Recent Advances in End-to-End Speech Recognition

Shigeki Karita
NTT Communication Science Laboratories

2019/11/13, NAIST

http://karita.xyz/talk/naist2019.pdf

Self introduction

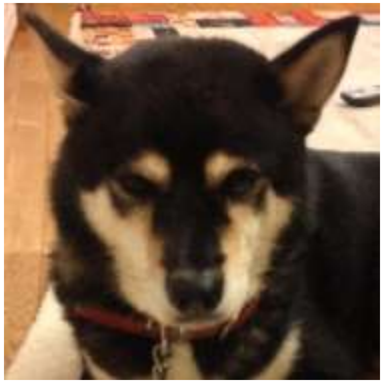
- Shigeki Karita (苅田 成樹)

- NTT Communication Science Laboratories (2016-)
  - Osaka University (2010-2016)

- Research: speech processing

- Favorite programming language: dlang

- Contact
  - GitHub https://github.com/ShigekiKarita
  - Twitter https://twitter.com/ShigekiKarita
  - Email karita@ieee.org



Agenda

1. Introduction of NTT CS Lab
2. Overview of End-to-End Speech Recognition
3. Semi-supervised End-to-End Speech Recognition
4. Transformer-based End-to-End Speech Recognition
5. Summary

Feel free to ask me anytime if you have any questions (in EN/JP)

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PART1:
Introduction of NTT CS Lab

NTT Group and R&D

NTT

- NTT is a holding company
- NTT Group provides the largest telecommunication services.
- NTT R&D does R&D of science and technologies mainly for NTT Group

Holding company

NTT

NTT R&D 2,500

Staff Section

Operation companies

Regional Communications Businesses
- NTT EAST
- NTT WEST

Long-Distance and International Communications Businesses
- NTT Communications Corp.
- Dimension Data Holdings

Mobile Communications Businesses
- NTT DOCOMO, INC.

Data Communications Businesses
- NTT DATA Corp.

Other Businesses
- Real Estate
- Financing
- Construction
- Etc.

NTT R&D Numbers at a Glance

NTT

2,500
researchers working

16,000+
patents granted

$1.0 billion
invested in R&D

1,300
technical papers annually

3 times
awarded IEEE Milestones

40
IEEE Fellows
(including former colleagues)

Top 100
Global Innovators
by Clarivate Analytics

NTT R&D Organization

NTT

2,500 researchers

President & Vice President

- R&D Planning Department【O】
- **Service Innovation Laboratory Group【Y】** — Communication services
  - Service Evolution Laboratories【Y•M】
  - Media Intelligence Laboratories【Y•M】
  - Software Innovation Center【M•S】
  - Secure Platform Laboratories【M】
- **Information Network Laboratory Group【M】** — Information networks
  - Network Technology Laboratories【M】
  - Network Service Systems Laboratories【M】
  - Access Network Service Systems Laboratories【T•Y•M】
- **Science and Core Technology Laboratory Group【A】** — Cutting-edge technologies
  - Network Innovation Laboratories【Y•M】
  - Device Innovation Center【A】
  - Device Technology Laboratories【A】
  - Communication Science Laboratories【K・A】
  - Basic Research Laboratories【A】
- **NTT Innovation Institute Inc.【V】** — Cloud development

NTT Communication Science Laboratories

100+
researchers

"Keihanna" (Kyoto)

- Signal processing
- Linguistic intelligence
- Learning and Intelligent Systems
- Interaction
- Machine learning

Atsugi

- Media search technology
- Human information science
- Quantum Computing
- Audio coding

etc

See also: http://www.kecl.ntt.co.jp/rps/english/organogram_e.html

Research Environment at NTT CS Lab

NTT

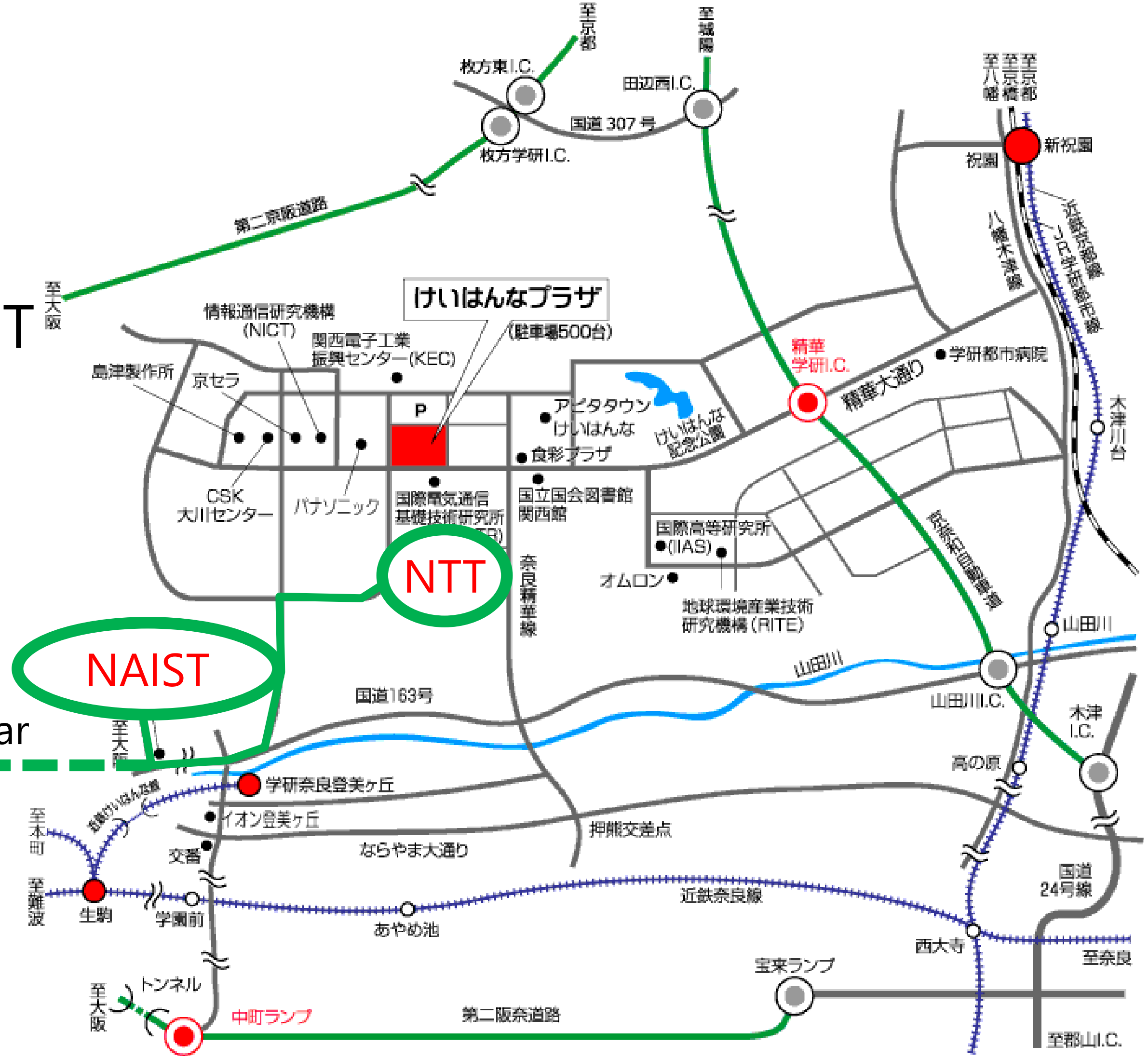
Keihanna SLURM system in 2019:

- 2460 CPU cores (INTEL Xeon)
- 412 GPUs (NVIDIA V100, 2080Ti, etc.)
- InfiniBand

+ group specific servers
+ cloud servers

NTT CS Lab Keihanna ⇔ NAIST

- Very near
- Many internship students from NAIST
- Many researchers from NAIST



My home

20 min by car

Signal Processing Group at NTT CS Lab

NTT

- Members (+25 speech researchers in other NTT R&D)


S. Araki (leader)


M. Delcroix


N. Ito


R. Ikeshita


S. Karita


K. Arai


K. Kinoshita


T. Nakatani


T. Ochiai


A. Ogawa


N. Tawara

- More info: http://www.kecl.ntt.co.jp/media/signal.html
- Open source: https://github.com/nttcslab-sp

Our research goal

- Develop key technologies for understanding natural human speech interactions

Background noise

Other speakers

Reverberation

Spontaneous speech

Frontend (Enhancement) + Backend (Recognition)

Our task

NTT

- Research interests: speech recognition/enhancement, speaker recognition/identification, language modeling, etc.
- Publish papers & file patents
  - 32 papers at ICASSP 2019
  - 18 papers at INTERSPEECH 2019
- Organize/participate challenges and conferences
  - Participant of CHiME-1, CHiME-3, REVERB
  - Organizer of REVERB, ASRU-2017, WASPAA…
- Collaboration with universities
- Occasionally, transfer our technologies to business sections

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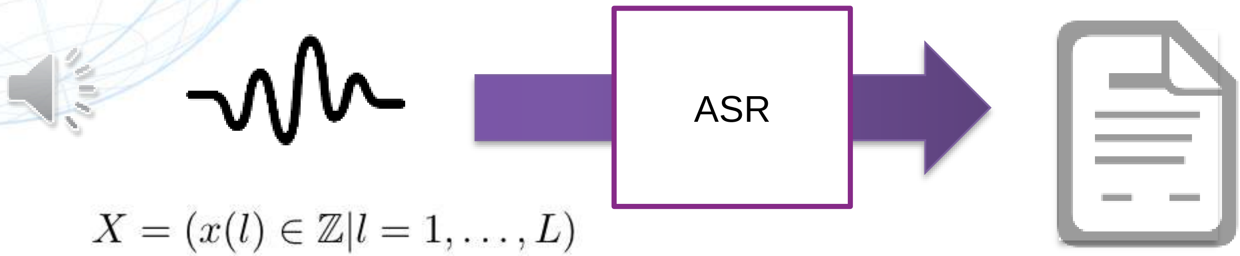
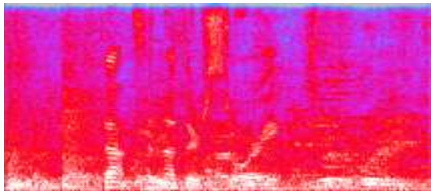
PART2:
Overview of End-to-End Speech Recognition

Automatic Speech Recognition (ASR)

- Mapping speech sequence to transcription sequence



$$X = (x(l) \in \mathbb{Z} | l = 1, \ldots, L)$$
$$L = 43263$$



$$X = (\mathbf{x}_t \in \mathbb{R}^D | t = 1, \ldots, T)$$
$$T = 268$$

"That's another story"

$$W = (\mathbf{w}_n \in \mathcal{V} | n = 1, \ldots, N)$$
$$N = 18$$

No official ASR example in DL frameworks?

- Tensorflow: https://github.com/tensorflow/examples

→ NO

- PyTorch: https://github.com/pytorch/examples

→ NO

- Chainer: https://github.com/chainer/chainer/tree/master/examples

→ NO

- MxNet: https://github.com/apache/incubator-mxnet/tree/master/example/speech_recognition

→ YES!

Why ASR is **not popular** in NN frameworks? Let me know!

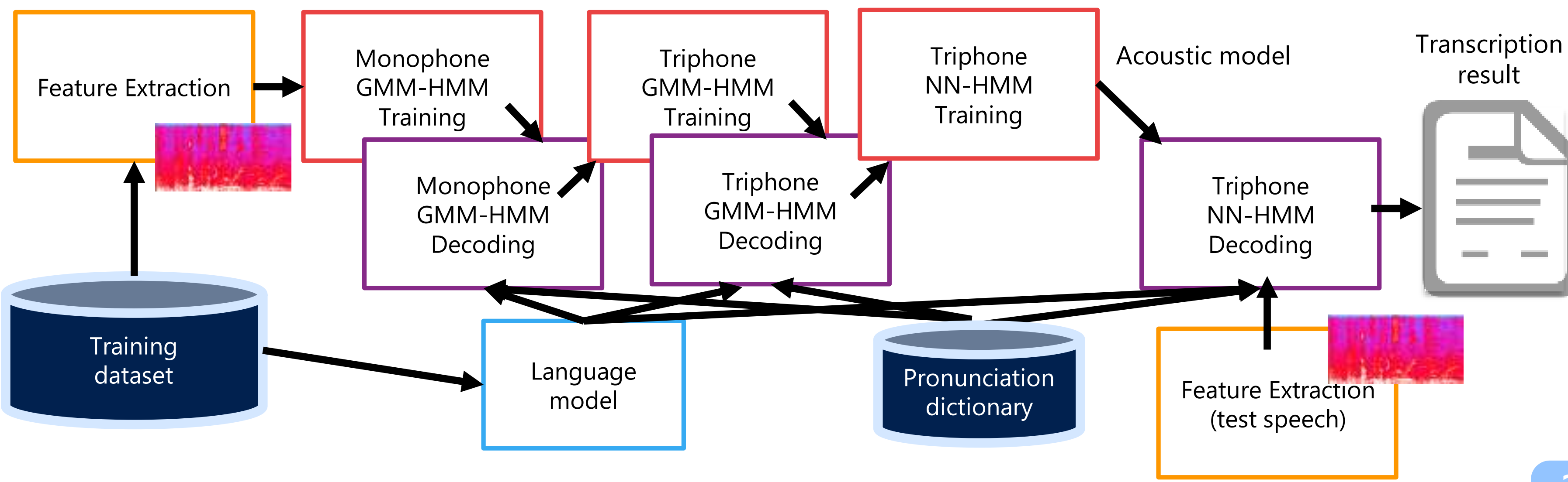
ASR problems

- Learning sequences
- Differences in source and target sequences
  - Length (speech is typically longer than text)
  - Modality (speech is continuous but text is discrete)

ASR methods (before End-to-End)

- Learning sequences
  → Hidden Markov model (HMM) with neural networks (NN)
- Differences in source and target sequences
  – Length (speech is typically longer than text)
  – Modality (speech is continuous but text is discrete)
  → Acoustic and language models, pronunciation dictionary, weighted finite-state transducers (WFST)

The previous HMM-based ASR systems are really complicated …



ASR problems (before End-to-End)

- Learning sequences

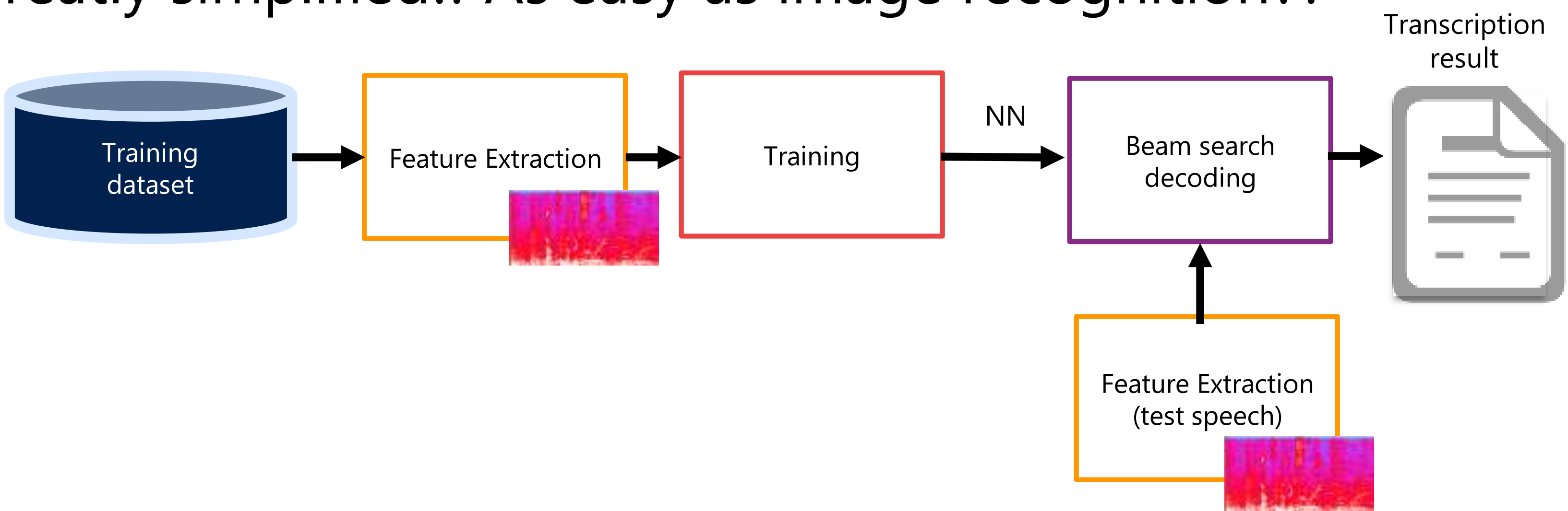
- Differences in source and target sequences
  - Length (speech is typically longer than text)
  - Modality (speech is continuous but text is discrete)

