Speech Representation Learning through Self-supervised Pretraining and Multi-task Finetuning

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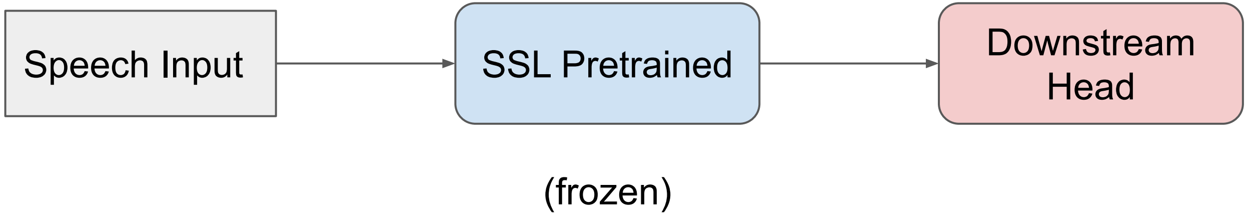
Motivation - Representation Learning via Pretraining

- For example,
  - ImageNet pretraining in CV -> object detection
  - BERT in NLP -> question answering
  - wav2vec in speech -> automatic speech recognition

Motivation - Representation Learning via SSL Pretraining

- Self-supervised Learning (SSL)
  - Generative losses
    - APC, Mockingjay, Tera, DeCoAR, …
  - Discriminative losses
    - CPC, wav2vec (2.0), HuBERT, …
  - Multiple losses
    - PASE(+), …



Motivation - Representation Learning via Multi-task Learning

- General representation learning for a variety of speech processing tasks
- Supervised multi-task learning (MTL) is to train a shared model on various downstream tasks.
- There has not been a systematic study of general representation learning models trained by MTL of various speech processing tasks.
- We want to investigate if MTL on various downstream tasks can further improve the representations from SSL.
- SUPERB Benchmark (Unconstrained)

