Adapting Multilingual Speech Representation Model for a New, Underresourced Language through Multilingual Fine-tuning and **Continued Pretraining**

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ABSTRACT

In recent years, neural models learned through self-supervised pretraining on large scale multilingual text or speech data have exhibited promising results for underresourced languages, especially when a relatively large amount of data from related language(s) is available. While the technology has a potential for facilitating tasks carried out in language documentation projects, such as speech transcription, pretraining a multilingual model from scratch for every new language would be highly impractical. We investigate the possibility for adapting an existing multilingual wav2vec 2.0 model for a new language, focusing on actual fieldwork data from a critically endangered tongue: Ainu. Specifically, we (i) examine the feasibility of leveraging data from similar languages also in fine-tuning; (ii) verify whether the model's performance can be improved by further pretraining on target language data. Our results show that continued pretraining is the most effective method to adapt a wav2vec 2.0 model for a new language and leads to considerable reduction in error rates. Furthermore, we find that if a model pretrained on a related speech variety or an unrelated language with similar phonological characteristics is available, multilingual fine-tuning using additional data from that language can have positive impact on speech recognition performance when there is very little labeled data in the target language.

The cost of speech transcription is a major bottleneck faced in language documentation projects. It is believed that this task could be facilitated by utilizing speech recognition technologies, but the fact that the amount of data (both annotated and unannotated) available for languages studied in such projects is typically very limited, has been a barrier

Recent studies (e.g., Conneau, Baevski, Collobert, Mohamed and Auli, 2021) have demonstrated the benefits of multilingual pretraining of speech representations for speech recognition in scenarios where data in the target language is scarce. However, given the prohibitive cost of pretraining such representations from scratch, it is expected that most users will restrict themselves to fine-tuning publicly available models. For this reason, in this paper we address the question of whether the benefits of cross-lingual transfer extend to fine-tuning, as well. Furthermore, we study the effect of additional pretraining using the small amount of data available for the target language. In contrast to most previous work, we focus on actual fieldwork data with all its flaws, rather than clean NLP datasets. Specifically, our goal is to transcribe unique speech data in Sakhalin Ainu, recorded on 50-year-old audio tapes.

Our results show that continued pretraining on target language data leads to a substantial reduction in error rates. Furthermore, we demonstrate that in a scenario where labeled data in the target language is extremely scarce, speech recognition performance can be improved by adding data from a related speech variety or an unrelated language with similar phonological traits during fine-tuning, provided that the underlying speech representation model was first pretrained on that language. Our model pretrained on the Ainu language is publicly available¹.

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¹https://huggingface.co/karolnowakowski/wav2vec2-large-xlsr-53-pretrain-ain

The remainder of this paper is organized as follows. In the following section we discuss how speech-to-text technology and recent developments in self-supervised learning of speech representations can support language documentation. We also introduce data on which we are focusing in this research. In Section 3, we describe our research method. In Section 4, we provide an overview of related work. Section 5 presents the resources used in this study, including speech representation models and data used to train them. In Section 6, we describe our experiments and analyze their results. Finally, Section 7 contains conclusions and ideas for future improvements.

2. Background

2.1. Speech Transcription Technology for Language Documentation

One of the main tasks in linguistic research concerned with endangered languages is the collection and analysis of primary linguistic data. A typical workflow involves recording speech during fieldwork and analyzing the data afterwards. A major challenge in this process is speech transcription, which is a very time-consuming task². As a result, large amounts of data remain untranscribed in archives and collections of individual researchers. Many of those materials are stored on obsolete types of media, such as audio tapes, and in poor conditions. Before they get to be transcribed, some of them may be destroyed by accident or after the researcher who collected them retires (Abney, 2011). For this reason, such materials are often referred to as "endangered data". It may be possible to solve (or at least reduce) the transcription bottleneck using speech-to-text technology, thus speeding up the process of language documentation (Hjortnaes, Partanen, Rießler and Tyers, 2020; Zahrer, Zgank and Schuppler, 2020). However, in order to reach high accuracy, traditional approaches require large amounts of annotated training data (on the order of thousands of hours (Baevski, Zhou, Mohamed and Auli, 2020)), which is typically not available in a language documentation scenario.

2.2. Cross-lingual Self-supervised Learning for Low-resource Speech Transcription

The past few years have witnessed substantial improvements in a wide range of Natural Language Processing applications, owing to the development of efficient techniques for self-supervised learning of language representation models, such as BERT (Devlin, Chang, Lee and Toutanova, 2019), ELECTRA (Clark, Luong, Le and Manning, 2020) (for text-based models), wav2vec 2.0 (Baevski et al., 2020) and HuBERT (Hsu, Bolte, Tsai, Lakhotia, Salakhutdinov and Mohamed, 2021a) (for speech representations). They have been shown to produce competitive results compared to traditional, fully supervised methods, while training on much fewer human-annotated samples (after having been pretrained on large amount of unlabeled data).

A major obstacle for applying self-supervised learning in a language documentation setting is the fact that for the majority of the world's languages, even raw text or speech data is not available in large quantities. To alleviate this problem, recent studies explore cross-lingual learning techniques (Conneau, Khandelwal, Goyal, Chaudhary, Wenzek, Guzmán, Grave, Ott, Zettlemoyer and Stoyanov, 2020; Singh, McCann, Keskar, Xiong and Socher, 2019). It has been demonstrated that learning a single model from unlabeled data in multiple languages can have positive impact on the quality of representations computed for each individual language. As an example, Conneau et al. (2021) pretrained their speech representation model on 56k hours of unlabeled data in 53 languages and found it to perform far better than monolingual models, particularly for languages with little data available. However, the cost of compute required to train such models and the energy consumed in doing so is extremely high³.

2.3. Sakhalin Ainu Speech Data

The aim of this research is to develop a system for automatic transcription of Ainu, a critically endangered language⁴ native to northern Japan, Sakhalin and Kuril Islands. In particular, we are focusing on the task of transcribing unpublished materials from several dialects of the Ainu language spoken in Sakhalin, recorded in the 1960s and 1970s by Professor Kyōko Murasaki, with some of the last speakers of those dialects: Haru Fujiyama (Rayciska dialect), Ōta Yuku (Maoka dialect), Chikama Kimura (Shirahama dialect) and others. The materials in question were originally recorded on over 30 magnetic tapes of an old type (so called "reel-to-reel" tapes or "open-reel" tapes), and were a

²Depending on the annotation scheme and the level of quality required, transcribing 1 minute of spoken language can take anywhere between several minutes and an hour (Cieri, Miller and Walker, 2004; Gries and Berez, 2017).

³For instance, Conneau et al. (2021)'s multilingual model was trained using 64 GPUs, while Conneau et al. (2020) trained their XLM-R model with 500 GPUs.

⁴From the second half of the 20th century Ainu has not been used as a language of everyday communication (Bugaeva, 2012), thus many specialists consider it extinct. There are, however, efforts to revitalize the language and a growing number of people are learning it.

Table 1

Examples of equivalent sentences in Sakhalin Ainu (Rayciska dialect) and Hokkaido Ainu (Horobetsu dialect) recorded in Hattori (1964). For comparison, we also include Japanese translations (romanized according to the Hepburn transliteration system).

