Automatic Severity Classification of Dysarthric speech by using Self-supervised Model with Multi-task Learning

Eun Jung Yeo*, Kwanghee Choi*, Sunhee Kim, Minhwa Chung

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Contents

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Main challenge of dysarthric speech

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→ Self-supervised pre-trained model

→ Multi-Task Learning

Our method

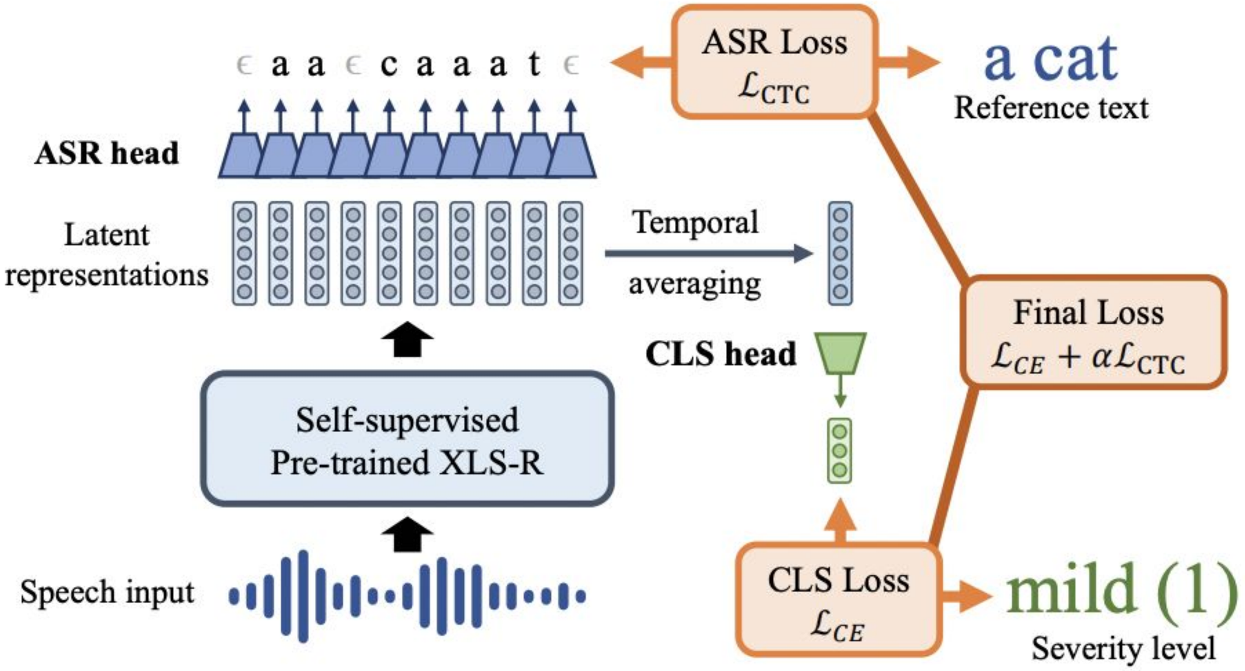
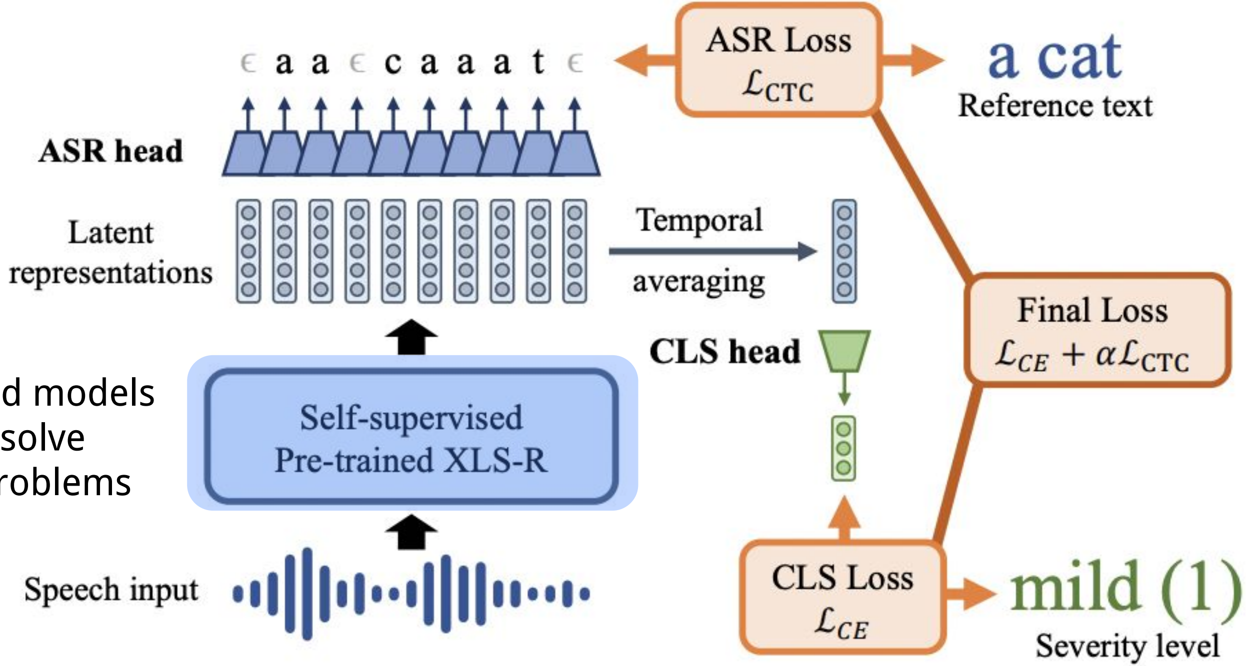