- **Complicated pipeline…**

End-to-End (E2E) ASR methods

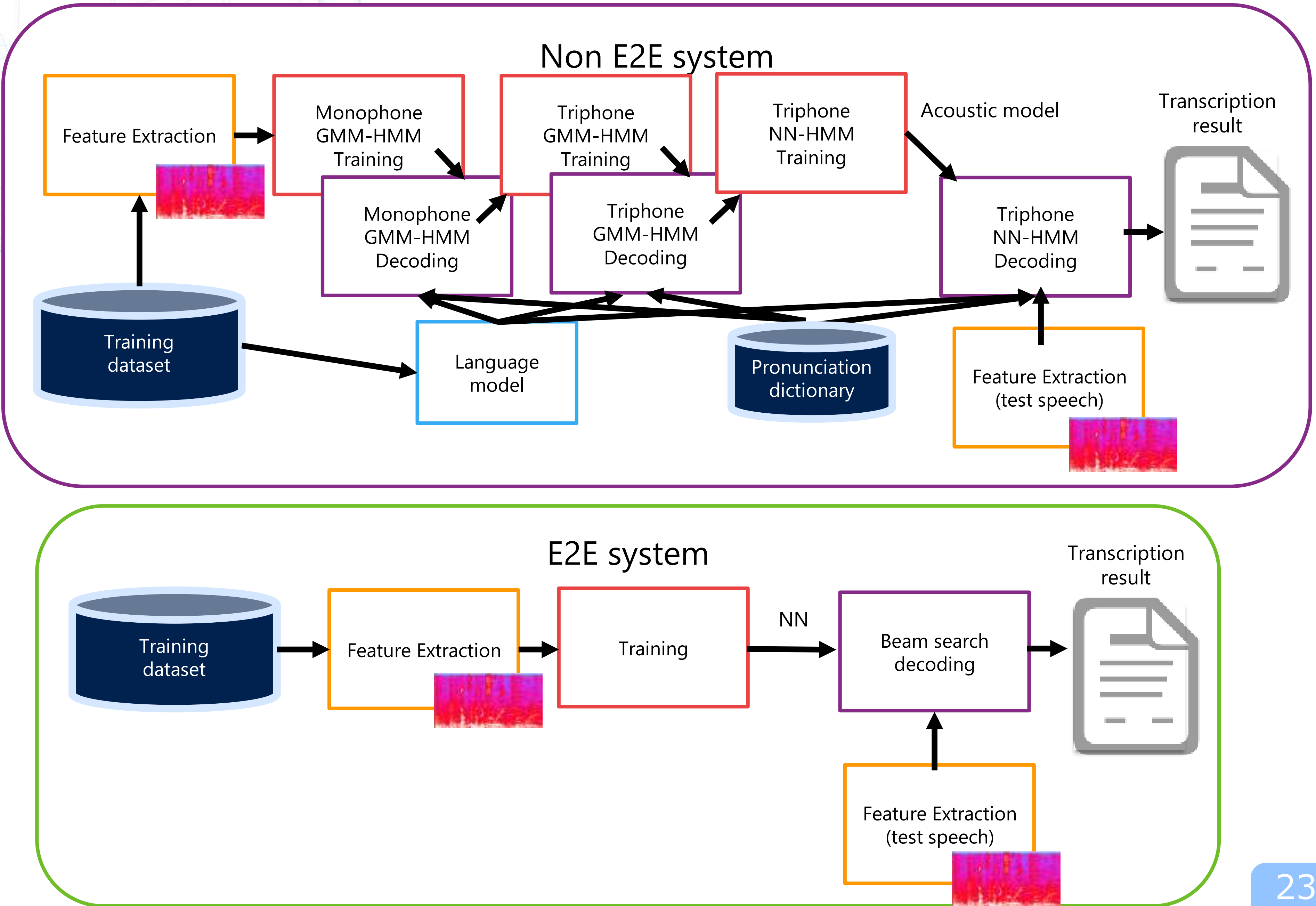
- Learning sequences
  → **Special neural networks (recurrent, convolutional, etc.)**
- Differences in source and target sequences
  – Length (speech is typically longer than text)
  – Modality (speech is continuous but text is discrete)
  → **Connectionist temporal classification (CTC), sequence-to-sequence (S2S)**

Greatly simplified!! As easy as image recognition??



Which one do you like to study?

NTT



Which one do you like to study?

- I think this is the reason why ASR is not popular in the frameworks

- In fact, this is the E2E ASR example using CTC

- MxNet: https://github.com/apache/incubator-mxnet/tree/master/example/speech_recognition

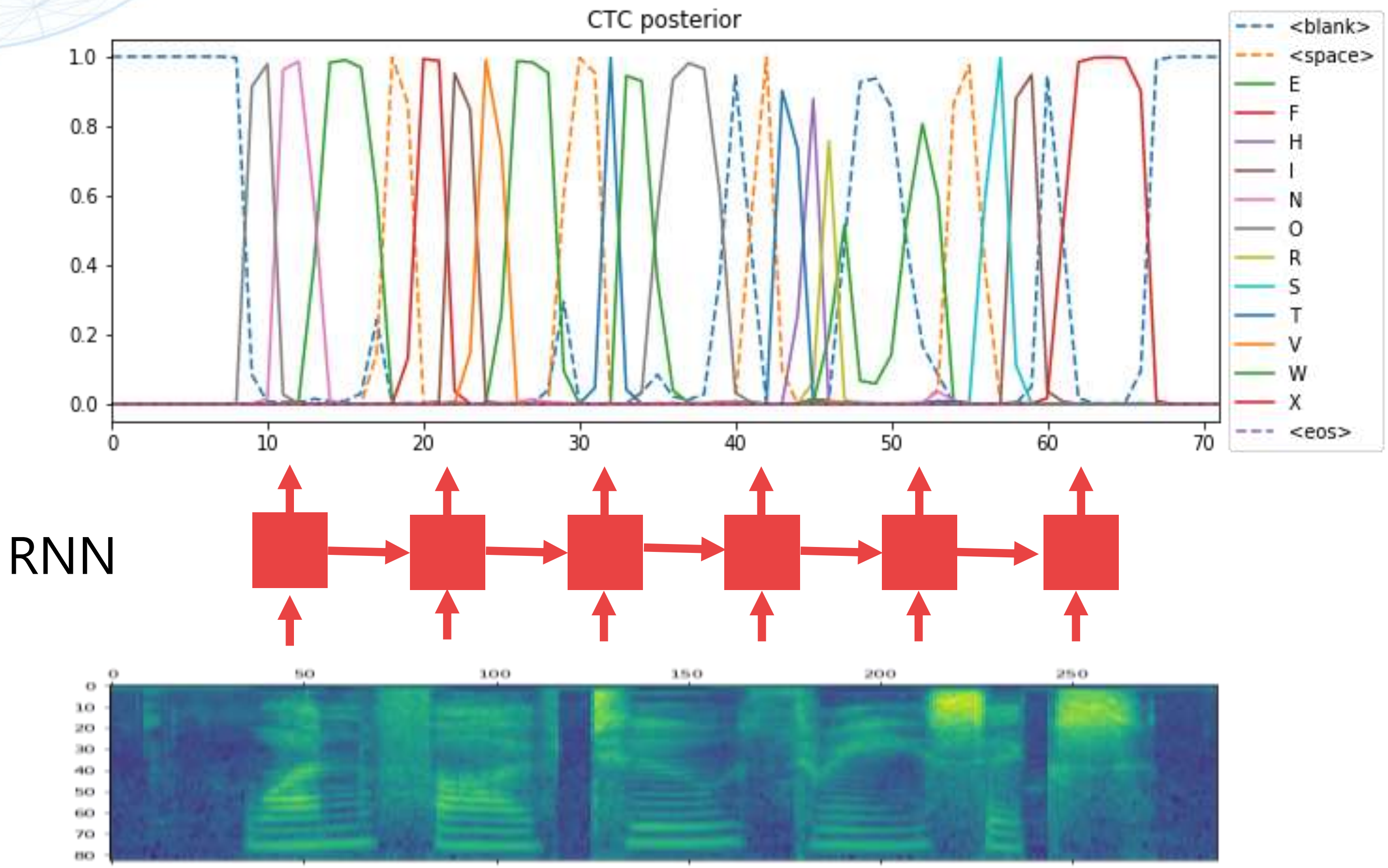
→ YES!

Connectionist temporal classification (CTC)

- The early E2E ASR method similar to HMM
  - A. Graves et al, "Connectionist Temporal Classification: Labelling Unsegmented Sequence Data with Recurrent Neural Networks," ICML2016
- **Input**: a sequence of speech feature frames
- **Output**: a sequence of transcription symbol probability aligned to the speech

Connectionist temporal classification (CTC)

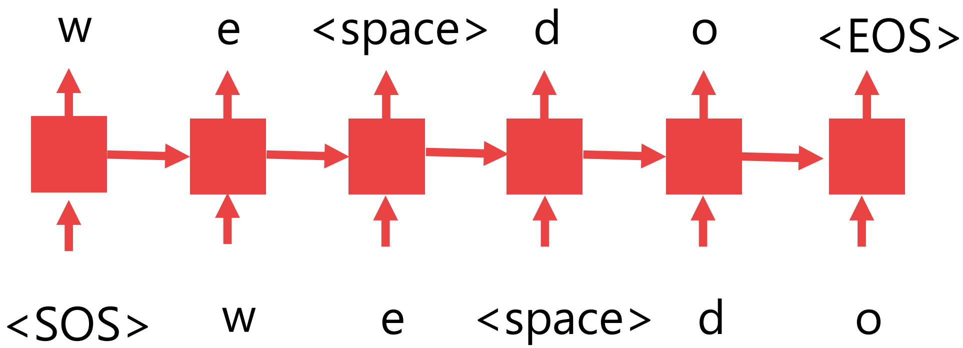
- Input: a sequence of speech feature frames
- Output: a sequence of transcription symbol probability **aligned to the speech**



Sequence-to-sequence (S2S)

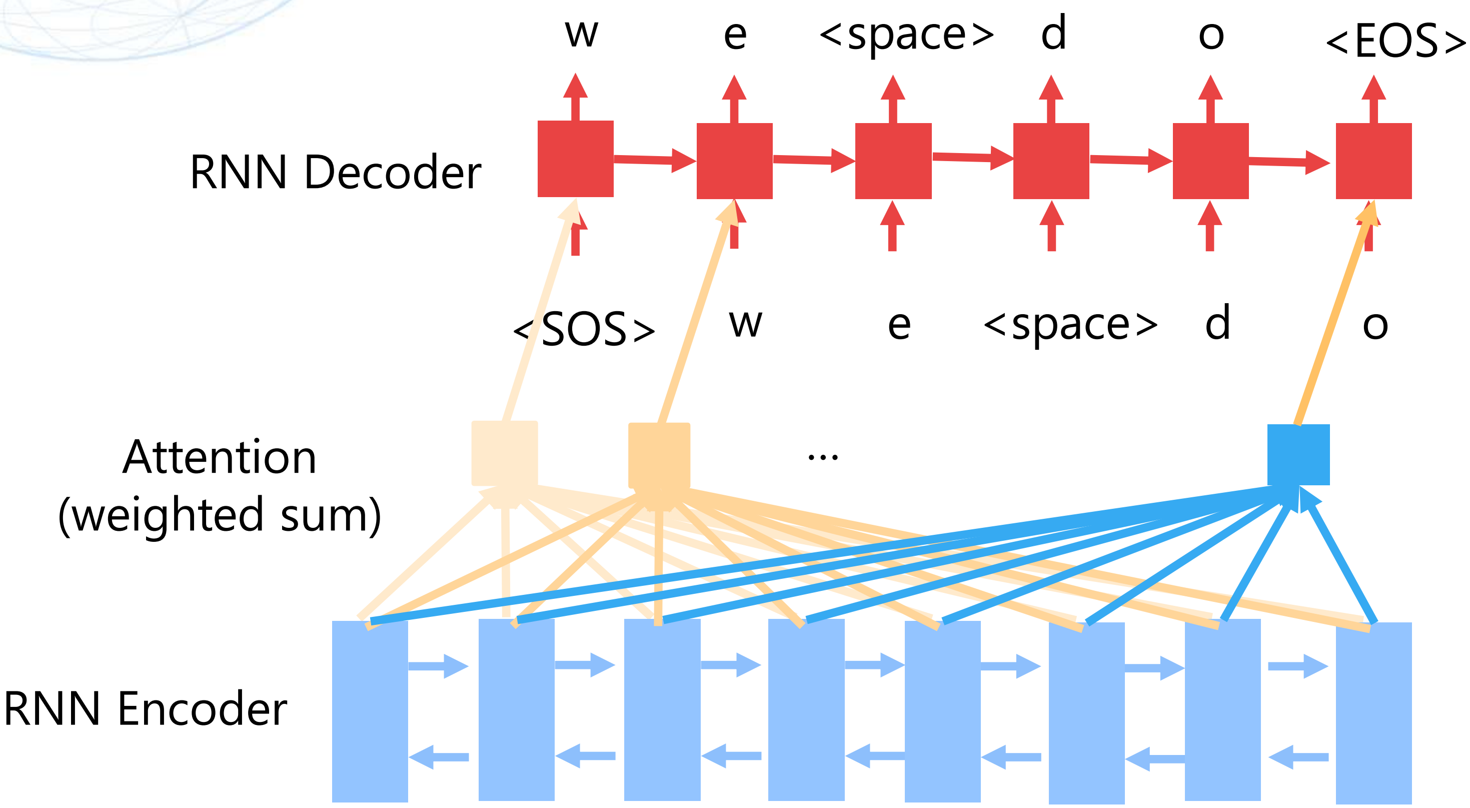
- The later E2E ASR method similar to RNN language models (RNNLMs)
  - J. Chorowski et al., “Attention-based Models for Speech Recognition,” NIPS2014 Deep Learning Workshop
  - RNNLM iteratively predicts the next symbols:

RNNLM



Sequence-to-sequence (S2S)

- Input: a sequence of speech feature frames and **the previous transcription symbol (and NN states)**
- Output: **the next transcription symbol**



Summary: PART2

- The non-E2E ASR system got too complicated
- E2E methods (CTC and S2S) greatly simplified ASR systems
- Start your ASR/TTS research!!
- More info:
  - Takaaki Hori, Tomoki Hayashi, **Shigeki Karita**, Shinji Watanabe, “Advanced methods for neural end-to-end speech processing – unification, integration, and implementation,” INTERSPEECH2019
    https://github.com/espnet/interspeech2019-tutorial
    Demo with a free GPU available in Google Colab!
  - Steve Renals and Hiroshi Shimodaira, “AUTOMATIC SPEECH RECOGNITION (ASR) 2018-19: LECTURES”
    http://www.inf.ed.ac.uk/teaching/courses/asr/lectures-2019.html
    The greatest lecture at the university of Edinburgh!

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PART3:
Semi-supervised End-to-End Speech Recognition

Motivation: semi/unsupervised learning

- Paired dataset: expensive, small
- Unpaired dataset: cheap, large

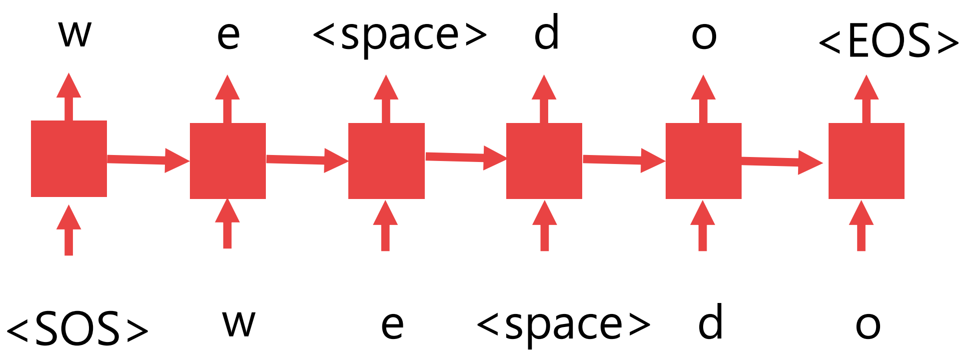
  – *"careful transcripts of speech* ***average 20xRT or 20 hours for each hour*** *of conversation …"*

  – C. Cieri, D. Miller, and K. Walker, "The Fisher corpus: a Resource for the Next Generations of Speech-to-Text," International Conference on Language Resources and Evaluation, vol. 4, pp. 69–71, 2004.

