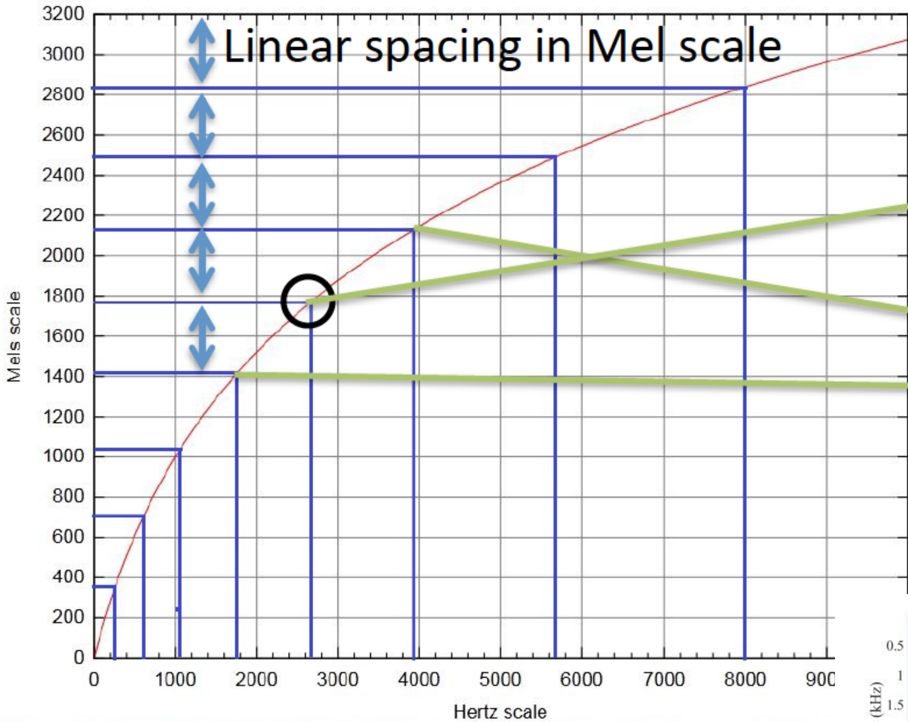


Feature extraction: MFCC



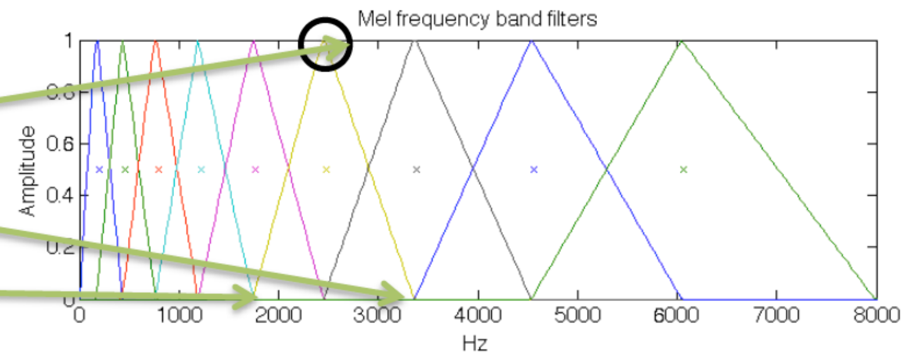
https://hyunlee103.tistory.com/46

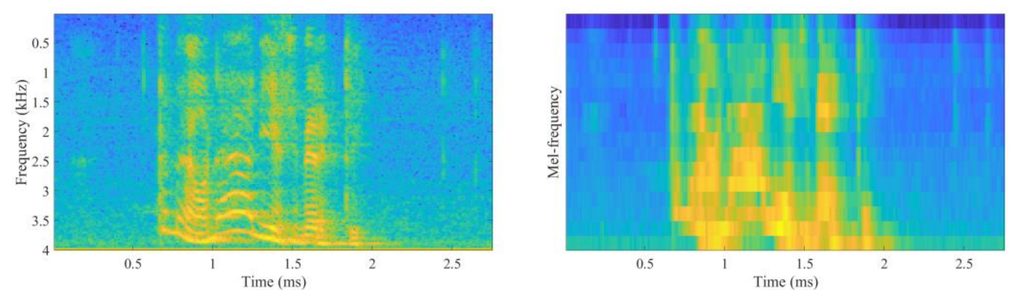
Mel Filterbank



https://hyunlee103.tistory.com/46

# of filters: 23 → 40 → 80+3





https://wiki.aalto.fi/display/ITSP/Cepstrum+and+MFCC

Feature Normalization

- CMS
  - Cepstral Mean Substraction

Log-mel

t=0: [3, 2, 3, 4, 4, 3]
t=1: [4, 1, 3, 3, 3, 1]
t=2: [2, 3, 3, 5, 8, 2]

⇩

mean vector = [3, 2, 3, 4, 5, 2]

⇨

Normalized log-mel

t=0: [0, 0, 0, 0, -1, 1]
t=1: [1, -2, 0, -1, -2, -1]
t=2: [-1, 1, 0, 1, 3, 0]

CMVN

- Cepstral Mean Variance Normalization
  - Zero-mean Unit Variance
- CMS: Cepstral Mean Substraction
  - Per Utterance
  - 채널/화자 효과를 제거하고 발성의 특성만 남김
- For Deep Learning
  - Global CMVN
  - For better convergence

실습

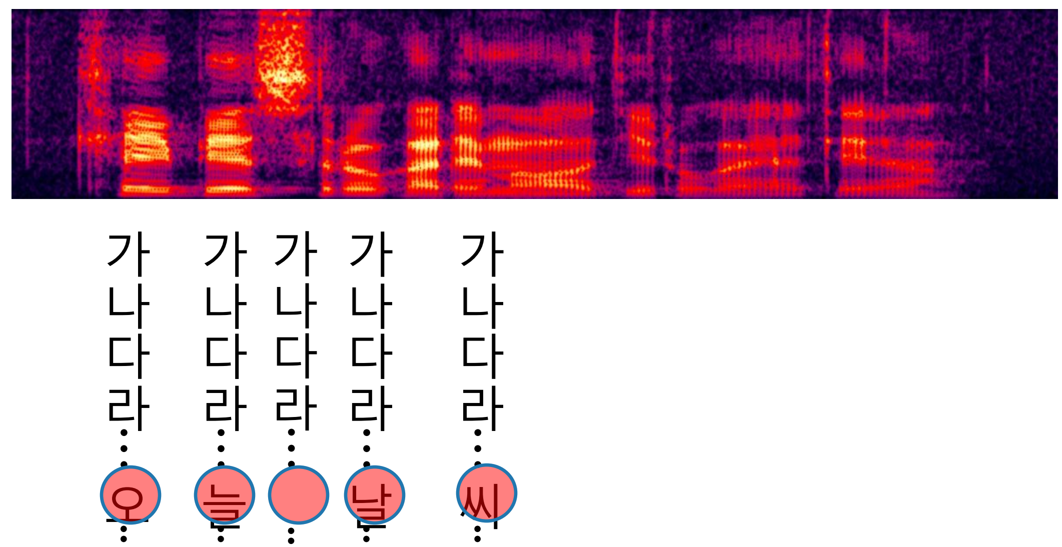
- 특징 추출 실습

- https://colab.research.google.com/github/pkyoung/a1003/blob/main/local/fx.ipynb

PART III:
트랜스포머 기반 종단형 음성인식 기술

확률모델 기반 음성인식

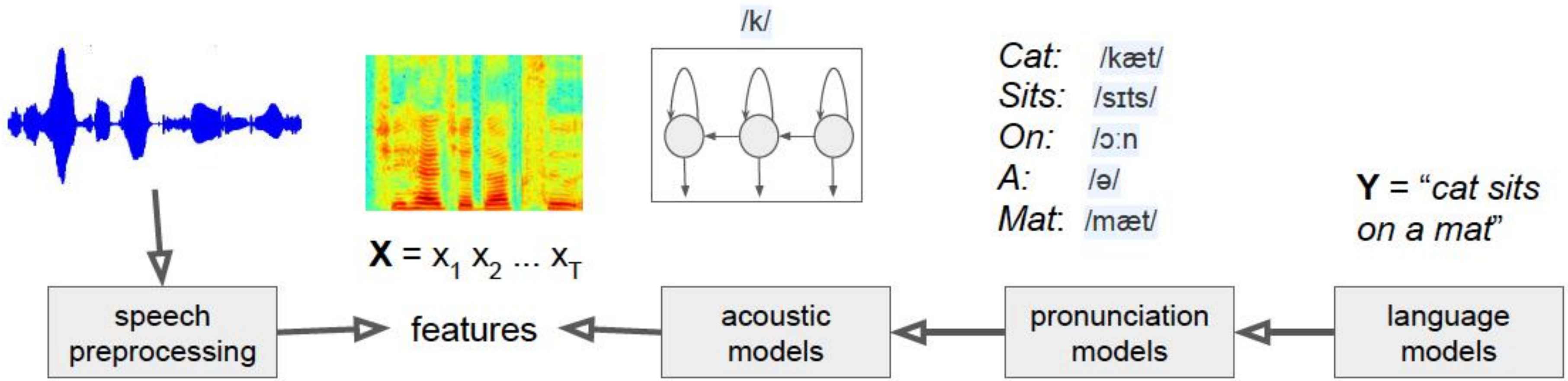
- W* = argmax P(W|X)
  - To Find Most Probable Word Sequence Given Input Signal/Feature



- Considerations
  - Boundary? Segmentation?
  - Output Units? Words, Characters, Phoneme, …
  - Classification Accuarcy? Unit Accuracy vs. Sentence Accuracy

How It really works

- W* = argmax log P(W|X)
- = argmax log P(X|Q)P(Q|W)P(W)
- To Find Most Probable Sequence Among Plausible Words Sequences



https://heartbeat.fritz.ai/the-3-deep-learning-frameworks-for-end-to-end-speech-recognition-that-power-your-devices-37b891ddc380

Guess who?