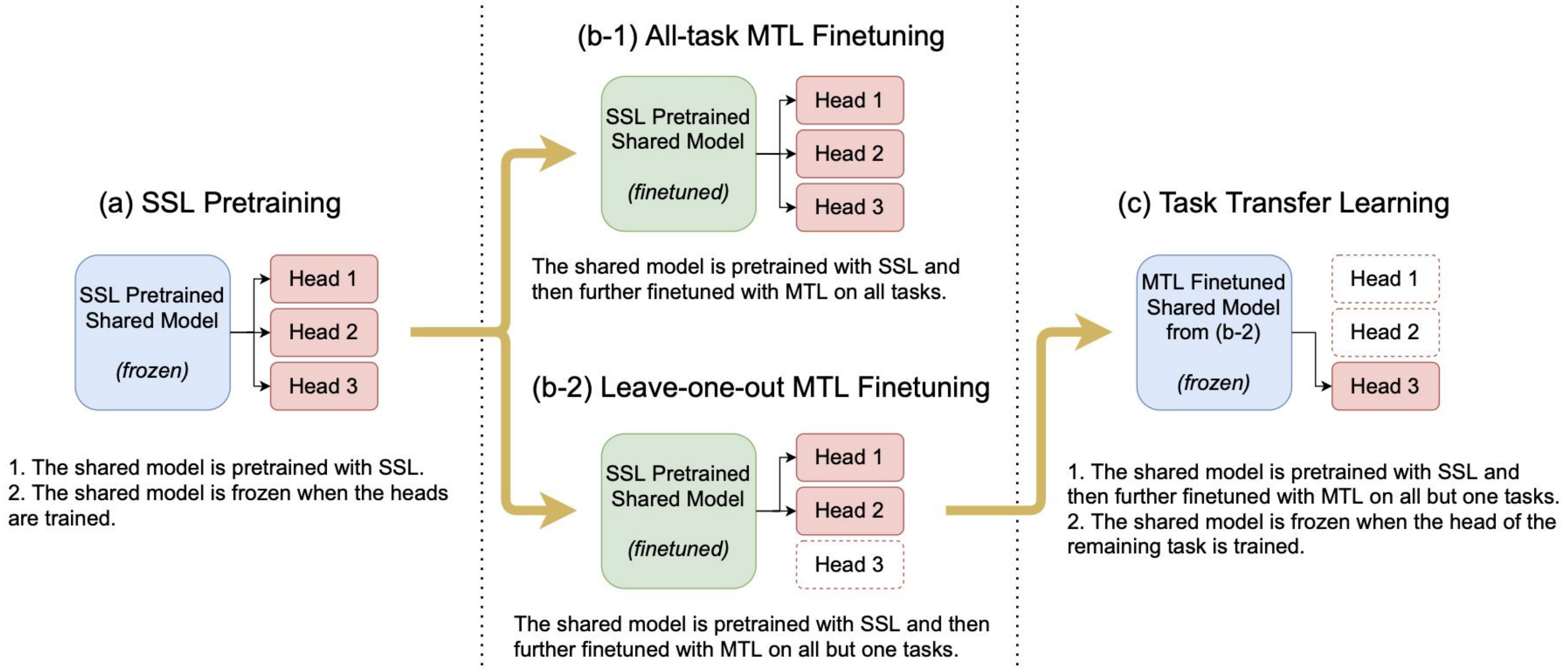
SUPERB

- Since no downstream model training is required in QbE, we only perform MTL experiments and compare the results on the other nine tasks.
  - Content
    - Phoneme Recognition (PR)
    - Automatic Speech Recognition (ASR)
    - Keyword Spotting (KS)
  - Speaker
    - Speaker Identification (SID)
    - Automatic Speaker Verification (ASV)
    - Speaker Diarization (SD)
  - Semantics
    - Intent Classification (IC)
    - Slot Filling (SF)
  - Paralinguistics
    - Emotion Recognition (ER)

Experimental Setup

- The SSL pretraining approach used in experiments:
  - HuBERT achieves the overall best performance on SUPERB.
  - We use a weighted sum of hidden representations of all layers in the HuBERT model as the representations for downstream heads, as in SUPERB.
- The model architecture and implementation details:
  - HuBERT Base is adopted as our shared model architecture.
  - For task-specific head architectures, we simply follow the settings in SUPERB.
  - The code is released: https://github.com/s3prl/s3prl/tree/multi-task-distributed

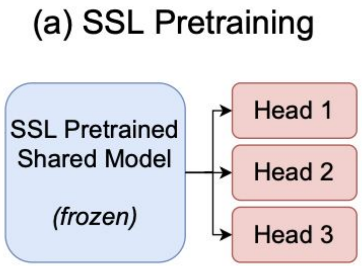
Training Scenarios



Experimental Results

Scenario	Tasks for MTL Finetuning	**ASR**	**PR**	**SF**		**SD**	**ER**	**IC**	**KS**	**ASV**	**SID**
		WER↓	**PER↓**	**F1↑**	**CER↓**	**DER↓**	**ACC↑**	**ACC↑**	**ACC↑**	**EER↓**	**ACC↑**
(a) SSL	N/A	6.42	5.41	88.53	25.20	5.88	64.24	98.34	96.30	5.11	81.42
(b-1) SSL+MTL	all	6.22	3.61	87.56	26.76	4.93	67.28	99.60	97.34	6.76	90.86
(b-2): SSL+MTL	all but ASR	X	3.63	87.28	27.11	**4.89**	65.07	**99.63**	**97.57**	7.78	90.69
	all but PR	6.79	X	86.94	27.66	**4.81**	66.73	**99.66**	**97.44**	7.94	**91.16**
	all but SF	**6.10**	**3.39**	X	X	**4.73**	65.71	99.58	97.18	7.61	90.70
	all but SD	6.28	**3.54**	**87.94**	**26.31**	X	66.73	**99.63**	97.11	7.49	90.79
	all but ER	**6.17**	**3.40**	87.45	26.90	**4.77**	X	99.55	97.27	7.19	90.51
	all but IC	**6.13**	**3.34**	**87.65**	26.94	**4.78**	66.08	X	97.27	**6.74**	90.55
	all but KS	**6.17**	**3.55**	**87.83**	26.88	**4.91**	66.27	**99.71**	X	7.86	90.67
	all but ASV	**5.90**	**2.79**	**87.88**	**26.52**	**3.61**	64.88	99.58	**97.44**	X	85.06
	all but SID	**5.95**	**3.25**	87.33	27.39	**4.50**	**68.66**	99.55	97.27	9.00	X
(c) Task Transfer	N/A	6.27	5.79	88.14	26.24	5.80	64.24	97.42	96.33	7.55	62.05

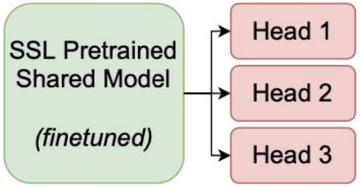
MTL Scenarios - SSL Pretraining



1. The shared model is pretrained with SSL.
2. The shared model is frozen when the heads are trained.

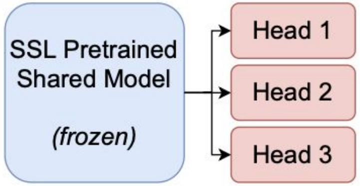
MTL Scenarios - SSL Pretraining

(b-1) All-task MTL Finetuning



The shared model is pretrained with SSL and then further finetuned with MTL on all tasks.

