Exploring Foundation Models for Seismic Event Processing

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Abstract

Nonproliferation monitoring efforts benefit from a glut of multi-modal data that related research must develop methods to process efficiently. Many of the highest performing methods for predictive modeling rely on a legacy of data curation and labeling that is available from decades of seismic catalog building but may not scale well for future uses. This work explores tools for predictive modeling with unlabeled datasets. Unlike clustering methods, which have outcomes that may not be dominated by phenomenologies of interest, self-supervised learning uses an objective function to direct attention to signal attributes that matter for predictive learning. The models developed in this work are patterned after breakthroughs in natural language processing and the work borrows two training methods from large language models adapted to the seismic domain. The first objective is a fill in the blank task where parts of the signal are masked, and the model learns to accurately predict missing values. The second objective is a classification task where a model must learn when two observations were generated by the same source (event). Model training with these two objectives results in a base model with contextual knowledge of characteristic event sequences. The base models are then used with various quantities of labeled data on the task of event discrimination. Classification performance is competitive with existing methods but does not reach state of the art. Temporal sequence modeling provides most of the performance while adding contextual knowledge augments performance by 1-3%. Evaluation of

the learned representations suggests that knowledge encoding fits domain expectations and future work should focus on adaptations to reduce complexity in the training pipeline and on the potential use of learned representations for event discrimination.

Background

Currently much or all deep learning exploration in seismic event processing involves raw or minimally transformed data as model input. One specific reason deep learning is attractive is the expectation of optimal feature learning with respect to a specific task. Feature learning is assumed to be optimized because it is tightly coupled with predictive model building. Using waveform or spectrogram data minimizes expectations and inductive bias assertions that may not always result in the best predictive performance, even when they are intuitive for a specific domain. For example, when we know that p/s spectral ratios and time-of-day information are important for explosive source identification, using these attributes directly enables the use of models that are simple and have dependencies and mechanics that are more transparent. For constrained problems where limited generalization is required, this approach may be sufficient (Rudin, 2019). By comparison, the deep neural network (DNN) approach expects a model to learn attributes that are useful for enhancing performance directly from the data but become difficult to understand causally. Currently, DNN methods have proven to be powerful and transformative in seismology for seismic event processing specifically on account of decades of investments in monitoring and observation that have resulted in informative and accurate labeled data in abundance. When the predictive capability of DNN models far surpasses simple models built on interpretable features, the future research directions necessarily shift to understanding what the boundaries on DNN model use are. For example, how to manipulate architectures and inference methods that give us a sense of the uncertainty on model predictions, or how to access the internal and intermediate representations that help us build intuition for how to believe, trust, and defend model decisions. These are important avenues of research that are needed to help bridge knowledge gaps between performance gains proven by machine learning research and practical applications at scale within current processing systems.

While labeled (supervised) learning research meets many near-term goals for advancing the current state of seismic event processing pipelines, exploration of methods that address the shortcomings of labeled deep learning in the face of expanding data landscapes and the need for information integration across dataspaces, domains, and tasks are increasing in importance for intermediate to long-term goals. Learning highly informative representations from unlabeled data may therefore be an important avenue for data modeling moving forward. This work explores representation learning as a foundation for a broad range of tasks in seismology that could benefit from the context available outside of specific labeled attributes. For example, models with an inherent understanding of temporal signal patterns from earthquakes observed at various scales may be helpful when those models are subsequently trained to predict onset times, event durations, and other related attributes. The analog for temporal signal learning in seismology as proposed in this work is self-training as realized in natural language processing, which has fundamentally changed the capabilities in that field.

Table 1. Reasons for transformative potential with self-supervised learning in the seismic domain.

Reasons self-supervised representation learning could be transformative in seismic event processing
Eliminates the need to train models bottom up for each task. Saves resources (power, time), minimizes engineering burden associated with experiment setup, standardizes input, increases accessibility to model building for non-experts.
Potential for increased performance and dataset integration. Fine-tuning (or transfer learning from base models) allows the efficient use of disparate datasets.
Encourages exploratory rather than prescriptive learning for seismic representations which could be vital for new knowledge discovery and introspection.
Expands the usability of the dataspace beyond labeled ground truth.

Method

The paradigm this work is patterned off relies on large text datasets that are translated into discrete numerical representations called tokens. The tokens are then used to train foundation models (Lacoste et al., 2021; Horawalavithana et al., 2022) on a range of tasks. Similarly, this work relies on a corpus of examples transformed through a series of steps. The **segmentation** process discretizes continuous waveforms into temporally discrete windows. The **tokenization** process maps the segmented data into a finite set of states akin to a vocabulary. Context specific representations are then built by observing the structure of the vocabulary over the duration of an event in the **pretraining** phase. Final **fine-tuning** for specific tasks then occurs with respect to the context learned over the vocabulary. The 4 processes (segmentation, tokenization, embedding, and modeling) that comprise the pipeline for developing a Bert-style model (Devlin et al., 2018) for seismic event processing (SeisBert) are shown in Figure 1.