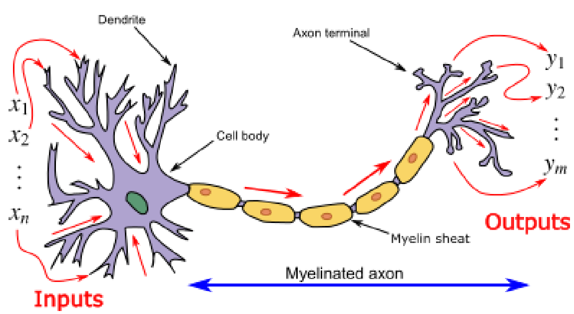
- Find A Criminal Among Suspects Given Evidence
- Criminal = argmax P(Suspect|Evidence)
- Criminal = argmax P(Evidence|Suspect)

  = argmax

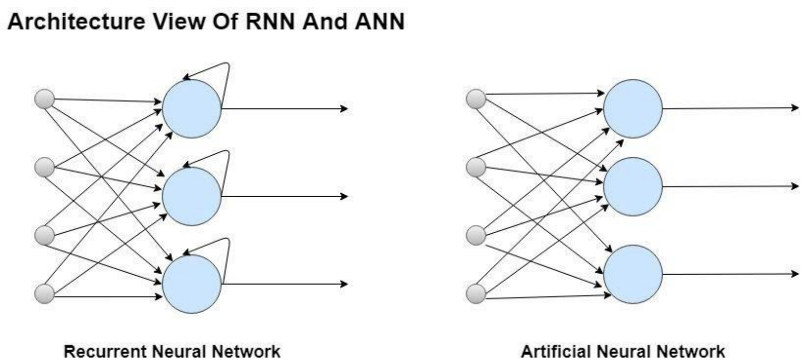
  P(Evidence|Behavior)P(Behavior|Suspect)P(Suspect)

RNN: Recurrent neural network

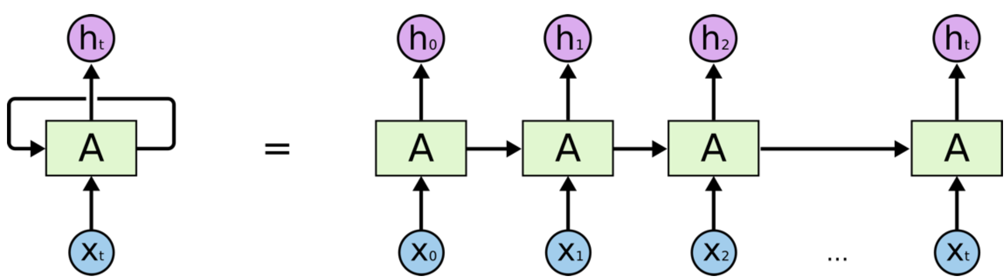
- Neural Networks
  - Mimic human brain: Neuron, Synapse



https://en.wikipedia.org/wiki/Nervous_system



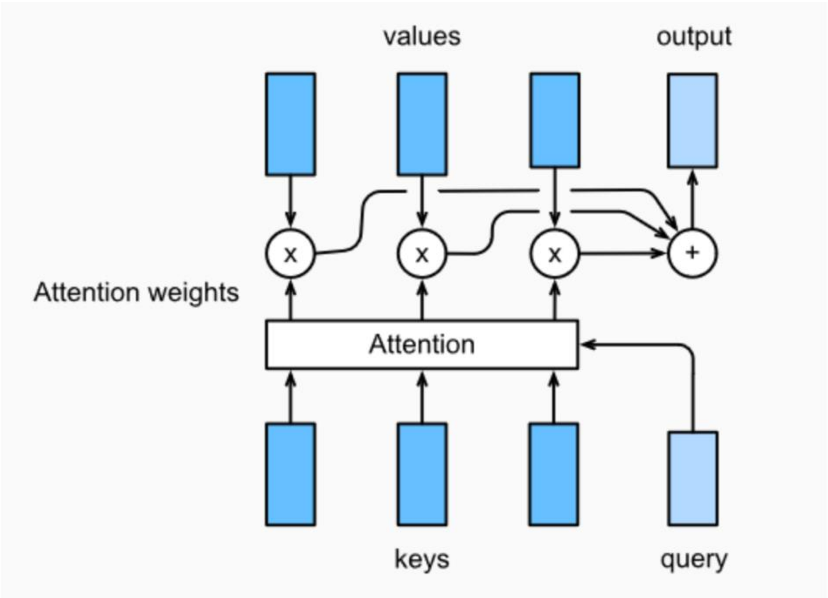
https://medium.com/datadriveninvestor/recurrent-neural-networks-in-deep-learning-part-1-df3c8c9198ba



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Attention

- Query, Key, Value
- Memory = Dictionary(Key,Value)
- Output = Weighted Sum of Value
- Weight = Similarity Between Query and Key



https://programming.vip/docs/5e4cadd75dc1d.html

Word Encoding

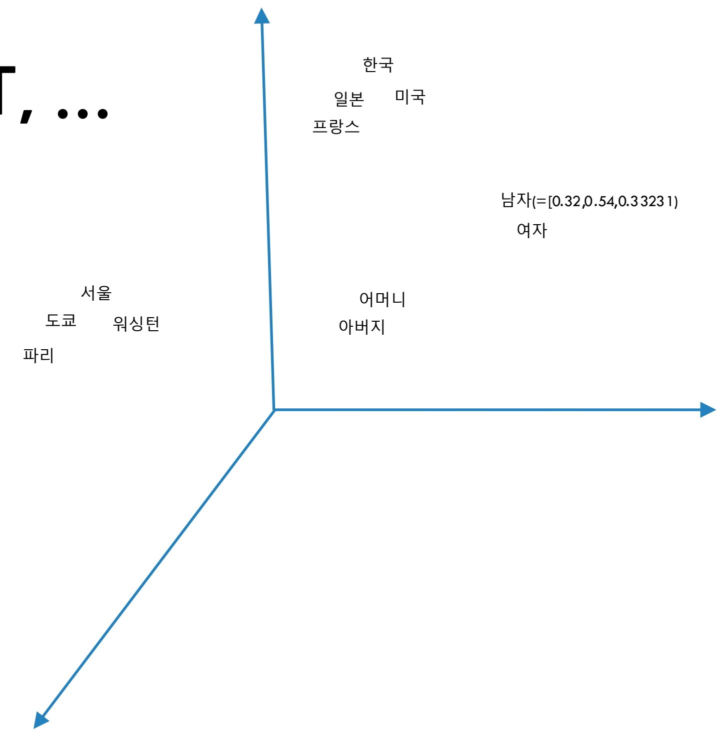
- Representation of a word as integer or vector
- Integer encoding vs one-hot vector encoding
- Sparse Representation vs. Dense Representation

raw_text="The sky turned red"
vocab = ["the", "sky", "turned", "red"]

Word	integer encoding	one-hot encoding
<pad>	0	[0, 0, 0, 0, 0]
<unk>	1	[1, 0, 0, 0, 0]
the	2	[0, 1, 0, 0, 0]
sky	3	[0, 0, 1, 0, 0]
turned	4	[0, 0, 0, 1, 0]
red	5	[0, 0, 0, 0, 1]

