SpeechJoey: Minimalistic Speech-to-Text Modeling with JoeyNMT

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statNLP

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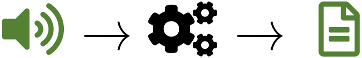
Today

1. **Speech-to-Text Modeling**
   - Speech-to-Text Tasks
   - Data Preprocessing
   - Architecture
2. **SpeechJoey**
   - Features
   - Performance
   - Code Complexity

assume: basic ML knowledge,
familiarity with neural machine translation with JoeyNMT

Speech-to-Text Tasks



→ `I'm going to talk today about energy and climate.`

Automatic Speech Recognition (ASR)

→ `Heute spreche ich zu Ihnen über Energie und Klima.`

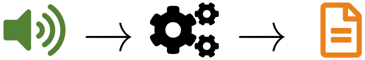
End-to-End Speech Translation (ST)

---

beyond ASR or ST (out of SpeechJoey's scope)

- Speaker identification (audio → speaker id)
- Speech separation (detect who spoke when)
- Spoken language Understanding (audio → sentiment / slots)

Speech-to-Text Tasks



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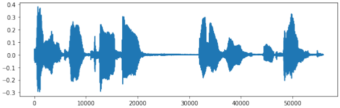
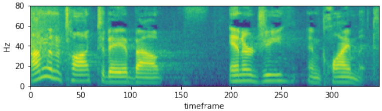
Input Features

🔊 Src: Wave form → Frequency-based 2d-array

ex.) <u>Mel-filterbank</u>, MFCC, etc.



→



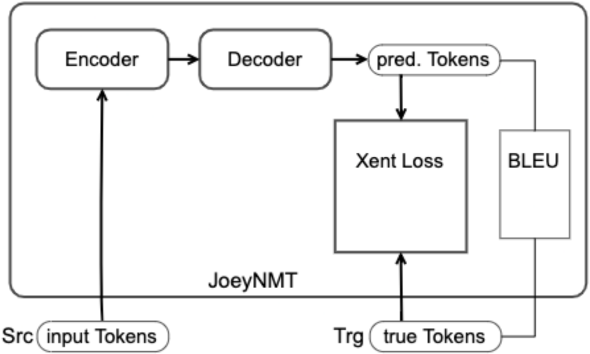
📄 Trg: Text string → Token sequence

ex.) Chars, <u>BPEs</u>, Words, etc.

```
"I’m going to talk today about energy and climate."
↓
["_I", "'", "m", "_going", "_to", "_talk", "_today",
"_", "about", "_energy", "_and", "_climate"]
```

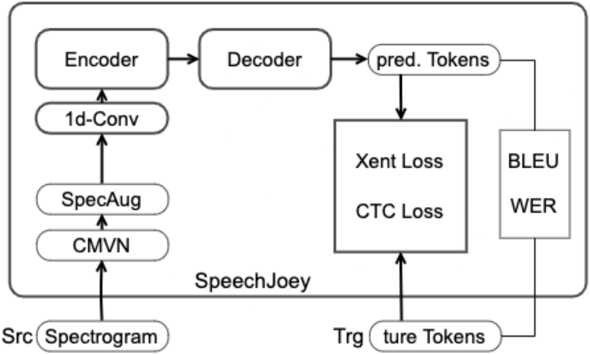
Encoder-Decoder Architecture

JoeyNMT

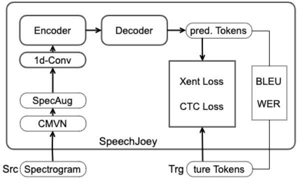


Encoder-Decoder Architecture

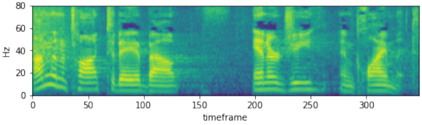
SpeechJoey



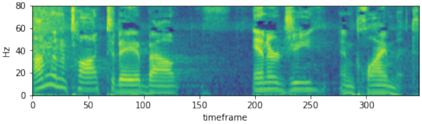
Normalization, Augmentation



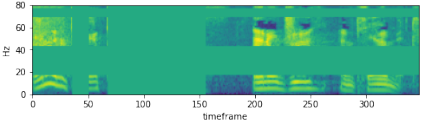
Original:



Cepstral mean and variance normalization (CMVN):

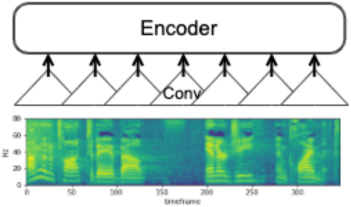


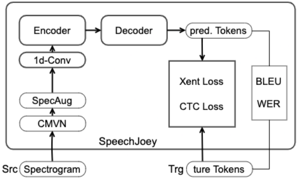
SpecAugment:



On-the-fly

Convolutional Layer





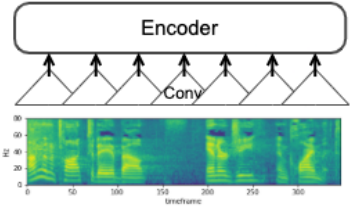
1. downsample the input length to make the computation tractable

$$L_{out} = \left\lfloor \frac{L_{in} + 2 \times \text{padding} - \text{dilation} \times (\text{kernel size} - 1) - 1}{\text{stride}} + 1 \right\rfloor$$

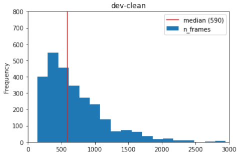
- computational complexity of self-attention is $\mathcal{O}(\ell^2 \cdot d)$
  where ℓ: time-frames, d: frequencies

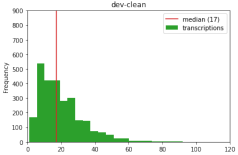
2. audio input is redundant (?)

Convolutional Layer



LibriSpeech dev





audio: 590, transcripts: 17 (median)

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2. audio input is redundant (?)

CTC loss

https://distill.pub/2017/ctc/

We start with an input sequence, like a spectrogram of audio.

The input is fed into an RNN, for example.

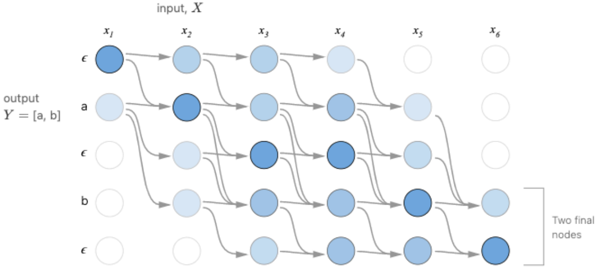
The network gives $p_t(a \mid X)$, a distribution over the outputs $\{h, e, l, o, \epsilon\}$ for each input step.

With the per time-step output distribution, we compute the probability of different sequences

By marginalizing over alignments, we get a distribution over outputs.

CTC loss

https://distill.pub/2017/ctc/



Node (s, t) in the diagram represents $\alpha_{s,t}$ – the CTC score of the subsequence $Z_{1:s}$ after t input steps.

$$\text{ctc prob}(Y|X) = \sum_{a \in \mathcal{A}} \prod_{t=1}^{T} p_t(a_t|X)$$

$$\text{ctc loss}(X; Y) = \sum_{(X,Y) \in \mathcal{D}} -\log \ \text{ctc prob}(Y|X)$$

What is most important to you?