(a) SSL Pretraining



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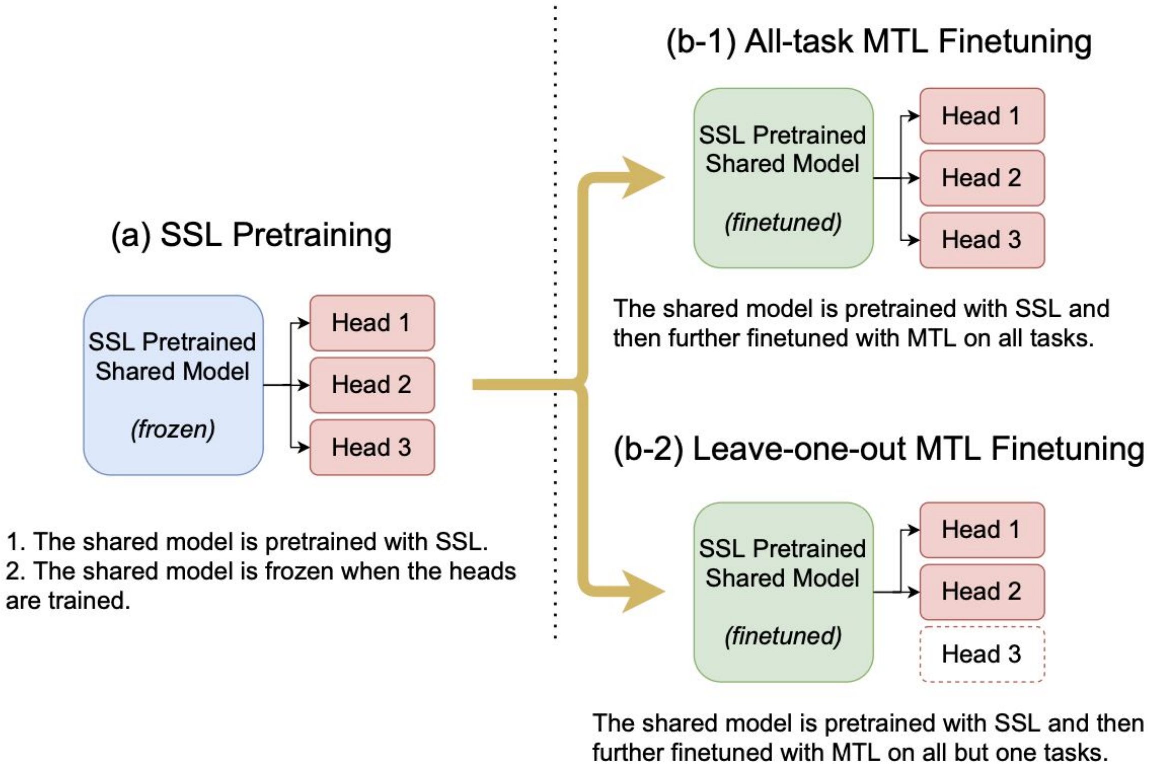
- Serve as a strong baseline for SSL pretraining or other representation learning approaches.
- How to select the model checkpoint based on validation scores of tasks?
  - ASV suffers from overfitting.