Word Embedding

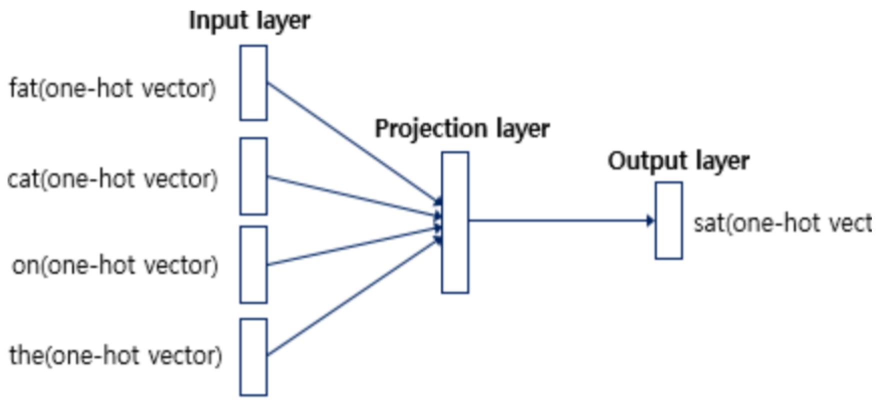
- Dense representation
  - One-hot: Sparse representation
  - Word2vec, GloVe, FastText, BERT, …
  - Dimension reduction
- Capture semantic relationship
  - 한국 - 서울 + 파리 = 프랑스
  - 어머니 - 아버지 + 여자 = 남자
  - 아버지 + 여자 = 어머니
  - Ehance generalization performance

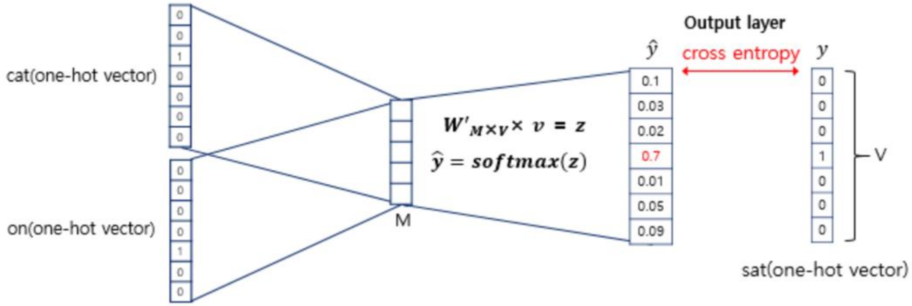


Word2Vec: CBOW

- Efficient Estimation of Word Representations in Vector Space, 2013, Tomas Mikolov, et al.
- CBOW: Continous Bag of Words
- No-nonlinearity in projection layer

예문 : "The fat cat sat on the mat"





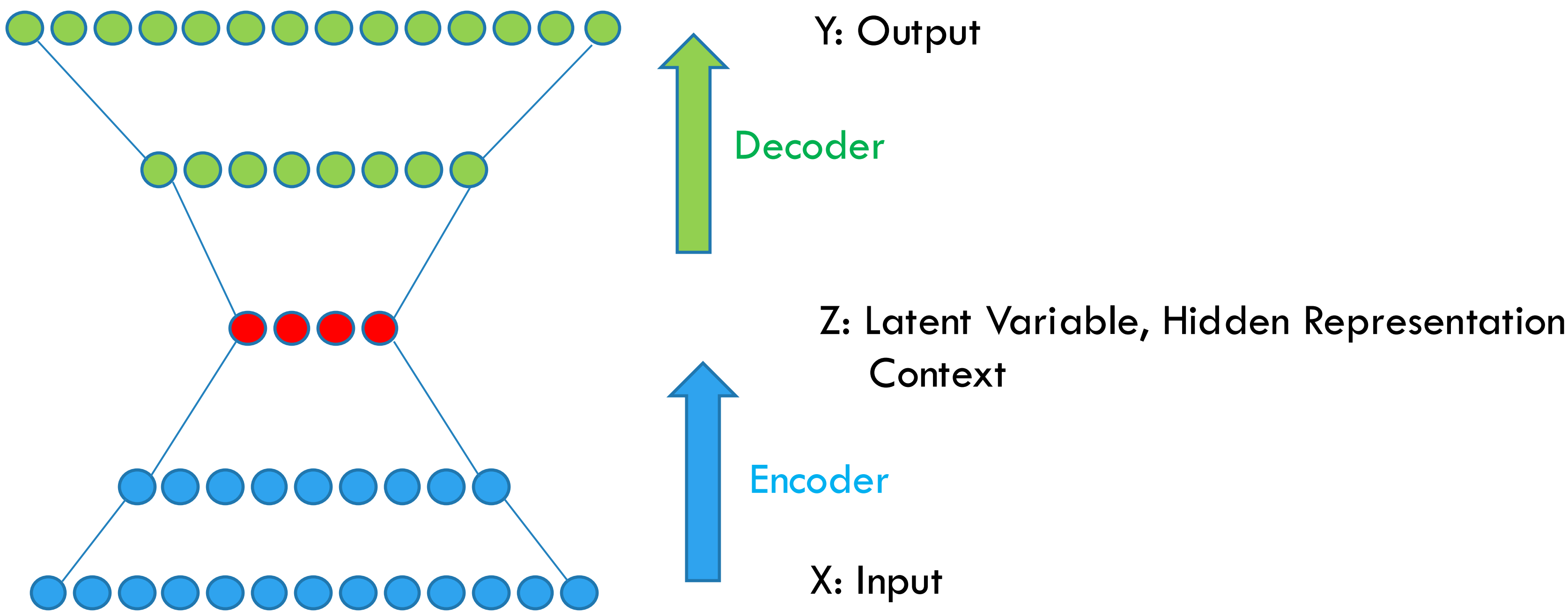
Tokenizing

- Token?
  - Basic unit of input and output
  - Char vs Word vs Subword (아버지?)
- Subword tokenizing: word → subword
  - To solve OOV problem
- Byte Pair Encoding
  - Neural Machine Translation of Rare Words with Subword Units, ACL, 2016
  - Not encoding but tokenization
  - A New Algorithm for Data Compression, 1994, C Users Journal

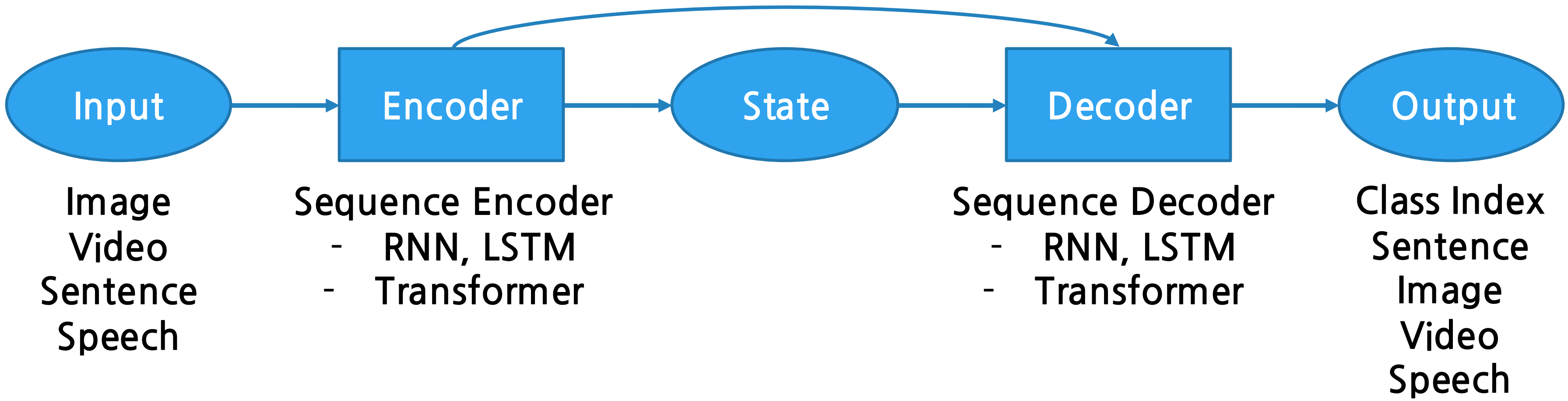
aaabdaaabac → ZabdZabac
Z=aa → ZYdZYac
Y=ab
Z=aa → XdXac
X=ZY
Y=ab
Z=aa