Sakhalin Ainu	Hokkaido Ainu	Japanese	English
ku'ani 'enahkari nee	'enmosma nen ka senne	watashi no hoka ni wa dare	There's no one going but me.
'aynuka hennehka 'oman.	'oman.	mo ikanai.	
'uneeno 'an 'itahpateh	sine 'itak 'ukoraci 'an 'itak	onaji koto bakari itte iru.	He always says the same
kisci.	patek ye kor an.		thing.
tah 'aynu'itakani temana	tanpe 'anak 'aynu'itak 'ari	kore wa ainugo de nan to	What is this called in Ainu?
ayyeepe?	nekona 'aye ya.	iimasu ka?	

good example of "endangered data". Sound quality is rather poor, with high levels of noise (both equipment noise such as hiss and hum, as well as occasional ambient noise) and a considerable amount of distortions. The bulk of the recorded materials consists of spontaneous monologues (mainly reciting folktales) by a single speaker, but there are also conversations between the informant and the interviewer or involving multiple informants, and occasionally multiple participants speak simultaneously. The tapes were recorded mainly at the home of one of the informants using a portable recorder.

The total duration of the recordings exceeds 20 hours, which – to the best of our knowledge – makes it larger than any collection of Sakhalin Ainu texts published so far⁵. A subset of the recordings has been transcribed, translated to Japanese and published: Murasaki (1976) released a collection of eleven folktales by Haru Fujiyama and five short conversations between two native speakers (Fujiyama and Ōta). Murasaki and Fujiyama (2010) produced a compilation of three different versions of a single folktale, "Wenenekaype", recited by Haru Fujiyama. Lastly, two volumes by Murasaki and Fujiyama (2013) and Murasaki and Fujiyama (2016) contain a total of 297 sentences.

Sakhalin Ainu is one of the three major dialect groups recognized within the Ainu language (the other two being Hokkaido Ainu and Kuril Ainu). There are significant differences between the dialects of Sakhalin and Hokkaido and they are mutually unintelligible (Refsing, 1986; Murasaki, 2009) (Table 1 includes examples of semantically equivalent sentences in both speech varieties). Vovin (2016) describes Ainu as a portmanteau language family with two primary branches: Hokkaido-Kuril and Sakhalin. In the case of Hokkaido Ainu, a sizeable body of audio and written materials have been recorded and published, and recently a growing number of them are digitized and released online. Data in Sakhalin Ainu, however, is far more scarce⁶.

Until now, none of the numerous hypotheses about genetic relationships between Ainu and other languages or language families has gained wider acceptance, and thus it is usually classified as a language isolate. In terms of linguistic typology, Ainu is an agglutinating language with SOV (subject-object-verb) word order and elements of polysynthesis, such as noun incorporation and concentration of various morphemes in the verbal complex (Shibatani, 1990). Phonemic inventory of Ainu consists of five vowel phonemes: /i, e, a, o, u/, and twelve consonant phonemes: /p, t, k, c, s, h, r, m, n, y, w, '/ (/'/ denotes a glottal stop). Syllables in Sakhalin Ainu conform to one of the following patterns: CV, CVV (VV represents a long vowel) or CVC. Most written texts in Ainu are transcribed using Latin alphabet and/or an extended version of the Japanese *katakana* syllabary (textual data in Ainu used in this research is written in Latin script). The majority of contemporary experts follow the phonemic orthographic rules devised by Hattori (1964) or a slightly modified version proposed by Hokkaidō Utari Kyōkai (1994). However, certain aspects of the writing system, such as word segmentation, have not been standardized (for more details, please refer to Nowakowski, Ptaszynski and Masui (2019)).

3. Research Method

Given the encouraging results achieved by multilingual speech representation models for underresourced languages, and the high cost of pretraining such a model from scratch, we explore two methods for adapting an existing model for a new language with a limited amount of available speech data.

⁵In addition to Sakhalin Ainu, the tapes in question also contain 2 hours of speech recordings in Hokkaido Ainu.

⁶For Kuril Ainu, there is almost no data available, apart from several lexicons and word lists.

Multilingual fine-tuning In addition to multilingual self-supervised pretraining, Conneau et al. (2021) conducted an experiment with fine-tuning using labeled data from 10 different languages simultaneously, and found the resulting model to perform competitively to models fine-tuned on each language individually. On the other hand, they did not analyze the correlation between language similarity and effectiveness of such multilingual fine-tuning⁷. In this study, we examine whether the benefits of cross-lingual transfer between closely related languages/dialects or unrelated languages sharing some phonological characteristics, apply to fine-tuning as well. To that end, we carry out fine-tuning experiments using data in the target language (Sakhalin Ainu) in combination with relatively large amounts of data from three different speech varieties: Hokkaido Ainu, Japanese and English. As mentioned in Section 2.3, Sakhalin Ainu and Hokkaido Ainu can be viewed as distant varieties of the same language or as closely related languages. As for Japanese, the theory of a genetic relationship between it and the Ainu language(s) is rejected by most experts (Refsing, 1986; Shibatani, 1990). That being said, and despite substantial differences in such aspects as consonants allowed in syllable coda and accent, the phonological system of Ainu has arguably more in common with Japanese^{8,9} than, e.g., English. This intuition is also corroborated by the analysis of language vectors computed using lang2vec (Littell, Mortensen, Lin, Kairis, Turner and Levin, 2017)¹⁰: upon calculating the distances between the Ainu language and all other languages in the database (specifically, we compared phonological and inventory features and took the mean distance), we found that Japanese is in 43rd position in terms of proximity to Ainu, out of 8070 languages.

Continued pretraining Secondly, we investigate if it is possible to improve the performance of a strong multilingual model on a language not seen during initial pretraining, by performing additional pretraining on small amount of target language data.

4. Related Work

Schneider, Baevski, Collobert and Auli (2019) introduced wav2vec, a technique for self-supervised learning of speech representations from raw audio data using convolutional neural networks trained to distinguish true audio samples from distractors. Their approach outperformed the previous state-of-the-art on the WSJ speech recognition benchmark while using two orders of magnitude less labeled data. Baevski, Schneider and Auli (2019) extended their work by adding a quantization module for computing discrete representations of audio segments and feeding the discretized sequence to a Transformer (BERT) model. Further improvements were introduced by Baevski et al. (2020) who proposed wav2vec 2.0, an end-to-end framework for jointly learning discretized speech units and contextualized speech representations, and fine-tuned the resulting model for speech transcription instead of feeding the pretrained features to a separate downstream model. Conneau et al. (2021) pretrained a single wav2vec 2.0 model (dubbed XLSR-53) using 56k hours of speech data in 53 languages and obtained a higher accuracy in speech recognition than monolingual models or previous methods. Hsu, Sriram, Baevski, Likhomanenko, Xu, Pratap, Kahn, Lee, Collobert, Synnaeve and Auli (2021b) combined speech data from different domains and investigated the impact of domain mismatches in self-supervised learning for ASR. Xu, Baevski and Auli (2021) performed zero-shot transcription of unseen languages by fine-tuning the XLSR-53 model and mapping phonemes of the training languages to the target language using articulatory features. Babu, Wang, Tjandra, Lakhotia, Xu, Goyal, Singh, von Platen, Saraf, Pino, Baevski, Conneau and Auli (2021) used wav2vec 2.0 and 436k hours of unlabeled data in 128 languages to train large-scale (up to 2 billion parameters) models, which after fine-tuning achieved state-of-the-art performance in speech recognition, speech translation and language identification. Sriram, Auli and Baevski (2022) obtained improved ASR performance by applying data augmentation techniques - such as pitch shift and adding random noise to the input signal – to the pretraining data, and introducing several modifications to the wav2vec 2.0 architecture. Sanabria, Hsu, Baevski and Auli (2022) used models pretrained on modified natural speech or synthetic data to measure the impact of individual domain factors (vocabulary, word order, phonetic features, etc.). They found that low-level domain factors, such as phonotactics and prosody, play a more important role than syntactic or lexical variation, and that speaker diversity in the pretraining data is crucial. Furthermore, they demonstrated that using a large amount of synthesized data can lead to better performance than with the small amount of real data used to train the synthesizer. Wu, Kim, Pan,

⁷They did perform such analysis for pretraining, and found that low-resource language performance benefits more from additional data in similar languages.

