Model Extraction Attack against Self-supervised Speech Models

Tsu-Yuan Hsu\textsuperscript{1*}, Chen-An Li\textsuperscript{2*}, Tung-Yu Wu\textsuperscript{3}, Hung-yi Lee\textsuperscript{4}

\textsuperscript{1}\textsuperscript{2}\textsuperscript{3}\textsuperscript{4} College of Electrical Engineering and Computer Science, National Taiwan University
\{b08201047, b08902123, b08901133, hungyilee\}@ntu.edu.tw

Abstract

Self-supervised learning (SSL) speech models generate meaningful representations of given clips and achieve incredible performance across various downstream tasks. Companies can provide services of these models by building APIs. However, each of these APIs may suffer a model extraction attack (MEA), which refers to an adversary stealing the model functionality with limited query access. In this work, we propose an MEA framework against the SSL speech models. Our MEA framework learns multiple output representations of given clips to extract the target SSL speech models. We demonstrate various selection methods on speech corpus to construct limited query access. We also study the MEA on different speech corpus. We evaluate the effectiveness of our MEA framework on four diverse downstream tasks. To our knowledge, this is the first attempt to steal a large-scale speech model.

Index Terms: Self-supervised learning, speech representation learning, model extraction attack

1. Introduction

Recent advances in self-supervised learning (SSL) speech models \cite{1, 2, 3} build meaningful representations of speech and achieve incredible performance in many tasks \cite{4}. Regarding the current SSL-based natural language processing APIs, such as official GPT-3 \cite{5} APIs, which provide services for generating data embeddings, it can be expected that SSL speech-processing APIs would also come into sight in the future. This kind of APIs take text or speech provided by users as input and generate corresponding feature representations for the training of downstream models.

However, each of these APIs may suffer a model extraction attack (MEA), which refers to an adversary stealing the model functionality by limited query access. MEA has posed a non-negligible threat to online deep learning applications. Previous work \cite{6} has shown that the adversary may extract models used in remote APIs simply by querying them. Since the training of models and the collection of datasets may have cost a tremendous amount of time and money, this kind of attack causes sizeable financial losses to victimized companies. Hence, it is an urgent task for researchers to study how the adversary may perform the attack.

MEAs against different classes of machine learning and deep learning models are broadly studied. Through some direct queries to the remote API, simple regression models and multilayer perceptrons (MLPs) can be easily stolen \cite{6}. Convolutional neural networks (CNNs) are also vulnerable to the attack \cite{7, 8}. \cite{7} randomly selects images on hand, queries the API with selected images to fetch fake labels, and utilizes the image-label pairs to train the local surrogate model. Knock-off Nets \cite{8} adopts reinforcement learning to actively sample images, which surpasses the random-selection approach. Recurrent Neural Networks (RNNs) have also been studied to be attacked. \cite{9} studies on attacks based on features of RNNs and LSTMs for classification and regression tasks. Advanced models such as graph neural networks (GNNs) have also been examined \cite{10, 11}. For instance, \cite{12} demonstrates that, after collecting query graphs, a surrogate model can be effectively learned by minimizing RMSE loss between the remote GNN-based API’s and its graph responses. Besides model-type-specific extraction attacks, there are also some works \cite{12, 13} committed to stealing certain information of remote APIs. Model hyper-parameters have been pointed out as a potential target, and a framework is proposed to verify the feasibility of hyperparameter extraction \cite{12}. Metamodelling methods \cite{13} learn a classifier to predict model attributes, such as model architectures, adopted optimizers, and types of training datasets.

Large-scale SSL models \cite{1, 2, 3, 14, 15, 16} are more critical potential targets of MEA since the SSL-model-based APIs can serve as a powerful feature extractor to generate representations of input data that help users implement various applications such as text question answering (QA) with BERT \cite{14} and automatic speech recognition (ASR) with wav2vec 2.0 \cite{1}. The training and fine-tuning of an SSL model require much time and effort. However, the MEAs against SSL models are still underexplored. Though there have been some works \cite{17, 18, 19, 20} investigating MEA against text models, to our knowledge, approaches for speech models have not been discussed. Moreover, current text-model-based methods still exist some restrictions. \cite{17, 18, 19} apply random sampling strategy to select query data, while \cite{20} presents a hybrid strategy that integrates algebraic-based and learning-based methods. Nonetheless, they all assume attackers have access to output logs of downstream tasks and that each time the attack merely focuses on stealing one task.