Encoder-Decoder

- Auto Encoder



Encoder-Decoder for Sequence

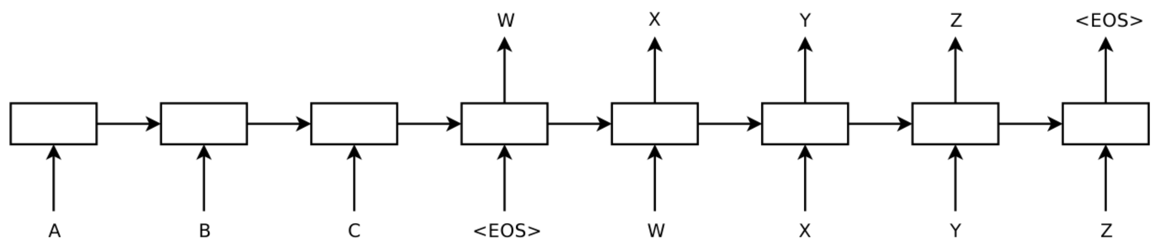


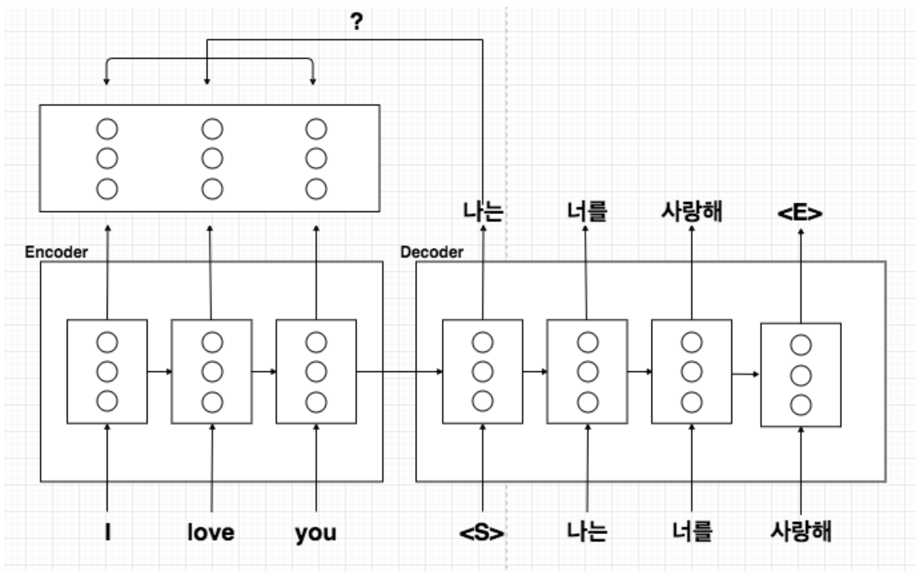
- Translation
- Image/Video Captioning
- Q&A, Document Summarization
- Speech
  - Recognition, Synthesis, Translation, Dialog System(Google Duplex, 2018)

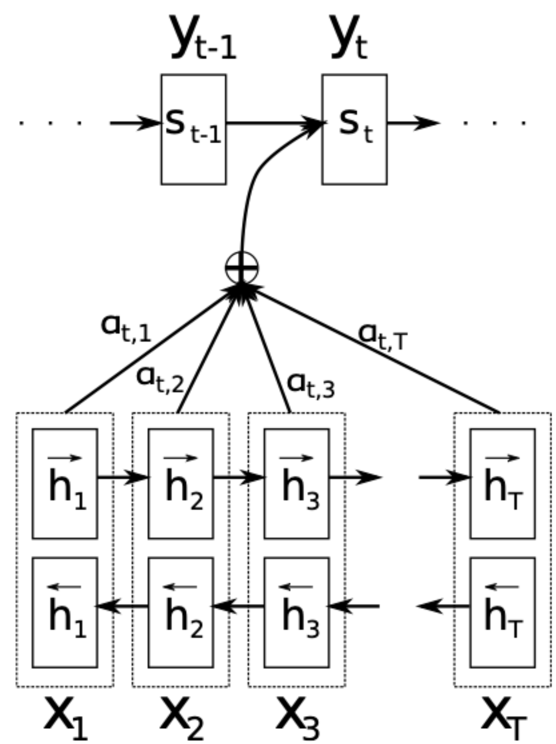
Era of Sequence-to-Sequence

- Natural Language Processing
- Sequence to Sequence Leanring with Neural Networks, NeurIPS, 2015
- Neural Machine Translation By Jointly Learning To Align And Translate, ICLR, 2016
- Attention Is All You Need, NuerIPS, 2017
- BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, ACL, 2019