Fig. 1: Illustration of our proposed method.

Our method - Self-supervised model

Fine-tuning self-supervised models are known to solve data-scarce problems effectively.



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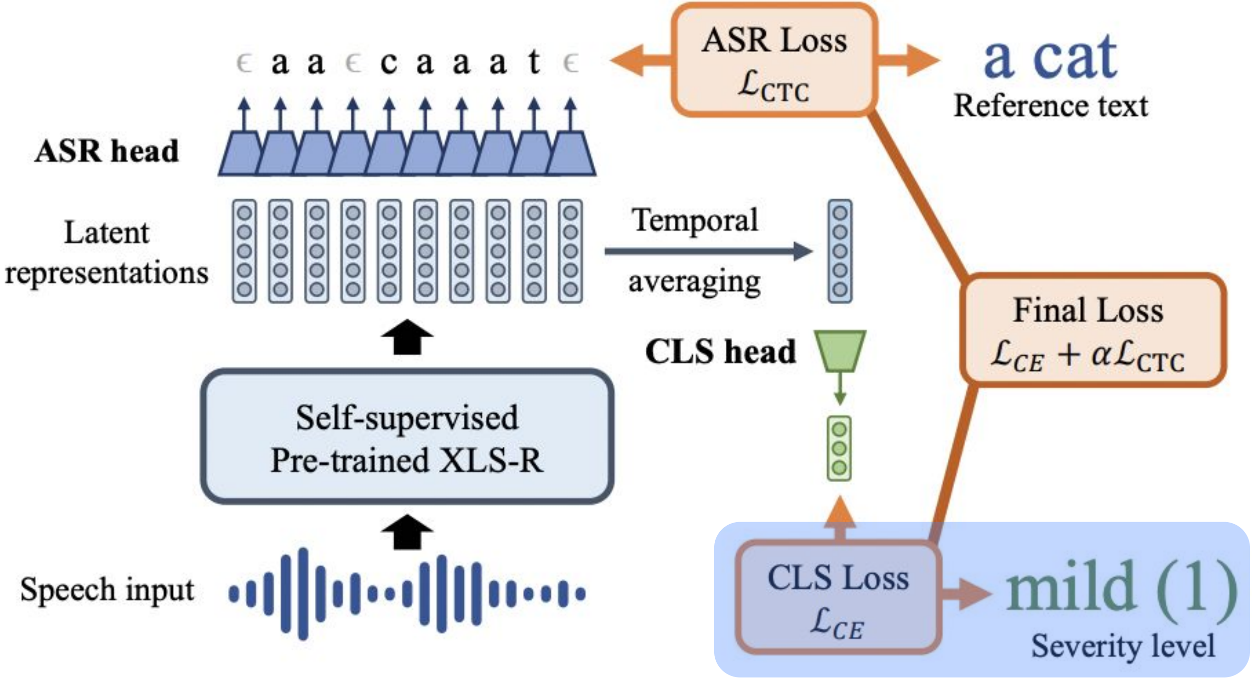