Recap: sequence-to-sequence (S2S)

- The later E2E ASR method **similar to language models (LMs)**
  - RNNLM iteratively predicts the next symbols:

RNN LM

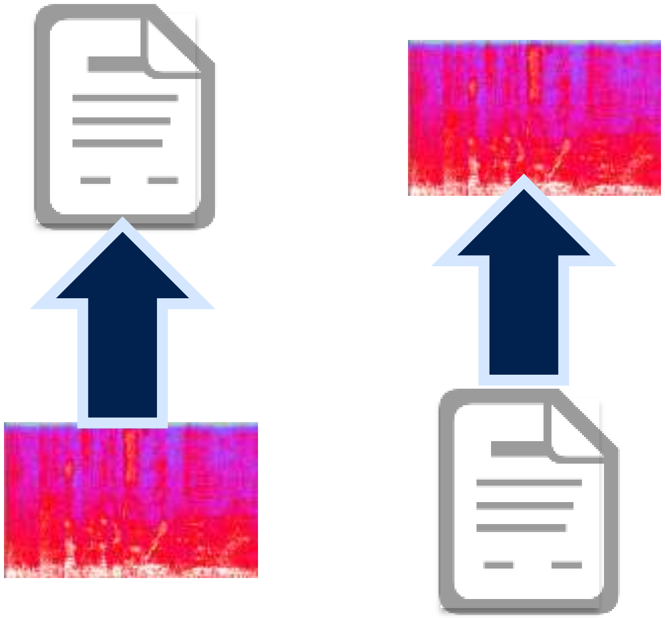


Can we use LM as unsupervised training in the ASR model?

Proposed method: overview

Supervised

- ASR: speech-to-text
- TTS: text-to-speech



Proposed method: overview

Supervised

- ASR: speech-to-text
- TTS: text-to-speech

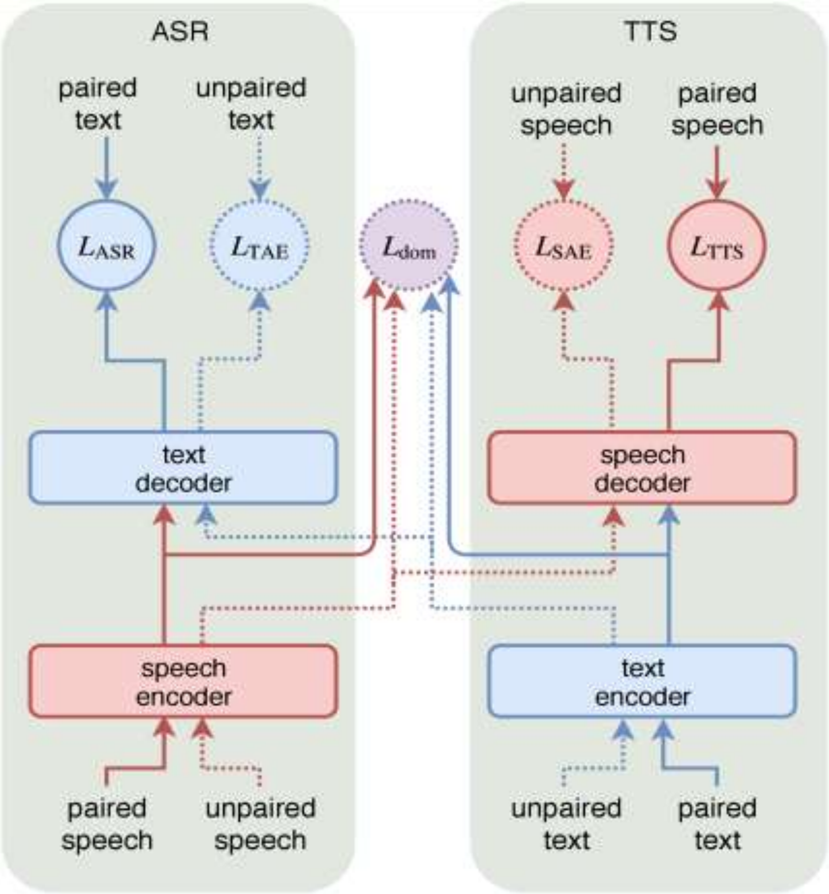
Unsupervised

- Text autoencoder (TAE): text-to-text
- Speech autoencoder: (SAE): speech-to-speech

Can we build ASR/TTS using TAE and SAE?

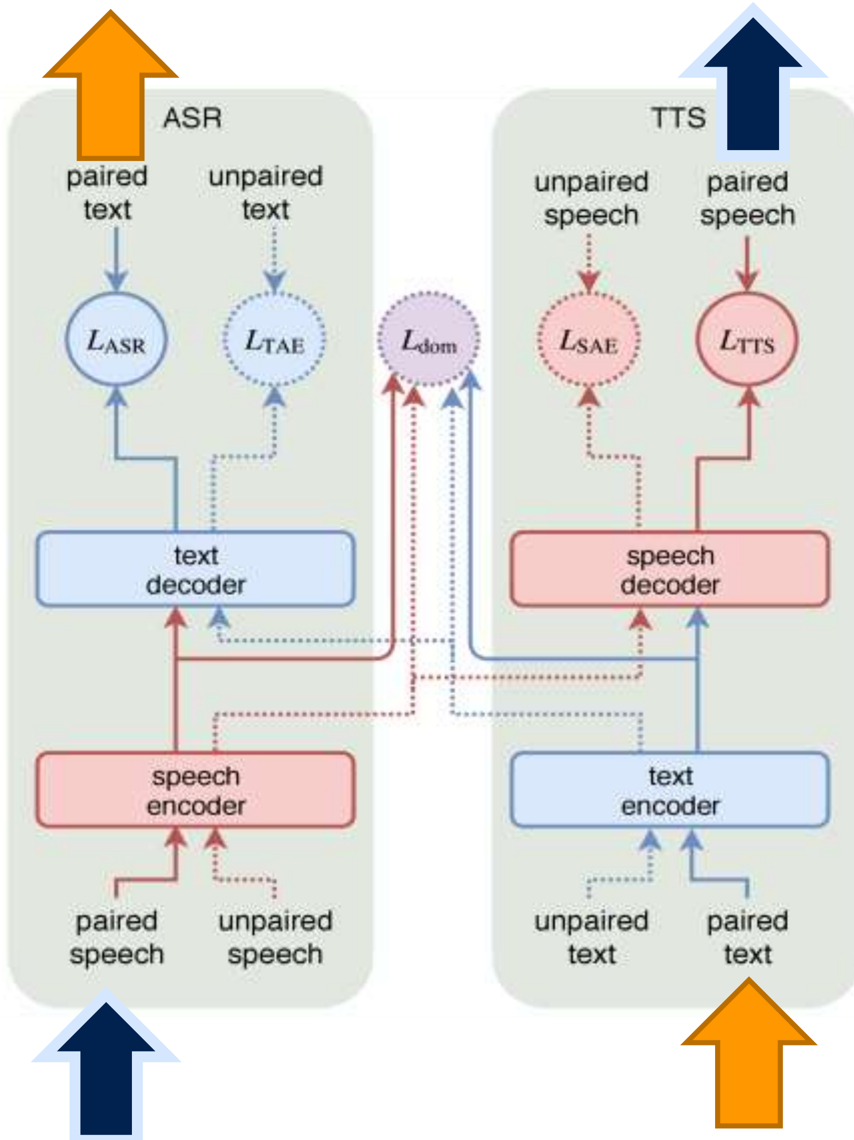
Proposed method: overview

- Combine ASR and TTS as two autoencoders (speech and text)
  - with an inter-domain loss L_{dom}



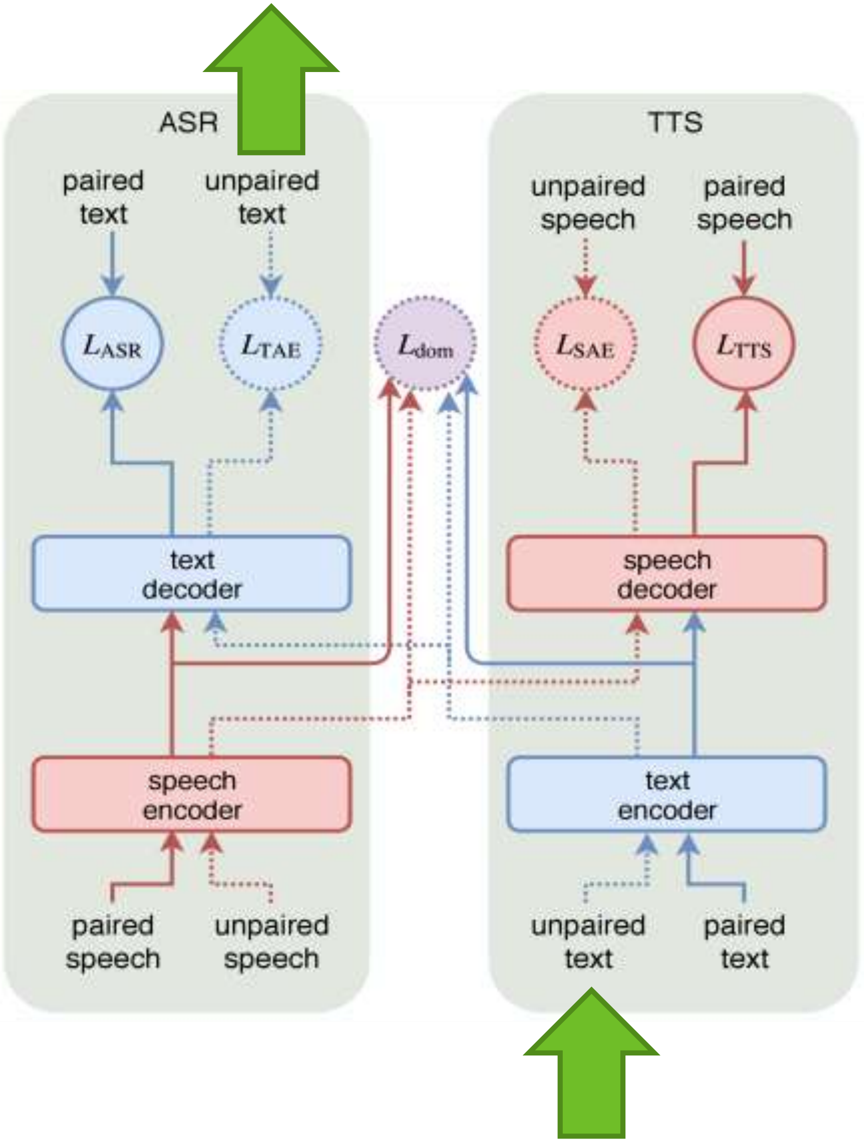
Proposed method: supervised training

- Conventional ASR (L_{ASR}: cross entropy) and TTS (L_{TTS}: L1+L2)



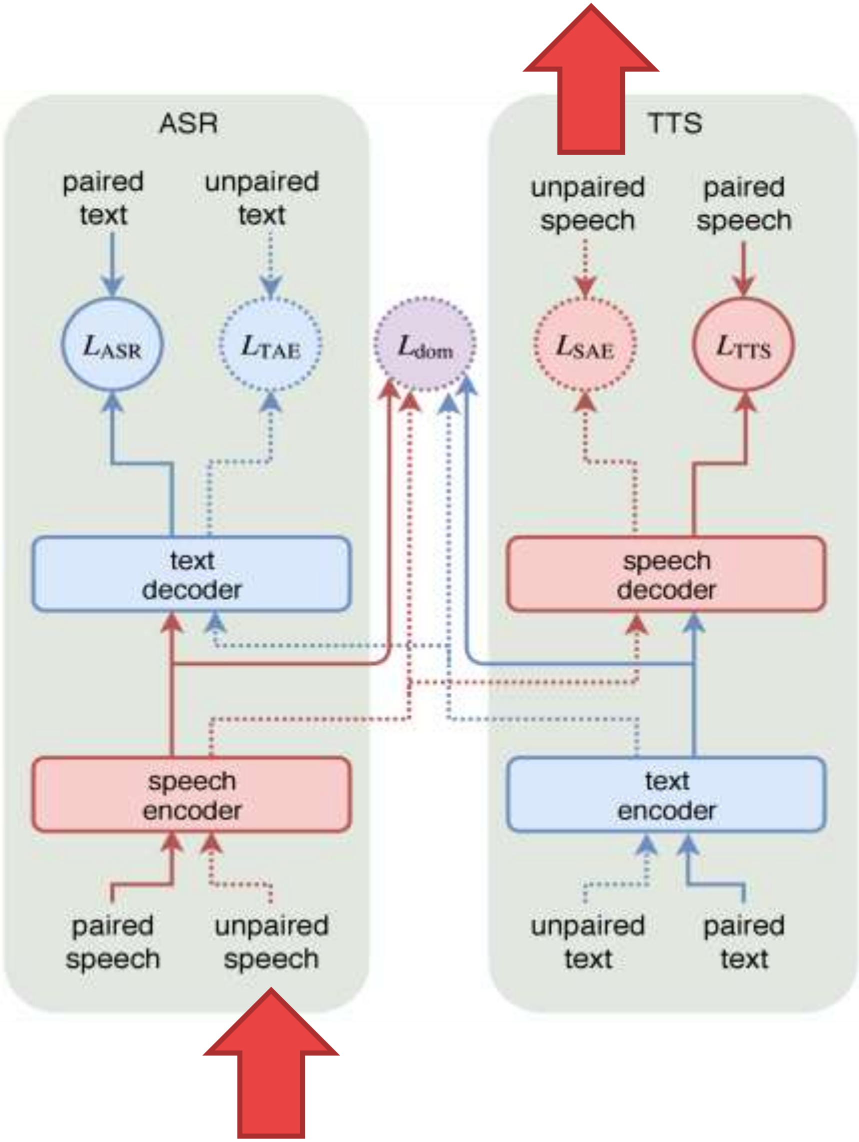
Proposed method: unsupervised text training

- Text autoencoder: usual LM (L_{TAE}: cross entropy)



Proposed method: unsupervised speech training

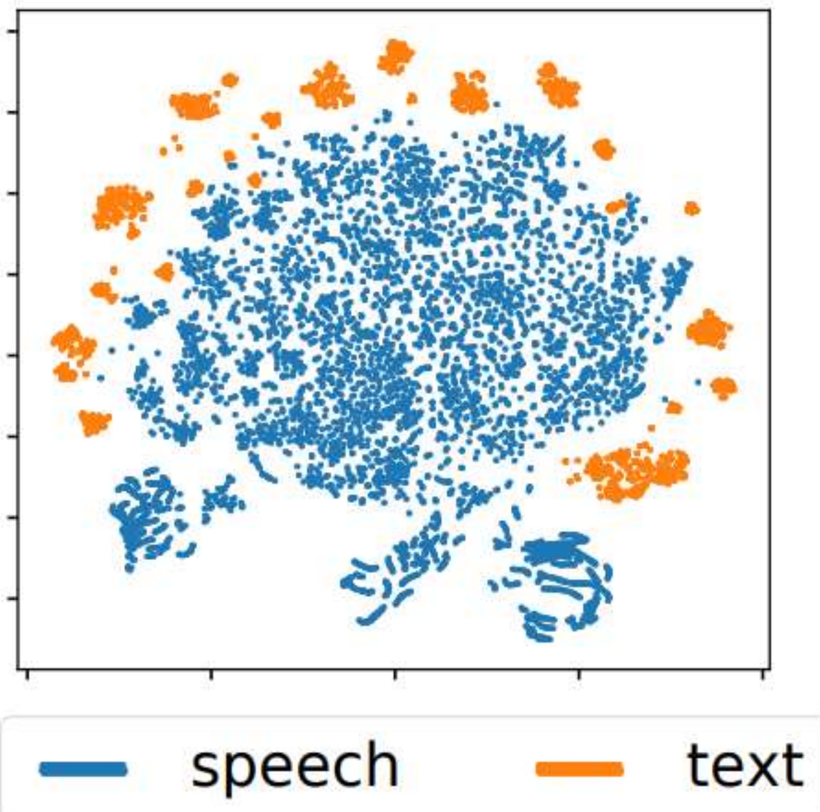
- Speech autoencoder (L_{SAE}: L1+L2)