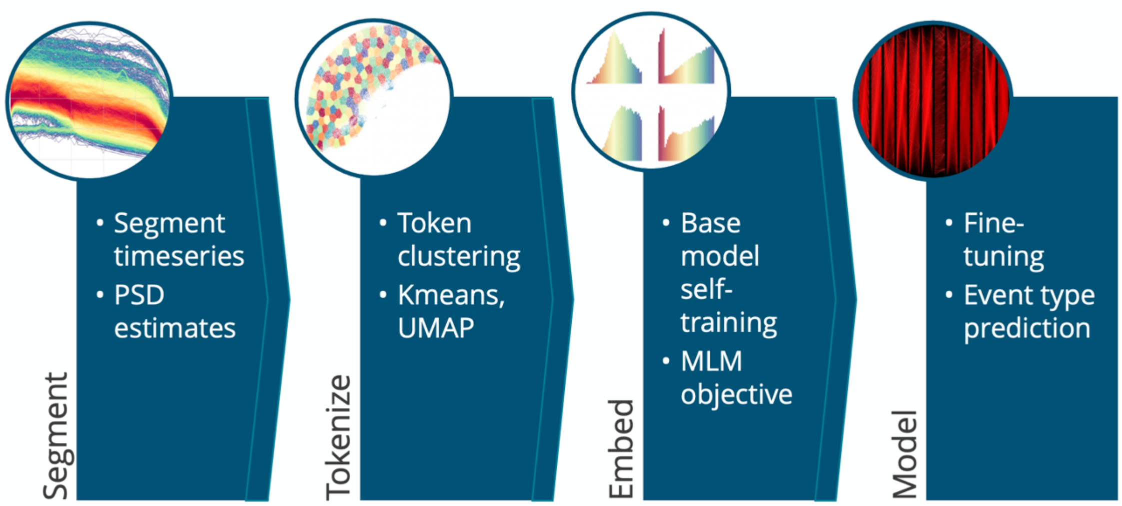


Figure 1. SeisBert Pipeline

Segmentation

Although a long-range goal is to use the proposed method to process continuous seismic data, this work constrains the dataspace to times during which a seismic event has been previously identified. This study uses only event-based waveforms where continuous seismic records are segmented to window discrete known seismogenic phenomena, specifically earthquakes and quarry blasts.

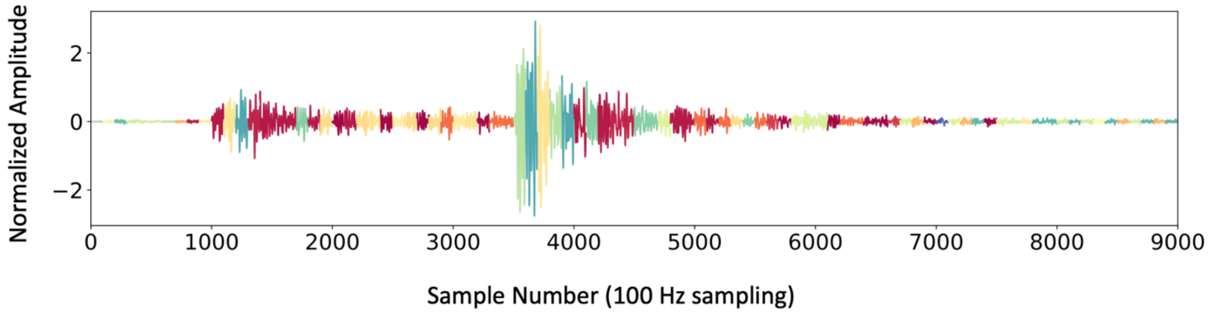


Figure 2. Event-based waveform for a single example. Raw waveforms are segmented into 1sec data windows and colored based on clustering results (see clustering section). Although this method is appealing for overall simplicity, practical application at scale requires an additional dimensionality reduction step that increases the complexity, computational burden, and reduces the interpretability without comparative benefits on performance.

In the past, time-frequency representations (spectrograms or continuous wavelet transforms-CWT) have been identified as being highly informative representations that result in efficient learning with DNN models compared with raw waveforms. Both time-frequency and waveform representations were explored based on their impact on downstream processes. While raw waveforms are attractive for the minimal preprocessing they require, the interpretability of the resulting 'states' (windowed parts of an event), and their inherent scaling after high-pass filtering (centered on zero), they did not prove to be as usable for reasons discussed in the tokenization section. Therefore, while tokenization of raw waveforms (Figure 2) or skipping the tokenization process entirely are ongoing research topics, the rest of this work focuses on exploration using time-frequency (specifically spectrogram) representations of the data.

This work relies on 1-2sec power spectral density (PSD) estimates over the duration of a seismic event starting 10 sec prior to the first arriving energy and lasting 80 sec following the first arrival on data sampled at 100 Hz. For an individual event there will be 45 (in the case of 2 sec windows) or 90 (in the case of 1 sec windows) individual PSD estimates. Although 3 channel (vertical, radial, transverse) seismic events were explored, the results and analysis rely on the 90

1 sec PSD estimates for vertical channels only. The PSD estimates have a frequency resolution of 1hz and the frequencies retained range of 1-20Hz for total of 20 frequency features at 90 independent times (no overlap). A dataset with 5 events, where each event was observed on 5 stations would result in 2.25k PSD examples (5*5*90) or a data array with the shape (25,90,20). The dataset used in this work comes from previous work on events compiled from the University of Utah (Linville et al., 2019; Linville, 2022) and uses a total of 15,282,720 PSD estimates (169808, 90, 20).

Scaling is usually an important data processing step that helps keep weights in a DNN centered on zero for more stable learning (Narkhede et al., 2022). In this work no scaling, a min/max scaling, and event-level whitening, and a median normalization approach were explored. Minimal differences were observed across the normalization methods and the analysis and results reported here rely on PSD estimates divided by the signal median for each frequency bin.