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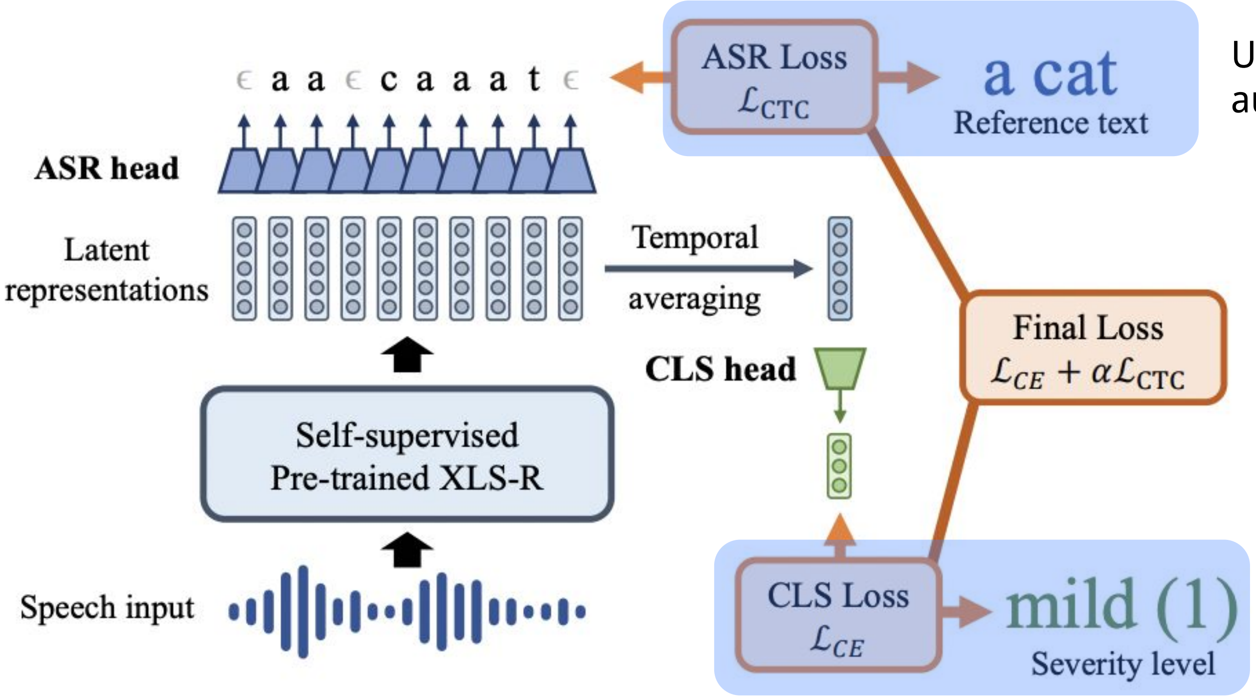
Our paper's focus!
Severity classification

Our method - Multi-Task Learning



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Use ASR as an auxiliary task

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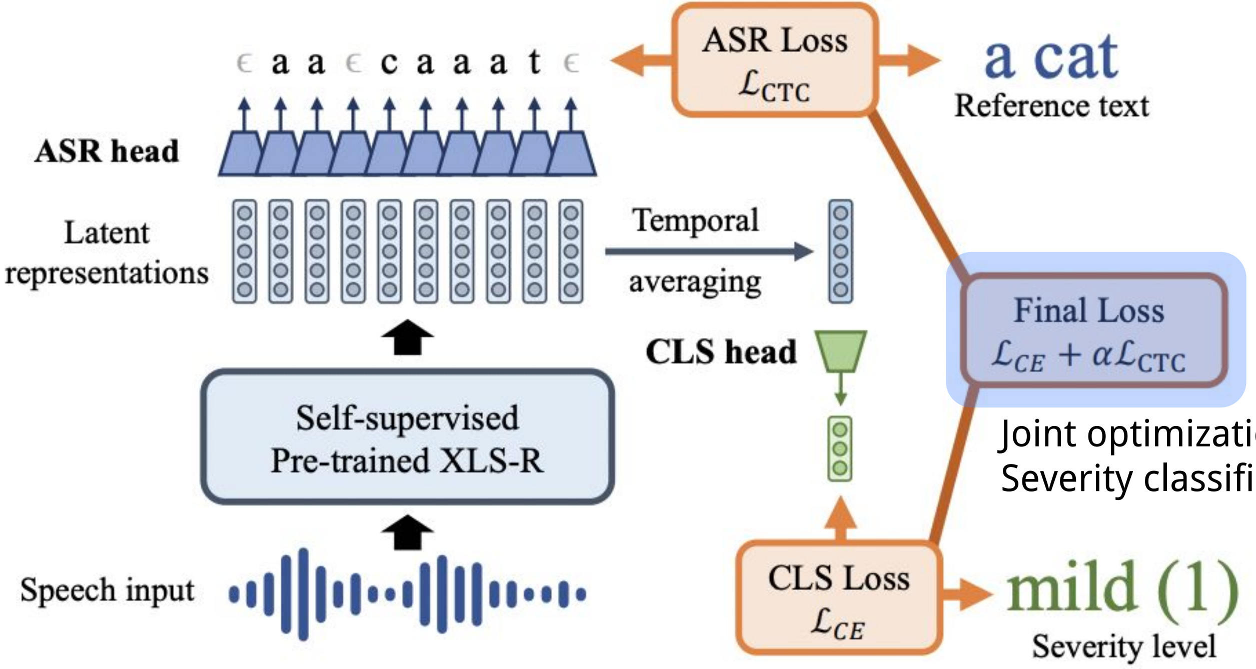

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Joint optimization of classification
Severity classification + ASR

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2. The auxiliary ASR task can act as a regularizer, as the model is trained to focus on two different tasks.

→ Prevents **overfitting** and yield **better performances**!

