Separation of seismic signal and ambient noise using deep neural network

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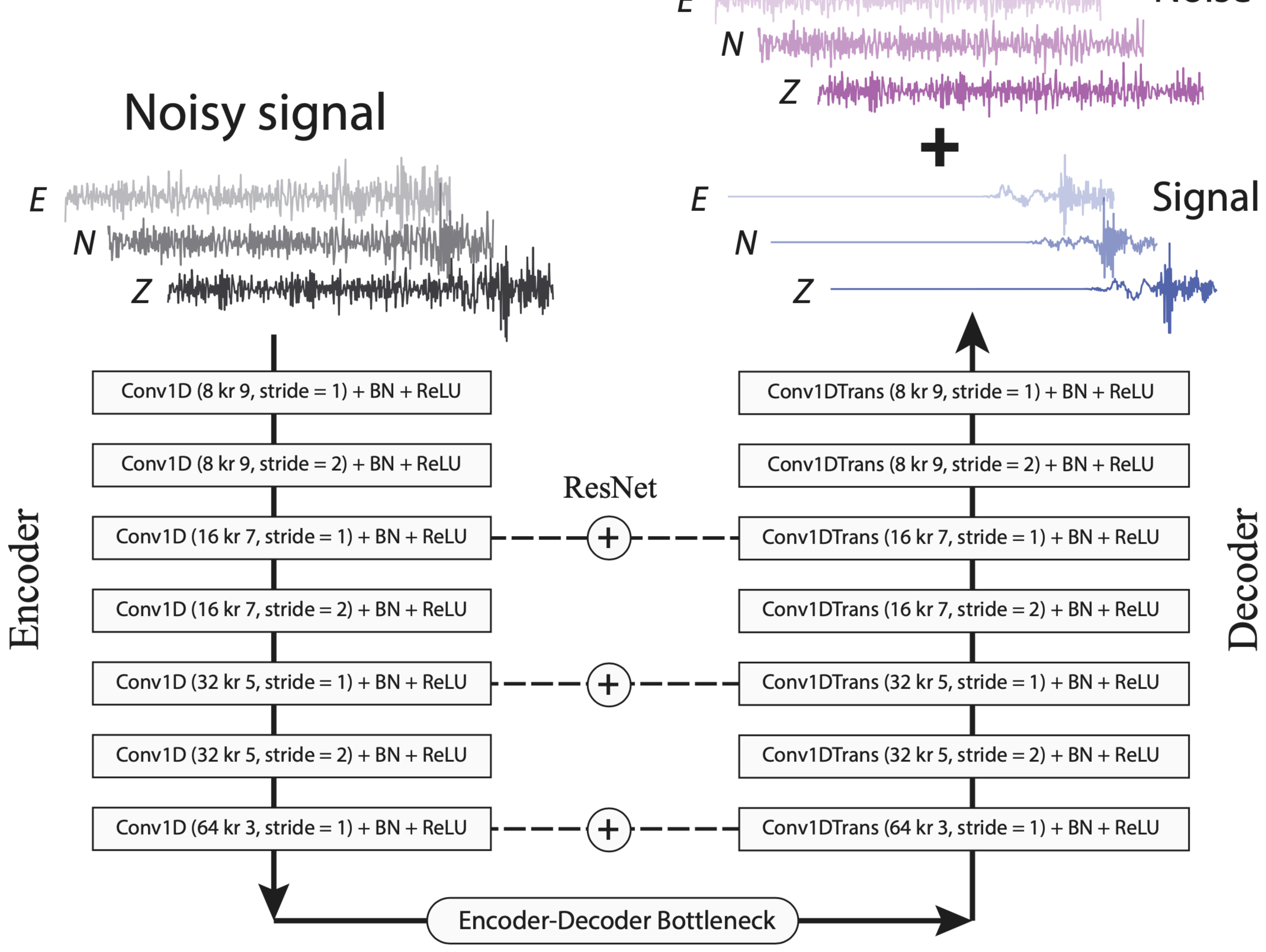
Summary

- We develop a machine learning method to separate the earthquake signal and noise signal in time domain.
- We validate the method with both synthetic and realistic datasets.
- We test various types of network architectures, LSTM outperforms others for separating signals.