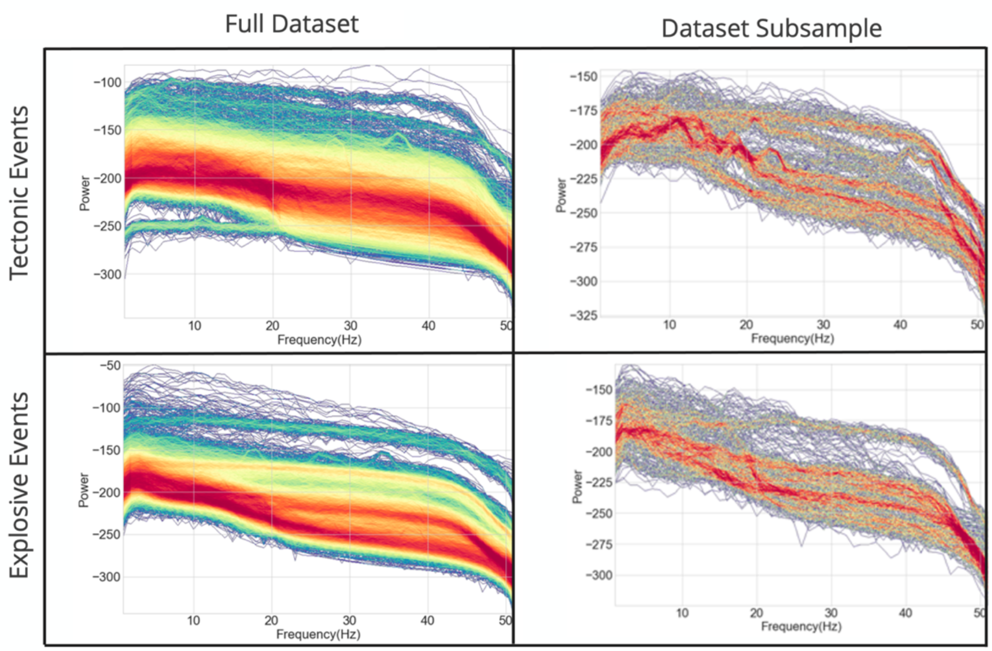


Figure 3. Differences between PSD collections for explosive and tectonic events. Vertical channel power spectral density (PSD) estimates for 2sec windows over earthquake (top) and explosive (bottom) waveforms compared to less dense sampling of just a few events compared to hundreds (right). The differences in character justify exploration of discrimination based on the temporal variation in PSD estimates.

Tokenization

Tokenization in natural language processing (NLP) breaks down text into a base constituency (word or subword level) that is combinatorially complete, yet retains more context than individual characters. The minimal number of tokens in a text corpus represents the vocabulary. In most cases, the vocabulary that foundational models are trained over is large (models used in industry for example such as GPT and GPT-2 have vocabularies of 40,478 and 50,257 respectively). Unlike the discrete alphabets and symbologies that comprise language across text and audio modalities, seismic data is generated by a continuous system. Decomposing audio into its constituent language parts (audio tokenization) discards information about the carrier, the emotional state, and many other phenomenologies that influence signal character. It may be valuable to remove speaker, emotional state, microphone response, etc. from an audio signal when source generating mechanics are the fundamental interest, but requiring audio representations to mirror text, or to be predictive as text is, can minimize the impact of the unique information the modality brings to bear. For example, shouting can change the sound and consequently the numerical mapping of a part of speech. It might not change the token, even when it changes the meaning. Token level ambiguity is part of why context from temporal sequences becomes vital compared to static embeddings such as Word2Vec (Mikolov et al., 2017). In the absence of diagnostic information from the immediate state, we turn to longer range context from a scenario as it unfolds over time, and this is likely why attention mechanisms have become a critical part of sequence processing. This work adheres to the single-modality tokenization paradigm of existing NLP models for the sake of knowledge building across these two application spaces.

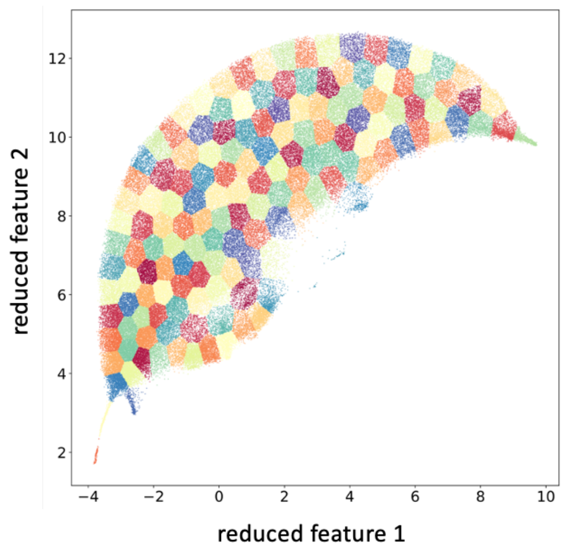


Figure 4. PSD features reduced to 2D and colored by cluster value. The colors show the k-means results. In the absence of user-defined clusters there is no clear way to segment data clouds with homogeneous density using methods such as DBSCAN. We observe similar behaviors when reducing waveform data directly.

K-means (Pedgregosa et al., 2011; Seinley, 2006) is one of the most straightforward ways to identify clusters within a dataspace but one drawback of using K-means is that the number of clusters must be specified. Methods that automatically identify and determine the number of clusters have been developed such as DBSCAN (Khan et al, 2014; Pedgregosa et al., 2011) and are attractive in the absence of knowledge regarding the expected scale, size, and content of a seismic vocabulary. However, low-dimensional remapping of the seismic data sets and iterative testing under various parameterizations suggests that samples fall within a continuum where segmentation rather than clustering is appropriate. For example, Figure 4 shows a lack of discrete clusters in the 2D remapping of PSD values within the training partition (80% of samples). The propensity for data samples to fall within a single majority cluster implies that the topology visualized in 2D space persists in higher dimensions. Therefore, categorizing PSD values according to their ‘differences’ requires the explicit specification of the number of expected or desired clusters (colors in Figure 4), making K-means a reasonable approach.

K-means on raw waveforms results in one or few dominant clusters, while K-means on dimensionally reduced waveforms discretized into 1 second intervals (McInnes et al., 2018) leads to the same cluster characteristics available through K-means performed directly on PSD estimates. For simplicity, this work performs clustering on PSD estimates. The temporal evolution of "states" related to source processes (for example: event onset, discrete wave phases, coda) are expected to be significantly less abundant than language vocabularies; this is the primary assumption driving the assigned number of clusters. The largest number of clusters tested was 150 and the minimum number was 8. Analysis in this work is focused on modeling with 150 tokens (clusters). For any 1 second of arriving energy during an event, the model has 150 options to describe the characteristic signal at that time.

The discretization of continuous waveform data into PSD estimates and subsequently tokens is one of many possible ways to leverage the context available in this domain. There are other frameworks worth mentioning which are left largely unexplored in this work. One main alternative to foundation models and subsequent fine-tuning is to develop word vector representations (wave2vec; Mikolov et al., 2017). Static embeddings with models like wave2vec may potentially be attractive future methods in non-proliferation monitoring if the range of use cases and the probability of their occurrences can be meaningfully encoded in a static representation that prove to be adequate for down-stream tasks.