Sequence to Sequence with Attention





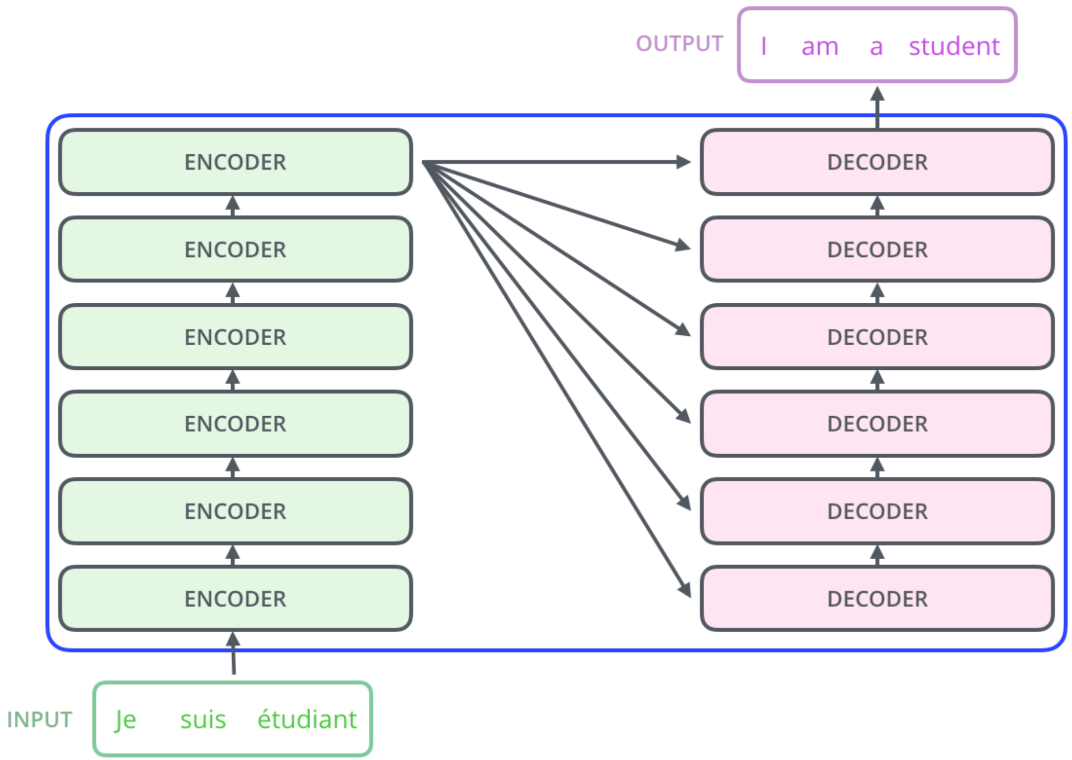


https://medium.com/platfarm어텐션-메커니즘과-transfomer-self-attention-842498fd3225

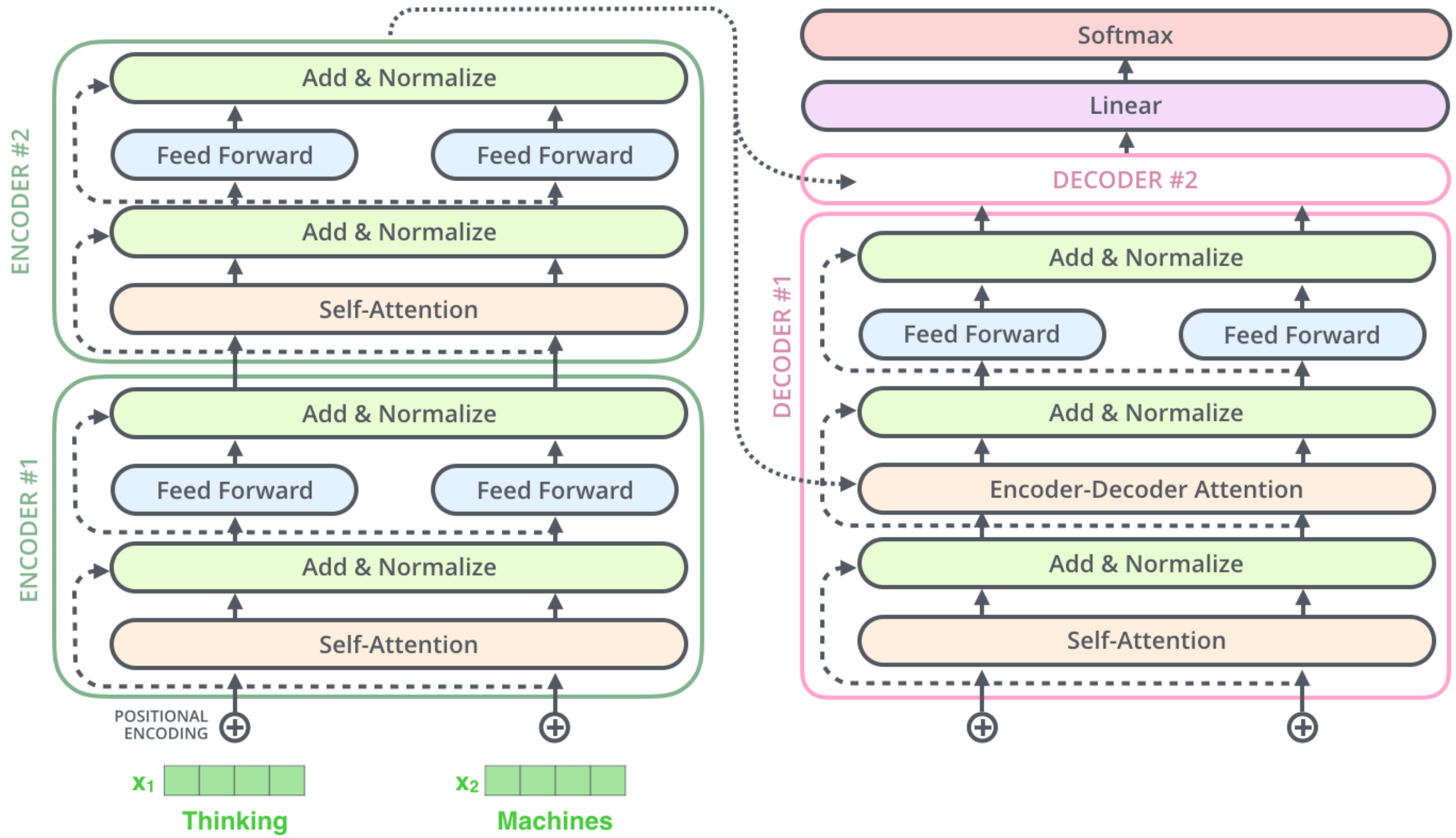
Transformer

Transformer: Overall Structure

- https://jalammar.github.io/illustrated-transformer/

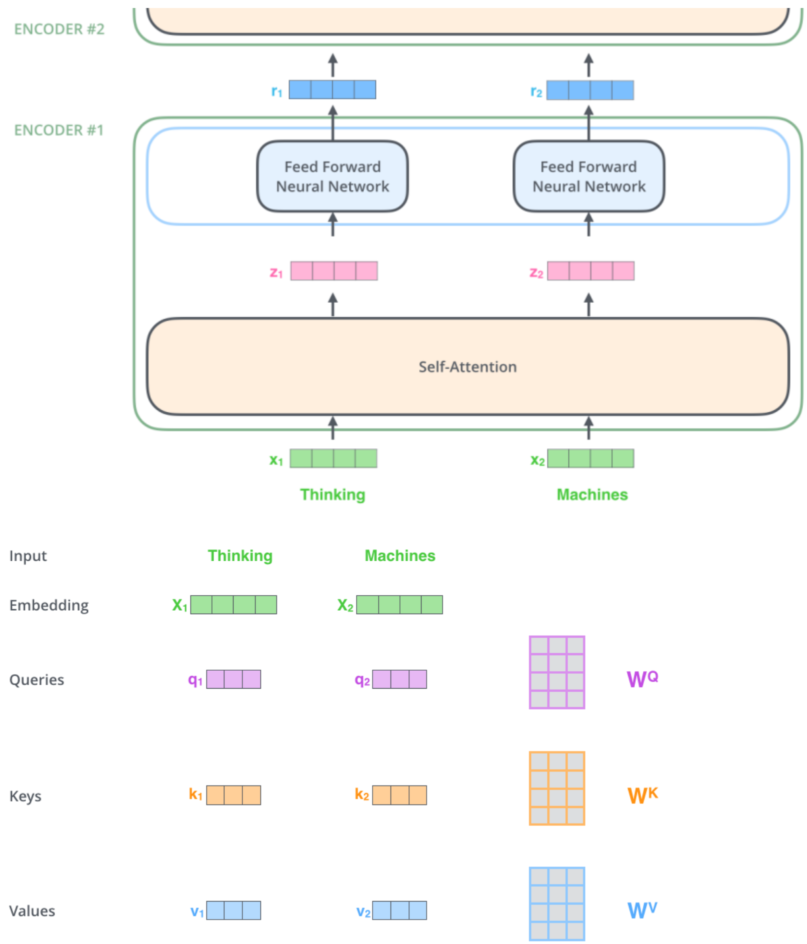


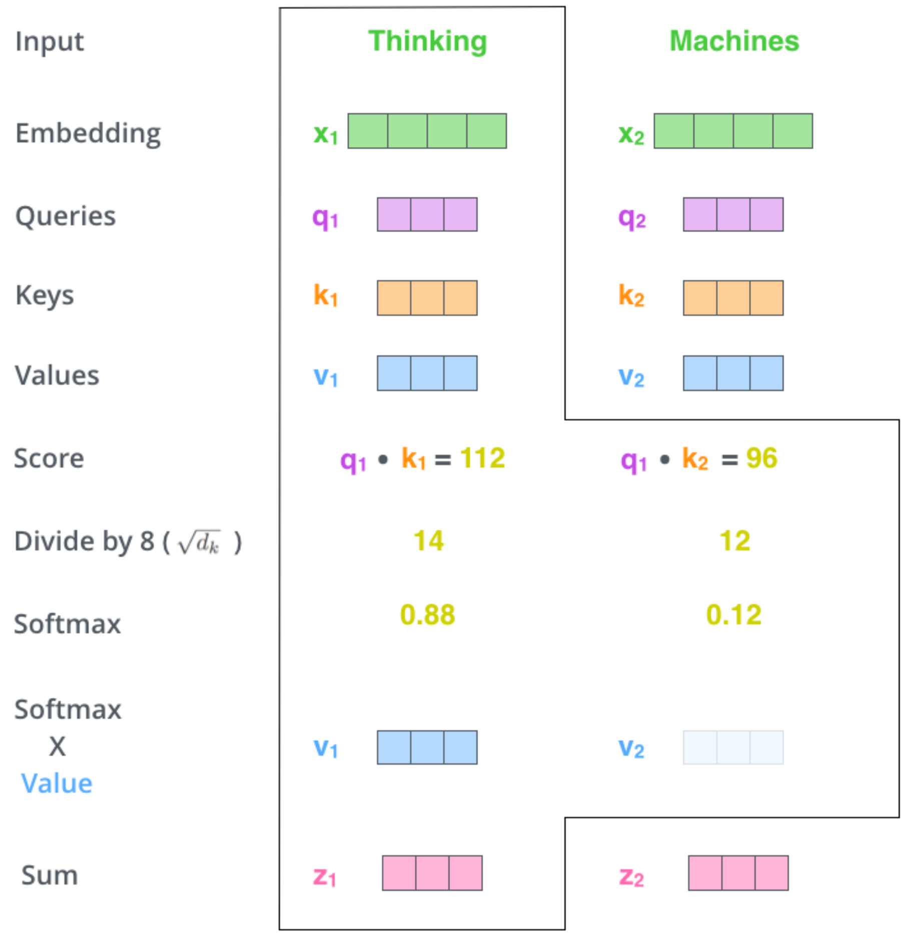
Transfomer: Detailed Structure



https://jalammar.github.io/illustrated-transformer/

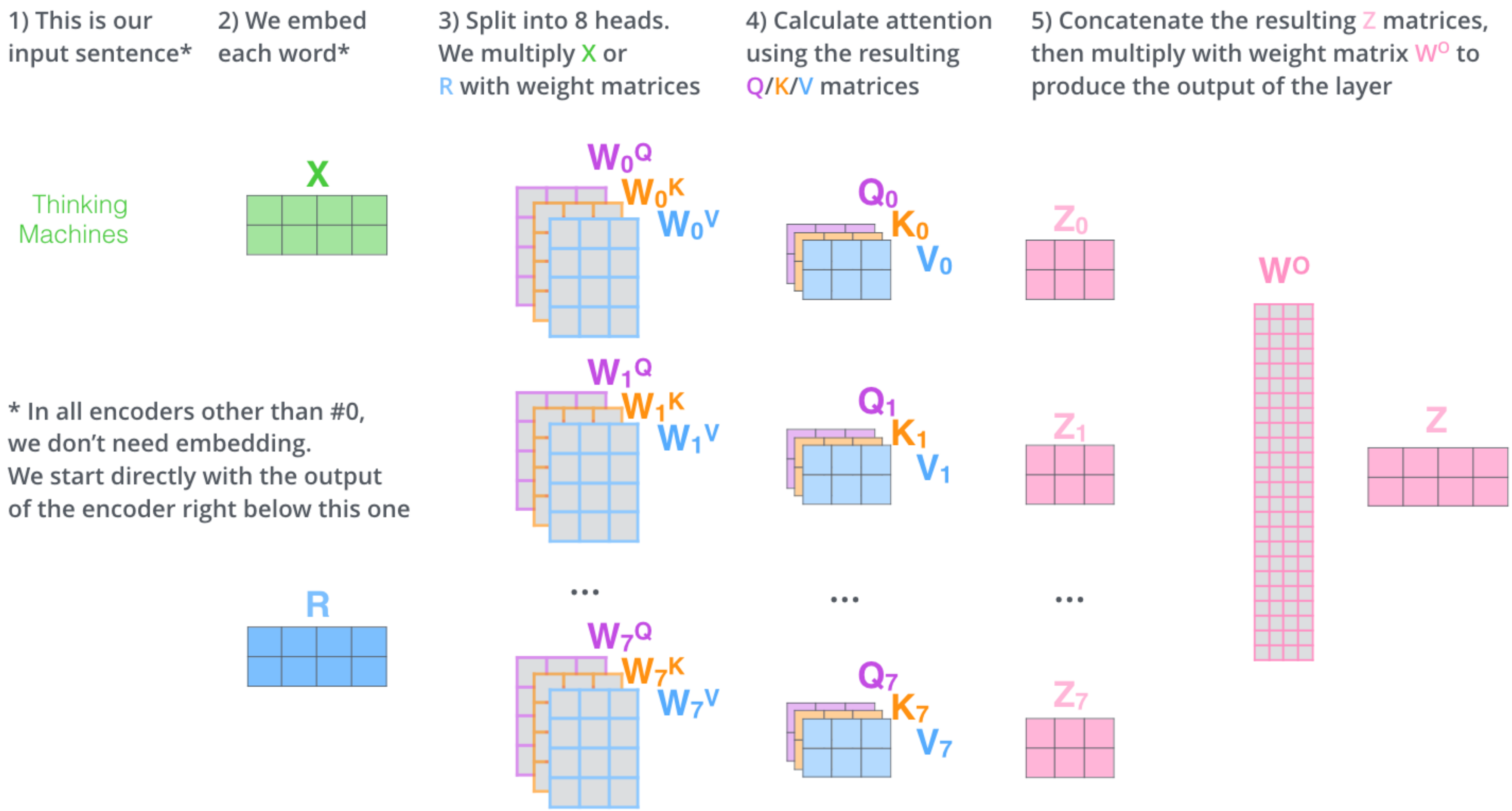
Self Attention





https://jalammar.github.io/illustrated-transformer/

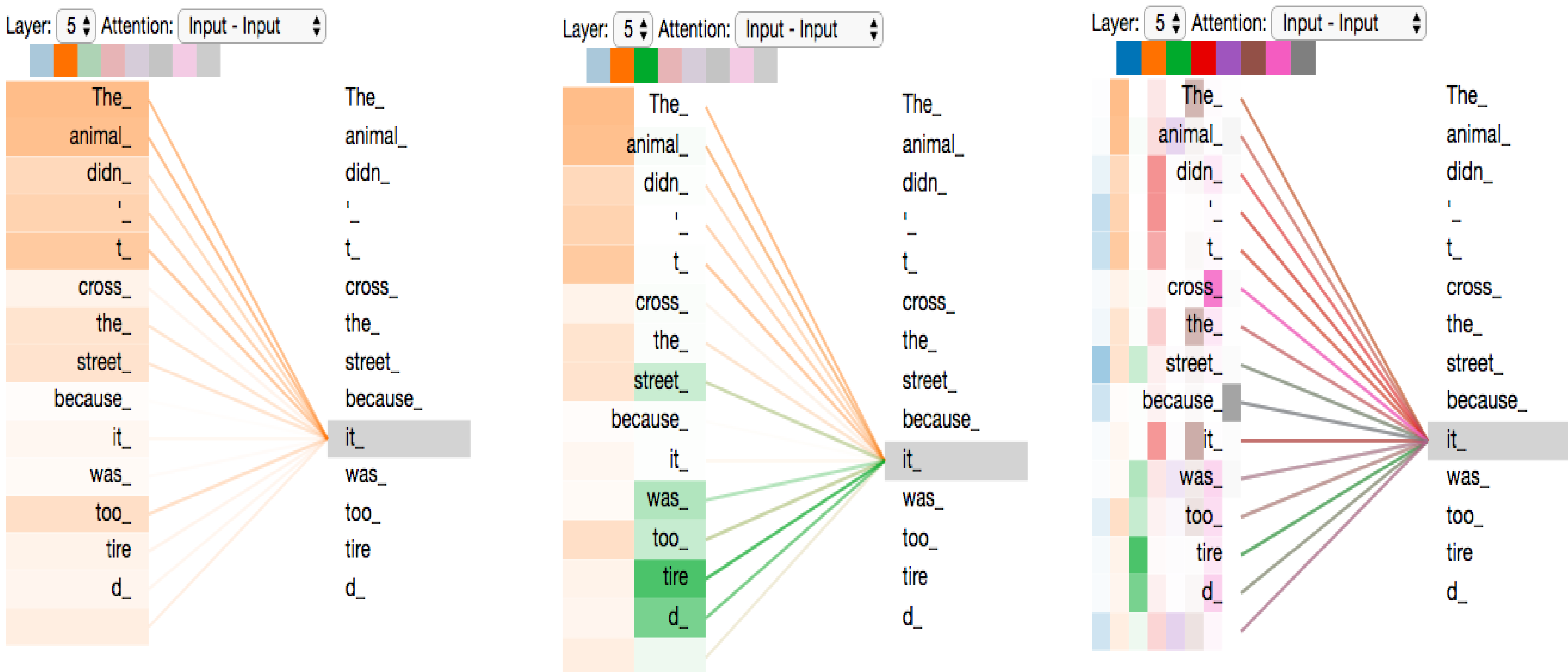
Multihead attention