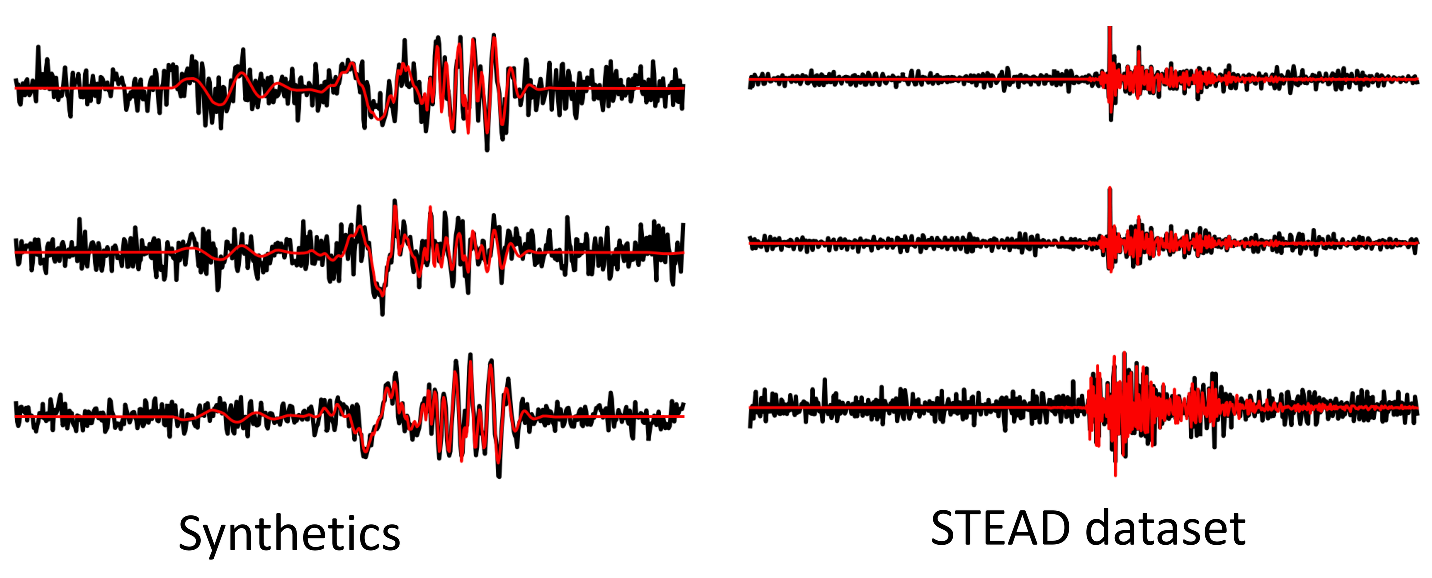
Network architecture



- We apply the classic encoder-decoder architecture (shown above) for this sequence-to-sequence regression problem.
- The bottleneck block is a key component for the encoder-decoder architecture. In this study, different choices of the bottleneck block for the feature-extraction of time-series are tested, including:
  - **None** (no specified block for the bottleneck)
  - **Linear** (fully-connected linear layer)
  - **LSTM** (Long-Short Term Memory block)
  - **attention** (dot-product self-attention mechanism)
  - **Transformer** (1-layer transformer encoder layer)

Datasets

- We test our network with two different types of datasets:
  1. **Synthetics**: synthetic earthquake waveform + realistic noise (124,800), realistic noises are from station **IU.XMAS** (https://www.fdsn.org/station_book/IU/XMAS/xmas.html)
  2. **STEAD**: Earthquake waveform + noise from STEAD dataset (100,000) (https://github.com/smousavi05/STEAD)
- Earthquake waveforms and noise are randomly combined to form the datasets with SNR (power ratio of signal and noise) varying from 0.01 to 10 for the network (Randomly scaling + shifting).