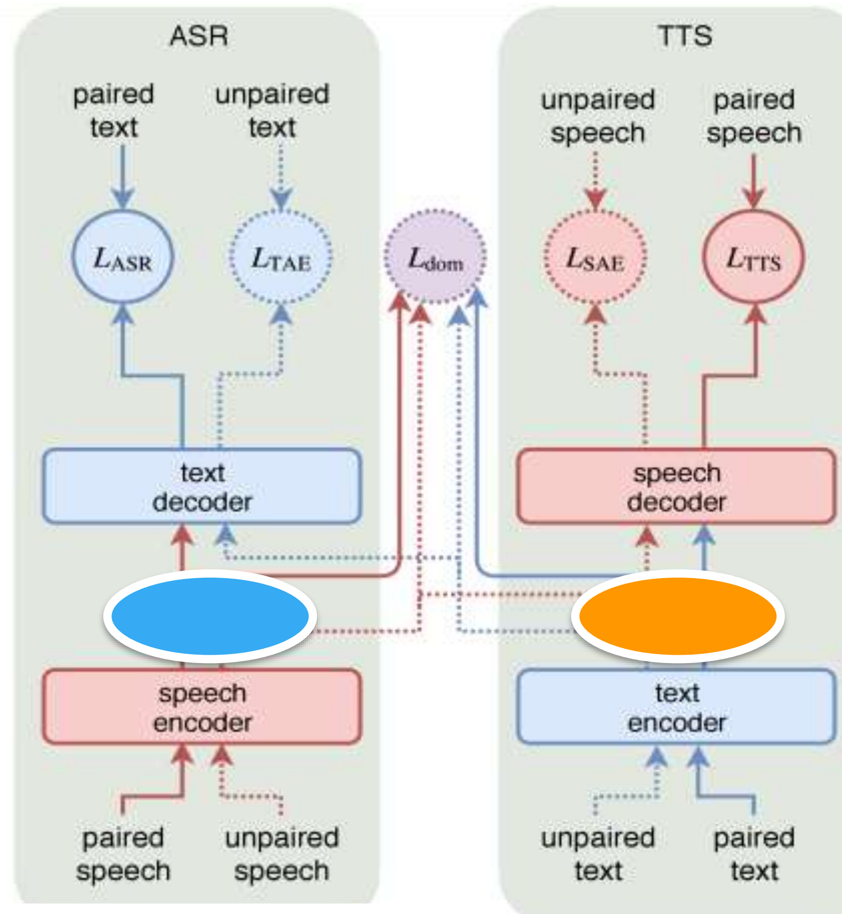


Problem: feature mismatch

- Incompatible features?

- t-SNE 256D → 2D visualization
  - Completely separated…





Proposed method: inter-domain loss

Minimize distance between features of speech h^X and text h^Y

- KL divergence: assume two distributions as Gaussians
- Generative Adversarial Networks: let NN learn distance between two
- Maximum Mean Discrepancy (MMD)
  - Kernel mean of minibatches of h^X, h^Y
    with Gaussian kernel function k: $E[K^{XX} - 2K^{XY} + K^{YY}]$

where

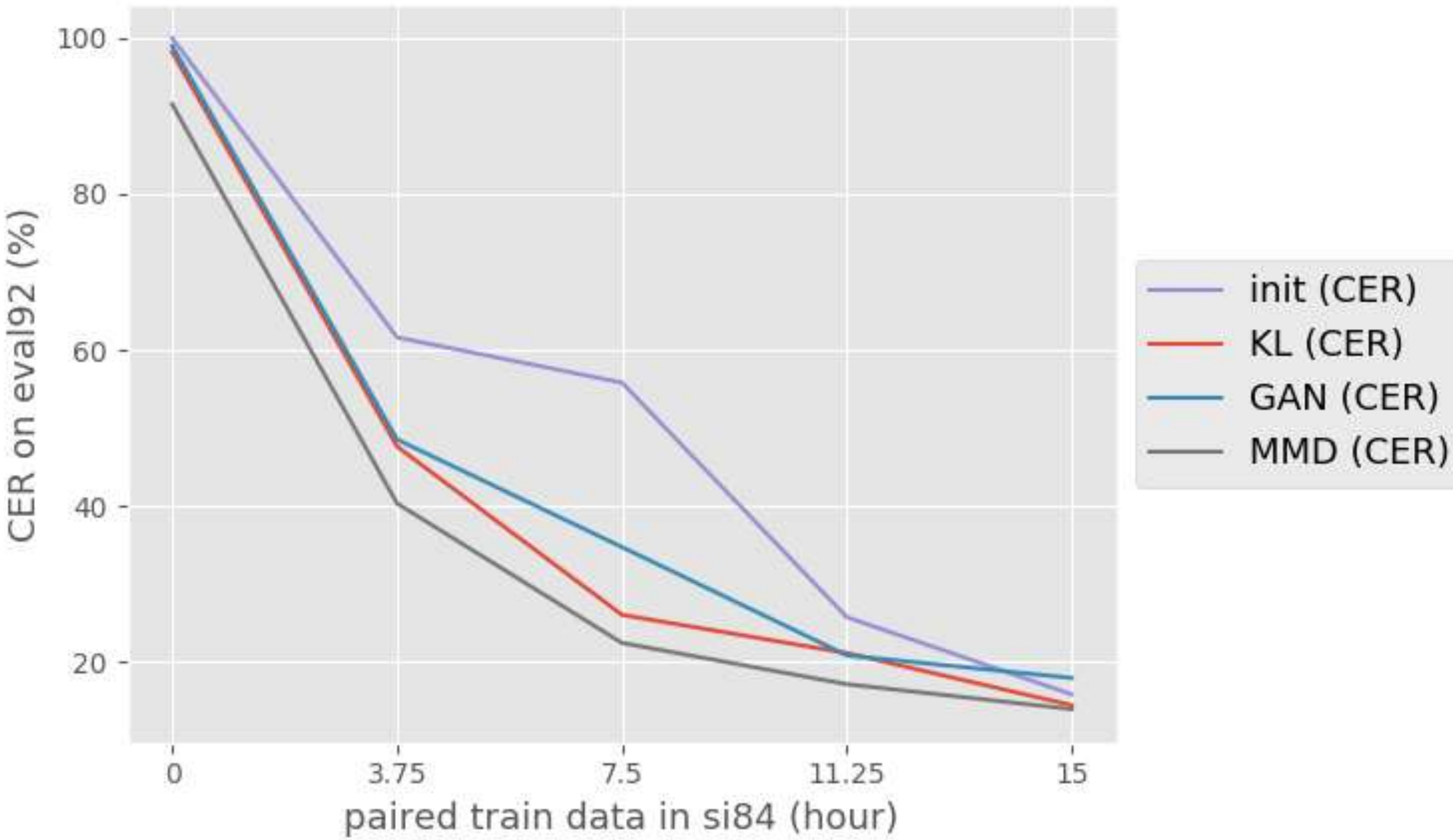
$$K^{XX} = \sum_{t=1}^{T}\sum_{t\prime=1}^{T}\frac{k(h_t^X, h_{t\prime}^X)}{T^2}, K^{YY} = \sum_{s=1}^{S}\sum_{s\prime=1}^{S}\frac{k(h_s^Y, h_{s\prime}^Y)}{S^2},$$

$$K^{XY} = \sum_{t}^{T}\sum_{s}^{S}\frac{k(h_t^X, h_s^Y)}{TS}$$

$$k(a, b) = \exp(-|a-b|^2)$$

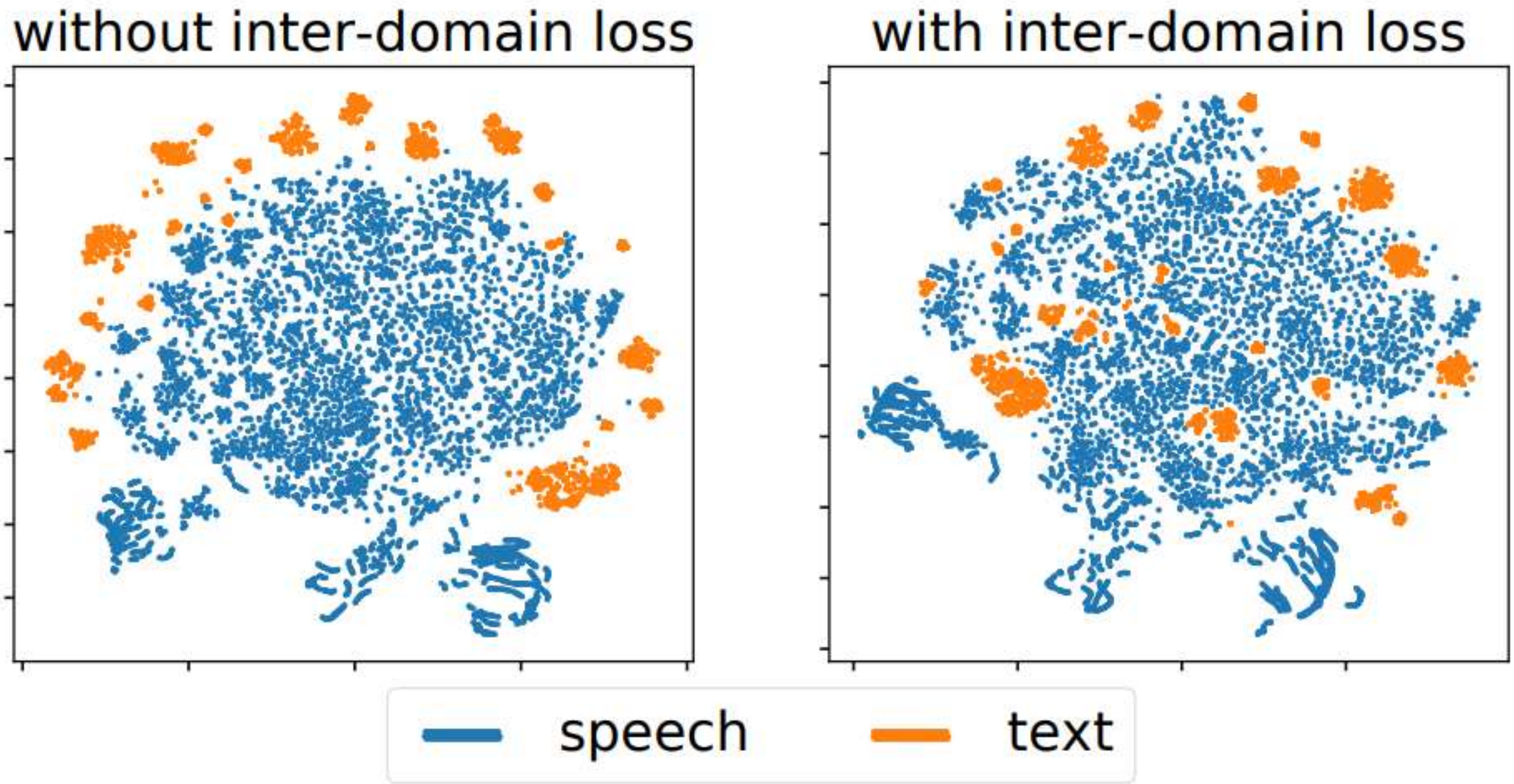
Preliminary experiment: dataset size and CER

- Experiments on WSJ SI84 (paired) and SI284 (unpaired)
  - Init: initial NN trained with the small paired train dataset
  - KL/GAN/MMD: retrained NN trained with the paired and unpaired



Preliminary experiment : visualization

- Experiments on WSJ SI84



Experiment settings

- ASR
  - Input: 80-dim FBANK
  - Output: characters, [sos] and [eos]
  - Layers: VGG+BLSTMP enc + BLSTMP dec
- TTS
  - Input: characters + speaker embeddings [4]
  - Output: 80-dim FBANK, stop flag
  - Layers: Tacotron2 [3], same hidden dim to ASR
- Dataset: LibriSpeech official subsets (100h, 360h, 500h)
- Supervised ASR/TTS training (baseline)
  - Dataset: train clean 100 (h) for ASR (subset)
  - Adam, learning rate=1e-3, minibatch=64, 30 epochs
- Semi-supervised ASR+TTS+SAE+TAE retraining
  - Dataset: train clean 100 (h) for ASR/TTS (subset)
    train clean 360 (h) for SAE (speech only)
    train other 500 (h) for TAE (text only)
  - Adam, learning rate=1e-5, minibatch=64, 10 epochs
- LM: word-level RNNLM trained on external language resource

Experiment results: char error rate (CER)

NTT

	multi-task loss ASR	TTS	SAE	TAE	dev clean CER/WER	test clean CER/WER
supervised (100h)	✓	-	-	-	14.1 / 26.2	15.0 / 25.0
+ char LM	✓	-	-	-	12.2 / 22.8	11.9 / 22.5
+ word LM	✓	-	-	-	12.1 / 21.3	11.7 / 22.0
+ ext LM (baseline)	✓	-	-	-	10.3 / 20.6	10.4 / 20.6
KL + ext LM	✓	✓	-	-	9.6 / 19.4	9.5 / 19.2
	✓	-	✓	-	11.6 / 21.8	12.0 / 22.1
	✓	-	-	✓	10.3 / 19.7	10.5 / 19.9
	✓	✓	✓	✓	12.2 / 21.8	12.1 / 21.8
MMD + ext LM	✓	✓	-	-	9.6 / 19.1	9.5 / 18.9
	✓	-	✓	-	9.2 / 18.9	8.7 / 18.4
	✓	-	-	✓	9.4 / 18.9	9.0 / 18.4
	✓	✓	✓	✓	**8.9 / 18.5**	**8.4 / 18.0**

Related works

- Copied from Murali Karthick Baskar et al., "Semi-Supervised Sequence-to-Sequence ASR Using Unpaired Speech and Text," INTERSPEECH2019 https://www.isca-speech.org/archive/Interspeech_2019/pdfs/3167.pdf

Model	Type	RNNLM	%CER	%WER
WSJ-SI84 (parallel) + WSJ-SI284 (unpaired)				
Speech chain [13]	Both	-	9.9	-
Adversarial [14]	Both	yes	-	24.9
this work	Both	-	9.1	26.1
this work	Both	yes	**7.8**	**20.3**
oracle	-	-	5.5	16.4
oracle [29]	-	yes	2.0	4.8
Librispeech 100 h (parallel) + 360 h (unpaired)				
Backtranslation-TTE [10]	Text	-	10.0	22.0
this work	Text	-	8.0	17.9
Crictizing-LM [12]	Text	yes	9.1	17.3
this work	Text	yes	8.0	17.0
Cycle-TTE [9]	Speech	yes	9.9	19.5
this work	Speech	yes	7.8	16.8
Adversarial-AE [15]	Both	yes	8.4	18.0
this work	Both	-	7.6	17.5
this work	Both	yes	**7.6**	**16.6**
oracle [9]	-	-	4.6	11.8

ours

Summary

NTT

- Semi-supervised ASR aims to exploit unpaired text and speech only datasets
- Our proposed **ASR+TTS+SAE+TAE joint training** and **MMD based inter-domain loss** can utilize more large unpaired datasets and result lower CER.
- Our system reduced the character error rate (CER) from **10.4% to 8.4%** with the small paired data TTS joint training and large unpaired data autoencoding in the LibriSpeech small set.
- Papers
  - INTERSPEECH2018: https://www.isca-speech.org/archive/Interspeech_2018/abstracts/1746.html
  - ICASSP2019: https://ieeexplore.ieee.org/abstract/document/8682890
  - Code : https://github.com/nttcslab-sp/espnet-semi-supervised