Dataset

- QoLT Korean dysarthric speech dataset
  - Speakers
    - 10 healthy speakers (5 males, 5 females)
    - 70 dysarthric speakers (45 males, 25 females)
      - 25 mild, 26 mild-to-moderate, 12 moderate-to-severe, 7 severe

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    - Each speaker recorded five sentences twice → Total of 800 utterances
  - Experiment
    - 5-way cross-validation in a speaker-independent manner.

Results

Table 1: Classification performance compared to the baselines.

Input	Classifier	Accuracy	Precision	Recall	F1-score
eGeMAPS	SVM	55.01	53.89	53.27	52.28
	MLP	50.79	44.46	48.60	46.58
	XGBoost	52.20	55.07	50.85	50.61
Hand-crafted features	SVM	61.02	64.19	63.19	62.41
	MLP	55.74	60.06	60.34	58.85
	XGBoost	55.72	61.14	56.21	56.16
eGeMaps + Hand-crafted features	SVM	57.83	58.83	57.59	56.65
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Raw audio	STL	61.02	64.09	57.93	57.13
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1. SSL > Feature-based
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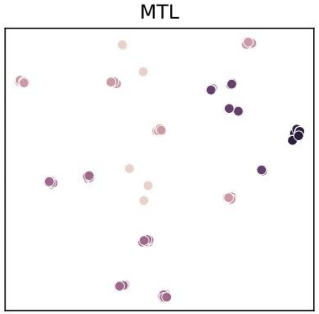
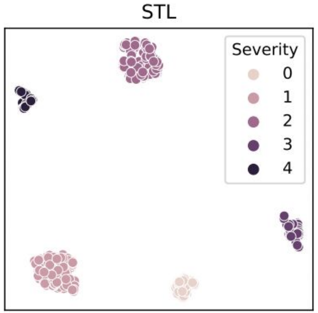
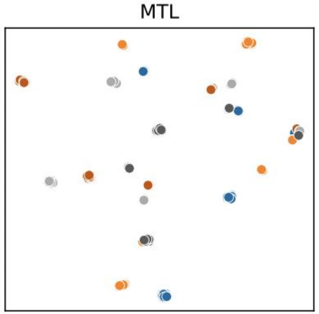
Analysis 1: Representation space visualization



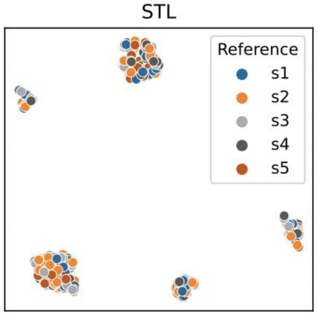
(a) Trained with MTL, color-coded with severity.



(b) Trained with STL, color-coded with severity.



(c) Trained with MTL, color-coded with setence.



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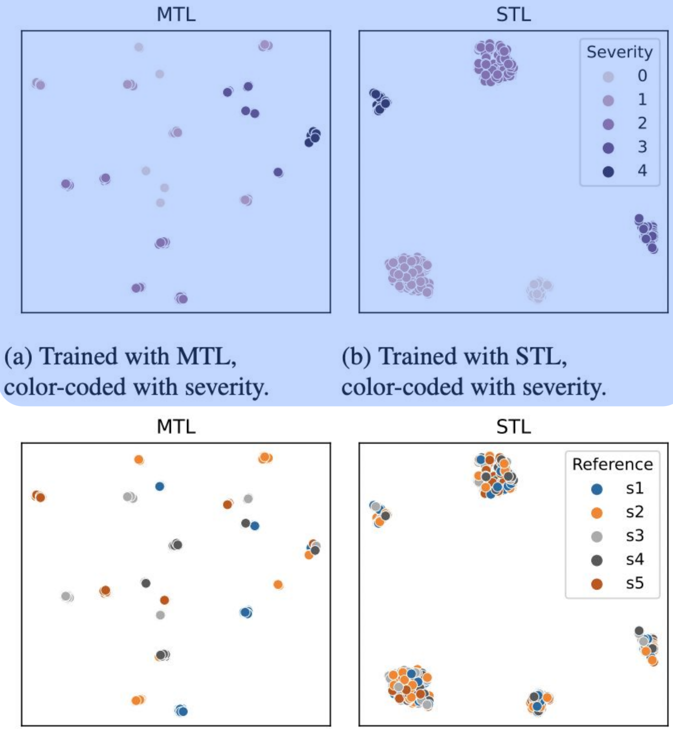

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Severity

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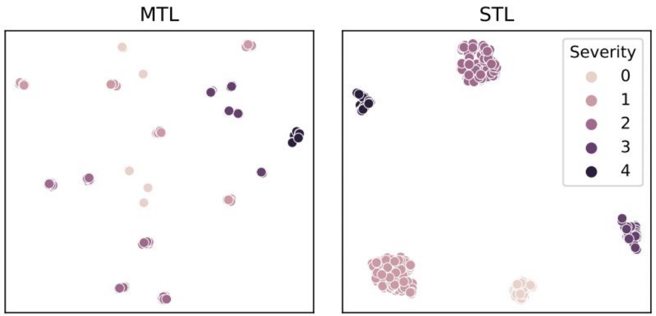