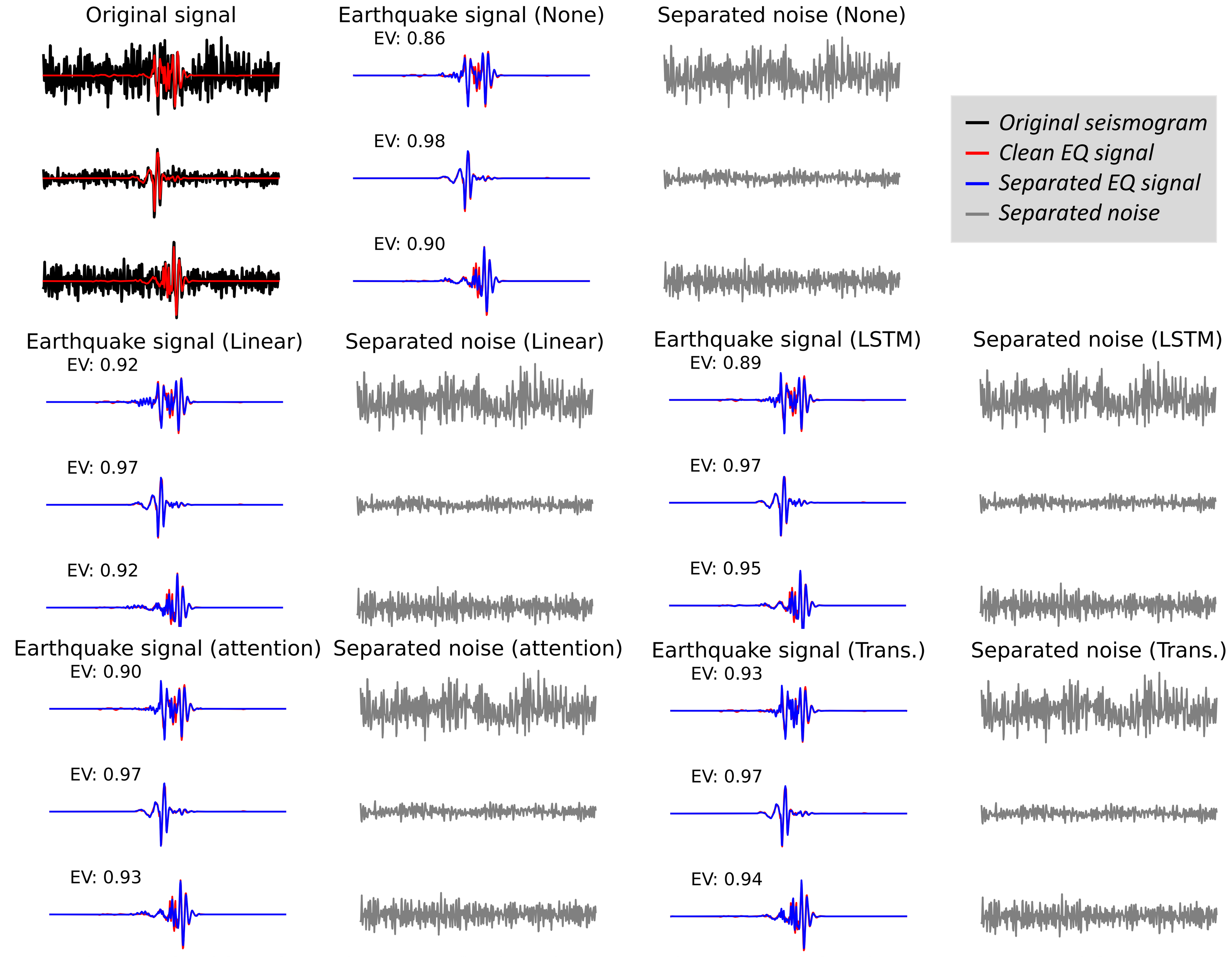


- We use the Explained Variance (EV) between the separated waveforms and true waveforms to quantify the performance of trained models