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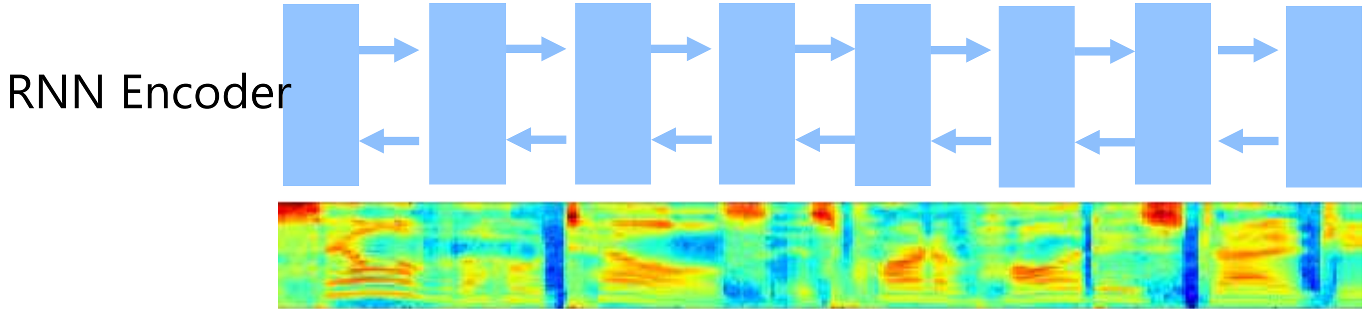
PART4: Transformer-based End-to-End Speech Recognition

Background: End-to-End ASR

- Seq2seq models directly learn speech-to-text mapping
- Encoder and decoder networks are often RNN

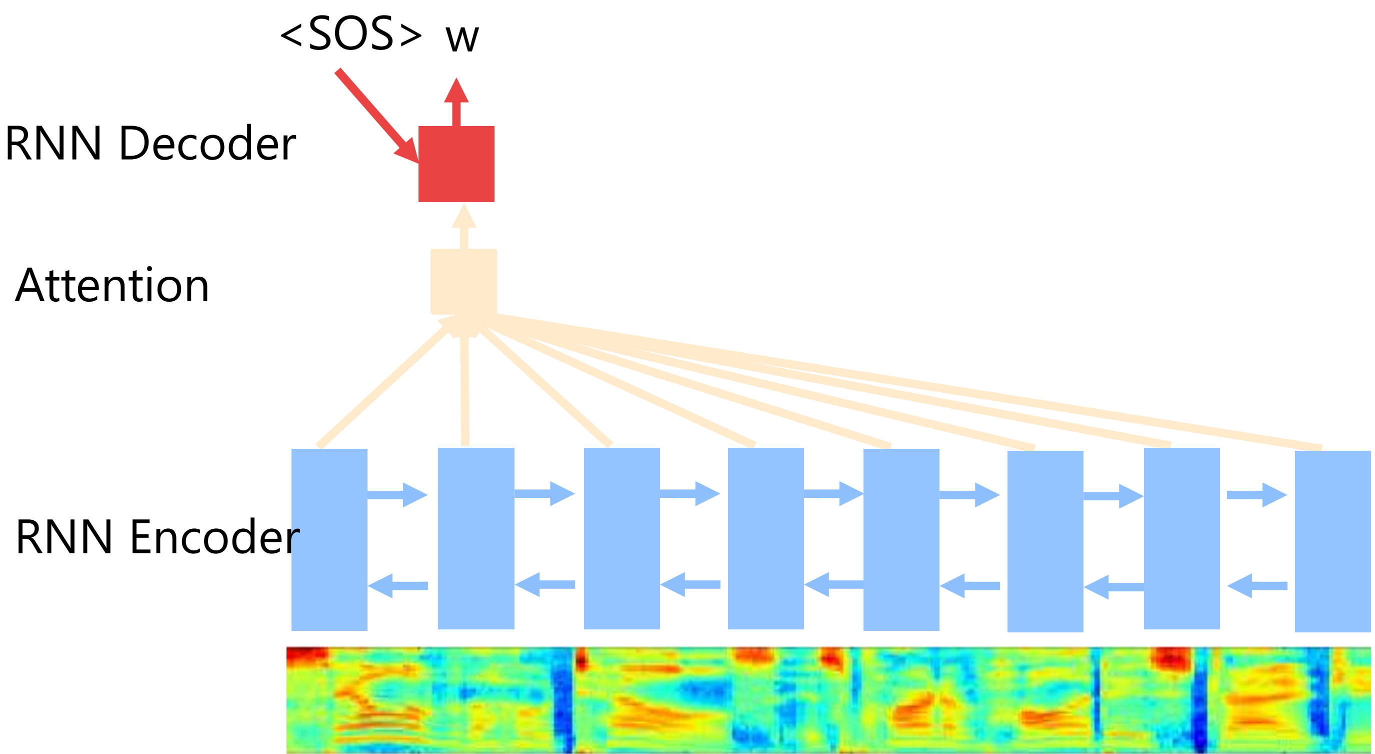
Background: End-to-End ASR

- Seq2seq models directly learn speech-to-text mapping
- Encoder and decoder networks are often RNN



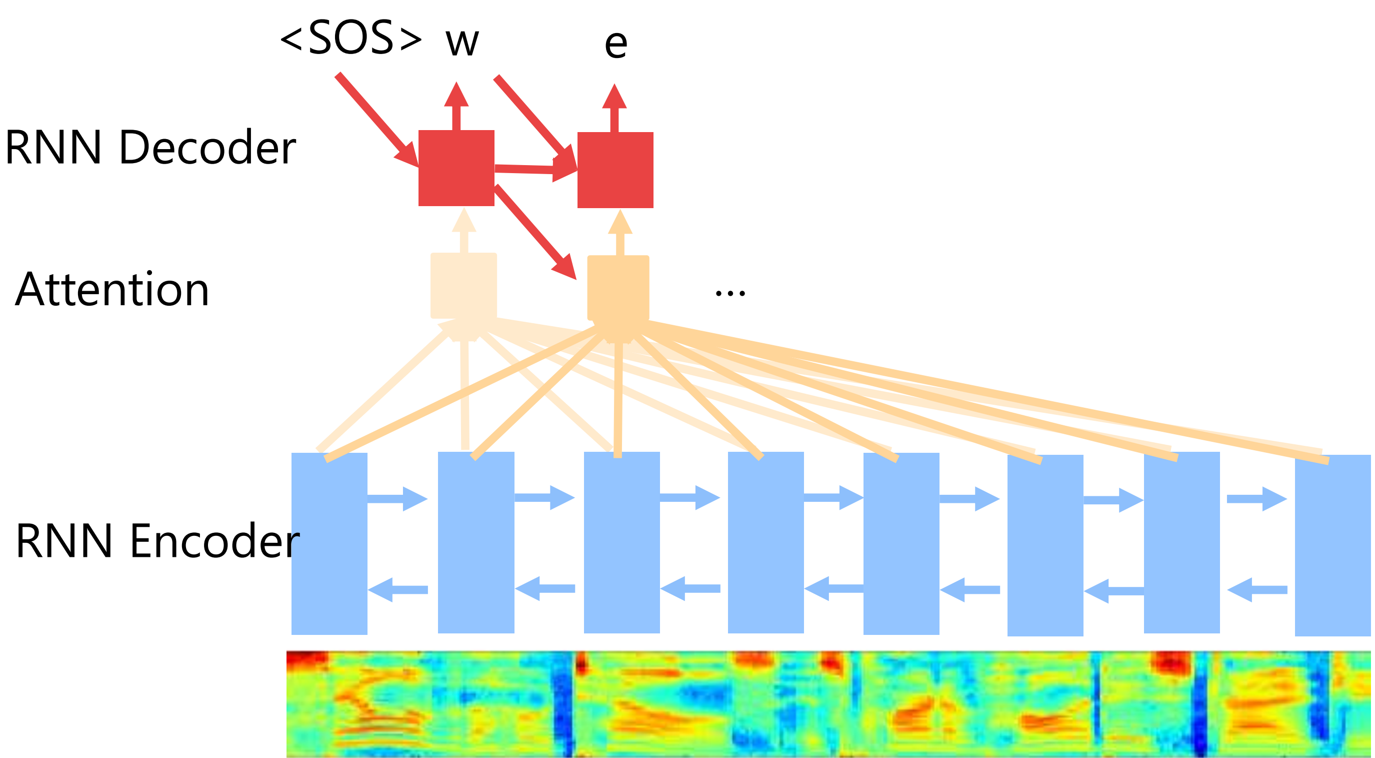
Background: End-to-End ASR

- Seq2seq models directly learn speech-to-text mapping
- Encoder and decoder networks are often RNN



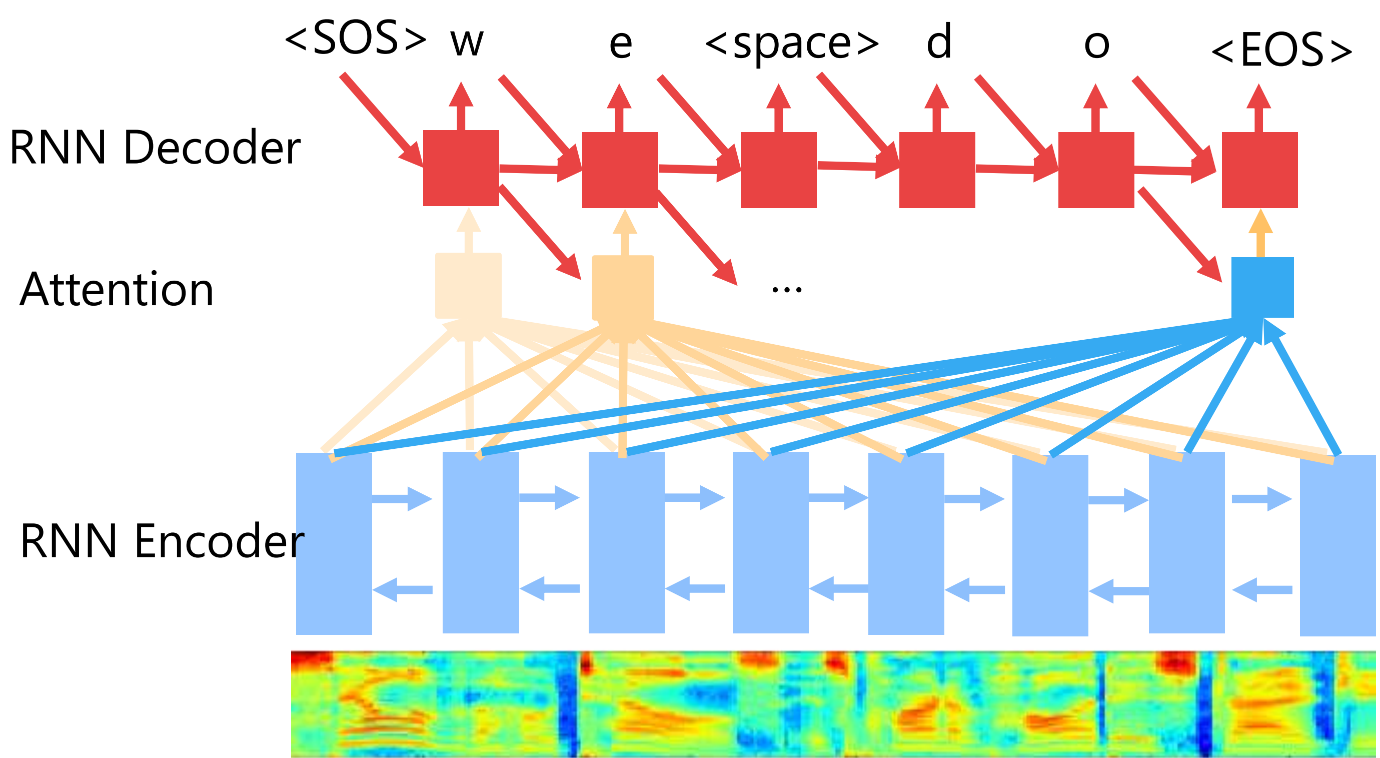
Background: End-to-End ASR

- Seq2seq models directly learn speech-to-text mapping
- Encoder and decoder networks are often RNN



Background: End-to-End ASR

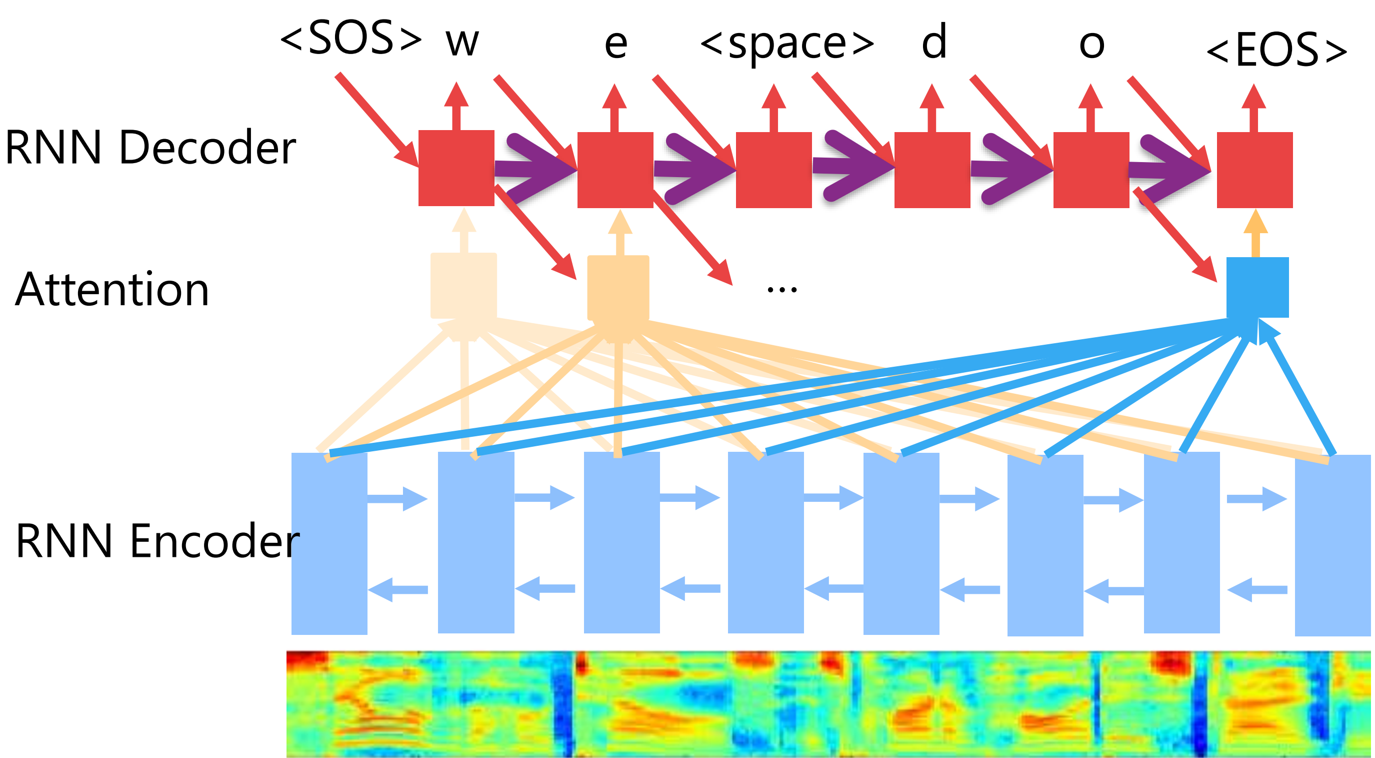
- Seq2seq models directly learn speech-to-text mapping
- Encoder and decoder networks are often RNN



Background: End-to-End ASR

- Seq2seq models directly learn speech-to-text mapping
- Encoder and decoder networks are often **RNN**