In this work, we propose and implement the MEA against SSL speech models. In particular, we design several clip-selection methods that identify informative data. The selected clips are further used as queries to the victim model to get corresponding representations for the local surrogate model’s supervised training. This enables our surrogate model to approximate the victim model’s performances with only a small number of clips, i.e., queries. We demonstrate MEA on various se-

\textsuperscript{*}equal contributions

Note that this work aims to capture the research community’s attention to potential issues in terms of speech-based SSL APIs, rather than simply an attempt to conduct MEA. With this work, we anticipate more discussions in this field to help build a more robust and comprehensive ecosystem of speech-based Machine Learning as a Service (MLaaS).
lection methods and different speech corpus. Specifically, four
diverse downstream tasks are conducted in Section 3 to eval-
uate the effectiveness of our proposed clip selection methods
and the whole extraction pipeline. To our knowledge, this is the
first attempt to steal a large-scale speech model. Furthermore,
since our framework’s presented active-sampling methods only
need access to data embeddings instead of logits, we can ex-
tract the remote SSL speech model directly rather than just a
downstream task.

![Illustration of our model extraction attack framework.](image)

**Figure 1: Illustration of our model extraction attack framework.**

## 2. Methods

In this paper, the victim model refers to the model being
queried, such as the APIs mentioned in Section 1. The pre-
trained surrogate model refers to the model pre-trained on un-
labeled corpus and the extracted surrogate model refers to the
model after performing model extraction on the victim model.
We assume the request to the victim model are limited, and the
knowledge of the victim model’s architecture and its training
corpus is lacking. The query limitation is defined as the total
length of waveforms. The information returned by the victim
model includes representations of input data.

As shown in Figure 1, our model extraction attack process
includes several steps:

1. Pre-train a model on unlabeled corpus $\mathcal{X}$ to get the Pre-
   trained Surrogate.

2. An active selection method is applied to sample a small
   portion of clips from dataset $\mathcal{X}$ to form a subset $\mathcal{X}_S$.
   The sampling process is done until the total length of the
   waveforms in $\mathcal{X}_S$ is no less than the preset length limita-
   tion $H$.

3. The Pre-trained Surrogate is trained with $\mathcal{X}_S$ and the ob-
   tained Victim’s representations to perform the model ex-
   traction, i.e., steal the functionality of the Victim to get the
   Extracted Surrogate.

### 2.1. Selection Methods

In this section, we elaborate on several proposed clip selection
methods used to construct $\mathcal{X}_S$ for model extraction.

#### 2.1.1. SSL Pre-training Loss Selection

We state that SSL pre-training loss can serve as a good metric
to sample waveforms. Clips with high pre-training loss are re-
garded as hard samples which baffle the current surrogate model
and are thus worth engaging in the afterward teacher-student su-
pervised training. As a result, we evaluate the dataset $\mathcal{X}$ on the
pre-trained surrogate model and calculate each waveform’s pre-
training loss. The dataset $\mathcal{X}_S$ iteratively samples waveform with
the highest loss in $\mathcal{X}$ until its total clip length reaches $H$.

#### 2.1.2. Content-based Selection

A selection approach based on the acoustic content of speech
clips is also proposed. We argue that, with the knowledge of
each recording’s acoustic information, it is possible to sample
a small portion of clips that represents the overall distribution
of the whole corpus. To achieve this, we first leverage the pre-
trained surrogate model to generate all the waveform represen-
tations. Secondly, each waveform timestamp’s token is deter-
dined by its representation into a clustering model fit on 10% of the representations, with consecutive same class re-
moved. We then take these tokens as the content of a speech
clip. Finally, we iteratively sample the corpus with the farthest
point sampling (FPS) [21]. To be specific, after randomly pick-
ing the first clip, we calculate its token-based trigram Jaccard
distance to all other clips:

$$D_{x,y} = 1 - J(X, Y) = 1 - \frac{|X \cap Y|}{|X \cup Y|},$$

(1)

where $x$ and $y$ are two distinct clips (a sampled clip and an
unsampled one in our case), while $X$ and $Y$ are their token tri-
gram sets. Specifically, each element in the set is a set contain-
ing three consecutive tokens generated by the clustering model.

#### 2.1.3. Transcription-based Selection

In this method, we select clips with different content. We as-
sume that every speech in the dataset has its corresponding tran-
scription. We utilize a pre-trained language model to generate
$[\text{CLS}]$ token embeddings for speech transcriptions. Next, a
clustering model is fit on $[\text{CLS}]$ token embeddings to get clus-
tering labels. Finally, we evenly select the corresponding clips
in $\mathcal{X}$ from each cluster to increase the data diversity into $\mathcal{X}_S$.

### 2.2. Model Extraction

In this paper, we adopt the objective function of DistilHuBERT
[22] to perform model extraction. We assume that the vic-
tim model returns multiple representations per query because
weighted-sum multiple hidden states of the pre-train model
could significantly improve the downstream performance [4].