$$explained\_variance(y, \hat{y}) = 1 - \frac{Var\{y - \hat{y}\}}{Var\{y\}}$$

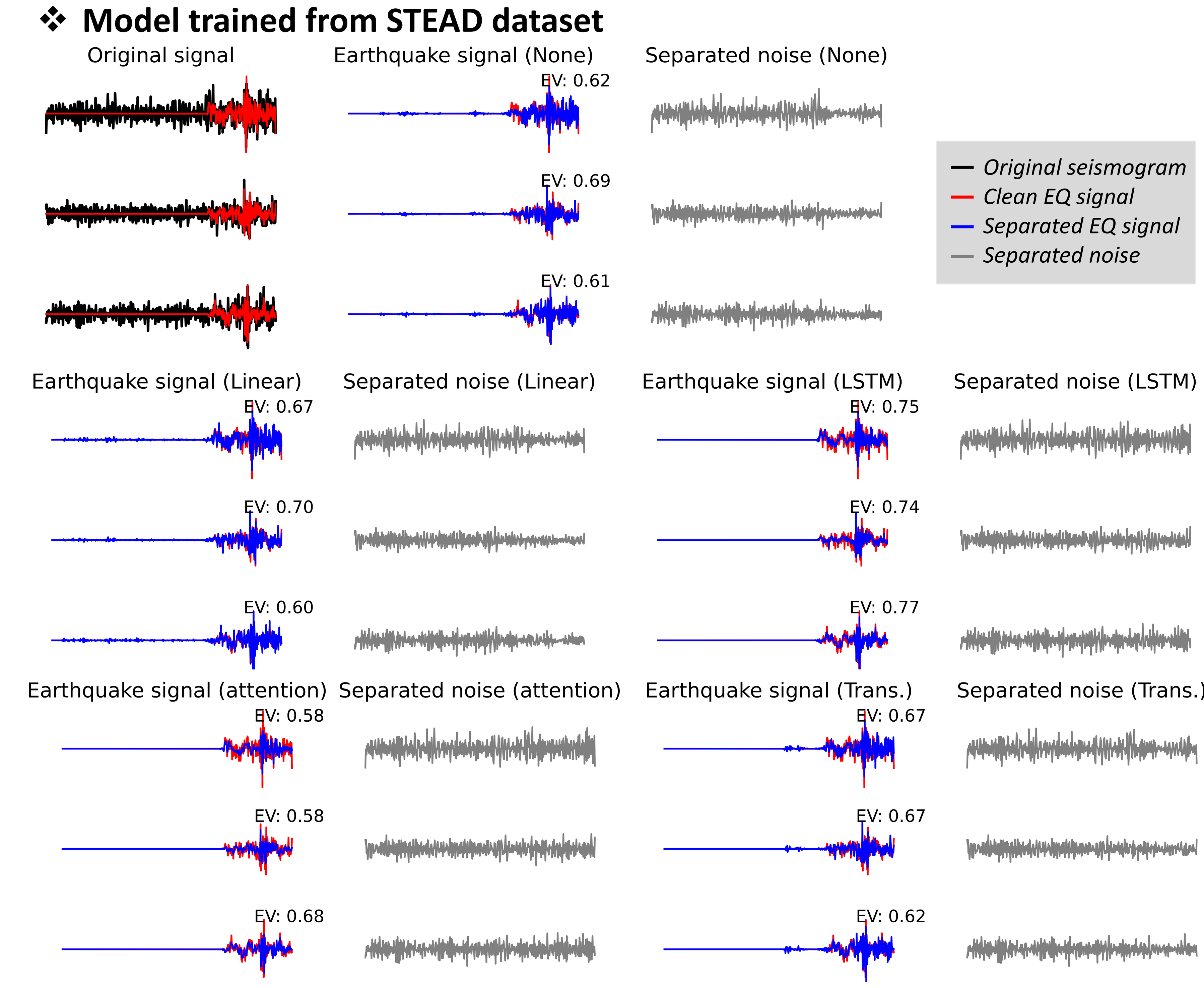
Examples of signal separation

Model trained from synthetics datasets

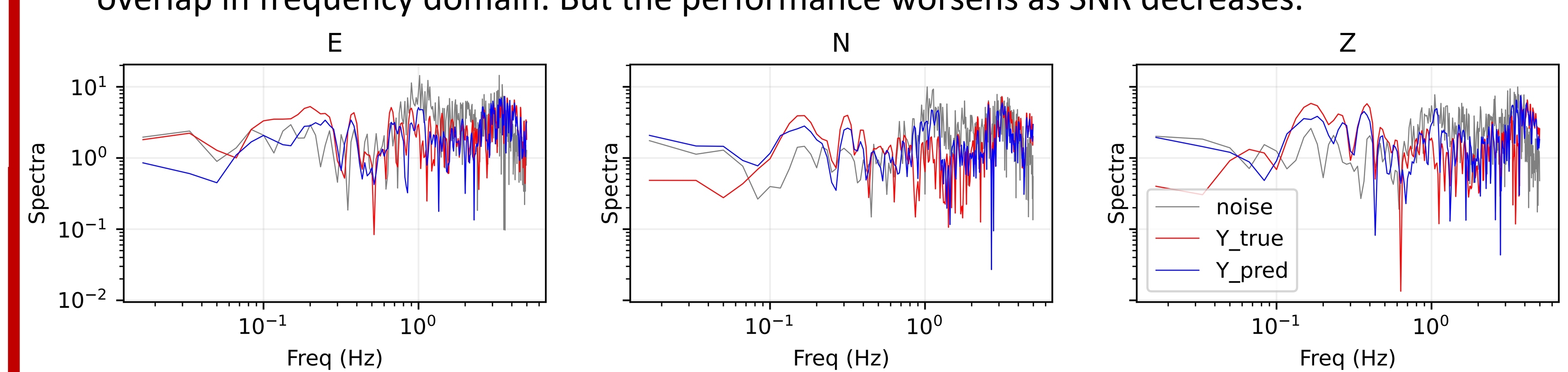


- The applied bottleneck is specified in the parentheses. For the dataset generated from synthetic earthquake waveforms and realistic noises, all the models can successfully separate