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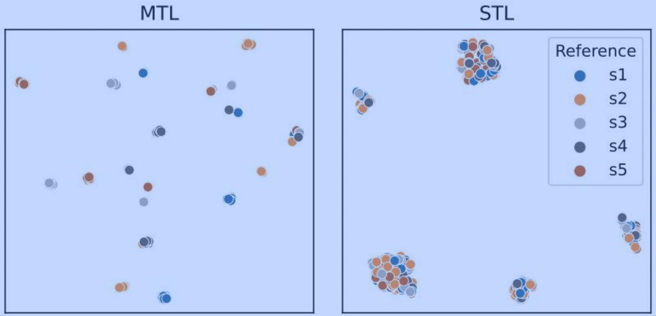

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Sentence

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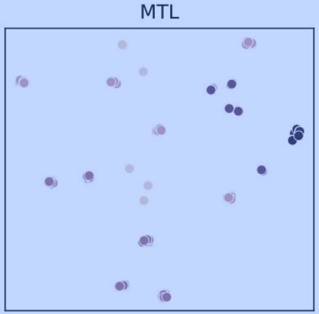

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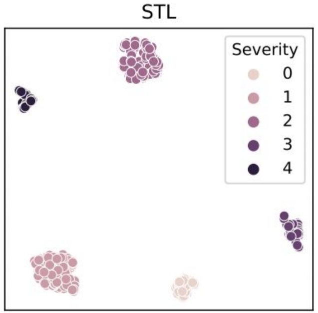

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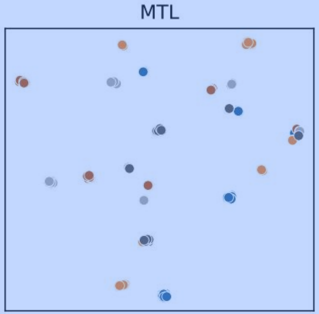

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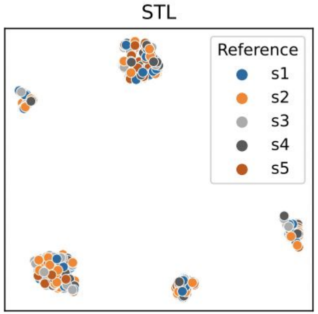

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CLS + ASR

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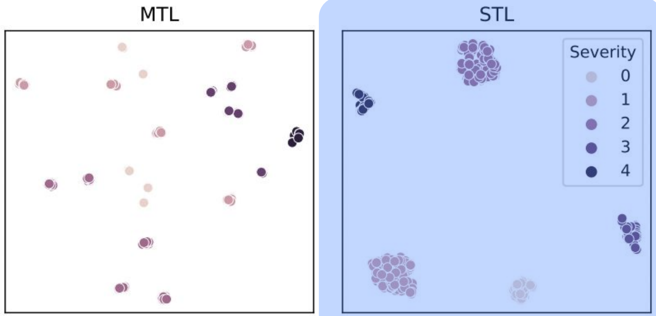

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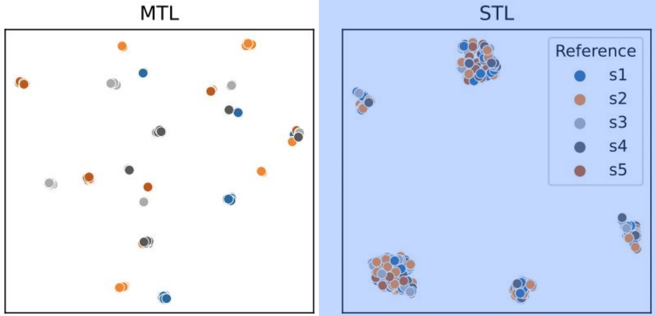
CLS Only



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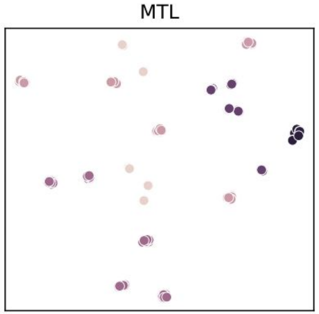

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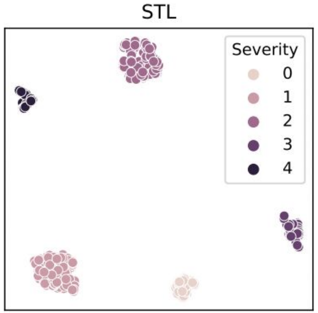

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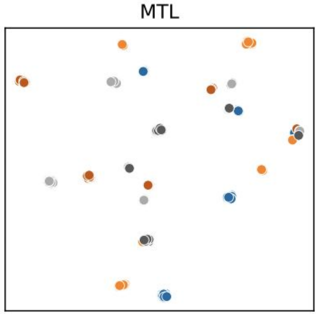

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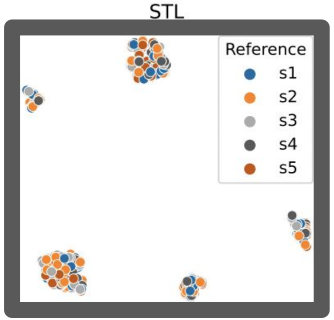

(d) Trained with STL, color-coded with setence.