The surrogate model is followed by multiple separate predic-
tion heads which learn the victim model’s representations from
different layers.

Given victim model’s $n$-th output representation $h_{(n)}^v$ and
the prediction head vector learn from victim model’s $n$-th out-
put $h_{(n)}$. The objective function $\mathcal{L}_{\text{extract}}$ can be shown as fol-
ows:

$$\mathcal{L}_{\text{extract}}^{(n)} = \mathcal{L}_{\text{cos}}^{(n)} + \mathcal{L}_{l_1}^{(n)} = \sum_{i=1}^{n} \left[ -\log \sigma \left( \cos \left( h_{(n)}^i, h_{(n)} \right) \right) + \frac{1}{D} \| h_{(n)}^{(n)} - \hat{h}_i^{(n)} \|_1 \right]$$

(2)

where $\sigma$ is the sigmoid function.
Table 1: Evaluation results with querying dataset LibriSpeech 960-hour for KS, IC, and ER in accuracy and SD in diarization error rate. The first three rows are w/o any query. Baseline$_R$ refers to performing model extraction on Random Surrogate w/ random selection. Baseline$_P$, Transcription, SSL, and Content refer to the Extracted Surrogate w/ random selection and the selection methods elaborated in Section 2. Topline$_P$ and Topline$_W$ refer to the Extracted Surrogate w/ unlimited queries to the HuBERT Base and WavLM Base+, respectively. Best result among Baseline$_R$, Baseline$_P$, Transcription (if any), SSL, and Content of each experiment is marked in bold.

| Method        | Victim Model | KS (Acc ↑) | IC (Acc ↑) | ER (Acc ↑) | SD (DER ↓) |
|---------------|--------------|------------|------------|------------|------------|
| Pre-trained Surrogate | | 92.41 | 77.91 | 57.7 | 7.86 |
| HuBERT Base | Baseline$_R$ | 96.30 | 98.34 | 64.92 | 5.88 |
| WavLM Base+ | Baseline$_P$ | 97.37 | 99.00 | 68.65 | 3.50 |
| Topline$_H$ | Transcription | 95.85 | 94.83 | 62.74 | 6.76 |
| Topline$_W$ | SSL | 96.33 | 95.68 | 64.02 | 6.72 |
| Content | HuBERT Base | | | | |
| HuBERT Base | Baseline$_R$ | 92.08 | 94.45 | 95.29 | 91.27 | 60.36 | 60.49 | 9.28 | 7.80 | 6.93 |
| WavLM Base+ | Baseline$_P$ | 81.50 | 88.93 | 93.02 | 60.77 | 78.01 | 86.45 | 55.18 | 58.00 | 61.55 | 12.46 | 10.48 | 7.56 |
| SSL | WavLM Base+ | 93.22 | 93.51 | 94.35 | 78.30 | 87.77 | 91.48 | 59.41 | 61.56 | 61.95 | 9.62 | 7.31 | 7.52 |
| Content | WavLM Base+ | 93.67 | 94.68 | 95.46 | 82.92 | 90.11 | 92.33 | 59.87 | 61.78 | 63.71 | 8.96 | 7.74 | 7.23 |

\[ \ell_{\text{extract}} = \sum_{n \in \mathbb{N}} \ell_{\text{extract}}^{(n)} = \sum_{n \in \mathbb{N}} \left( \ell_{\cos}^{(n)} + \ell_{11}^{(n)} \right) \] (3)

where \( t \in [T] \), \( T \) is the number of timestamps, \( N \) is the set of the layers’ indices, \( \sigma(\cdot) \) denotes sigmoid function, \( \cos(\cdot, \cdot) \) denotes cosine similarity function, \( D \) is the feature dimension of the representation.

3. Experiments

3.1. Experimental Setup

Experiments are implemented with s3prl v0.3.4 and fairseq [23] 0.12.2. We use fairseq for pre-training our surrogate model. For s3prl, we use it for performing model extraction and evaluation.

3.1.1. Data and Preprocessing

We use LibriSpeech 960-hour [24] to pre-train the surrogate model and as the querying dataset to the victim model in our main results. Extensive experiments are conducted using Wall Street Journal [25] and Aishell-1 [26] as querying datasets. Considering the victim model should have an instance-wise querying-length constraint, the maximum input sequence length is set to 15.6 seconds, and each clip longer than 15.6s is split. Also, we set the minimum waveform length to 2s, which means the clip less than 2 seconds will be dropped.