The primary method of evaluating the effectiveness of a clustering approach is the impact it has on downstream learning, which is discussed in the modeling section. Another indirect approach is to observe how often a token occurs, and when, over the duration of a seismic event observed on an individual sensor (Figure 5). The tokens developed through k-means clustering of 1 sec PSD estimates reflect states that occur over the duration of a seismic event. For example, some tokens are most commonly sensitive to first arrivals, pre-event background, or coda and scattered energy. This analysis suggest that tokens may link to domain phenomenologies such as P-wave, S-wave, ambient, and coda wave energy. It also suggests that the number of states may be over-represented in a vocabulary of this size (150 tokens).

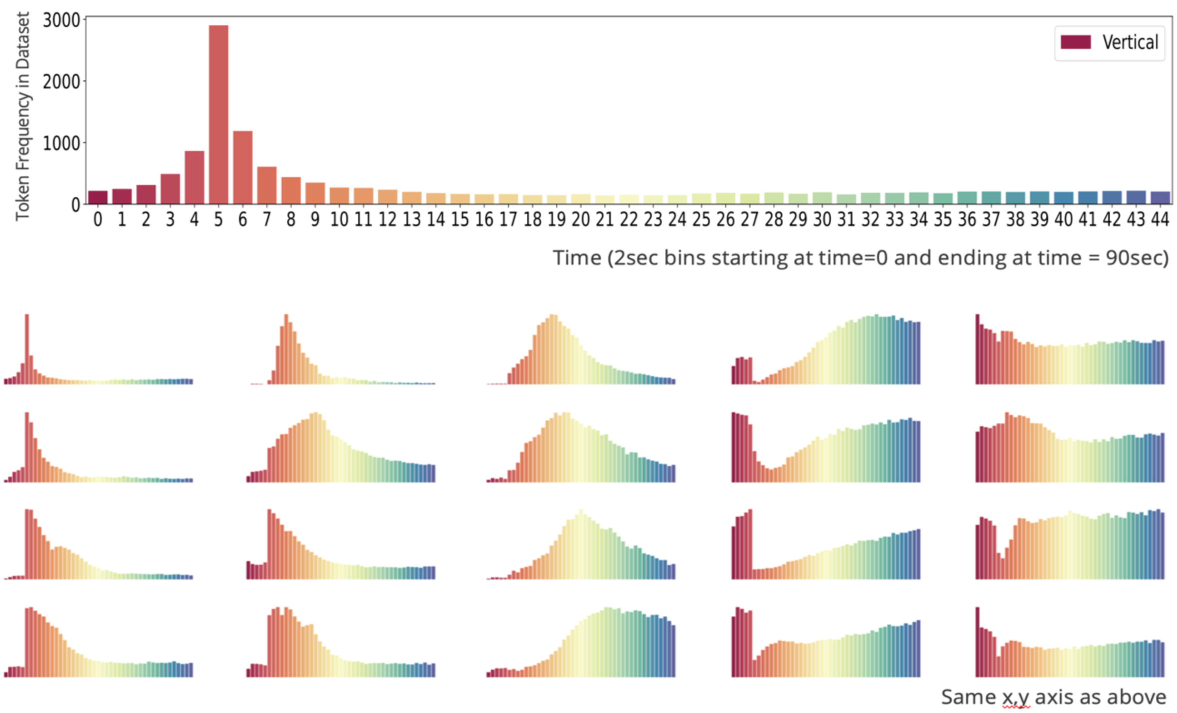


Figure 5. Frequency of occurrence for individual tokens over the duration of a seismic event. Out of 150 tokens there are broadly 6-8 categorizations for how each token is observed over the duration of an event. In this figure 20 tokens are chosen out of the full vocabulary and organized in columns according to their similarity. For example, the 4 tokens in the fourth column from the left show that they are all highly sensitive to the pre-event noise and insensitive to first arrival characteristics.

Embedding: pretraining (with masked language modeling and source linking)

The premise of successful self-supervised learning is that structure in a dataset provides powerful context for what a model understands when making observations. The success of model learning requires objectives capable of providing useful constraints. Masked language modeling (MLM) is one common objective used in bidirectional sequence modeling. The expectation is that if a model can correctly predict missing words within a sentence, it will do so successfully by learning to understanding basic rules of grammar and syntax and using context clues from the surrounding text. Translated to the seismic domain, that would suggest that applying token masking and requiring the model to 'fill in the blank' forces a model to develop an understanding of the typical structure of a seismic event sequence, in essence an understanding of where a 1 sec data example is likely to belong within an event sequence. The idea is that this learned 'context' is subsequently helpful when a model is asked to perform a specific task such as p-wave identification or event classification.

There are other common self-supervised objectives such as next word prediction or next sentence prediction (NSP). Directly applied to the seismic learning NSP could look like mix-match sampling for the first and second half of an event sequence. NSP in this work is applied as a source forcing identifier across stations that observe a specific event. If the first half of a token sequence comes from a different event than the second half, the model is required to recognize this state as different from when the first and second half come from the same event but different stations. The labels associated with NSP in this case designate where in the sequence the data origin changes and whether that origin change is from a new event, or a new station from the same event. The sequence label is 45 characters that take on values between 0 and 1. The NSP label is then binary depending on if all 45 tokens share a source (0) or not (1).

The most effective self-supervised learning objectives may be domain and task specific and assessing their value is currently quantified indirectly through model performance on downstream tasks. This work utilizes MLM and MLM+NSP for base model building. The DNN model architecture uses the transformer architecture (Vaswani et al., 2017). Transformers have recently supplanted Long-Short-Term-Memory networks, providing the same sequence modeling objectives which higher computational efficiency (e.g., parallelization of sequence processing). A common NLP model architecture that utilizes both forward and backward sequence modeling is the Bidirectional Encoder Representations for Transformers or BERT models (Devlin et al, 2018). This work tests BERT models with variations in model complexity and capacity (the number of attention heads and the depth, or number of layers) on a small event-based dataset (~10k events).