⁸Some of the similarities are presumably a result of contact-induced change (Bugaeva, 2012).

⁹See Nowakowski, Ptaszynski and Masui (2020) for an example of using Japanese speech models to recognize and generate speech in Ainu. Matsuura, Ueno, Mimura, Sakai and Kawahara (2020) trained an end-to-end ASR model for Hokkaido Ainu using additional Japanese and English data and found the former to be more helpful.

¹⁰https://github.com/antonisa/lang2vec

Han, Weinberger and Artzi (2022) and Vyas, Hsu, Auli and Baevski (2022) proposed modifications to the wav2vec 2.0 architecture aimed at reducing the computational cost of pretraining and inference.

Previous studies found continued self-supervised training of textual language representation models to be an effective method for adapting them for a new domain (Howard and Ruder, 2018; Sun, Qiu, Xu and Huang, 2019; Gururangan, Marasović, Swayamdipta, Lo, Beltagy, Downey and Smith, 2020) or expanding their coverage to languages unseen in initial pretraining (Pfeiffer, Vulić, Gurevych and Ruder, 2020; Tang, Tran, Li, Chen, Goyal, Chaudhary, Gu and Fan, 2020; Ebrahimi and Kann, 2021). Further pretraining of a speech representation model on new languages was investigated by Kessler, Thomas and Karout (2021). However, they only conducted experiments with a monolingual (English) model and focused on a high-resource setting, where the available speech data in the newly added language is ample (800 hours or more). Khurana, Laurent and Glass (2022) used self-training to adapt monolingual English wav2vec 2.0 models for several other languages in a simulated low-resource scenario. Multilingual fine-tuning was studied in the context of text-based machine translation by Tang et al. (2020) and resulted in improved performance, especially on low-resource languages.

5. Materials

5.1. Wav2vec 2.0

In all speech transcription experiments described in this paper, a publicly available pretrained wav2vec 2.0 model was employed. Specifically, we used the XLSR-53 – a model trained on 56k hours of data in 53 languages – compiled and released¹¹ by Conneau et al. (2021). Furthermore, we performed an additional pretraining of the XLSR-53 model on Ainu language data described in the next section. Both pretraining and fine-tuning of the model were conducted using the fairseq library.

5.2. Pretraining Data

In the experiments with continued pretraining of the XLSR-53, we used a total of 234 hours of speech data in Sakhalin Ainu and Hokkaido Ainu¹². Specifically, we pretrained our model on data obtained from tapes described in Section 2.3 and from publicly available data collections listed in Table 2.

The recordings from open-reel tapes were transferred to a digital format (WAV) using an audio recorder connected to a tape deck. The tapes are double-sided and we found that many of the recordings were audible in data obtained from both sides of the same tape. Upon inspection it turned out that in some instances, data retrieved from the reverse side (or certain parts of it) is superior to the corresponding data on the front side in terms of quality of the audio signal. For this reason, we included the duplicate recordings in the pretraining data, hence two numbers are reported in Table 2 (the number in brackets corresponds to the duration of unique recordings).

All files were converted to a single channel WAV sampled at 16 kHz. Files longer than 15 seconds were automatically split on silence intervals (using pydub) into separate clips 2 to 15 seconds in length. Files shorter than 1 second were excluded from pretraining.

5.3. Fine-tuning Data

Data used for fine-tuning is listed in Table 3. In monolingual fine-tuning, we used Sakhalin Ainu data from two sources: one story from Murasaki and Fujiyama (2010) (namely, Fu12-690401; the remaining two recordings were used for validation and testing) and data from Murasaki and Asai $(2001)^{13}$. In multilingual fine-tuning, we added data from Hokkaido Ainu (64.5h), Japanese (validated subset of the Japanese data in the Common Voice Corpus 8.0 (Ardila et al., 2020)¹⁴, version ja_43h_2022-01-19, and the JSUT corpus (Sonobe et al., 2017)¹⁵; 50.9h in total) and English (the 100h "clean" subset of LibriSpeech).

Speech data obtained from Murasaki and Fujiyama (2010) was automatically split on silence intervals (using pydub) into separate clips 2 to 15 seconds in length. Transcriptions from the book were digitized and aligned with the audio clips.

All audio files were converted to a single channel WAV sampled at 16 kHz. Punctuation marks and metadata were removed from all transcriptions. All alphabetic characters in the transcriptions of Sakhalin Ainu and Hokkaido Ainu

¹¹https://github.com/pytorch/fairseq/tree/main/examples/wav2vec

¹²While it might be informative to also pretrain a model on Sakhalin data only, we decided not to do so, due to the high cost of pretraining.

¹³Also available online at: http://www.aa.tufs.ac.jp/~mmine/kiki_gen/murasaki/asai01.html

¹⁴https://commonvoice.mozilla.org/ja/datasets

¹⁵https://sites.google.com/site/shinnosuketakamichi/publication/jsut

Table 2

Statistics of the data used for continued pretraining. In the case of the Sakhalin Ainu data obtained from tapes, we included duplicate recordings, hence two numbers are reported (the number in brackets corresponds to the duration of unique recordings).

Data	(Main) language/dialect	Total duration (h)
Sakhalin Ainu tapes	Sakhalin Ainu	35.9 (21.5)
Tuytah (Murasaki and Asai, 2001)	Sakhalin Ainu	8.9
"Wenenekaype" (Murasaki and Fujiyama, 2010)	Sakhalin Ainu	1.9
Ainu Language Archive (An=ukokor Aynu ikor oma kenru (National Ainu Museum), 2017–2022)	Hokkaido Ainu	103.1
Dictionary of Mukawa Ainu (Chiba University Graduate School of Humanities and Social Sciences, 2014)	Hokkaido Ainu	26.5
Ainu Language & Ainu Oral Literature (Nibutani Ainu Culture Museum, n.d.)	Hokkaido Ainu	19.2
Ainu language audio materials in the Waseda University Repository (https://waseda.repo.nii.ac.jp/)	Hokkaido Ainu	14.1
ILCAA's Project for the Publication of Ainu Language Materials (Information Resources Center, Research Institute for Languages and Cultures of Asia and Africa, Tokyo University of Foreign Studies, n.d.)	Hokkaido Ainu	12.1
Glossed Audio Corpus of Ainu Folklore (Nakagawa et al., 2016)	Hokkaido Ainu	6.2
Shigeru Kayano's Ainu dictionary (Kayano, 1996)	Hokkaido Ainu	3.0
A Topical Dictionary of Conversational Ainu (National Institute for Japanese Language and Linguistics, 2015)	Hokkaido Ainu	2.3
<i>Nyū ekusupuresu Ainugo</i> (Nakagawa, 2013)	Hokkaido Ainu	1.0

texts were converted to lower case. In order to prevent a large increase in the output vocabulary size and reduce data sparsity, transcriptions in Japanese were transliterated (using pykakasi) to the *katakana* syllabary. This also applies to data in the Ainu language which contains many words and utterances in Japanese (code-switching, comments about the text, questions from an interviewer, etc.). LibriSpeech transcriptions were used in their original form, i.e., in all upper case letters.