the earthquake and noise signals for very low SNR signals (~10^{-1}).

Model trained from STEAD dataset



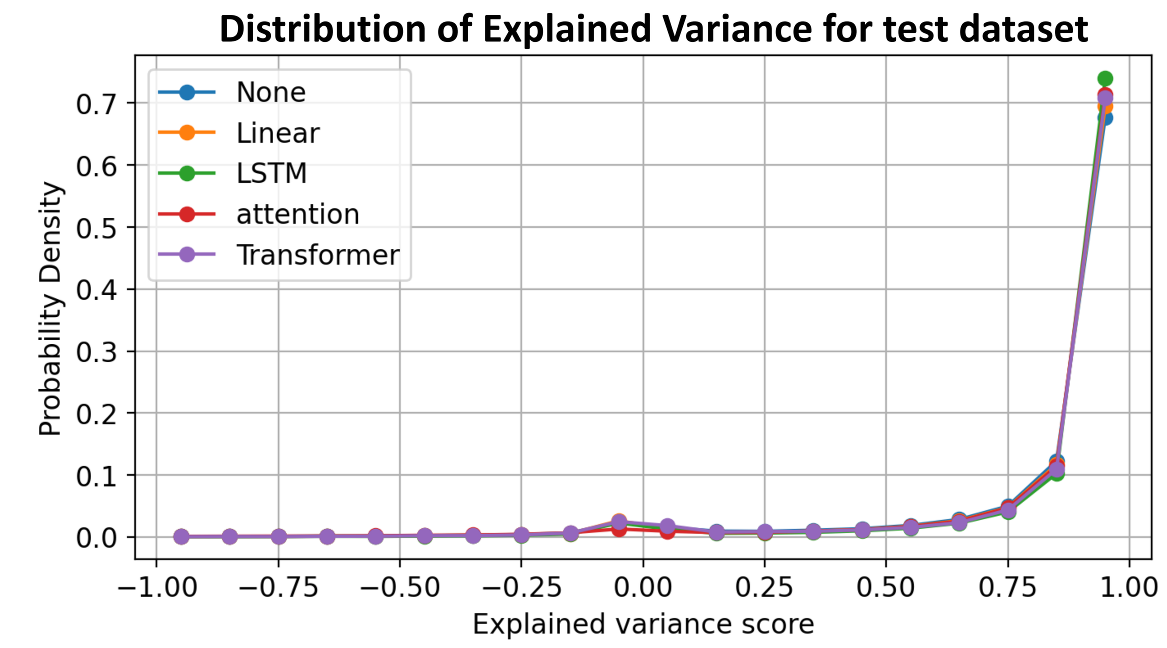
- When applied to realistic waveforms from the STEAD dataset, the network we build can still separate earthquake and noise signals quite well for SNR > $10^{-0.5}$, even when signal and noise overlap in frequency domain. But the performance worsens as SNR decreases.