Model: finetuning

To limit the engineering complexity of this pilot investigation the modeling task is constrained to be binary event type classification. In the process of finetuning a model we take as input the segmented, tokenized, embedded data and the trained base model, and then use labels to learn a classification network that can successfully discriminate tectonic from explosive sources. None of the layers are fixed during finetuning, meaning the encoding layers of the model can change according to how adeptly they lead to successful classification. In this work base models are trained with the MLM objective, the MLM and NSP objectives jointly. Models with the same architecture and no base training are also tested to evaluate how much impact representation learning at this scale has on model performance for the discrimination task.

Results

During pretraining the point of self-supervised training is to learn valuable data representations and relationships. The ultimate metric of successful representation learning is how well it enhances performance on a model fine-tuned for downstream tasks, in this case binary classification. However, metrics over pretraining are needed to select, with validation data, which models to use in subsequent finetuning trials. Here the multiclass accuracy score on masked tokens is used. Only the models that perform the best on filling in the blanks (MLM) go on to train with labels. Models rarely achieve scores that perform better than 30% across all tokens. Although this leaves room for improvement, the values are considerably better than random guessing (0.6%) or using the average token per time step from the training data (1.1% accuracy). Visualization for what 30% accuracy looks like on a 150-class problem is shown in Figure 6. Perfect prediction would result in the brightest colors along the diagonal only with blue background elsewhere.

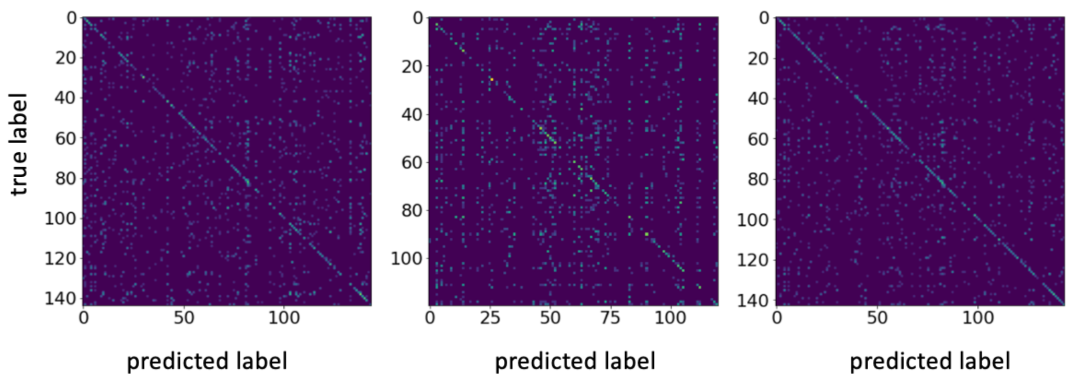


Figure 6. Confusion matrix for prediction on the second half of the signal when the first half is masked (left), predictions on the first half when the second half is masked (middle), and predictions for random signal locations masked events (right).

Classification performance reaches 95% and is highest with the largest base models (12 heads per layer, 12 layers). MLM and MLM+NSP base models perform similarly. Although typically this would be an indictment of NSP as being unhelpful for source prediction, the performance of both MLM and NSP models continues to increase together with increasing model size (number of heads and number of layers), an indication that model performance for both training objectives may be architecture limited at the least, and potentially both data and architecture limited. Masking the first half of the input reduces event type prediction to 66.6%, increasing to 70.3% when masking the second half and 86.4% for random (76% masking). If all tokens are masked the model always predicts the positive class (quarry blast).

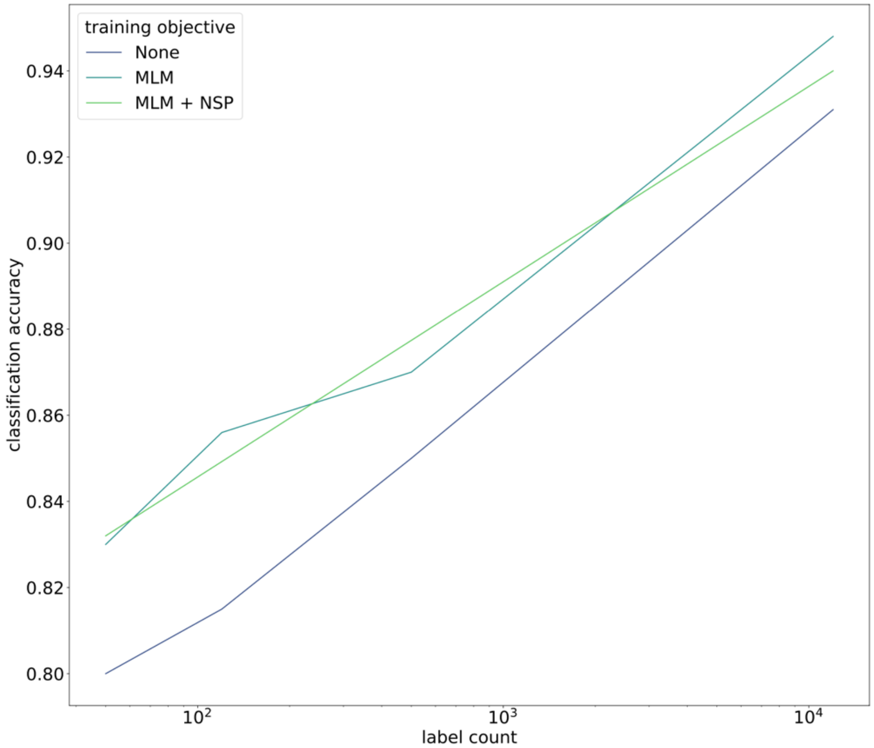


Figure 7. Classification accuracy given a set of randomly sampled event labels. Sample sizes are 50, 120, 500 and the entire dataset. Note there is only data for the first and last label counts for the MLM + NSP objective.