An excerpt from the transcriptions for "Wenenekaype" is shown in Table 4.

6. Experiments

6.1. Continued Pretraining

A random subset of 1% of the data was used for validation. Pretraining was performed using four Nvidia GTX 1080Ti GPUs. We continued pretraining for 100k updates, which took a total of 5 weeks. A small learning rate (1e-4, compared to 1e-3 used by Conneau et al. (2021) in initial pretraining) was set to prevent catastrophic forgetting (Sun et al., 2019). We used a batch size of 150k samples per GPU and applied gradient accumulation to simulate 512 GPUs, reaching an effective batch size of 80 minutes. Other hyperparameters were set according to the configuration for the LARGE model reported by Baevski et al. (2020).

6.2. Fine-tuning

We fine-tuned the pretrained models for speech transcription with a CTC loss (Graves, Fernández, Gomez and Schmidhuber, 2006). The best checkpoint for each experiment run was selected according to Word Error Rate on the validation set (for this purpose, we used the shortest, 10-minute recording from Murasaki and Fujiyama (2010), namely, Fu13-700326). The output of the fine-tuned models was decoded with a Viterbi decoder and a 4-gram language model trained on the Sakhalin Ainu part of the data used in fine-tuning of the corresponding model (see Table 5).

Table 3

Statistics of the speech data and transcriptions used for fine-tuning. Japanese is written without spaces and we did not perform tokenization, hence we don't report token counts and vocabulary sizes for the Japanese data.

Data	(Main) language/dialect	Total duration (h)	Token count	Vocab. size
Tuytah (Murasaki and Asai, 2001)	Sakhalin Ainu	8.9	52,172	4,415
"Wenenekaype" (Fu12-690401) (Murasaki and Fujiyama, 2010)	Sakhalin Ainu	0.8	5,817	1,165
Ainu Language Archive (An=ukokor Aynu ikor oma kenru (National Ainu Museum), 2017–2022)	Hokkaido Ainu	62.2	396,755	10,618
A Topical Dictionary of Conversational Ainu (National Institute for Japanese Language and Linguistics, 2015)	Hokkaido Ainu	2.3	13,007	2,260
Common Voice (Japanese) (Ardila et al., 2020)	Japanese	40.6	N/A	N/A
JSUT (Sonobe et al., 2017)	Japanese	10.3	N/A	N/A
LibriSpeech (Panayotov et al., 2015)	English	100.6	990,101	33,798

Table 4

Excerpt from the transcriptions for "Wenenekaype", used in fine-tuning of our speech recognition models.

Original transcription (Murasaki and Fujiyama, 2010)	Preprocessed for fine-tuning	English translation
sine, sine 'oyanruru kotan 'ohta sine, 'oyanruru kotan 'an manu. 'an manuyke reekoh wenporo kotan 'an manu. 'ani ike, hemanta ka, hemanta 'oyasi hee, 'an manuyke neyan wen- poro kotan 'oma 'aynu ka 'emuyke ruhpa 'ike tuy wa (tuy)pa wa 'isam. 'isam mayne tani 'ampene 'oha kotan nee manu.	sine sine 'oyanruru kotan 'ohta sine 'oyanruru kotan 'an manu 'an manuyke reekoh wenporo kotan 'an manu 'ani ike hemata ka hemata'oyasi hee 'an manuyke neyan wenporo kotan 'oma 'aynu ka 'emuyke ruhpa nike tuy wa tuypa wa 'isam 'isam mayne tani 'ampene 'oha kotan nee manu	There was a big village. A really big village. But then, there was some kind of monster that ate away all the people in that big village, and there was no one left. They're all gone, and now it's just an empty village.

Table 5

Statistics of the KenLM language models used for decoding, including perplexity and out-of-vocabulary token rates on the evaluation data.

Training	Vocabulary	Perplexity	Perplexity	Out-of-vocabulary
data	size	(including OOVs)	(excluding OOVs)	token rate
"Wenenekaype"	1,168	152.1	92.9	563/4911 (11.5%)
"Wenenekaype" + Tuytah	5,095	290.7	181.9	403/4911 (8.2%)

Language models were computed using the KenLM toolkit¹⁶. The performance in speech transcription was evaluated on a 37-minute subset of the data from Murasaki and Fujiyama (2010) (namely, Fu11-690328). Before the evaluation, transcriptions generated by the system were preprocessed by converting all alphabetic characters to lower case. We report Character Error Rate (CER) and Word Error Rate (WER).

All fine-tuning experiments were conducted using a single Nvidia RTX 3090 GPU. The baseline models were finetuned for 15k updates on the few labeled samples from the target domain (i.e., "Wenenekaype") only, with a batch size of 2.56M samples and the learning rate set to 3e-4. Other hyperparameters were set in accordance with the configuration for the LARGE model reported by Baevski et al. (2020). On our system, fine-tuning with these settings took less than

¹⁶https://kheafield.com/code/kenlm/

Table 6

Comparison of models fine-tuned on monolingual or multilingual data, with or without additional pretraining on target language data, in speech transcription on "Wenenekaype" test set. We report Character Error Rates and Word Error Rates.

Fine-tuning data	Additional Viterbi pretraining decoder		terbi coder	KenLM decoder	
	steps	CER	WER	CER	WER
"Wenenekaype"	0	13.9	42.3	18.0	36.5
Sakhalin Ainu (''Wenenekaype'' + Tuytah)	0	11.8	37.3	14.1	31.8
Sakhalin Ainu + Hokkaido Ainu	0	15.9	50.6	20.2	38.6
"Wenenekaype" + Hokkaido Ainu	0	16.4	51.1	21.8	41.2
"Wenenekaype" + Japanese	0	15.7	41.8	19.0	38.0
"Wenenekaype" + English	0	13.9	43.0	17.5	38.0
"Wenenekaype" + Hokk. Ainu + Jap.	0	16.0	52.0	22.1	41.1
"Wenenekaype" + Hokk. Ainu + Jap. + Eng.	0	15.2	47.4	20.5	40.4
"Wenenekaype"	100k	10.6	33.5	14.6	33.0
Sakhalin Ainu (''Wenenekaype'' + Tuytah)	100k	9.7	29.8	13.4	30.2
Sakhalin Ainu + Hokkaido Ainu	100k	10.1	31.1	12.6	30.8
"Wenenekaype" + Hokkaido Ainu	100k	10.2	30.5	15.1	32.1
"Wenenekaype" + Japanese	100k	10.8	32.2	15.2	33.0
"Wenenekaype" + English	100k	12.0	40.1	16.8	34.2
"Wenenekaype" + Hokk. Ainu + Jap.	100k	10.9	33.7	16.2	33.4
"Wenenekaype" + Hokk. Ainu + Jap. + Eng.	100k	10.9	33.9	16.8	34.3

1.5h to complete. After adding more data from Sakhalin Ainu, we fine-tuned for 20k steps with a learning rate of 1e-4. While the batch size was reduced to 800k samples, we applied gradient accumulation to simulate 16 GPUs, which resulted in an effective batch size of 12.8M, and training time of around 10 hours. In this setting, the "Wenenekaype" data was oversampled by a factor of 10 (we found that without oversampling, performance on the validation set was much worse). For models fine-tuned on a combination of data from two speech varieties, we set the learning rate to 3e-5 and executed 80k updates. When fine-tuning on Sakhalin Ainu and Hokkaido Ainu data together, the "Wenenekaype" data was oversampled by a factor of 200 and the Tuytah data was oversampled by a factor of 10. In experiments not using the latter data, "Wenenekaype" was oversampled by a factor of 100. In this case, a single fine-tuning run took roughly 2 days. After adding data from a third language (i.e., Japanese), we fine-tuned for 120k steps and almost 3 days. Finally, when fine-tuning on data from all four languages, we executed 160k updates, which took 4 days. In both cases, the "Wenenekaype" data was oversampled to comprise roughly half of the training data.