MTL Scenarios - SSL Pretraining



Experimental Results - Removing One Task In MTL

Scenario	Tasks for MTL Finetuning	ASR	PR	SF		SD	ER	IC	KS	ASV	SID
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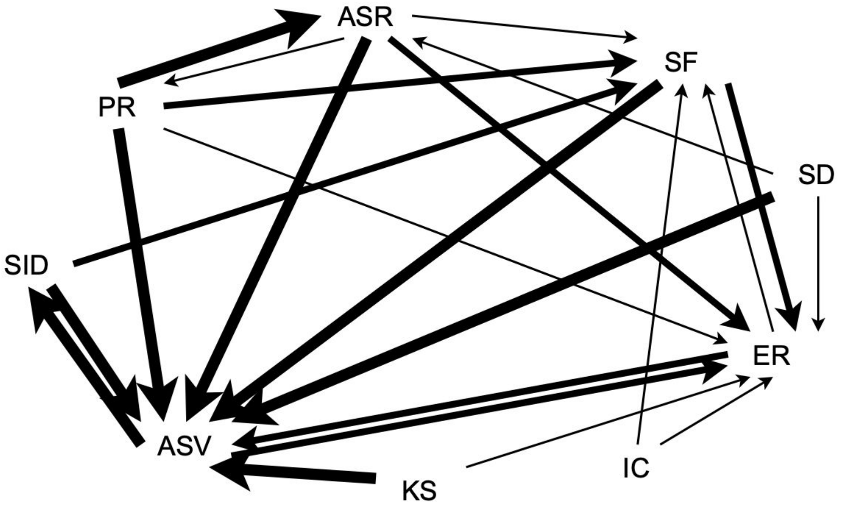
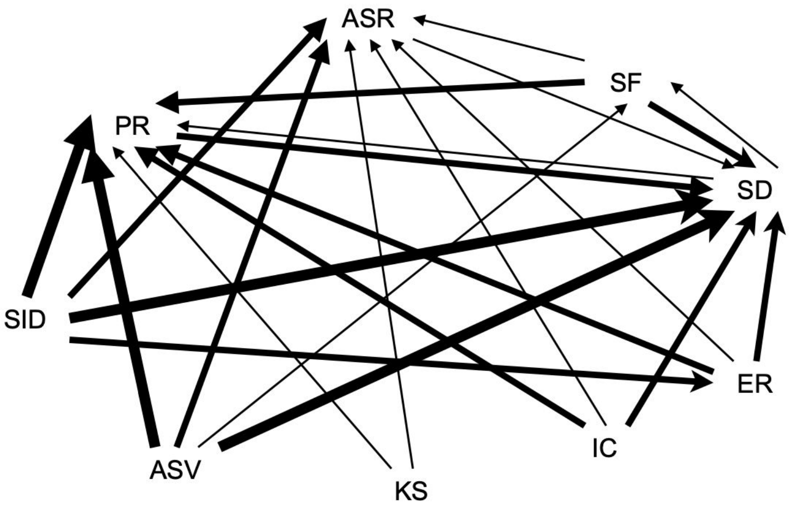


The improvement relations of tasks.



The hurt relations of tasks.

- If we focus on a certain primary task, we may select proper auxiliary tasks to assist the primary task based on these MTL experimental results.

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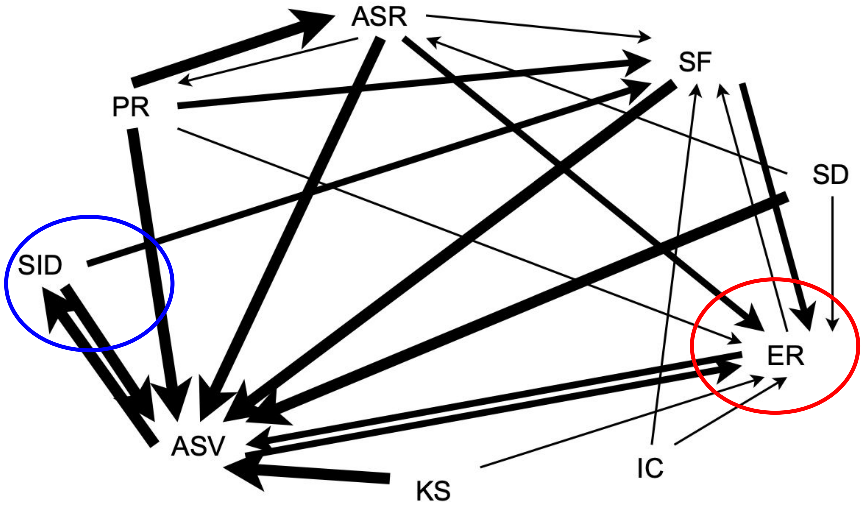

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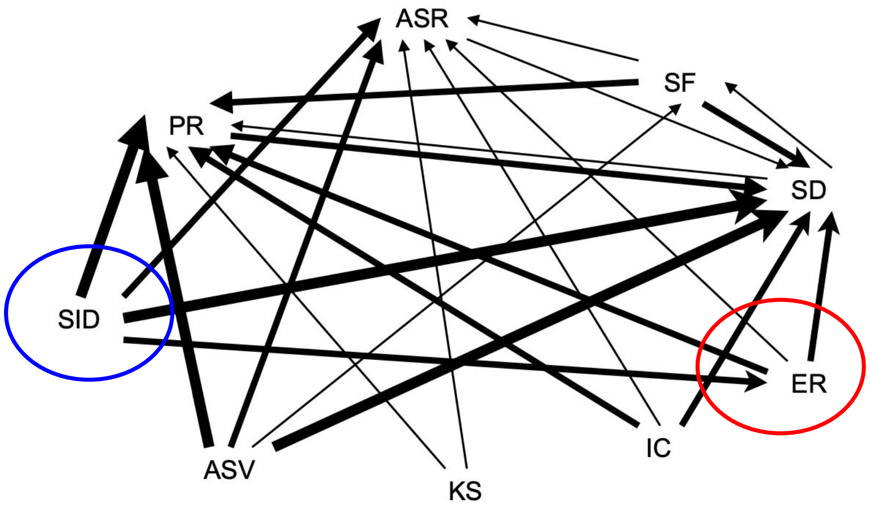