1. STL cannot distinguish **different sentences**

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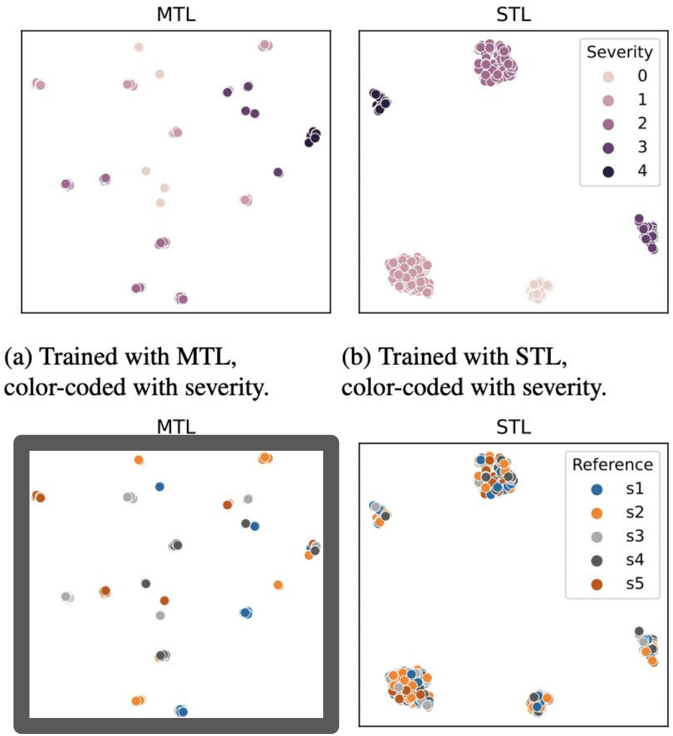

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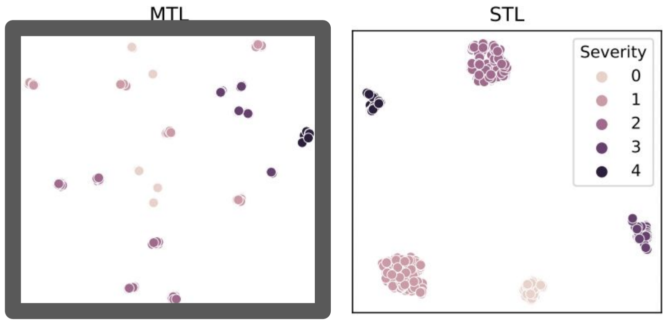

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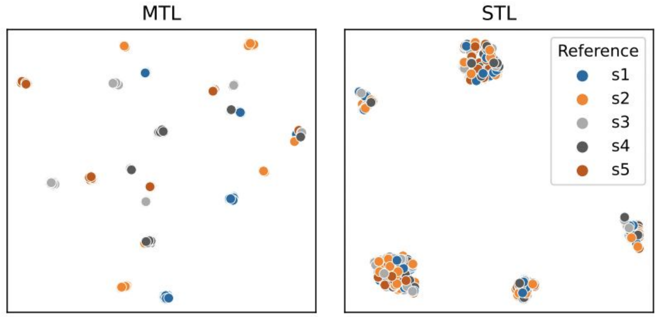

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1. STL cannot distinguish different sentences, while MTL's representations are clustered in terms of both sentences and **severity levels**.

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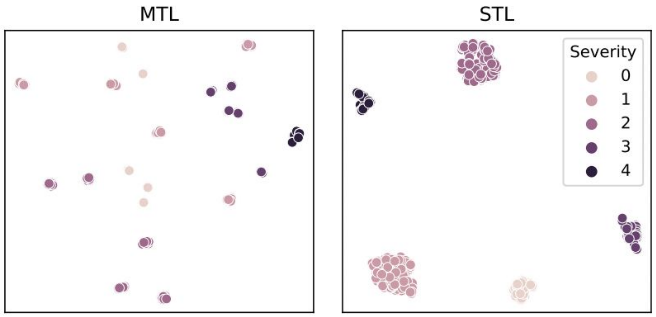

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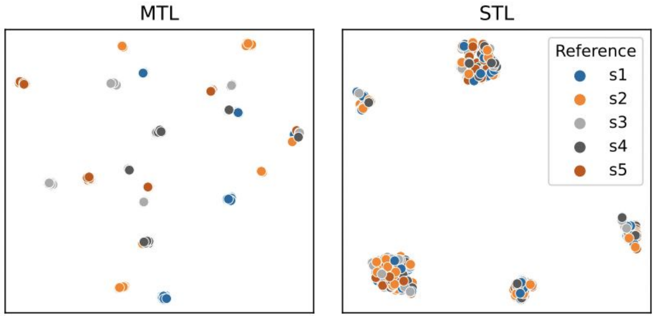

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   → Indicates that the MTL model also encodes phonetic/pronunciation information.