6.3. Results and Analysis

In Table 6 we compare error rates yielded by models fine-tuned on monolingual or multilingual data, and with or without additional pretraining on Ainu data, in speech recognition on the test set. Figure 1 provides an analysis of the impact of additional pretraining using target language data.

Our results show that continued pretraining is clearly the most effective way to adapt a speech representation model for a new language. With just 10k updates (half a week on our system), we were able to obtain a reduction in CER by nearly 13% (when decoding the model's output with a Viterbi decoder). After two weeks and 40k updates, we reached an improvement by 24.5%. The best relative performance on our test data in terms of CER was obtained after 60k updates. Concerning WER, the lowest values were measured after 60k and 90k updates (32.7 and 32.5, respectively) when decoding with a Viterbi decoder, and after 40k steps (32.3) when using a language model.

Fine-tuning on all the available Sakhalin Ainu data and decoding without a language model yielded the best overall results. With the model before conducting further pretraining, multilingual fine-tuning was not helpful, regardless of which language combination was used and how much target language data was available (the addition of Japanese data did result in slightly lower WER, but at the cost of an increase in CER). Quite surprisingly, adding Hokkaido Ainu data not only had negative impact on the model's performance, but also resulted in significantly higher error rates than in experiments using data in Japanese and English. There are two possible reasons for this behavior: (i) not having learnt a representation for either of the Ainu languages, the model was unable to take advantage of their similarities, and (ii)



Figure 1: Effect of further pretraining using target language data. The models were fine-tuned using "Wenenekaype" data only.

Japanese and English are distant enough from the target language for the model to be able to easily discern between them, thus making relatively few errors due to confusion between languages.

After additional pretraining, the results of multilingual fine-tuning were completely different: adding data from another variety of Ainu produced the best performing model, followed by fine-tuning on unrelated languages sharing some phonological characteristics (i.e., Ainu and Japanese), whereas combining Ainu with English was clearly harmful. While additional data from Hokkaido Ainu did not lead to an improvement compared to the model trained on 10 hours of Sakhalin data, the results did improve in the scenario with less than 1 hour of target language data available. In this case, a drop in WER was also observed after including Japanese data.

In experiments using labeled data from two or three additional languages, we observed worse results, even with languages which were helpful when used individually (namely, Hokkaido Ainu and Japanese). We think that this behavior might be associated with lower capacity in the fine-tuned model for each of the languages, but it requires further analysis.

Analysis of the transcriptions generated when using a Viterbi decoder revealed that some of the errors were caused by an incorrect choice of the writing system (i.e., the use of *katakana* characters to represent sounds of the Ainu language or, conversely, transcribing parts spoken in Japanese using Latin alphabet letters; an example is shown in Table 7). In fact, linguists often transcribe Japanese code-switched words found in Ainu language texts using a romanization system, rather than the Japanese script. For this reason, we decided to examine how the results would change if we relax our problem by converting all Japanese characters in both the system's output and ground truth data to Latin alphabet. Specifically, we used pykakasi to romanize Japanese according to the Hepburn transliteration system. Results are presented in Table 8. While the modification resulted in a slightly lower CER in almost all configurations, the biggest improvements were observed for models fine-tuned using Japanese data. Under this evaluation scheme, it can be concluded that fine-tuning jointly on "Wenenekaype" data and Japanese speech data is clearly beneficial.

The above results are consistent with our hypothesis that labeled data from similar languages can be leveraged in fine-tuning to obtain better performance on the target language. On the other hand, they indicate that any improvement can only take place if the following two conditions are met: (i) the model was first pretrained on the languages involved in fine-tuning, or at least on one of them (namely, the transfer language whose data one intends to use in addition to the target language data), and (ii) the amount of labeled data in the target language is extremely low.

Some of the errors made by the system can be attributed to inconsistencies in the annotations used for fine-tuning and evaluation, namely, differences between the transcriptions of multiple instances of the same lexical item (which

Table 7

Excerpt from the transcriptions generated by a fine-tuned model, showing errors caused by an incorrect choice of the writing system.

Model output: Transliteration:	tanna 'an 'opompaki nah ramupe オota'asi nee manu 'タ 'asi ソ'oヤw nah 'anramu 'ampe アノ ジ ンkoy nee manu [tanna 'an 'opompaki nah ramupe oota'asi nee manu 'ta 'asi so'oyaw nah 'anramu 'ampe ano jinkoy nee manu]
Ground truth:	tani neya アノ 'opompaki nah ramupe 'ota'asi nee manu 'ota'asi suy 'oyaw nah 'anramu'ampe アノ cinkov nee manu
Transliteration:	[tani neya ano 'opompaki nah ramupe 'ota'asi nee manu 'ota'asi suy 'oyaw nah 'anramu'ampe ano cinkoy nee manu]

Table 8

Evaluation results after preprocessing the Viterbi decoder's output and ground truth data by romanizing Japanese characters. Numbers in brackets indicate the change of CER/WER compared to results in Table 6.

Fine-tuning data	Additional pretr. steps	CER	WER
"Wenenekaype"	0	13.7 (-0.2)	42.3
Sakhalin Ainu (''Wenenekaype'' + Tuytah)	0	11.6 (-0.2)	37.3
Sakhalin Ainu + Hokkaido Ainu	0	15.6 (-0.3)	50.5 (-0.1)
"Wenenekaype" + Hokkaido Ainu	0	16.0 (-0.4)	51.0 (-0.1)
"Wenenekaype" + Japanese	0	13.4 (-2.3)	40.9 (- 0.9)
"Wenenekaype" + English	0	13.6 (-0.3)	43.0
"Wenenekaype" + Hokk. Ainu + Jap.	0	15.8 (-0.2)	52.0
"Wenenekaype" + Hokk. Ainu + Jap. + Eng.	0	14.8 (-0.4)	47.4
''Wenenekaype''	100k	10.5 (-0.1)	33.5
Sakhalin Ainu (''Wenenekaype'' + Tuytah)	100k	9.6 (-0.1)	29.8
Sakhalin Ainu + Hokkaido Ainu	100k	9.8 (-0.3)	31.1
"Wenenekaype" + Hokkaido Ainu	100k	9.9 (-0.3)	30.5
"Wenenekaype" + Japanese	100k	10.1 (-0.7)	31.9 (-0.3)
"Wenenekaype" + English	100k	11.9 (-0.1)	40.1
"Wenenekaype" + Hokk. Ainu + Jap.	100k	10.3 (-0.6)	33.5 (-0.2)
"Wenenekaype" + Hokk. Ainu + Jap. + Eng.	100k	10.9	33.9

in turn, are a result of the absence of a standardized orthography for the Ainu language). For instance, the part of "Wenenekaype" used for evaluation includes 19 instances of the token *wenporo* ("very big"; a combination of *wen*, "bad(ly)", and *poro*, "big"), whereas in the training data it is transcribed in two different ways: *wenporo* (11 instances) or *wen poro* (14 instances). As a result, both variants can be found in the model's predictions. In the future, we will investigate methods for automatic detection of discrepancies like this in the data.