Information about what the models learn to pay attention to can provide insight regarding what kind of information the model uses for context and decision making. Figure 8 shows how different attention heads in different layers learn to allocate attention in similar ways as receptive fields with variable kernel sizes in common computer vision processing models (convolution neural networks). Similarly, the attention strength across different heads within a single layer shows that the model has developed filters that attend to nearly all aspects of the signal with variable overlap and strength, and that these regions of importance change according to where your prediction target is within the example. Figure 9 shows what layer 7 of 12 passes to layer 8 in terms of signal weighting from each head with respect to the 15th token in the sequence of this input example. While various heads attend to different portions of the waveform, there are some heads that dominate signal importance. Figure 9 is meant to convey intuition for the comprehensive piecewise attention coverage across the waveform and illuminate the differences in receptive field and weight complexity. The model is of sufficient depth that attention heads across various layers can become specialized without excessive redundance (because these attention filters respond differently from each other given a new input). A more easily interpretable summary of what a model responds to may be gained by a summation of the attention over all heads and layers. In this case, we get a sense of which parts of the waveform for a specific input are most important for prediction at a specific point in the event sequence overall (Figure 10). A catalog of animations over the progression of an event highlights that 1) learned attention makes physical sense and 2) there is an abundance of information available to exploit in understanding statistical event classification for this catalog of signals.

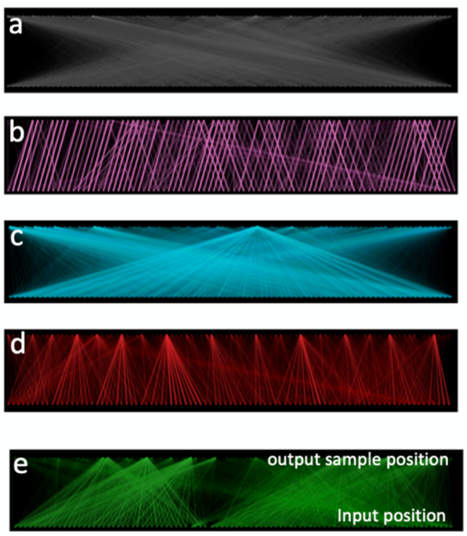
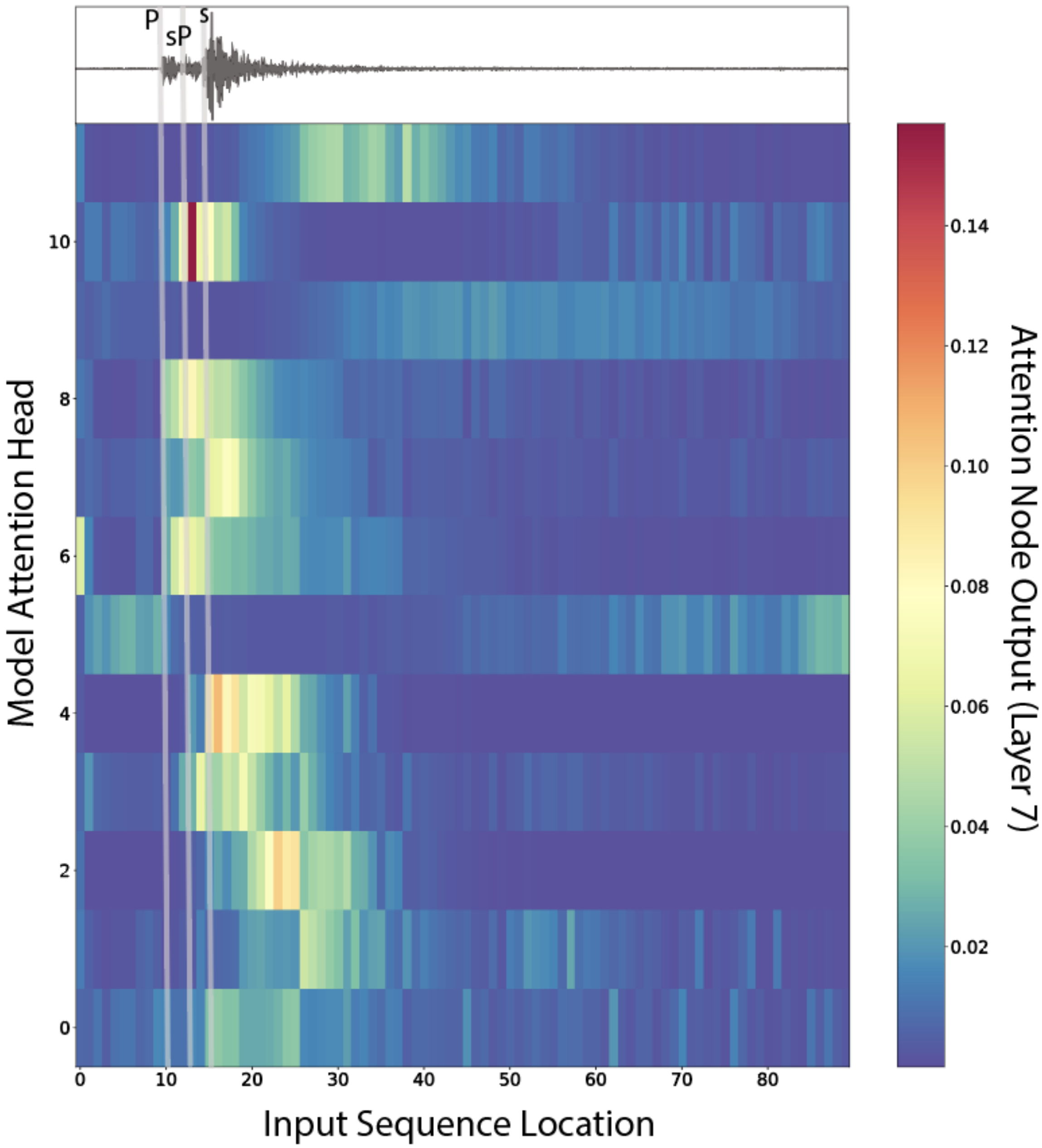


Figure 8. Bidirectional examples of model attention. Input to a layer (bottom) are connected by lines with transparency equivalent to the position and relative strength of attention given to the output sequence (top). The figure panels show which aspects of the temporal sequence are attended to at different locations within the model. For example, the attentions in (a) are nearly equally distributed across the timesteps. Whereas the purple/magenta layer has learned to pay attention to the next value in the sequence. By comparison there are layers where a substantive attention is paid to one location in the output sequence (b), or where discrete outputs are sensitive to surrounding timesteps with receptive fields of various size (c,d,e). Bertviz was used to generate attention views (https://github.com/jessevig/bertviz; Vig, 2019)