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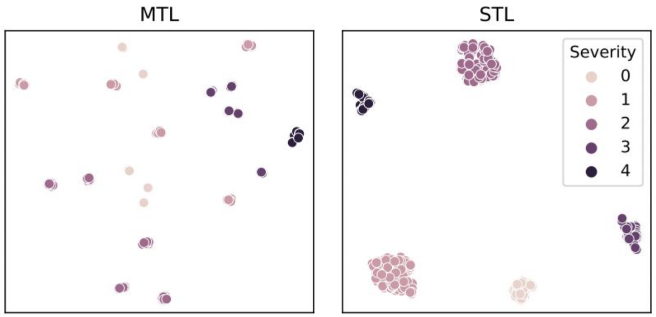

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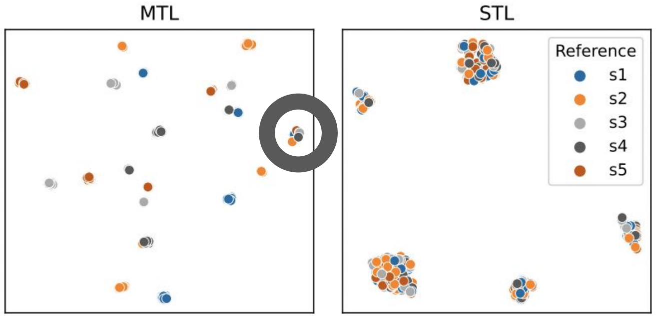

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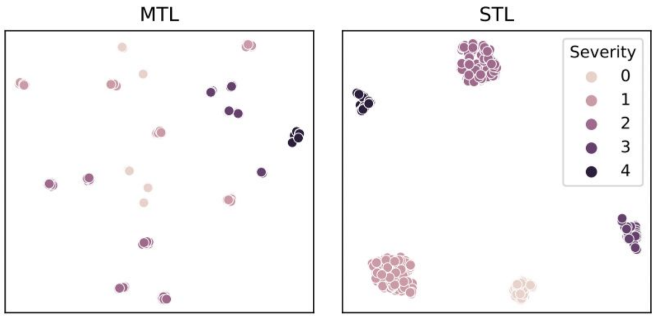

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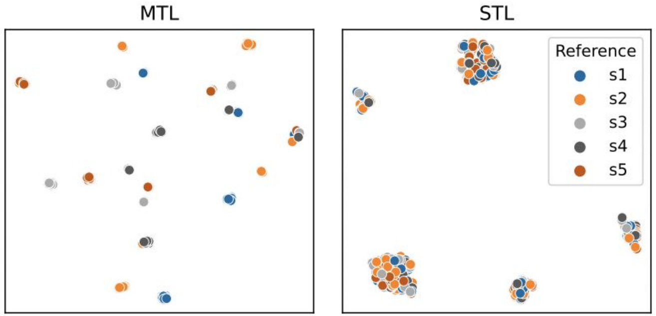

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   → May be due to significantly distorted speech, difficult for ASR

Analysis 2. Regularization effect of ASR

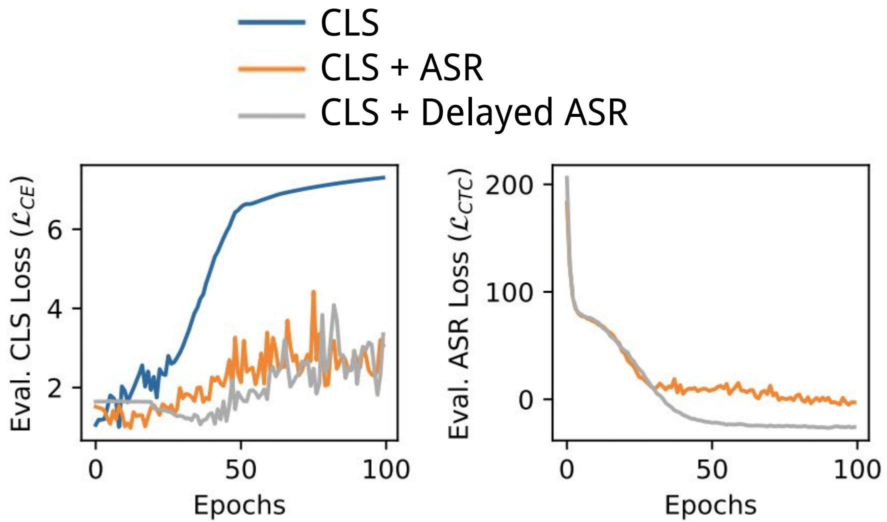

Fig. 3: Classification loss $\mathcal{L}_{\mathrm{CE}}$ and ASR loss $\mathcal{L}_{\mathrm{CTC}}$ on validation set. $\alpha = 0$ denotes the STL case when we use the $\mathcal{L}_{\mathrm{CE}}$ only.