6.3.1. Impact of the Decoding Method

Baevski et al. (2020) reported large improvements in WER when decoding their model's output with a textual language model. As shown in Table 6, for the model before additional pretraining we also observed significant reduction of WER, but at the cost of higher CER. For instance, when decoding the model fine-tuned on all Sakhalin Ainu data ("Wenenekaype" + Tuytah) with the 4-gram model, we achieved a 15% reduction of WER while at the same time CER increased by nearly 20%, compared to the Viterbi decoder. Table 9 shows an example of transcriptions generated by using both decoding methods for a single sample from the test data.

Continued pretraining on Ainu data closed the gap in terms of WER between the two decoding methods (see Figure 1) and the best overall results were obtained by decoding without a language model. This outcome indicates that after having been taught a representation of the target language, a speech representation model is capable of learning an implicit language model from the fine-tuning data which is more powerful than a count-based n-gram model computed from the same data. A major difference between Baevski et al. (2020)'s and our setting is that while their language models were trained on a book corpus comprising over 800 million tokens (Panayotov et al., 2015),

Table 9

Output of a fine-tuned model for a single test sample, decoded with two different methods. The KenLM model forces the use of in-vocabulary words (e.g., *reekoh* instead of *reepoh* and *'ekasihi* rather than *'ekasihii*) which often leads to lower Word Error Rates. On the other hand, Viterbi decoder is better at handling out-of-vocabulary items (e.g., *'ankopuri* is transcribed as *'ankopuuri*, whereas the language model replaced it with a completely different word, *'ankopisi*) which results in lower CER.

Viterbi decoder:	ne'ohah nay kohnean tani macirih 'oho nay kohne 'anu wa reekoh ne'an cispuurikara 'ankii manuyke 'awwen 'ekasihii 'ireske 'ankamuy henke 'ohta 'ankopuuri 'ahsin manuyke reepoh ne'an henke 'ihunke kii manuyke reekoh
KenLM decoder:	'oha nay konna tani maciri 'ohonkesehe ne'an cispuurikara 'ankii manuyke 'awwen 'ekasihi 'ireske 'ankamuy henke 'ohta 'ankopisi 'asin manuyke reekoh ne'an henke 'ihunke kii manuyke reekoh
Ground truth:	'ohah naykoh ne 'an tani macirihi 'ohoo naykoh ne 'a nu wa reekoh ne'an cispuurikara 'ankii manuyke 'awwen 'ekasihi 'ireske 'ankamuy henkehe 'ohta 'ankopuri'ahte manuyke reekoh ne'an henke 'ihunke kii manuyke reekoh

Sakhalin Ainu textual data available to us was limited to the transcriptions of the speech data which we also used to fine-tune our model. This leads to a conclusion that in a language documentation scenario, where large amounts of textual data are typically not available, decoding with an external language model may be of limited use. However, future work should investigate whether similar trends would also occur when using other types of language models, such as a character-level language model. Another factor that may be influencing our results is the characteristics of the writing system: Baevski et al. (2020) conducted their experiments on English, which exhibits many-to-many correspondences between graphemes and phonemes. Ainu, on the other hand, is transcribed according to a phonemic orthography, which reduces the need for explicit information about the correct spelling of individual lexical items.

6.3.2. Impact of Overlapping Character Vocabulary

Conneau et al. (2021) found that using a shared phoneme vocabulary in multilingual fine-tuning yields better results than maintaining a separate vocabulary for each language. While our system is not operating on phonemes, we wanted to verify if an overlap in the character vocabularies representing the target language and other languages used in fine-tuning had an influence on the accuracy of speech transcription. Specifically, we fine-tuned additional models with (i) Hokkaido Ainu transcriptions converted to upper case letters, (ii) LibriSpeech (English) transcriptions converted to lower case letters. In all cases we used the model pretrained on Ainu language data. The output of the models was decoded with a Viterbi decoder. To minimize the influence of code-switched parts written with Japanese script in Ainu language data, *katakana* characters in the generated transcriptions and ground truth data were transliterated into Latin letters before evaluation.

Results are presented in Table 10. With less than 1h of target language data (i.e., "Wenenekaype" only) and additional data from a similar language (Hokkaido Ainu or Japanese), using a shared output vocabulary resulted in lower error rates. Converting English text to lower case produced mixed results, with improved WER but higher CER. After increasing the quantity of labeled Sakhalin Ainu data, the opposite outcome was observed: the model trained on Hokkaido Ainu text in upper case yielded better performance. In contrast to the experiment with shared character vocabulary, in this setting fine-tuning jointly on Sakhalin and Hokkaido Ainu data resulted in a small improvement compared to using Sakhalin Ainu data only.

Given these results, we conclude that when there is very little labeled target language data and additional data from a similar speech variety is utilized, it is better to use a shared character vocabulary, as it seems to facilitate cross-lingual transfer. This recommendation should be treated with caution, as similarity between languages is not necessarily matched by similarity in their writing systems (or transliteration methods), and thus the results for other combinations of languages may be different. On the other hand, as long as the phoneme-grapheme mappings differ in predictable ways, mismatches can be handled by applying rule-based preprocessing to the transcriptions. With more target language data available, the model is more often confused by the cross-lingual signal than it benefits from it, and therefore it would probably be best to just execute monolingual fine-tuning (which also saves compute), but it may be worth experimenting with a separate character vocabulary. Future research should perform similar analyses for other languages.

Table 10

Effect of using separate or shared character vocabularies for the target language and additional languages represented in fine-tuning.

Fine-tuning data	Char. vocabulary size	CER	WER
"Wenenekaype"	76	10.5	33.5
"Wenenekaype" (lower case) + Hokk. Ainu (UPPER CASE)	102	10.2	31.2
"Wenenekaype" (lower case) + Hokk. Ainu (lower case)	86	9.9	30.5
"Wenenekaype" (alphabet) + Japanese (<i>katakana</i>)	137	10.1	31.9
"Wenenekaype" (alphabet) + Japanese (alphabet)	119	9.7	31.0
"Wenenekaype" (lower case) + English (UPPER CASE)	102	11.9	40.1
"Wenenekaype" (lower case) + English (lower case)	86	12.3	39.6
Sakhalin Ainu	94	9.6	29.8
Sakh. Ainu (lower case) + Hokk. Ainu (UPPER CASE)	111	9.4	29.6
Sakh. Ainu (lower case) + Hokk. Ainu (lower case)	95	9.8	31.1

7. Conclusions and Future Work

We have demonstrated that a strong multilingual speech representation model, such as XLSR-53, can be adapted for a new, low-resource language through multilingual fine-tuning and additional pretraining, resulting in improved downstream performance. Through experiments with automatic transcription of Sakhalin Ainu, we found that continued pretraining on target language data leads to substantial reduction in error rates. Furthermore, our results show that in a scenario where labeled target language data is extremely scarce, the model can take advantage of data from a related speech variety (or – to a lesser extent – an unrelated language with similar phonological traits) added during fine-tuning, if that additional language was seen during pretraining.

Our findings confirm the hypothesis that language similarity should be taken into consideration and can be leveraged in the process of multilingual fine-tuning. They also indicate that self-supervised pretraining of a language representation model is not only effective in adapting it for a particular language, but the representations learned during that process can also serve as a bridge for transfer to similar languages in the form of cross-lingual supervision. We expect this observation to also be true for cross-domain supervision within the same language – future work should investigate this assumption.