https://jalammar.github.io/illustrated-transformer/

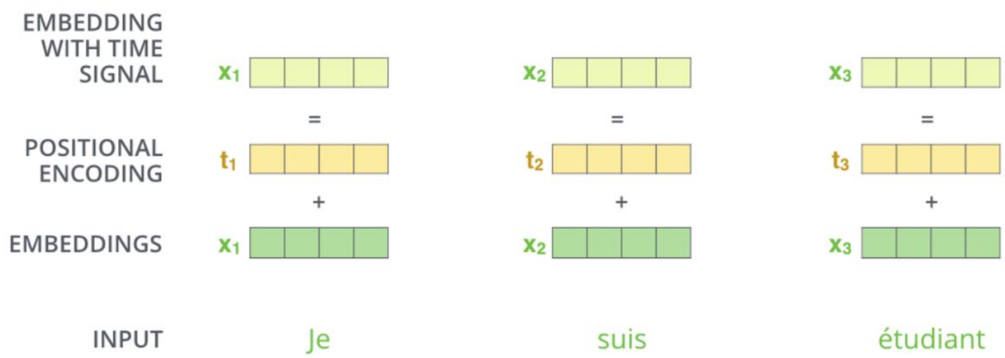
Effect of Self Attention

The animal didn't cross the street because it was too tired



Positional Encoding

- No Position Depenent Computation in Transfomer



0 :	0	0	0	0
1 :	0	0	0	1
2 :	0	0	1	0
3 :	0	0	1	1
4 :	0	1	0	0
5 :	0	1	0	1
6 :	0	1	1	0
7 :	0	1	1	1

- Absolute/Relative Position Encoding
  - Sinusoidal Positional Encoding

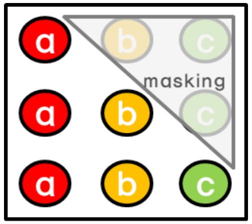
$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$

$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

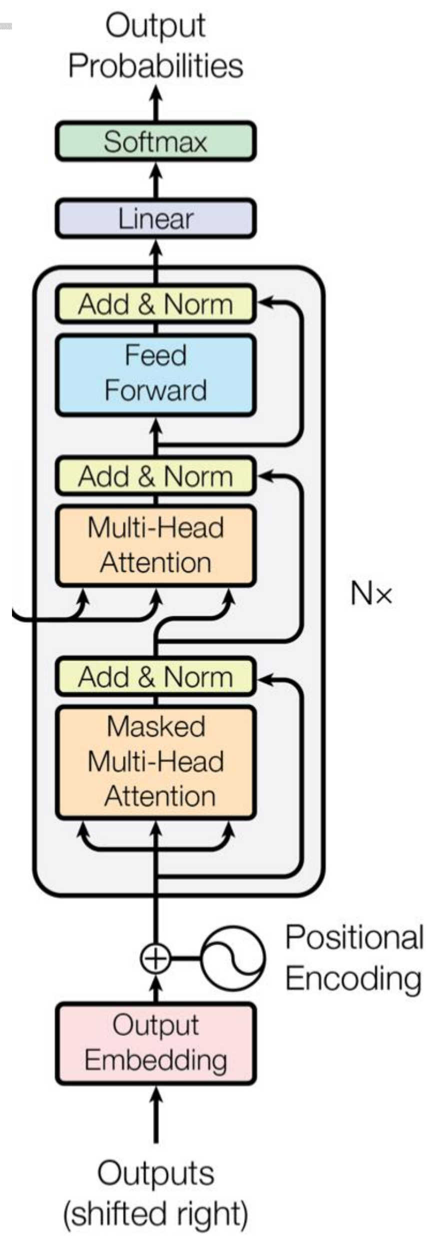
https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