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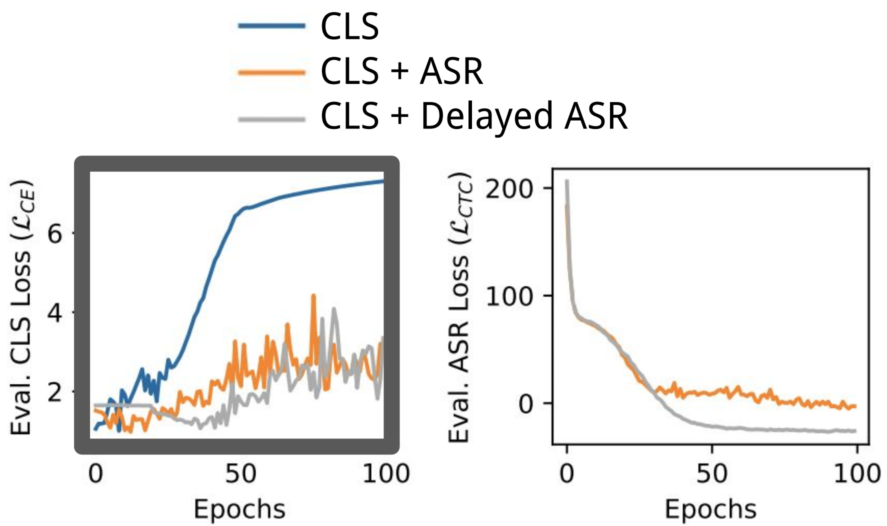

Fig. 3: Classification loss $\mathcal{L}_{\mathrm{CE}}$ and ASR loss $\mathcal{L}_{\mathrm{CTC}}$ on validation set. $\alpha = 0$ denotes the STL case when we use the $\mathcal{L}_{\mathrm{CE}}$ only.

1. With joint optimization, model overfits much slower.

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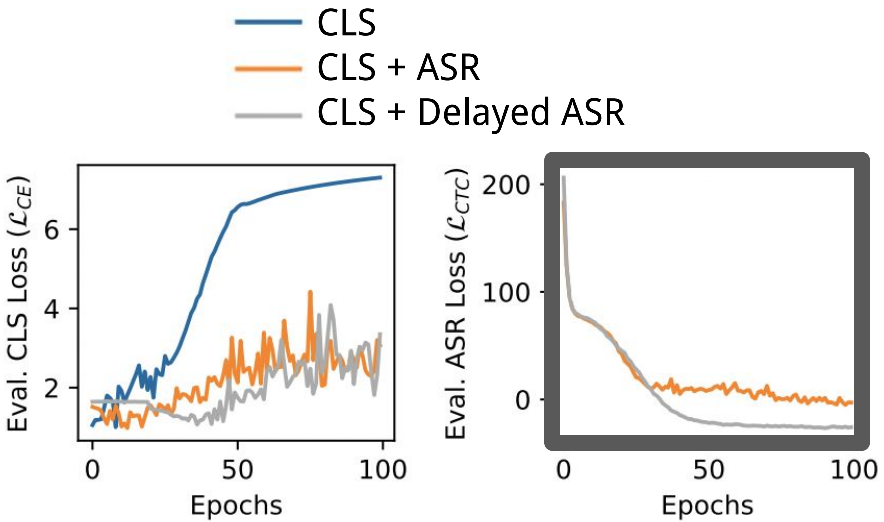

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2. Delaying the optimization of ASR loss = stable optimization and better performances

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Accuracy	$\alpha = 1.0$	$\alpha = 0.1$	$\alpha = 0.01$	$\alpha = 0.001$
$e = 0$	60.51	60.69	56.21	54.94
$e = 10$	61.82	63.12	57.14	57.00
$e = 20$	54.77	64.69	59.84	61.27
$e = 30$	57.74	**65.52**	60.10	62.72
$e = 40$	55.47	60.11	62.00	57.96

PER	$\alpha = 1.0$	$\alpha = 0.1$	$\alpha = 0.01$	$\alpha = 0.001$
$e = 0$	17.50	21.86	88.49	96.91
$e = 10$	14.83	22.37	82.59	96.49
$e = 20$	16.66	18.10	31.12	90.08
$e = 30$	15.87	17.72	23.10	74.54
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   → **Premature training of CLS** leads to the model being under-trained with the ASR task, which fails to inject enough information.

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2. Automatic dysarthria severity classification method

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   : latent representation

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   : regularization effect → prevents overfitting

Thank you for your attention!