As a next step in our research, we are planning to increase the amount of labeled in-domain data by digitizing and aligning speech data and transcriptions from Murasaki (1976) and Murasaki and Fujiyama (2013, 2016). Apart from that, we will test other types of language models for decoding (specifically, neural and character-level language models). Furthermore, we will examine potential methods for reducing negative cross-lingual signal while retaining as much as possible of the benefits, such as fine-tuning with language embeddings and ensemble models. We also plan to explore data augmentation techniques.

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References

Abney, S., 2011. Language Digitization. URL: http://www.vinartus.net/spa/p102-v2.pdf.

- An=ukokor Aynu ikor oma kenru (National Ainu Museum), 2017–2022. Ainu-go Ākaibu [Ainu Language Archive]. URL: https://ainugo.nam.go.jp/.
- Ardila, R., Branson, M., Davis, K., Henretty, M., Kohler, M., Meyer, J., Morais, R., Saunders, L., Tyers, F.M., Weber, G., 2020. Common Voice: A Massively-Multilingual Speech Corpus, in: Proceedings of the 12th Conference on Language Resources and Evaluation (LREC 2020), pp. 4211–4215.
- Babu, A., Wang, C., Tjandra, A., Lakhotia, K., Xu, Q., Goyal, N., Singh, K., von Platen, P., Saraf, Y., Pino, J., Baevski, A., Conneau, A., Auli, M., 2021. XLS-R: Self-supervised Cross-lingual Speech Representation Learning at Scale. arXiv abs/2111.09296.
- Baevski, A., Schneider, S., Auli, M., 2019. vq-wav2vec: Self-Supervised Learning of Discrete Speech Representations. CoRR abs/1910.05453. URL: http://arxiv.org/abs/1910.05453, arXiv:1910.05453.
- Baevski, A., Zhou, H., Mohamed, A., Auli, M., 2020. wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations. ArXiv abs/2006.11477.

Bugaeva, A., 2012. Southern Hokkaido Ainu, in: Tranter, N. (Ed.), The languages of Japan and Korea. Routledge, London, pp. 461-509.

- Chiba University Graduate School of Humanities and Social Sciences, 2014. Ainugo Mukawa Hōgen Nihongo Ainugo Jiten [Japanese Ainu Dictionary for the Mukawa Dialect of Ainu]. URL: https://www.gshpa.chiba-u.jp/cas/Ainu-archives/index.html.
- Cieri, C., Miller, D., Walker, K., 2004. The fisher corpus: a resource for the next generations of speech-to-text, in: Proceedings of the Fourth International Conference on Language Resources and Evaluation (LREC'04), European Language Resources Association (ELRA), Lisbon, Portugal. URL: http://www.lrec-conf.org/proceedings/lrec2004/pdf/767.pdf.
- Clark, K., Luong, M.T., Le, Q.V., Manning, C.D., 2020. ELECTRA: Pre-training Text Encoders as Discriminators Rather Than Generators, in: ICLR. URL: https://openreview.net/pdf?id=r1xMH1BtvB.
- Conneau, A., Baevski, A., Collobert, R., Mohamed, A., Auli, M., 2021. Unsupervised Cross-lingual Representation Learning for Speech Recognition, in: Interspeech.
- Conneau, A., Khandelwal, K., Goyal, N., Chaudhary, V., Wenzek, G., Guzmán, F., Grave, E., Ott, M., Zettlemoyer, L., Stoyanov, V., 2020. Unsupervised Cross-lingual Representation Learning at Scale, in: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, Association for Computational Linguistics, Online. pp. 8440–8451. URL: https://aclanthology.org/2020.acl-main.747, doi:10.18653/v1/2020.acl-main.747.
- Devlin, J., Chang, M.W., Lee, K., Toutanova, K., 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, in: Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), Association for Computational Linguistics, Minneapolis, Minnesota. pp. 4171–4186. URL: https://aclanthology.org/N19-1423, doi:10.18653/v1/N19-1423.
- Ebrahimi, A., Kann, K., 2021. How to Adapt Your Pretrained Multilingual Model to 1600 Languages, in: Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), Association for Computational Linguistics, Online. pp. 4555–4567. URL: https://aclanthology.org/2021.acl-long.351, doi:10.18653/v1/2021.acl-long.351.
- Graves, A., Fernández, S., Gomez, F., Schmidhuber, J., 2006. Connectionist Temporal Classification: Labelling Unsegmented Sequence Data with Recurrent Neural Networks, in: Proceedings of the 23rd International Conference on Machine Learning, Association for Computing Machinery, New York, NY, USA. p. 369–376. URL: https://doi.org/10.1145/1143844.1143891, doi:10.1145/1143844.1143891.
- Gries, S.T., Berez, A.L., 2017. Linguistic Annotation in/for Corpus Linguistics, in: Ide, N., Pustejovsky, J. (Eds.), Handbook of Linguistic Annotation. Springer, pp. 379–409.
- Gururangan, S., Marasović, A., Swayamdipta, S., Lo, K., Beltagy, I., Downey, D., Smith, N.A., 2020. Don't Stop Pretraining: Adapt Language Models to Domains and Tasks, in: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, Association for Computational Linguistics, Online. pp. 8342–8360. URL: https://aclanthology.org/2020.acl-main.740, doi:10.18653/v1/2020. acl-main.740.
- Hattori, S., 1964. Ainugo hōgen jiten [Dictionary of Ainu dialects]. Iwanami Shoten, Tōkyō.
- Hjortnaes, N., Partanen, N., Rießler, M., Tyers, F.M., 2020. Towards a Speech Recognizer for Komi, an Endangered and Low-Resource Uralic Language, in: Proceedings of the Sixth International Workshop on Computational Linguistics of Uralic Languages, Association for Computational Linguistics, Wien, Austria. pp. 31–37. URL: https://aclanthology.org/2020.iwclul-1.5, doi:10.18653/v1/2020.iwclul-1.5.
- Hokkaidō Utari Kyōkai, 1994. Akor Itak [Our language]. Hokkaidō Utari Kyōkai, Sapporo.
- Howard, J., Ruder, S., 2018. Universal Language Model Fine-tuning for Text Classification, in: Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Association for Computational Linguistics, Melbourne, Australia. pp. 328–339. URL: https://aclanthology.org/P18-1031, doi:10.18653/v1/P18-1031.
- Hsu, W.N., Bolte, B., Tsai, Y.H.H., Lakhotia, K., Salakhutdinov, R., Mohamed, A., 2021a. HuBERT: Self-Supervised Speech Representation Learning by Masked Prediction of Hidden Units. IEEE/ACM Transactions on Audio, Speech, and Language Processing 29, 3451–3460.
- Hsu, W.N., Sriram, A., Baevski, A., Likhomanenko, T., Xu, Q., Pratap, V., Kahn, J., Lee, A., Collobert, R., Synnaeve, G., Auli, M., 2021b. Robust wav2vec 2.0: Analyzing Domain Shift in Self-Supervised Pre-Training, in: Interspeech.
- Information Resources Center, Research Institute for Languages and Cultures of Asia and Africa, Tokyo University of Foreign Studies, n.d. AA-ken Ainu-go shiryō kōkai purojekuto [ILCAA's Project for the Publication of Ainu Language Materials]. URL: http://ainugo.aa-ken.jp/.
- Kayano, S., 1996. Kayano Shigeru no Ainugo jiten [Shigeru Kayano's Ainu dictionary]. Sanseidō, Tōkyō.
- Kessler, S., Thomas, B., Karout, S., 2021. Continual-wav2vec2: an Application of Continual Learning for Self-Supervised Automatic Speech Recognition. ArXiv abs/2107.13530.
- Khurana, S., Laurent, A., Glass, J., 2022. Magic dust for cross-lingual adaptation of monolingual wav2vec-2.0, in: ICASSP 2022 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 6647–6651. doi:10.1109/ICASSP43922.2022.9746276.
- Littell, P., Mortensen, D.R., Lin, K., Kairis, K., Turner, C., Levin, L., 2017. Uriel and lang2vec: Representing languages as typological, geographical, and phylogenetic vectors, in: Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, pp. 8–14.
- Matsuura, K., Ueno, S., Mimura, M., Sakai, S., Kawahara, T., 2020. Speech Corpus of Ainu Folklore and End-to-end Speech Recognition for Ainu Language, in: LREC.
- Murasaki, K., 1976. Karafuto Ainu-go / Sakhalin Rayciska Ainu Dialect. Kokusho Kankōkai, Tokyo.
- Murasaki, K., 2009. Karafuto Ainugo nyūmon kaiwa / First Step for the Sakhalin Ainu Language. Ryokugeisha, Kushiro.
- Murasaki, K., Asai, T., 2001. Karafuto Ainu no mukashi-banashi: Tuytah [Sakhalin Ainu folktales: Tuytah]. Sofūkan, Tokyo.