Decoder

- Masked Multi-Head Self Attention

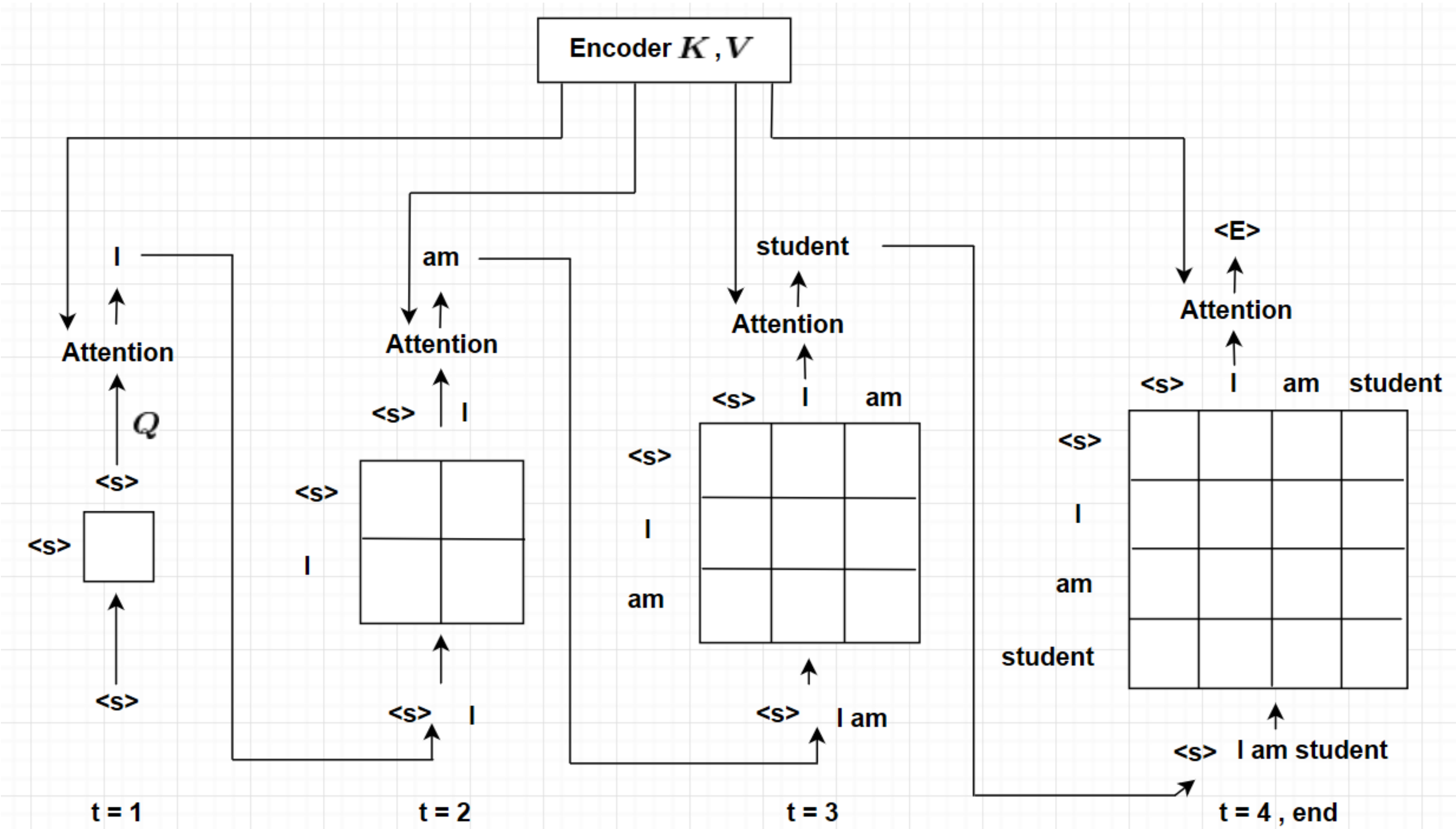


- Encoder-Decoder Attention
  - K, V from Encoder Last Layer
  - Q from Self Attention
- Beam Search



Attention Is All You Need, NuerIPS, 2017

Decoder in action



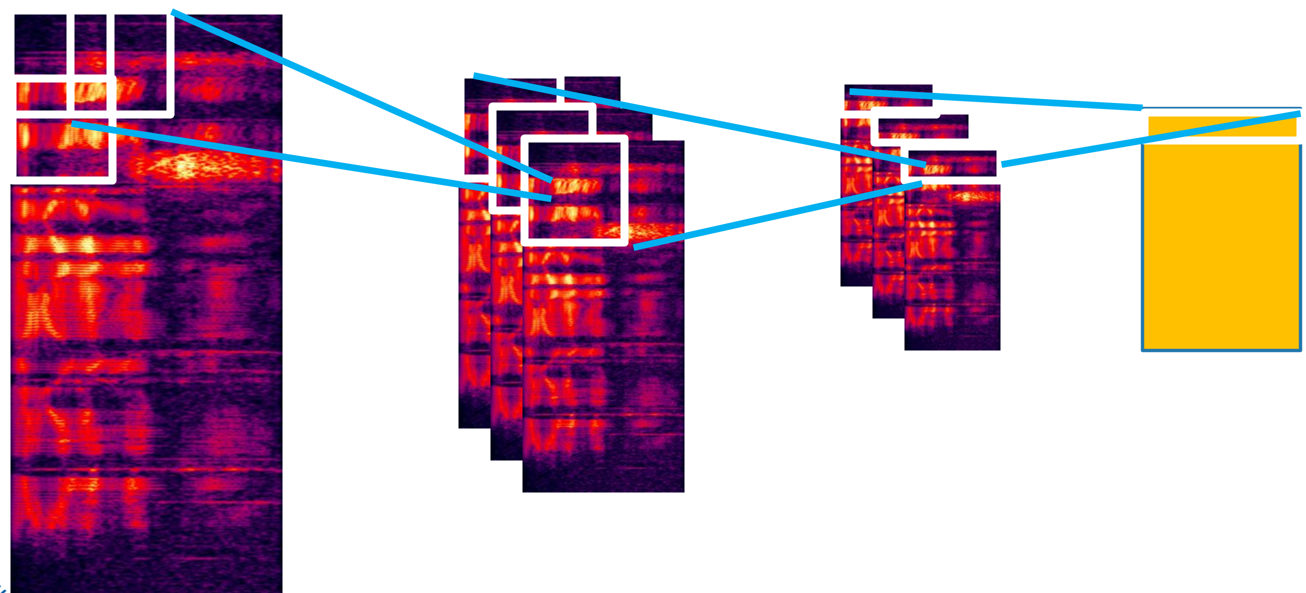
https://medium.com/platfarm/어텐션-메커니즘과-transfomer-self-attention-842498fd3225

End-to-end For ASR

- ESPNet: End-to-end Speech Processing Toolkit
  - ASR, TTS, Speech Translation
  - https://github.com/espnet/espnet
- CTC Hybrid*: Connectionist Temporal Classification
  - Multi-task training with CTC Criteiron
  - Increase Stability while Training
  - Hybrid CTC/Attention Architecture for End-to-End Speech Recognition, IEEE Journal of Selected Topics in Signal Processing, 2018
- Input Embedding

Input embedding

- TEXT: Input = Word: One-hot → Vector
- ASR: Input = MELFB: Vector → Vector
- 2x Conv2d layer, 3x3 kernel with stride=2
  - TxF → adim x T/2 x F/2 → adim x T/4 x F/4 → T/4 x adim



End-to-End ASR In Practice

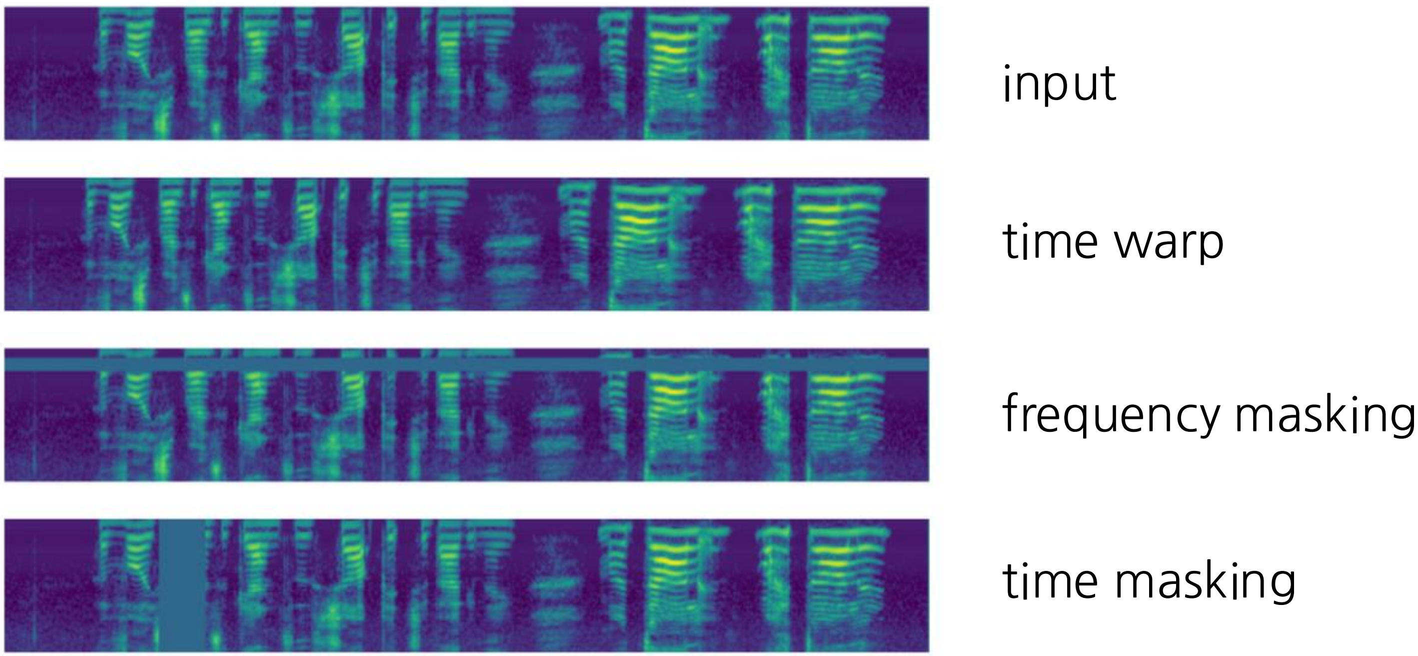
- Output Units
  - 영어: Alphabet, BPE(Byte Pair Encoding), Word
  - 한국어: Char(음절~2500), BPE(~5000), 형태소분석기
- Relative Performance
  - WER/CER
  - 25% (GMM-HMM) → 15% (DNN-HMM) → 10% (LSTM-HMM)
  - 7% Transformer
- Limitation
  - Process Whole Sentence → Streaming ASR