3.1.2. Victim Model

We consider HuBERT Base and WavLM Base+ as the victim models. Each of them has a 12-layer transformer encoder. Features from different layers contain various information [3, 22], such as speaker-related, semantic, and content information. Therefore, we assume the victim model returns the representations of each transformer layer, and the 4th, 8th, and 12th-layer representations are used to perform the model extraction.

The pre-training dataset of HuBERT Base is exactly the same as our querying dataset, i.e. LibriSpeech 960-hour while that of WavLM Base+ is a 94k-hour dataset, implying the overlap with our querying dataset is less than 1.1%. We assume the latter one to be more realistic. That is, the API (victim model) is pre-trained on a large-scale dataset and should cope with speech clips from various domains well. However, we only have a small piece of the dataset, and we intend to query the victim model as efficiently as possible.

3.1.3. Surrogate Model

Our surrogate model is initialized as a 7-layer CNN extractor following a 2-layer transformer encoder, called Random Surrogate. HuBERT pre-training is applied on Random Surrogate with LibriSpeech 960-hour to obtain Pre-trained Surrogate. The first iteration is trained for 250k steps by the MFCC clustered labels. The second iteration is trained for 400k steps by the clustered labels generated from the 1st transformer encoder layer features of first-iteration Pre-trained Surrogate.

In the selection stage, the corresponding features of sampled clips are retrieved by querying the victim model, where the clips are obtained by either random, pre-training loss, content-based, or transcription-based selection. We adopt the k-means model [27] as the clustering model used for content- and transcription-based selection where the number of clusters is 250. For SSL pre-training loss selection, we use the self-supervised cluster-prediction loss of HuBERT. For transcription-based selection, we use RoBERTa [16] as our language model.

In the model extraction stage, our surrogate model (Random Surrogate or Pre-trained Surrogate) is trained on the clip-
Table 2: Performances of SID and SD with victim model WavLM Base+. Results better than Pre-trained Surrogate (65.80 for SID and 7.86 for SD) are marked in bold.

| Method          | SID | SD |
|-----------------|-----|----|
| Baseline         | 0.1h | 1h | 10h |
| Most Speakers    | 55.17 | 65.90 | 71.42 |
| Baseline         | 9.62 | 7.31 | 7.52 |
| Most Speakers    | 56.55 | 64.76 | 71.55 |
| Baseline         | 9.83 | 7.31 | 7.52 |

Table 3: Performances of SD with the victim model HuBERT Base. The querying datasets are denoted in parentheses.

| Method          | SD (Aishell-1) | SD (WSJ) |
|-----------------|---------------|---------|
| Baseline         | 0.1h | 1h | 10h | 0.1h | 1h | 10h |
| Baseline         | 9.09 | 8.25 | 7.21 | 8.55 | 8.44 | 7.80 |
| SSL              | 8.31 | 7.46 | 6.90 | 9.45 | 7.73 | 7.78 |
| Content          | 9.21 | 8.20 | 6.88 | 9.50 | 7.82 | 7.93 |

Figure 2: Performances of Baseline, Content, SSL, and Topline on KS with victim model WavLM Base+. Agreement refers to the prediction consistency between the victim model and the surrogate model.

Figure 3: IC performances of Content, SSL, and Baseline with querying dataset Aishell-1 and WSJ.

Most Speakers, referring to the most-speaker selection, which samples as many speakers as possible, to tackle speaker tasks. The results are shown in Table 2. However, the performance still does not improve under the low-resource setting.

3.4. Mismatched Querying Datasets

The checkpoints of the pre-trained models are often released while the pre-training datasets are not publicly available due to commercial use, privacy issue, etc. Therefore, we examine WSJ and AISHELL-1 as querying datasets to simulate the situation that the pre-training dataset of Pre-trained Surrogate is unknown. It is worth mentioning that AISHELL-1 is a Chinese corpus, which means the surrogate model’s pre-training dataset and our querying dataset are in different languages.

As shown in Figure 3, there is no obvious performance difference between our proposed methods and Baseline (the same conclusion can be drawn on KS, ER, and SD). From Table 1 and Table 3, we observe that extracting the models with the AISHELL-1 corpus achieves a slightly better performance on SD than with the WSJ and the LibriSpeech corpus. On the other hand, extracting the victim model with the LibriSpeech corpus usually outperforms the other two corpora in other tasks, which means that performing model extraction with the different datasets pre-trained on the surrogate model may significantly affect the performance.

4. Conclusion and Future Works

This work makes the first attempt to conduct the model extraction attack against SSL speech models. Experimental results on four diverse tasks in SUPERB show that our proposed selection methods outperform the naive random data selection. In the future, we expect to explore a more effective data selection method and find a way to avoid ineffective data selection resulting from the mismatch between pre-training and querying dataset as mentioned in Section 3.4.
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