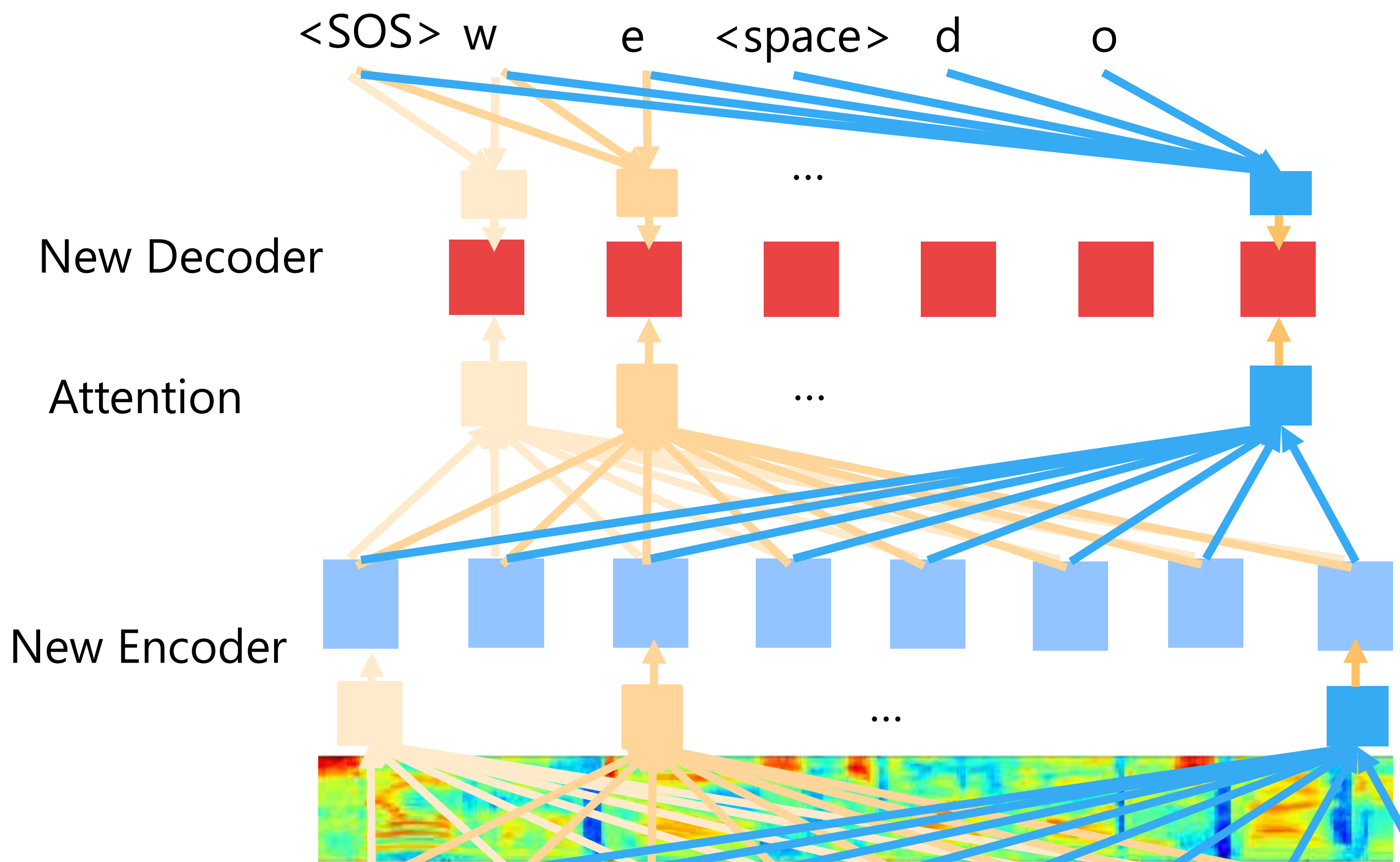
Question: Can we remove **this recurrent connection?**



Background: End-to-End ASR

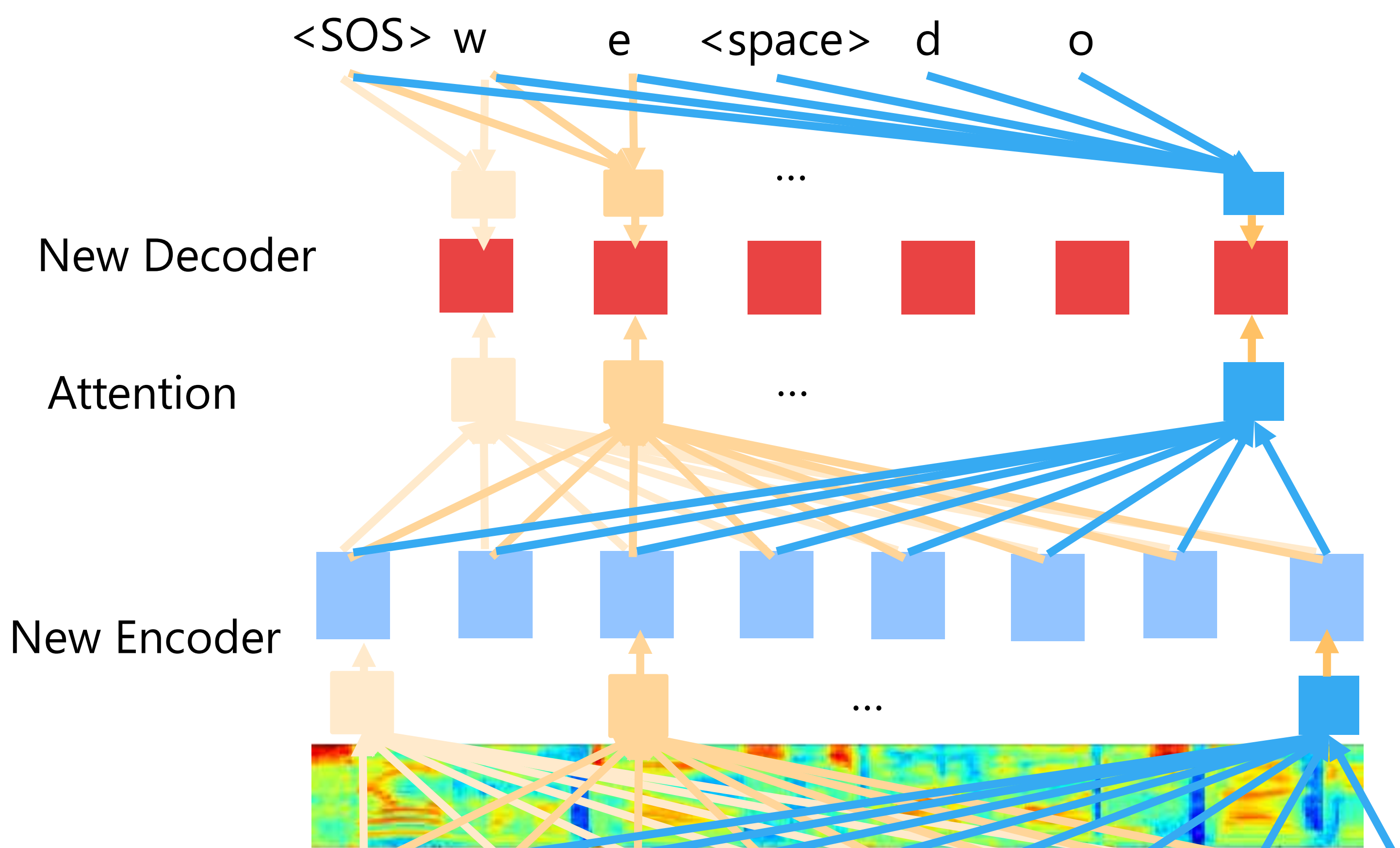
Q: Can we remove **this recurrent connection?**
Then, we can train NN purely in parallel

Answer: use attentions everywhere



Transformer

- Originally proposed in machine translation [Vaswani17]
- Transformer-based ASR [Dong18]
- **Self attentions** in encoder and decoder

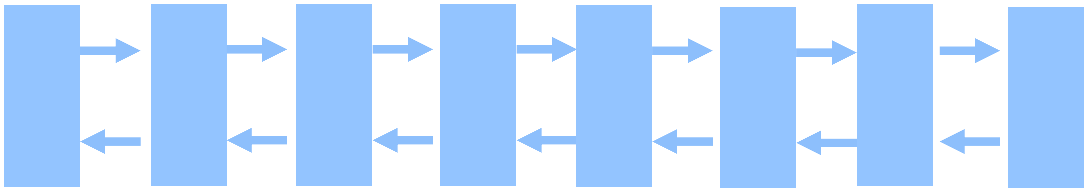


Transformer vs RNN encoder decoder

- RNN
  - Needs to wait for the previous output:

$$h_{\mathrm{t}} = x_t W_x + h_{t-1} W_h$$
$$(t = 1,2,\ldots,T, x \in R^{T\times N}, h \in R^{T\times M}, W_x \in R^{N\times M}, W_h \in R^{M\times M})$$

  - Decoder needs to be unidirectional

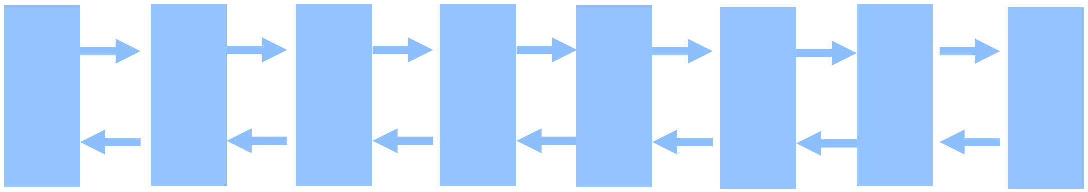


Transformer vs RNN encoder decoder

- RNN
  - Needs to wait for the previous output:

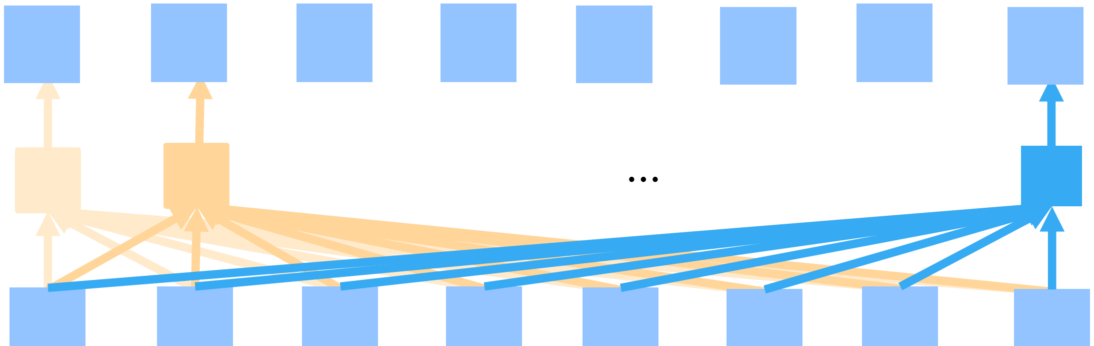
$$h_t = x_t W_x + h_{t-1} W_h$$
$$(t = 1,2,\dots,T, x \in R^{T\times N}, h \in R^{T\times M}, W_x \in R^{N\times M}, W_h \in R^{M\times M})$$

  - Decoder needs to be unidirectional not to input future frames



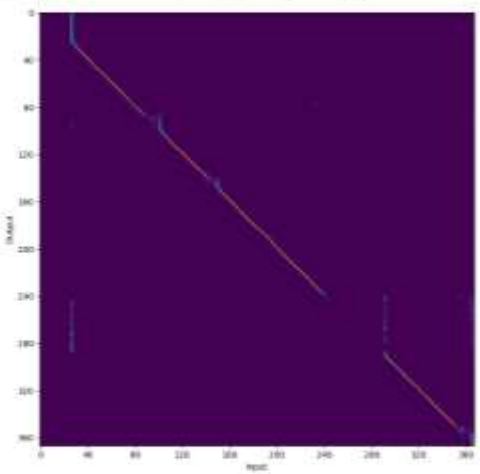
- Transformer
  - Everything in self-attention is parallel:

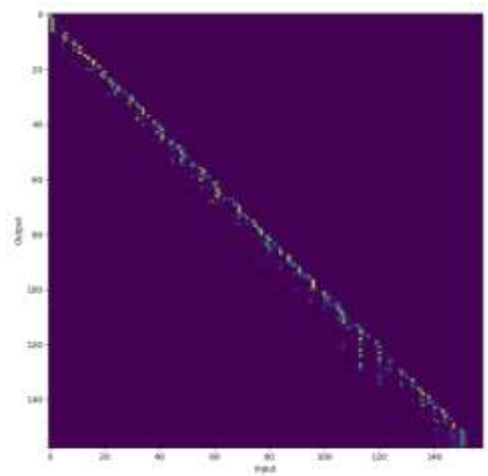
$$h = A(x)(xW_q), \qquad A(x) = \mathrm{softmax}((xW_v)(xW_k)^T)$$
$$(x \in R^{T\times N}, h \in R^{T\times M}, W_v, W_k, W_q \in R^{N\times M})$$



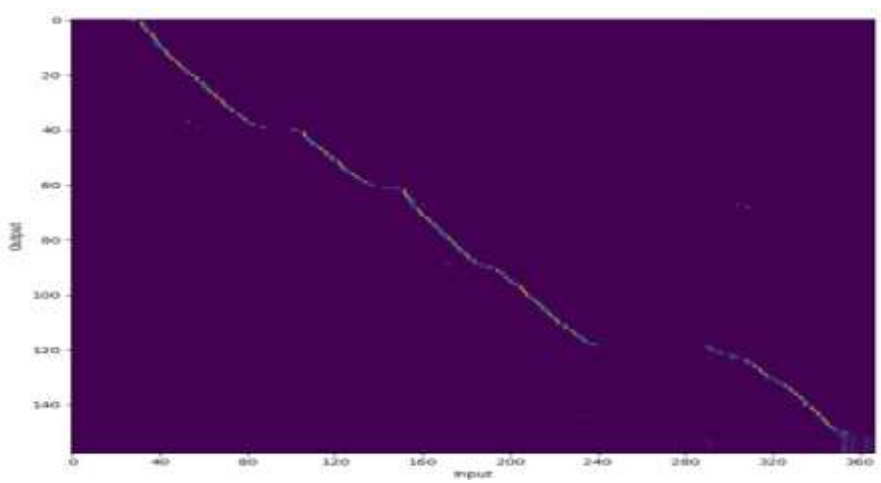
Attentions in Transformer

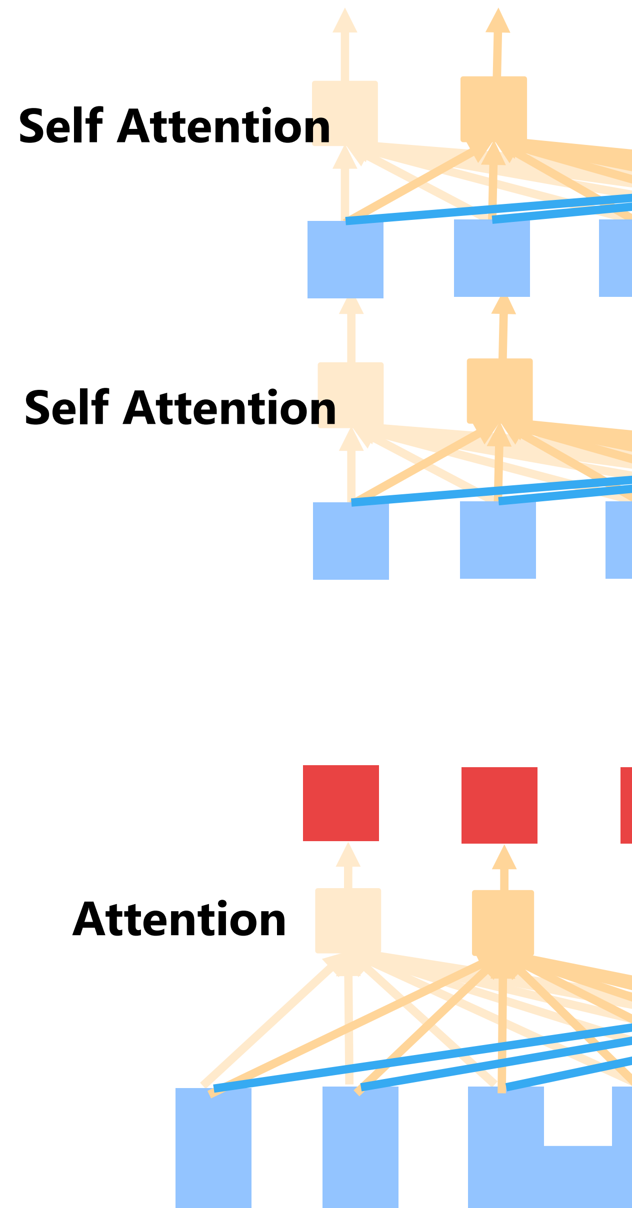
- **Self attention** in encoder and decoder networks





- **Attention** between encoder and decoder networks
  - I refer to this as "**Attention**" in the rest of this talk