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343 *Figure 9. 12 attention heads for layer 7 responding to the input signal on top at timestep 15.*

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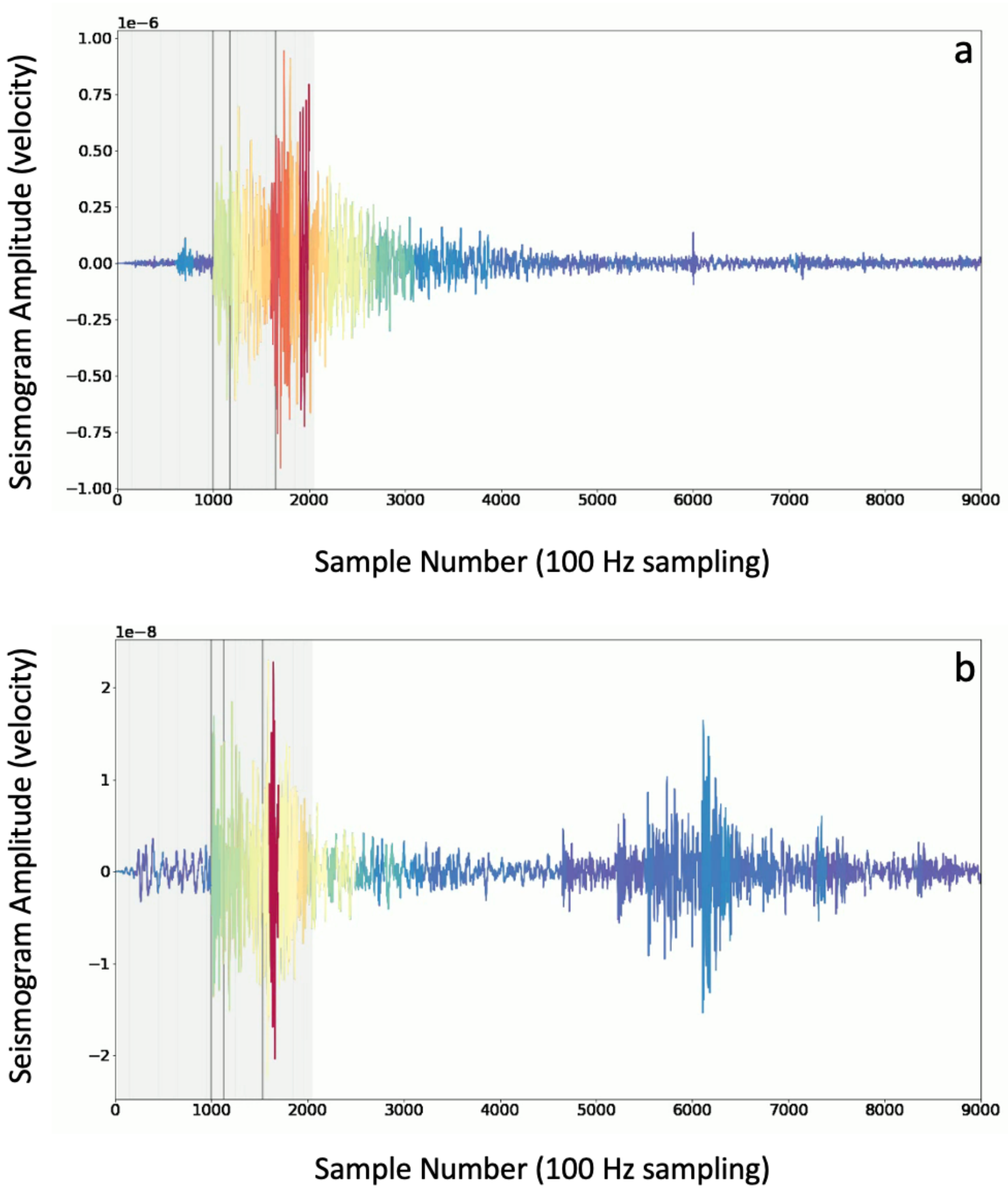

Figure 10. Bulk model attention (summed over all layers/heads) for an input signal colored by relative attention strength (red =high, blue=low). The grey progress bar shows the timestep that the attention strength is depicting, and the vertical grey lines show calculated body wave arrival times using TauP and the ak135 velocity model available in the Obspy python library

(Beyreuther et al.,2010). At timestep 2000 for example, there are discrete segments, perhaps phase arrivals or scattered energy that are most important in making accurate predictions about what the signal should look like at that time.

Discussion

One of the foremost challenges of this work was in deciding the best method of data preprocessing for representation learning. Power spectral density estimates are compact and descriptive compared to waveform attributes when the spatio-temporal granularity that results from the PSD transform is sufficient for the problem. This work discretized PSD estimates at 1 sec resolution into tokens that comprise a seismic vocabulary. Discretization of the PSD estimates into tokens allowed for the use of existing architectures and training paradigms. The token sequences (90 tokens per event) without temporal modeling by themselves are only predictive up to ~81 %. Using random forest at 12-30 tree depths, the differences between test and train reach a maximum around a tree depth of 30 where train accuracy is above 99% but test accuracy remains at 81%. Therefore, representation learning and the temporal modeling of the token sequences both improve learning, although temporal learning plays a larger role than representation learning based on the difference between fine-tuning results with and without pretraining (81% with deep RF, 93% with temporal learning, 94.5% with pretraining). For comparison, binary event prediction on the same dataset can achieve accuracies near the error rate of this dataset (96-98%) using convolutional architectures. So, while base model training improves learning, and temporal modeling improves learning substantially, neither are required for high performance on this task and neither perform as well as other deep learning methods. White the above findings do not make these models competitive with state-of-the-art in event discrimination they demonstrate that this method may be excessive if used for the sole learning problem of binary discrimination when abundant labels are available in a constrained geographic area.