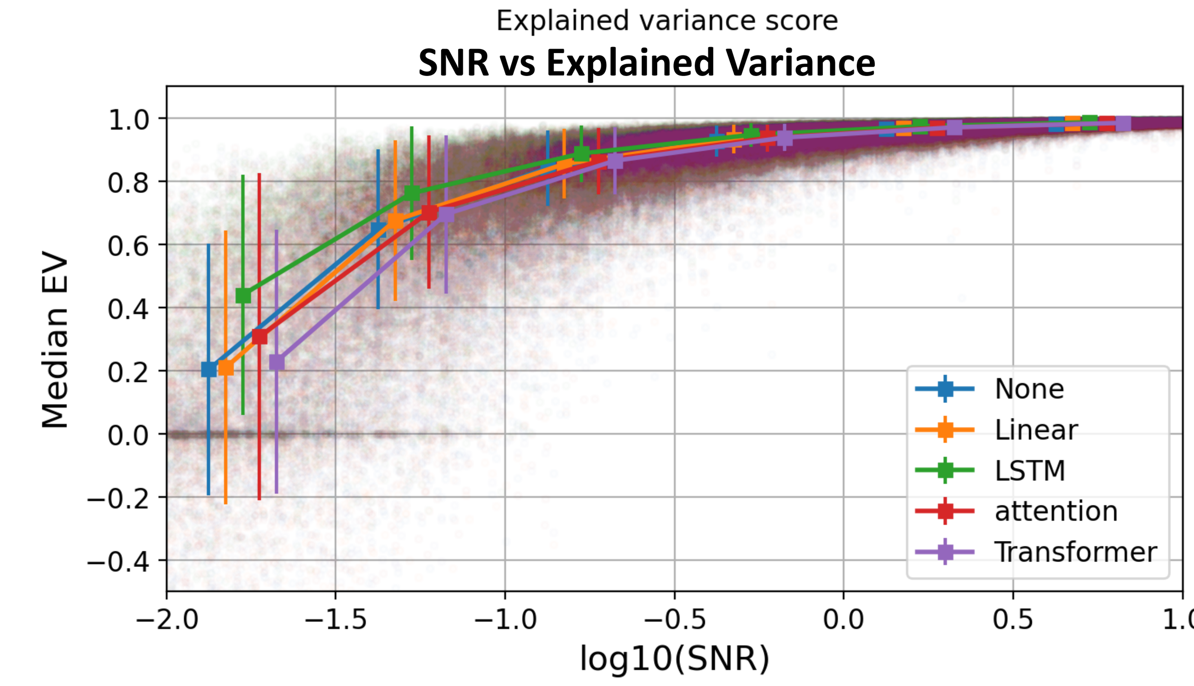


- For more complex waveforms, the choice of "bottleneck" block is critical as shown by our results. Therefore, we further quantitatively compare the performance of models with different bottlenecks.