Motivation

NTT

- ASR performance in previous work
  - RNN < Transformer [Dong18] < RNN+CTC [Watanabe18]
  - **Can Transformer+CTC be better?**
  - **Apply Transformer to more ASR tasks (not only WSJ)**

- In our preliminary experiments
  - Transformer's training convergence is **slower** than RNN
  - Transformer results in **higher word error rate (WER)** than RNN+CTC in our system as well as previous work
  - Difficulty in decoding Transformer with language model (LM)

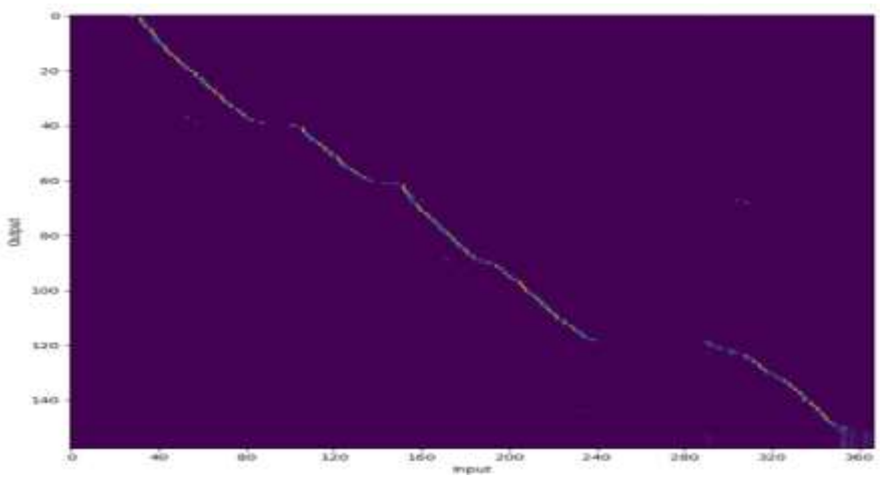
Contribution

- **Improve Transformer for faster training and lower WER**
  - Revisit effective methods in RNN [Watanabe18]
    - Connectionist temporal classification (CTC)
    - Language modeling (LM)
  - Analyze settings and results in training and decoding
    - Training speed
    - Char/word error rate
    - Model size
  - Open source reproducible implementation
    https://github.com/espnet/espnet

Proposed Method: Transformer with CTC and LM

Why CTC Joint Training

- Attention plot is useful for monitoring convergence
  - It often gets **monotonic in ASR**

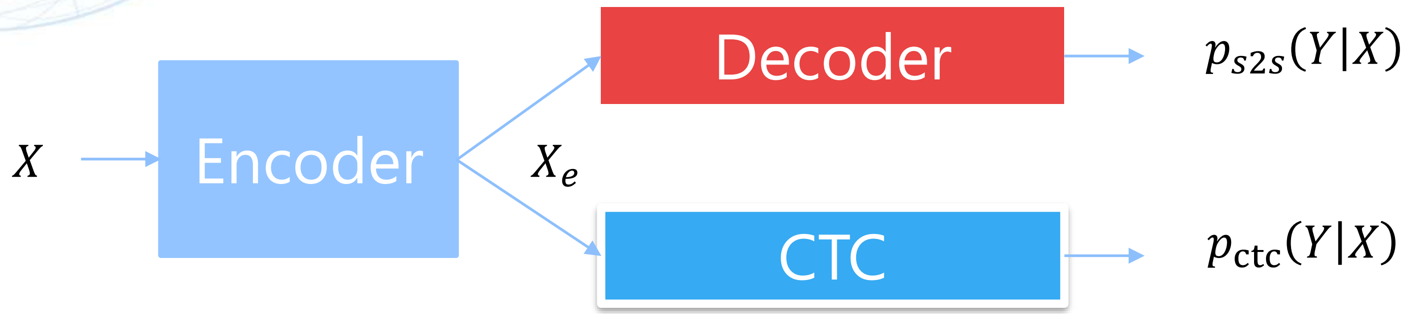


- Transformer attention is not monotonic until ~20 epochs
  - While RNN attention is monotonic at ~3 epochs

- How to accelerate monotonic attention in Transformer?
  - Window diagonal elements [Bahdanau16]: higher WER
  - Guided attention loss [Tachibana18]: higher WER
  - Connectionist temporal classification: **our choice**

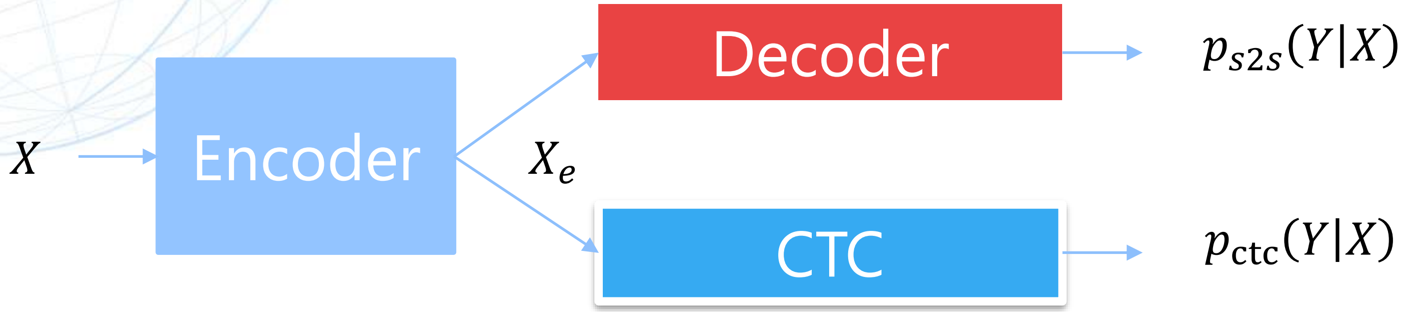
CTC Joint Training

- New branch from the encoder output



CTC Joint Training

- New branch from the encoder output



$$C = \mathrm{softmax}(X_e W^{\mathrm{ctc}} + b^{\mathrm{ctc}}),$$

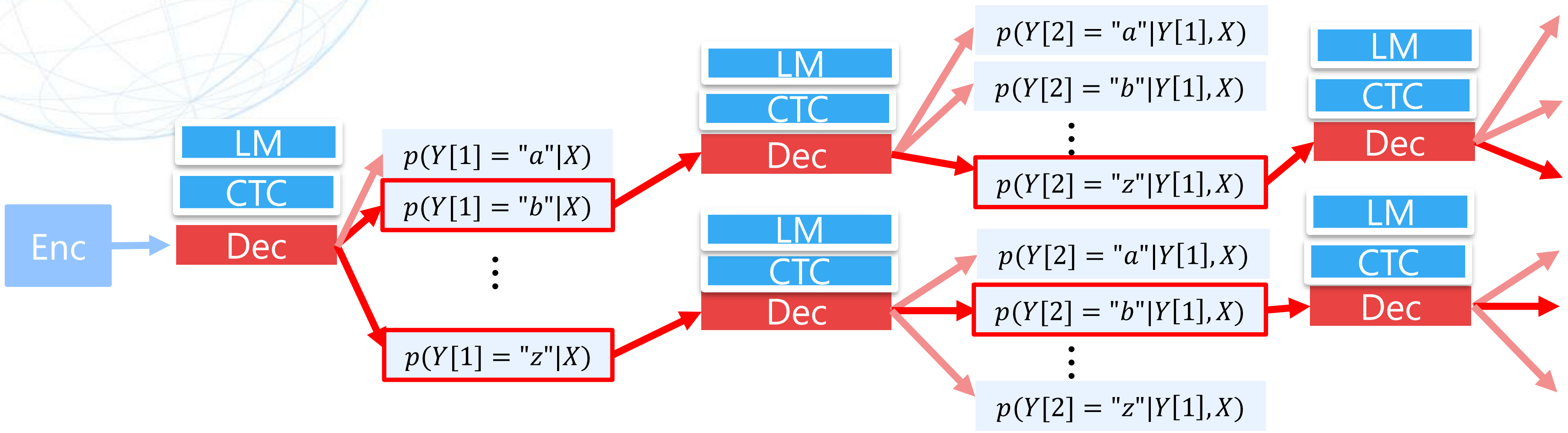
$$p(\mathcal{B}(\pi) = Y | X_e) = \prod_{t=1}^{n^{\mathrm{sub}}} C[t, \pi[t]],$$

$$p_{\mathrm{ctc}}(Y|X_e) = \sum_{\pi' \in \mathcal{B}^{-1}(Y)} p(\mathcal{B}(\pi) = Y | X_e),$$

- π: tokens at each speech frames (**alignment**)
- Objective: $-(1-\alpha)\log p_{s2s}(Y|X) - \alpha \log p_{ctc}(Y|X)$
- Explicit alignment loss makes Transformer faster and more accurate?

CTC/LM Joint decoding

- Prefix tree search with the decoder, CTC and LM



- Recognized text:

$$\hat{Y} = \mathrm{argmax}_Y \log p_{s2s}(Y|X) + \lambda \log p_{\mathrm{ctc}}(Y|X) + \gamma \log p_{\mathrm{lm}}(Y)$$

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Experiments (INTERSPEECH 2019)

ASR NN settings

RNN

- Character output
- **We followed the same config in [Watanabe18]:**
  - Subsampling two conv + maxpooling layers for speech input
  - 320 or 1024 units per layer (depends on tasks)
  - 6 or 8 BLSTM encoder layers, 1 or 2 LSTM decoder layer (depends on tasks)
  - Location-based attention
  - CTC joint training, CTC+RNNLM joint decoding
  - Adadelta optimizer + dev-set eps decay

Transformer

- Character output
- **We followed the same "BIG" config in [Dong18]:**
  - Subsampling two conv layers for speech input
  - 2048 feedforward units
  - 256 attention units
  - 4 heads attention
  - 12 encoder layers, 6 decoder layers
  - CTC joint training, CTC+RNNLM joint decoding
  - Adam optimizer + linear-warmup/inverse-sqrt LR scheduler

Settings except for ASR NN settings above are **shared (best for the RNN system)**

Learning Curve

- CTC joint training accelerated Transformer’s convergence
  - Wall clock time to reach 90% valid accuracy on WSJ
    - RNN+CTC: 1.2 hour
    - Transformer: 1.8 hour
    - **Transformer+CTC: 1.0 hour**

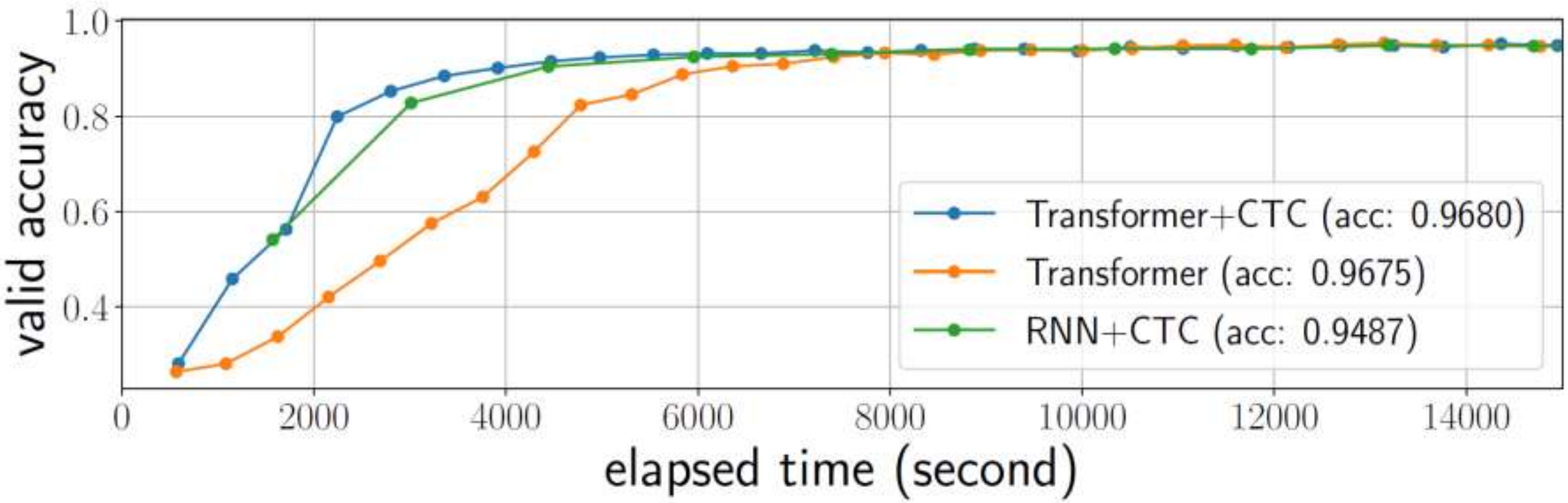


Figure 1: *Validation accuracy on WSJ dev93 over time. Each data point corresponds to the end of each epoch.*

Attention Plot

NTT

- Transformer with CTC learns monotonic attention at 3rd epoch

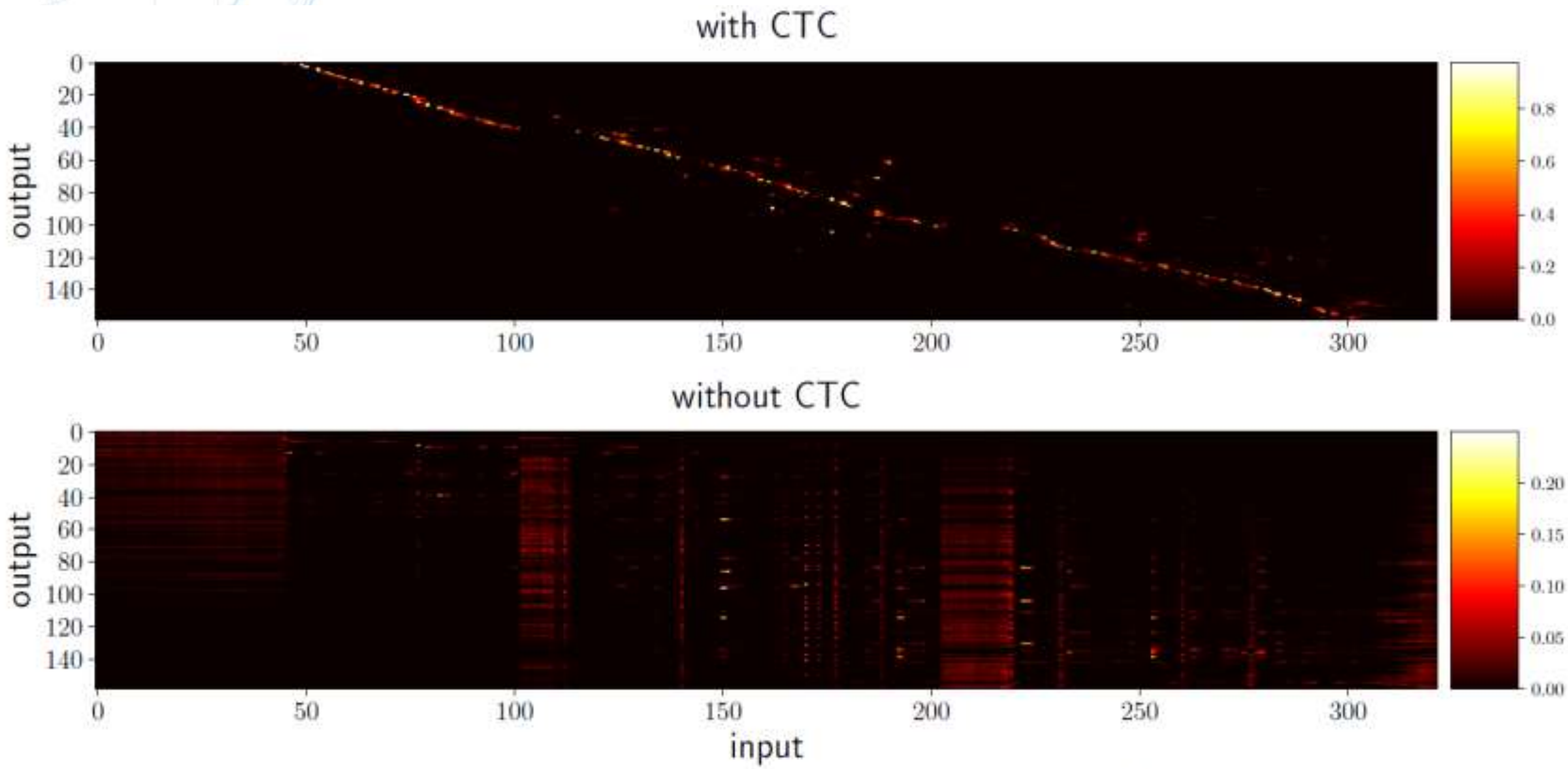


Figure 2: *Attention plots between the encoded input speech and last decoder output for a WSJ 4k0c301 provided by Transformer*