Murasaki, K., Fujiyama, H., 2013. Short Sentences in Sakhalin Ainu Spoken by Fujiyama Haru (1). volume 3 of *Sakhalin Ainu Language Series*. Aynu Teetawanoankur Kanpinuye Cise (Center for Ainu & Indigenous Studies), Hokkaido University, Sapporo.

Murasaki, K., Fujiyama, H., 2010. Sakhalin Ainu Folktales (ucaskuma): Wenenekaype. volume 2 of *ILCAA Norheast Asian Studies*. Research Institute for Languages and Cultures of Asia and Africa, Tokyo University of Foreign Studies, Tokyo.

Murasaki, K., Fujiyama, H., 2016. Short Sentences in Sakhalin Ainu Spoken by Fujiyama Haru (2). volume 4 of *Sakhalin Ainu Language Series*. Aynu Teetawanoankur Kanpinuye Cise (Center for Ainu & Indigenous Studies), Hokkaido University, Sapporo.

Nakagawa, H., 2013. Nyū ekusupuresu Ainugo. Hakusuisha, Tōkyō.

Nakagawa, H., Bugaeva, A., Kobayashi, M., Kimura, K., 2016. Glossed Audio Corpus of Ainu Folklore. URL: https://ainu.ninjal.ac.jp/folklore/corpus/en/.

- National Institute for Japanese Language and Linguistics, 2015. A Topical Dictionary of Conversational Ainu. URL: https://ainu.ninjal.ac.jp/topic/.
- Nibutani Ainu Culture Museum, n.d. Ainu Language & Ainu Oral Literature. URL: http://www.town.biratori.hokkaido.jp/biratori/ nibutani/culture/language/.
- Nowakowski, K., Ptaszynski, M., Masui, F., 2019. MiNgMatch A Fast N-gram Model for Word Segmentation of the Ainu Language. Information 10, 317. doi:10.3390/info10100317.
- Nowakowski, K., Ptaszynski, M., Masui, F., 2020. Spicing up the Game for Underresourced Language Learning: Preliminary Experiments with Ainu Language-speaking Pepper Robot, in: The 6st Workshop on Linguistic and Cognitive Approaches to Dialog Agents (LaCATODA 2020). URL: http://arakilab.media.eng.hokudai.ac.jp/IJCAI2020/LACATODA2020/Program_files/Spicing%20up% 20the%20Game%20for%20Underresourced%20Language%20Learning%3A%20Preliminary%20Experiments%20with%20Ainu% 20Language-speaking%20Pepper%20Robot.pdf.
- Panayotov, V., Chen, G., Povey, D., Khudanpur, S., 2015. Librispeech: An ASR corpus based on public domain audio books, in: 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 5206–5210. doi:10.1109/ICASSP.2015.7178964.
- Pfeiffer, J., Vulić, I., Gurevych, I., Ruder, S., 2020. MAD-X: An Adapter-Based Framework for Multi-Task Cross-Lingual Transfer, in: Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), Association for Computational Linguistics, Online. pp. 7654–7673. URL: https://aclanthology.org/2020.emnlp-main.617, doi:10.18653/v1/2020.emnlp-main.617.

Refsing, K., 1986. The Ainu language. The morphology and syntax of the Shizunai dialect. Aarhus University Press, Aarhus.

- Sanabria, R., Hsu, W.N., Baevski, A., Auli, M., 2022. Measuring the impact of individual domain factors in self-supervised pre-training. ArXiv abs/2203.00648.
- Schneider, S., Baevski, A., Collobert, R., Auli, M., 2019. wav2vec: Unsupervised Pre-training for Speech Recognition, in: INTERSPEECH.
- Shibatani, M., 1990. The languages of Japan. Cambridge University Press, London.
- Singh, J., McCann, B., Keskar, N.S., Xiong, C., Socher, R., 2019. XLDA: Cross-Lingual Data Augmentation for Natural Language Inference and Question Answering. ArXiv abs/1905.11471.
- Sonobe, R., Takamichi, S., Saruwatari, H., 2017. JSUT corpus: free large-scale Japanese speech corpus for end-to-end speech synthesis. ArXiv abs/1711.00354.
- Sriram, A., Auli, M., Baevski, A., 2022. Wav2vec-aug: Improved self-supervised training with limited data. ArXiv abs/2206.13654.
- Sun, C., Qiu, X., Xu, Y., Huang, X., 2019. How to Fine-Tune BERT for Text Classification?, in: Sun, M., Huang, X., Ji, H., Liu, Z., Liu, Y. (Eds.), Chinese Computational Linguistics, Springer International Publishing, Cham. pp. 194–206.
- Tang, Y., Tran, C., Li, X., Chen, P.J., Goyal, N., Chaudhary, V., Gu, J., Fan, A., 2020. Multilingual Translation with Extensible Multilingual Pretraining and Finetuning. ArXiv abs/2008.00401.
- Vovin, A., 2016. ON THE LINGUISTIC PREHISTORY OF HOKKAIDO. Studia Orientalia 117, 29-38.
- Vyas, A., Hsu, W.N., Auli, M., Baevski, A., 2022. On-demand compute reduction with stochastic wav2vec 2.0. ArXiv abs/2204.11934.
- Wu, F., Kim, K., Pan, J., Han, K.J., Weinberger, K.Q., Artzi, Y., 2022. Performance-efficiency trade-offs in unsupervised pre-training for speech recognition, in: ICASSP 2022 - 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 7667–7671. doi:10.1109/ICASSP43922.2022.9747432.
- Xu, Q., Baevski, A., Auli, M., 2021. Simple and Effective Zero-shot Cross-lingual Phoneme Recognition. ArXiv abs/2109.11680.
- Zahrer, A., Zgank, A., Schuppler, B., 2020. Towards Building an Automatic Transcription System for Language Documentation: Experiences from Muyu, in: Proceedings of the 12th Language Resources and Evaluation Conference, European Language Resources Association, Marseille, France. pp. 2893–2900. URL: https://aclanthology.org/2020.lrec-1.353.