This work was meant primarily to prove out that a modeling framework was viable given the discretization required to utilize NLP ideas developed for language on seismic data. A 1-3% decrease in overall accuracies on the task of event discrimination is modest compared to the relatively low competence of non-ML tools for discrimination on the full diversity of events that exist in regional catalogs (specifically for low signal-to-noise ratios; Tibi et al., 2019). If, in addition to being useful for event discrimination, base models maintain value across multiple seismic processing tasks and generalized across seismic catalogs or with fewer labels, substantive benefits could be realized in this domain. Proving that the value of the current models extends beyond binary event prediction is outside the scope of the current work and would be an important avenue for continued research.

The second objective of this work was to begin to use the rich contextual information available through unlabeled data in exploratory ways. While labeled learning dominates most deep learning studies in seismic processing, exploratory data analysis with new methods is currently one of the most underutilized applications in this domain (Mousavi and Beroza, 2022). Exploration of the locus of attention paid to incoming signals suggests that a model's understanding of an event sequence at any specific time depends on bidirectional context from the rest of the event. For example, predicting what happens at the end of the event window depends highly on what happens in the pre-event signal. As you traverse across a signal it is not simply local bidirectional context but highly specific frames within an event that matter the most. These may link to meaningful physical phenomena such as discrete phase arrivals or dispersed energy, or simply express statistically meaningful states for this dataset. Ongoing investigation may yield valuable insight into the importance these states have on task performance that in the future lead to simple and powerful predictive models using this new insight.

Beyond further exploratory work, the value of representations that use bidirectional context make them an ideal and potentially valuable tool for tasks such as gap filling. Other tasks that require acausal observations (first arrival picking or earthquake early warning, as examples) would necessitate alternate training strategies. These open questions and many more remain targets for future work.

There are many outstanding computational challenges in self-supervised learning settings with continuous sensor data. The models tested here required input (batch size) of relatively modest size when trained on a single GPU (32G memory). While training times also remained modest, on the order of 1-5 days on a single GPU, parameter optimization was consistently challenging.

Many open questions remain regarding the performance ceilings observed here. Advances in LLM required modeling and data at minimum scales that this work does not approach. It is not clear if performance in this work was limited by token representations or the need for more and diverse data, or any number of architecture or search space options that remained unexplored. Future work may benefit from recent advances in transformer architectures such as Perceiver networks (Jaegel et al., 2021) which are well suited for NLP style processing without the need for tokenization and could be a more natural fit for seismic data. A brief trial of a transformer model's ability to recreate a seismic waveform for a discrete sample interval (1 sec) was tested using the perceiver with promising initial results (Figure 11). Future work should focus on improving learning through scale (dataset and model size) and self-supervised objectives for richer representation learning in the seismic domain.

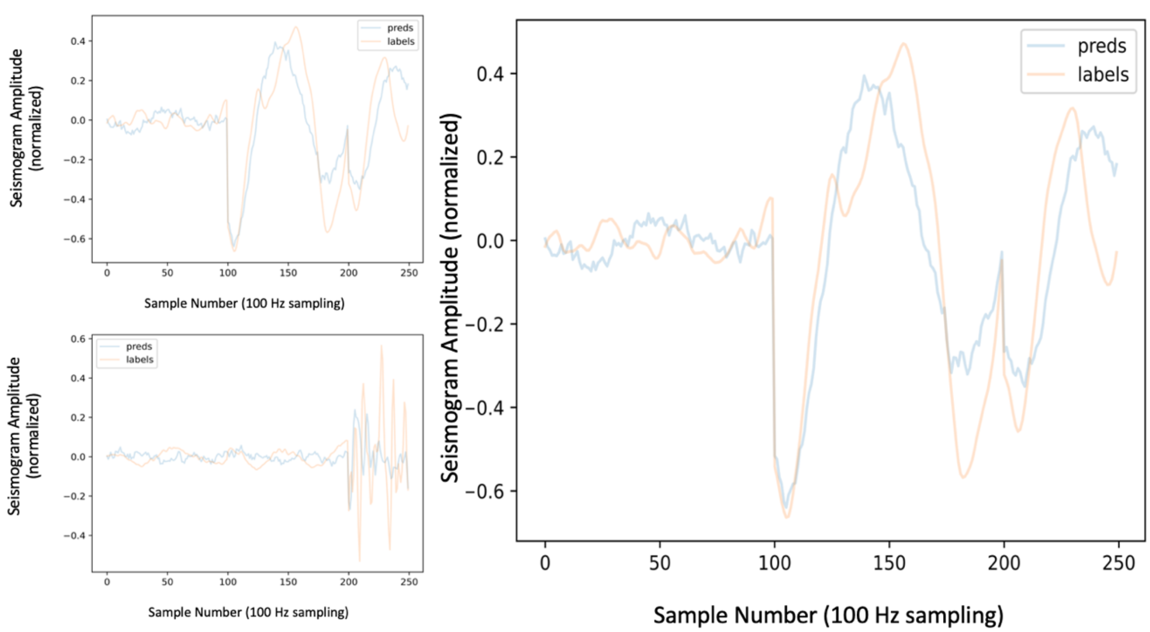

Figure 11. Waveforms compared to waveform predictions by tokenless transformer architectures. Perceiver models learned to regenerate signals across frequencies of interested but still struggled to recreate random tokens and masked tokens consistently and with high fidelity.

Conclusion

As we approach ceilings in performance from existing labeled data, self-supervised learning may be an important tool for utilizing abundant open-source datasets with variable curation legacies at scale. Base models that are built with self-supervised learning may be important in the efficient development of a range of models across tasks in a specific domain. Seismic data is well positioned to take advantage of advancement in the field of self-supervised learning, even though there are several open questions for the field. Self-supervised learning carries the additional burden of defining domain appropriate optimization objectives. This work does not resolve many of the previously unanswered questions about how to exploit seismic data for better representation learning but it does validate that temporal learning and self-training together on seismic data result in representations that are physically meaningful and that using those representation in signal classification achieves better performance than temporal signal modeling alone.

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