Joint Decoding

- CTC helps joint decoding with LM
- Prefix search:
  $\hat{Y} = \text{argmax}_Y \log p_{s2s}(Y|X) + \lambda \log p_{\text{ctc}}(Y|X) + \gamma \log p_{\text{lm}}(Y)$

Table 4: *Transformer WERs on WSJ dev93.*

		LM γ				
		0.0	0.01	0.1	1.0	10.0
CTC λ	0.0	14.2	69.9	83.4	93.3	95.2
	0.1	13.7	13.6	12.3	7.8	86.3
	0.3	14.4	14.2	12.8	**7.7**	74.0
	0.5	15.7	15.5	13.5	8.5	56.9

Word error rate on WSJ

- Read English ASR task
- Transformer+CTC+LM joint decoding is the best
  - Even only CTC joint training or decoding improved Transformer

	Dev WER	Test WER
RNN	20.8	16.7
RNN + CTC/LM decode	9.0	6.0
Transformer	14.3	11.1
Transformer + CTC train	14.2	10.6
Transformer + CTC decode	13.8	10.2
Transformer + CTC/LM decode	**7.7**	**4.5**

Word error rate on TED-LIUM2

- Lecture English ASR task
- Transformer+CTC+LM joint decoding is the best
  - Even only CTC joint training or decoding improved Transformer

	Dev WER	Test WER
RNN	24.8	19.0
RNN + CTC/LM decode	19.8	18.6
Transformer	24.6	16.1
Transformer + CTC train	20.9	15.1
Transformer + CTC decode	15.8	14.2
Transformer + CTC/LM decode	**13.1**	**11.6**

Char/word error rates in CSJ

- Lecture Japanese ASR task
- Transformer+CTC+LM joint decoding is the best
  - Even only CTC joint training or decoding improved Transformer

	Dev CER	Eval1/2/3 CER
RNN	-	11.4 / 7.9 / 9.0
RNN + CTC/LM decode	-	6.8 / 4.8 / 5.0
Transformer	6.0	7.7 / 5.8 / 5.9
Transformer + CTC train	5.9	7.3 / 5.0 / 5.8
Transformer + CTC decode	5.8	7.1 / 4.9 / 5.6
Transformer + CTC/LM decode	**5.5**	**5.7 / 4.1 / 4.5**

We split the first 4k utterances in the official training as “dev” here.
We retrieved RNN results from egs/csj/asr1/RESULTS in ESPnet
LM in this result was updated after the Interspeech submission

Model parameter size

On CSJ, Transformer has the smallest size and the lowest CER.

	Model size	CSJ CER (eval1/2/3)
Transformer	**120MB**	**5.7 / 4.1 / 4.5**
RNN	476MB	6.6 / 4.8 / 5.0
Kaldi TDNN + HCLG.fst(*)	235MB	7.5 / 6.3 / 6.9

(*) Kaldi default LF-MMI recipe at the commit “c7876a33.”

LARGER Experiments (ASRU2019)

Difference from INTERSPEECH2019

- Data augmentation
  - Speed perturbation [Ko2015]
  - SpecAugment [Park2019]

- More faster training
  - Multi GPUs (up to 8)
  - Mixed precision (fp16 + fp32)

- More experiments
  - Comparison to non-end-to-end ASR system: Kaldi
  - Total 15 monolingual + 1 multilingual ASR tasks!
    - In the paper, we also provided text-to-speech and speech translation results but I skip this today…

Monolingual ASR Datasets

NTT

Table 1. ASR dataset description. Names listed in "test sets" correspond to ASR results in Table 2. We enlarged corpora marked with (*) by the external WSJ train_si284 dataset (81 hours).

dataset	language	hours	speech	test sets
AISHELL [27]	zh	170	read	dev / test
AURORA4 [28] (*)	en	15	noisy read	(dev_0330) A / B / C / D
CSJ [29]	ja	581	spontaneous	eval1 / eval2 / eval3
CHiME4 [30] (*)	en	108	noisy far-field multi-ch read	dt05_simu / dt05_real / et05_simu / et05_real
CHiME5 [31]	en	40	noisy far-field multi-ch conversational	dev_worn / kinect
Fisher-CALLHOME Spanish	es	170	telephone conversational	dev / dev2 / test / devtest / evltest
HKUST [32]	zh	200	telephone conversational	dev
JSUT [24]	ja	10	read	(our split)
LibriSpeech [33]	en	960	clean/noisy read	dev_clean / dev_other / test_clean / test_other
REVERB [34] (*)	en	124	far-field multi-ch read	et_near / et_far
SWITCHBOARD [35]	en	260	telephone conversational	eval2000 / RT'03
TED-LIUM2 [36]	en	118	spontaneous	dev / test
TED-LIUM3 [37]	en	452	spontaneous	dev / test
VoxForge [38]	it	16	read	(our split)
WSJ [39]	en	81	read	dev93 / eval92

We tested various ASR tasks in language, hours, and recoding.

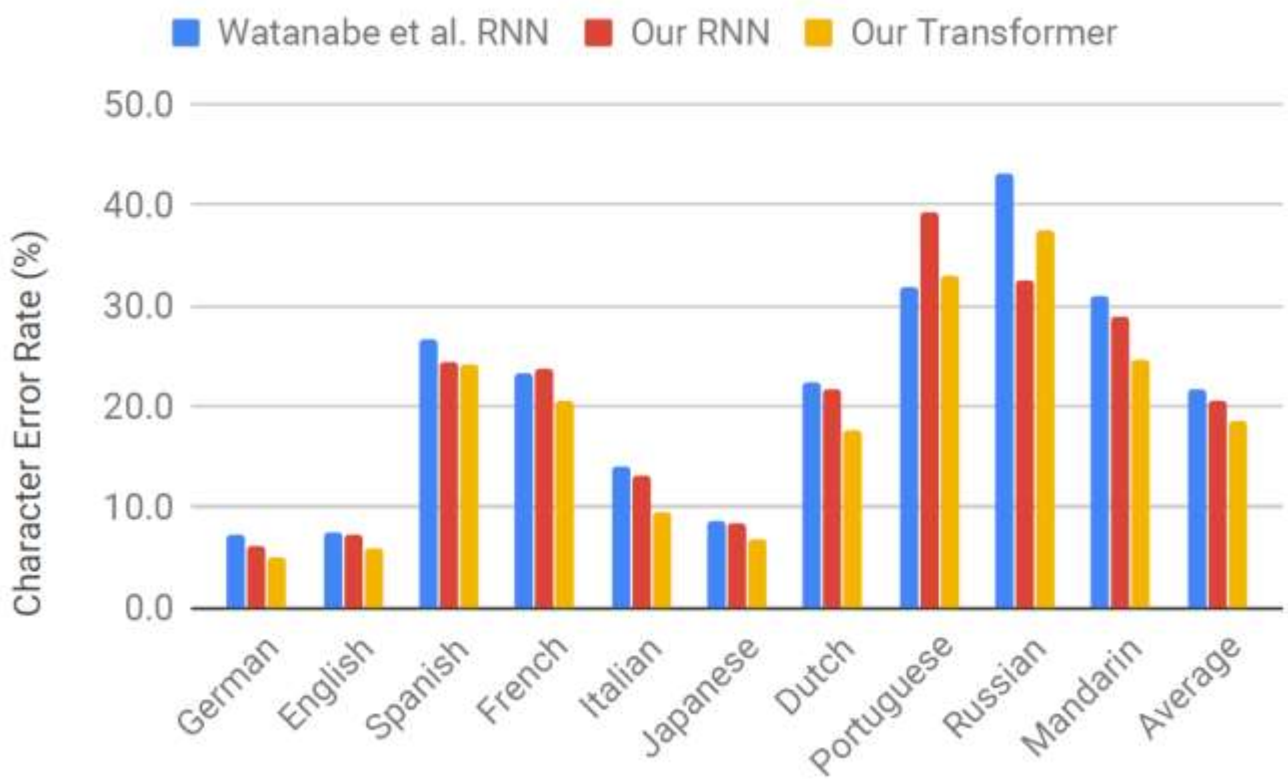
Monolingual ASR Results

- Transformer achieved lower CER/WER than RNN in 13/15 tasks
  - Including noisy, far-field low resource, etc

dataset	token	error	Kaldi	Our RNN	Our Transformer
AISHELL	char	CER	N/A / 7.4	6.8 / 8.0	**6.0 / 6.7**
AURORA4	char	WER	(*) 3.6 / 7.7 / 10.0 / 22.3	3.5 / 6.4 / 5.1 / 12.3	**3.3 / 6.0 / 4.5 / 10.6**
CSJ	char	CER	(*) 7.5 / 6.3 / 6.9	6.6 / 4.8 / 5.0	**5.7 / 4.1 / 4.5**
CHiME4	char	WER	**6.8 / 5.6 / 12.1 / 11.4**	9.5 / 8.9 / 18.3 / 16.6	9.6 / 8.2 / 15.7 / 14.5
CHiME5	char	WER	**47.9 / 81.3**	59.3 / 88.1	60.2 / 87.1
Fisher-CALLHOME Spanish	char	WER	N/A	27.9 / 27.8 / 25.4 / 47.2 / 47.9	**27.0 / 26.3 / 24.4 / 45.3 / 46.2**
HKUST	char	CER	23.7	27.4	**23.5**
JSUT	char	CER	N/A	20.6	**18.7**
LibriSpeech	BPE	WER	3.9 / 10.4 / 4.3 / 10.8	3.1 / 9.9 / 3.3 / 10.8	**2.2 / 5.6 / 2.6 / 5.7**
REVERB	char	WER	18.2 / 19.9	24.1 / 27.2	**15.5 / 19.0**
SWITCHBOARD	BPE	WER	**18.1 / 8.8**	28.5 / 15.6	26.0 / 14.0
TED-LIUM2	BPE	WER	**9.0** / 9.0	11.2 / 11.0	9.3 / **8.1**
TED-LIUM3	BPE	WER	**6.2 / 6.8**	14.3 / 15.0	9.7 / 8.0
VoxForge	char	CER	N/A	12.9 / 12.6	**9.4 / 9.1**
WSJ	char	WER	**4.3 / 2.3**	7.0 / 4.7	6.8 / 4.4

Multilingual ASR results

- Previous system: [Watanabe2017] RNN
  - Except for Russian, Transformer results in the best



Multi GPU Training

- Transformer could be trained faster in multi GPU
  - More #GPUs results in better accuracy
  - Scaling ASR!!

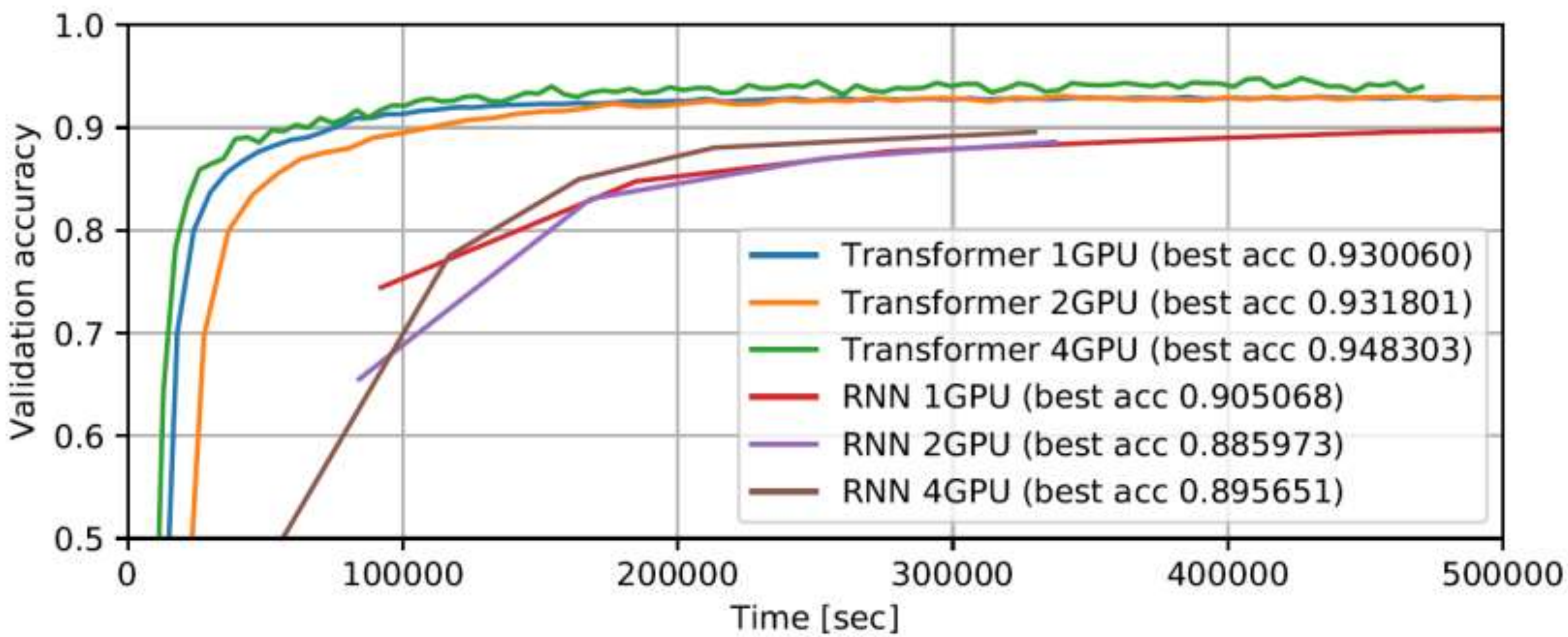


Fig. 2. ASR training curve with LibriSpeech dataset.

Training tips: minibatch

- Transformer prefers larger mini batch (backprop in parallel)
  – More suitable for HPC servers
- Multiple backprop per single update (backprop interatively)
  – If you do not have HPC servers

# Utts in minibatch	# Backprop	# GPU	Dev clean WER
32	4	2	4.0
32	8	1	4.0
32	12	1	3.7
32	12	8	2.7

Training tips: data augmentation

- Speed perturbation (sp) [Ko2015]: speed up/down playback speed
- SpecAugment (sa) [Park2019]: random freq/time mask on spectrogram

greatly improve both Transformer and RNN

	TEDLIUM2 Dev WER	TEDLIUM2 Test WER
RNN	19.6	18.6
Transformer	12.8	11.0
RNN + sp	11.2	11.0
Transformer + sp	11.2	10.4
RNN + sa	11.4	10.6
Transformer + sa	11.2	9.6
RNN + sp + sa	11.4	10.6
Transformer + sp + sa	**9.3**	**8.1**

Summary

NTT

- Transformer can replace RNN in ASR when we combined it with CTC and LM

- Our open source implementation and pretrained models: https://github.com/espnet/espnet

- Open paper access
  - INTERPSEECH2019: https://www.isca-speech.org/archive/Interspeech_2019/abstracts/1938.html
  - ASRU2019 preprint: https://arxiv.org/abs/1909.06317

Agenda

1. Introduction of NTT CS Lab
2. Overview of End-to-End Speech Recognition
3. Semi-supervised End-to-End Speech Recognition
4. Transformer-based End-to-End Speech Recognition
5. Summary

Feel free to ask me anytime if you have any questions (in EN/JP)

PDF: http://karita.xyz/talk/naist2019.pdf

Summary

NTT

- **PART1: NTT is the best place for research in Japan**
- **PART2**: E2E systems greatly simplify the ASR pipeline
  - with NN, CTC, seq2seq, etc
  - without pronunciation dictionary, multi-stage training
  - ASR research for everyone! https://github.com/espnet/espnet
- **PART3**: Our semi-supervised training improves E2E ASR in low-resource scenario with unsupervised data
  - using speech/text autoencoders and inter-domain loss
- **PART4**: Transformer makes E2E ASR faster and more robust
  - can easily replace RNNs in many ASR tasks
- **However, E2E ASR still has many unresolved problems**
  - unsupervised/few-shot learning, online/real-time decoding, sequential training, joint speech enhancement, data cleaning, etc

References in PART4

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