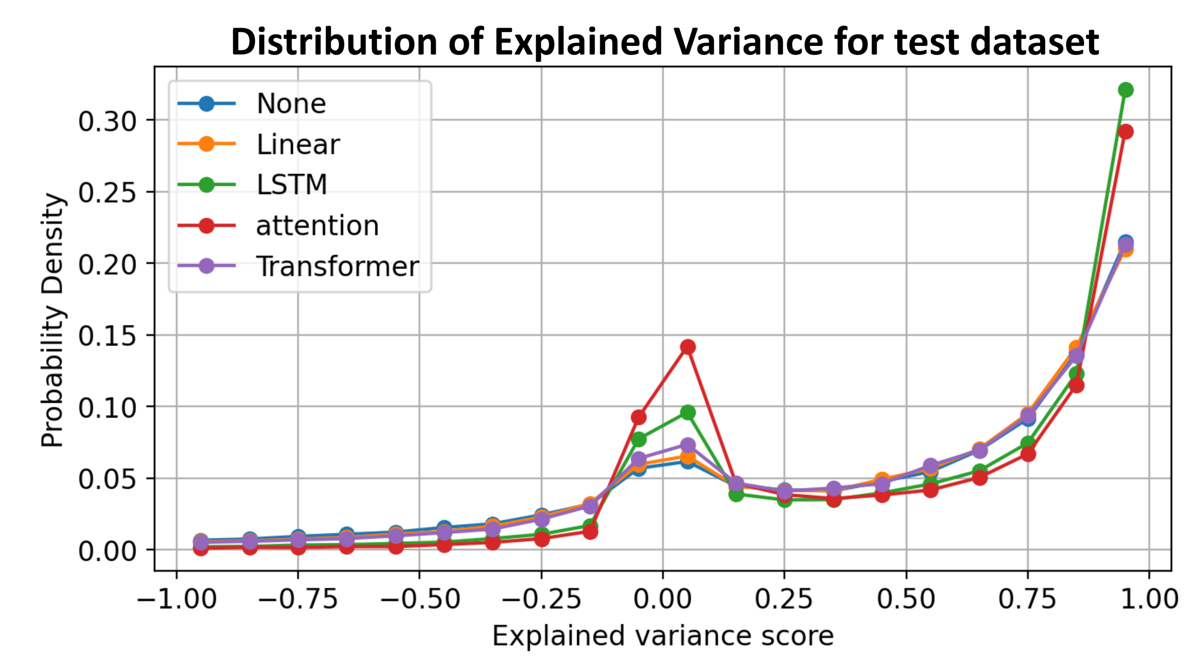
Comparison between models

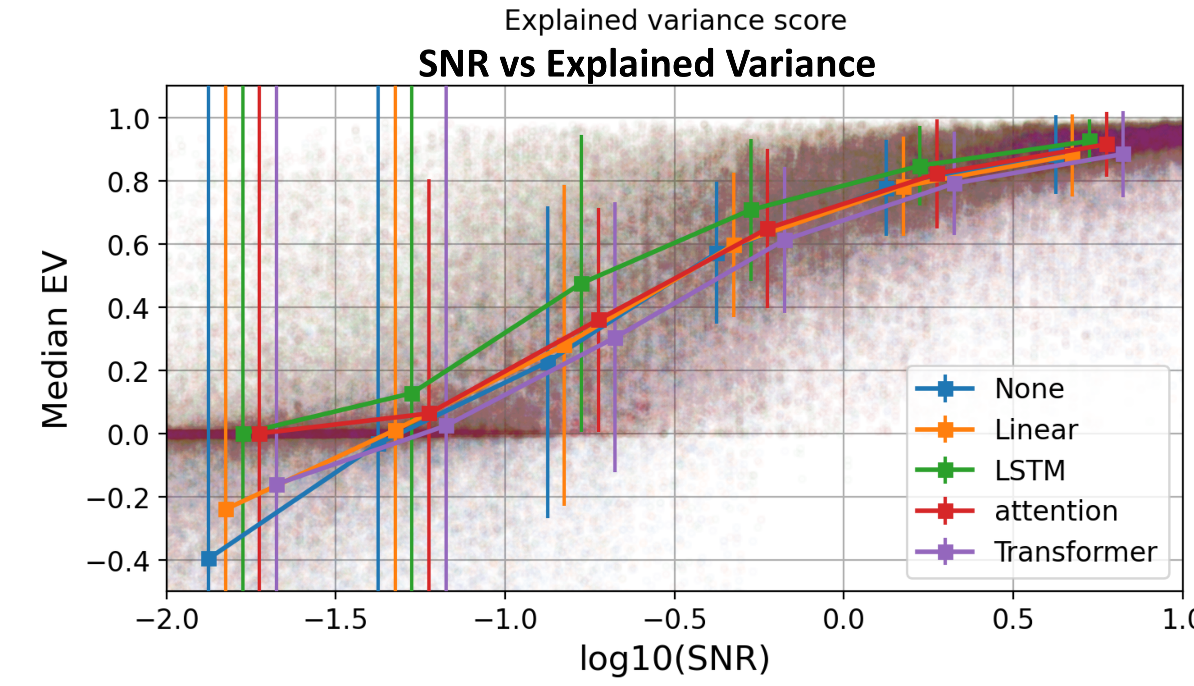
Performance of models for synthetics





Performance of models for STEAD dataset





- Synthetics: all models perform similarly for SNR > 10^{-1}, LSTM has the best performance (higher EV) for lower SNR < 10^{-1}.
- STEAD dataset: Self-attention and LSTM models perform best in term of the EV distribution. For the same SNR, LSTM outperforms other models for all tested SNR range.

Conclusion and Future work

- *The Encoder-Decoder network is shown to successfully separate the earthquake signal and noise signal directly in the time domain.*
- *LSTM block outperforms others in accurate separation of the signals.*
- *Future work:*
  - *Cross-validate with other datasets (realistic continuous seismic data)*
  - *Investigate the quality of separated noise signals (e.g., CC).*