성능개선방안

- 데이터!
  - 실환경 데이터수집: 적응훈련/연결학습
  - 음향모델/언어모델?
- 데이터!!
  - 데이터 증강
  - SpecAug, Speed/Volume perturbation, Noise addition, Simulated data
- 모델 파라미터
  - Number of epoch
  - Number of paramerters: layers, dimension etc
  - Gradient scale: batchsize, learning rate etc
  - Robustness: dropout rate,

SpecAug

- SpecAugment: A Simple Data Augmentation Method for Automatic Speech Recognition (2019)
- https://ai.googleblog.com/2019/04/specaugment-new-data-augmentation.html



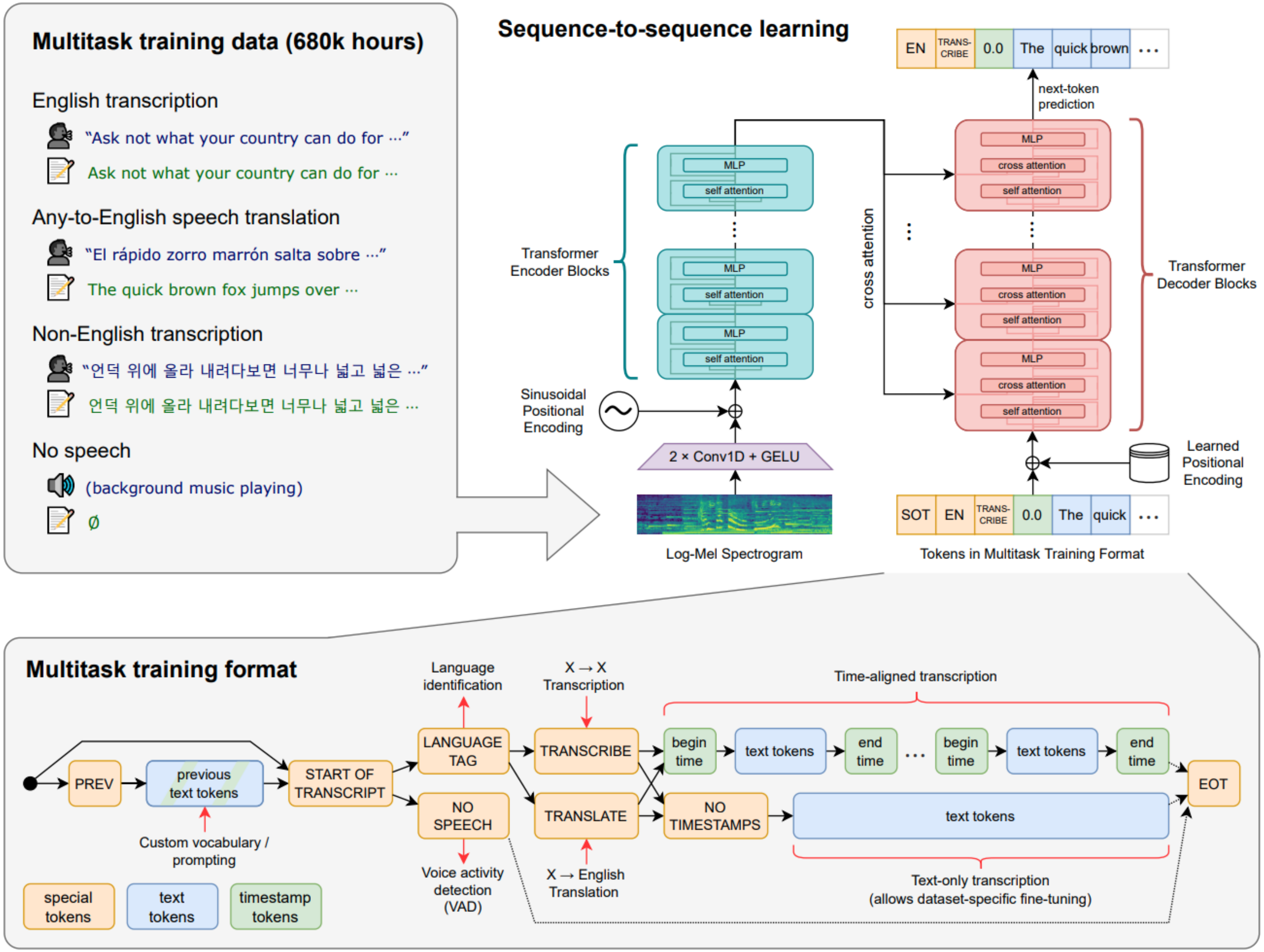
OpenAI Whisper

- Transformer-based Encoder-Decoder Model
  - No CTC
  - Multi-task Training
  - Model Card

Size	Parameters	English-only model	Multilingual model
tiny	39 M	✓	✓
base	74 M	✓	✓
small	244 M	✓	✓
medium	769 M	✓	✓
large	1550 M		✓
turbo	798 M		✓

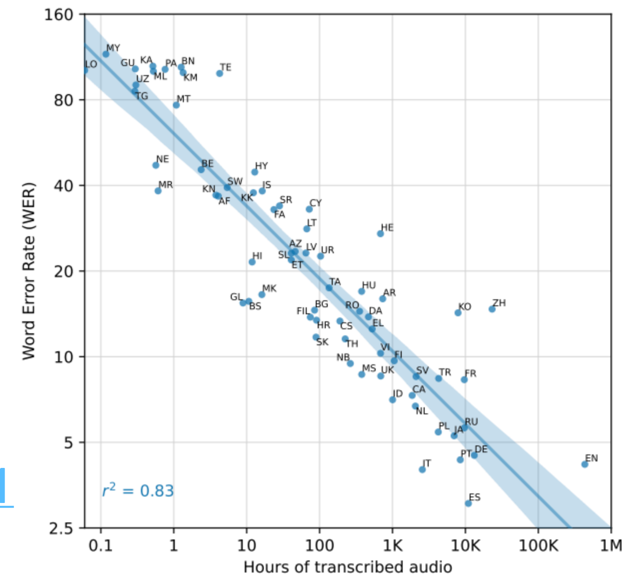
  - Release
    - September 2022 (original series), December 2022 (large-v2), November 2023 (large-v3), September 2024 (large-v3-turbo)

Whisper Model Archtecture



Whisper: Training Data

- large-v2(22.9)
  - 680k hours of audio
  - Weakly labelled
- large-v2 (22.12)
  - 2.5x more epochs with
    added regularization for improved performance
  - https://github.com/openai/whisper/discussions/661
- large-v3(23.11)
  - https://huggingface.co/openai/whisper-large-v3
  - 1M hours of weakly labeled audio
  - 4M hours of pseudo-labeled audio
- large-v3-turbo(24.11)
  - https://github.com/openai/whisper/discussions/2363
  - decoding layers have reduced from 32 to 4



Whisper as Foundation Model

- Finetuning Whisper
  - https://huggingface.co/blog/fine-tune-whisper
- Multimodal Encoder
  - Text: BERT
  - Video: ResNet
  - Audio:
    - MFCC, wav2vec, HuBERT
    - Whisper Encoder
- Decoder
  - Whisper Decoder, LLM

실습

- ESPnet 기반 음성인식
  - https://colab.research.google.com/github/pkyoung/a1003/blob/main/local/espnet.ipynb

- OpenAI Whisper 기반 음성인식
  - https://colab.research.google.com/github/pkyoung/a1003/blob/main/local/whisper.ipynb

Discussion
and
Q&A