Compressing Self-Supervised Models

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Universality

Self-supervised models enable semi-supervised learning for various downstream tasks.

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Usage

- Feature extraction
- Fine-tuning

Goal

Can we find small networks (e.g., subnetworks) that enjoy the same universality?

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Approach

- Low-rank approximation
- Pruning
  - Weight pruning
  - Head pruning
  - Layer pruning
- Distillation
- Other architectures
- Anytime inference

Progress

- Baseline (Tzu-Quan Lin)
- FLASH (Chun-Yao Chang)
- Structured pruning (Huan Yang)
- Weight pruning (Tzu-Hsun Feng)
- Low-rank approximation (Guang-Ming Chen)

Progress

- **Baseline (Tzu-Quan Lin)**
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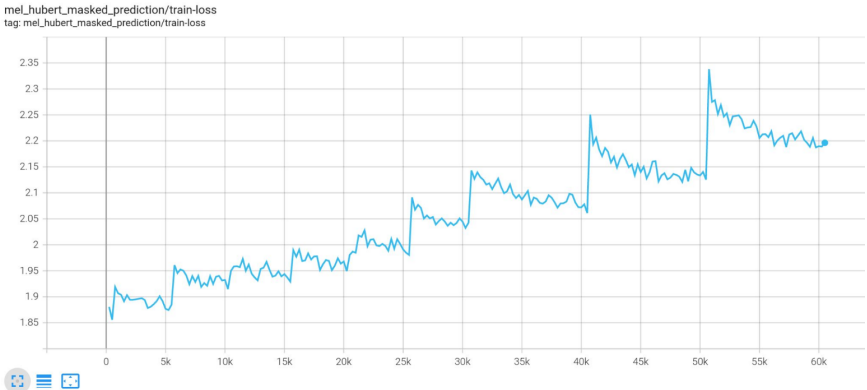
ℓ_1 norm of the heads

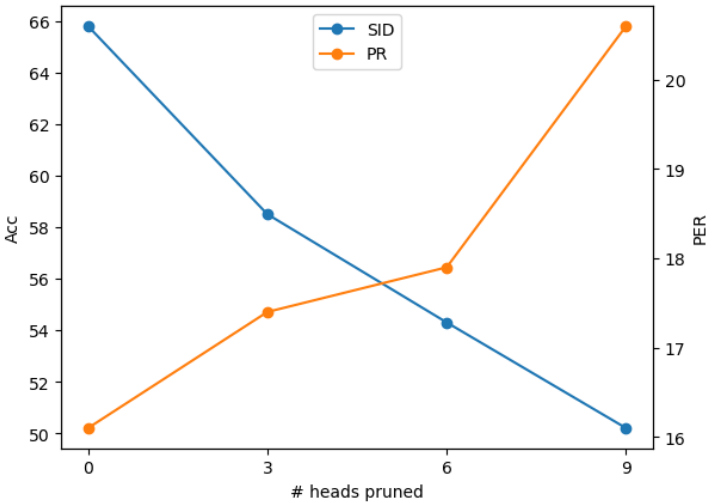
Pruning algorithm

- Prune heads based on ℓ_1
- Fine-tune

Training loss



Downstream tasks



Plan

- Before the workshop
  - MelHuBERT on 360 hours of LibriSpeech
  - Head pruning
  - Low-rank approximation
- During the workshop
  - Weight pruning
  - Scaling up to 960 hours of LibriSpeech
  - Distillation
  - Anytime inference

Scientific questions

- Is there a subnetwork that can match the self-superised loss?
- Does the subnetwork enjoy the same universality?
- Should we prune based on the downstream tasks?