1. state-of-the-art performance
2. clean, open-source code
3. minimalistic system design
4. walk-through tutorial
5. comprehensive API documentation
6. easy to install (no Kaldi!)
7. ready to use
   - pretrained models
   - preprocessing, evaluation included
   - recipe for major benckmarks

Fast prototyping

Education

Performance: ASR on LibriSpeech

	100h (WER ↓)			
	dev-clean	**dev-other**	**test-clean**	**test-other**
[Lüscher et al., 2019]	14.7	38.5	14.7	40.8
[Kahn et al., 2020]	14.0	37.0	14.9	40.0
[Laptev et al., 2020]	10.3	24.0	11.2	24.9
SpeechJoey	9.43	20.29	10.52	21.10
	960h (WER ↓)			
ESPNET	1.9	4.9	2.1	4.9
fairseq	3.0	7.5	3.2	7.5
SpeechBrain	-	-	2.46	5.77
wav2vec-U	1.6	3.0	1.8	3.3
[Zhang et al., 2020]	1.3	2.6	1.4	2.6
SpeechJoey	3.99	9.11	4.54	9.09

*WER=lower is better. *SpeechJoey snapshot as of March 2021.

Performance: ST on MuST-C en-de

	ASR (WER ↓)		**MT** (BLEU ↑)		**ST** (BLEU ↑)	
	CM	**HE**	**CM**	**HE**	**CM**	**HE**
	MuST-C version 1					
[Gangi et al., 2019]	27.0	-	25.30	-	-	-
[Zhang et al., 2020]	-	-	-	-	22.4	-
ESPNET	12.7	-	27.63	-	22.9	-
NeurST	13.6	-	27.9	-	22.8	-
fairseq S2T	18.2	-	-	-	22.7	-
	MuST-C version 2					
SpeechJoey	10.83	8.50	27.77	26.17	22.96	22.53

*$\mathbf{CM}$=tst-COMMON; **HE**=tst-HE

*WER=lower is better; BLEU=higher is better.

*SpeechJoey results on MuST-C v1 will be available soon!

What SpeechJoey can do / can't do

- ✔ ASR / ST
- ✔ colab tutorial (coming soon!)
- ✔ preprocessing scripts
- ✔ CMVN, SpecAugment
- ✔ WER, BLEU
- ✔ baseline benchmark configs
- ✔ easy to install
- ✔ pretrained models
- ✔ module-wise initialization (ASR and MT pre-training for ST)

- 🛇 Audio-to-Audio
  - speech enhancement
  - speech separation
- 🛇 Text-to-Speech
- 🛇 various architectures (RNN, transducers, ...)
- 🛇 self-supervised training (wav2vec)

Code Complexity

Counts	ESPNET [1]	fairseq [2]	SpeechJoey[3]
Files	653	587	50
Code	80710	81763	7079
Comments	17997	13383	2313
Comment/Code Ratio	0.22	0.16	0.33

Table: Code complexity

Note: computed on the whole github repo

Tool: https://github.com/AlDanial/cloc

commit hash: [1]`c36294ea` [2]`3796a80f6` [3]`3ccff729` as of June 2021

Stack Trace in fairseq S2T

for CTC extension, where to change?

- `fairseq_cil/train.py`
- `fairseq/trainer.py`
- `fairseq/tasks/fairseq_task.py`
- `fairseq/models/speech_to_text/s2t_ctc_transformer.py`
- `fairseq/data/audio/speech_to_text_dataset.py`
- `fairseq/criterions/xent_ctc_loss.py`
- `fairseq/sequence_generator.py`

  ⋮

Abstract, hierarchical structure

Stack Trace in SpeechJoey

for CTC extension, where to change?

- `joeynmt/__main__.py`
- `joeynmt/training.py`
- `joeynmt/model.py`
- `joeynmt/loss.py`
- `joeynmt/search.py`

  ⋮

Shallow directory structure

Simple class inheritance

Have I convinced you of the advantages of SpeechJoey?

Q & A

References I

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ESPNET https://github.com/espnet/espnet/blob/master/egs/librispeech/asr1/RESULTS.md

fairseq S2T https://github.com/pytorch/fairseq/blob/master/examples/speech_to_text/docs/librispeech_example.md

NeurST https://github.com/bytedance/neurst/tree/master/examples/speech_to_text/must-c

SpeechBrain https://github.com/speechbrain/speechbrain