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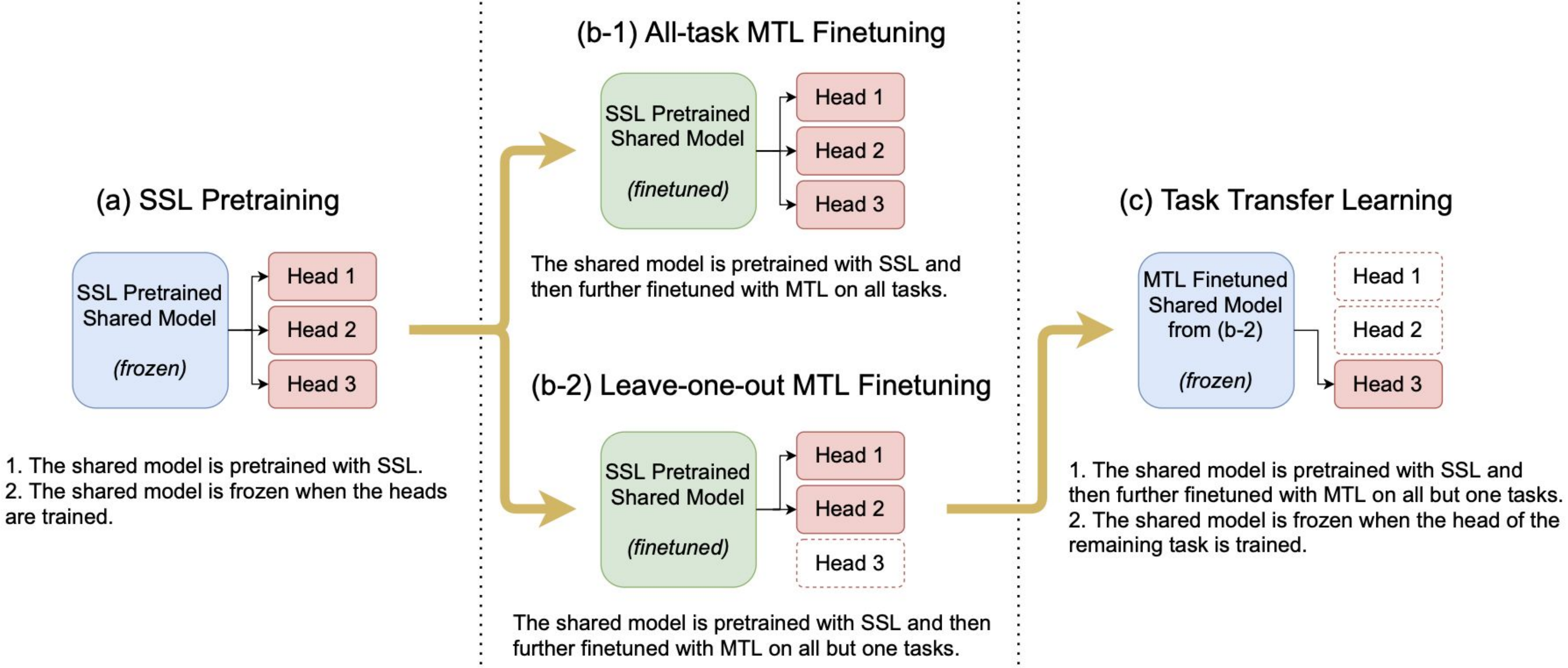

Experimental Results - Task Transfer Learning

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- Whether a task is involved in MTL is crucial to the performance of this task.

Conclusion and Discussion

- In this work, we investigate different training scenarios of supervised MTL as a speech representation learning approach along with SSL pretraining on a benchmark with various speech processing tasks.
  - We analyze the generalizability of representations learned with supervised MTL empirically.
- The performance of MTL is dependent on many factors.
  - the amount of data
  - task relationships
  - noise
  - These factors should be isolated and investigated with more analyses.
- Future directions:
  - exploring a better method to select the model checkpoint with MTL
  - more in-depth research of MTL and its optimization on speech processing tasks
  - trying to train the shared model with both SSL, MTL and self training simultaneously as a semi-supervised representation learning approach