Deep Learning Seismic Arrival Picks

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Contributions

1. We introduce atrous layers to a basic CNN architecture to identify sesimic phase arrivals in waveform data.
2. We show additional improvements with spectrogram input without significant cost.

Seismic Arrivals

- Obtaining accurate arrival times of earthquake waves is important for earthquake detection, determining epicenter locations and seismic tomography studies.
- Earthquake phase arrival identification is often performed by analysts (figure 1) that can be costly and add bias to their results.

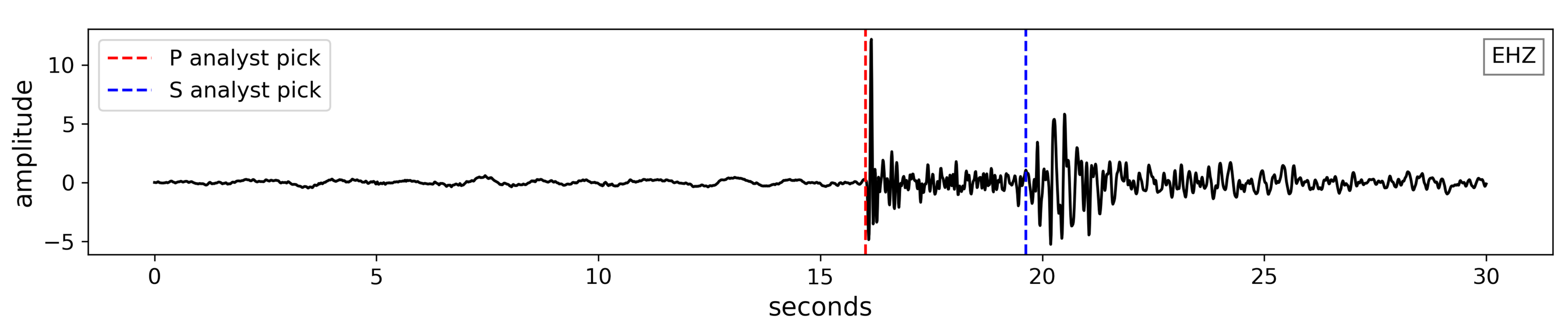

Figure 1. The EHZ component of a seismogram with the P and S wave analyst picks.

Creating an accurate automated phase picker can reduce dependence on analysts, which could decrease the variability in quality while increasing the quantity of databases.

Study Area and Data

Using the New Zealand GeoNet database we look at 9436 earthquakes that occured on the North Island of New Zealand from 2012 to 2013. We process the data by applying standardization (equation 1) and a bandpass filter between 0 and 25 Hz.

$$\frac{x - mean(x)}{std(x)} \tag{1}$$

Spectrograms

While deep learning phase picking models, such as PhaseNet [3] and EQTransformer [2] have used 1D waveform data, we investigate using 2D spectrogram data (figure 4). Spectrograms convert the waveform data from the spatial to the frequency domain. At every point along the x-axis, it shows the power of the frequency that makes up the waveform at that time.

References

[1] Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *IEEE transactions on pattern analysis and machine intelligence*, 40(4):834–848, 2017.

[2] S Mostafa Mousavi, William L Ellsworth, Weiqiang Zhu, Lindsay Y Chuang, and Gregory C Beroza. Earthquake transformer-an attentive deep-learning model for simultaneous earthquake detection and phase picking. *Nature communications*, 11(1):1–12, 2020.

[3] Weiqiang Zhu and Gregory C Beroza. Phasenet: a deep-neural-network-based seismic arrival-time picking method. *Geophysical Journal International*, 216(1):261–273, 2019.

Atrous Convolutional Layers

We introduce atrous layers that serve as a way to increase the reception field to achieve more of a global context of the waveform with less memory consumption compared to other methods such as max pooling. More importantly to this problem, as shown in figure 2, DeepLab [1] demonstrated how atrous layers can conserve resolution better than traditional methods of downsampling while still achieving global context.

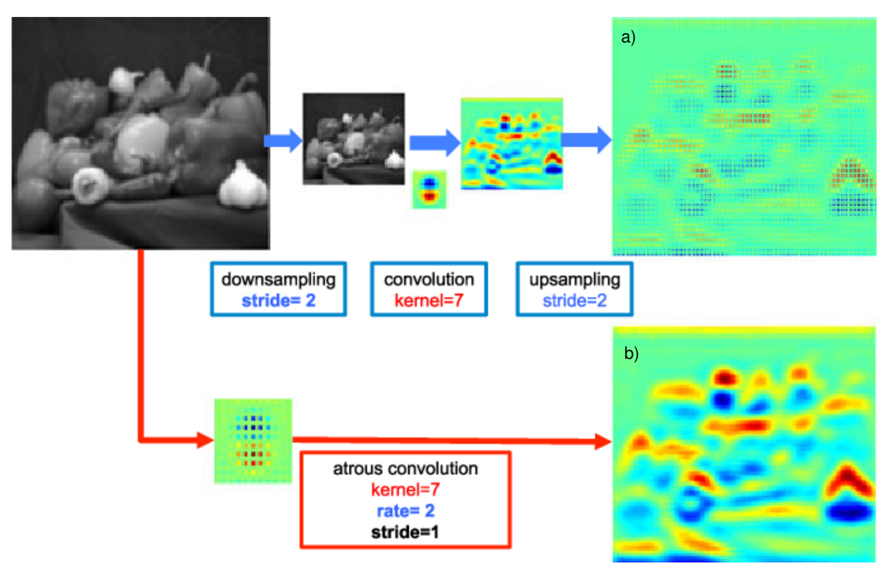

Figure 2. Figure taken from Chen et al. [1] where they demonstrate differences in resolution from downsampling using a) traditional downsampling method and b) atrous convolutional layers.

CNN architecture

To demonstrate the significant impact of atrous layers, we used a very basic architecture shown in figure 3.

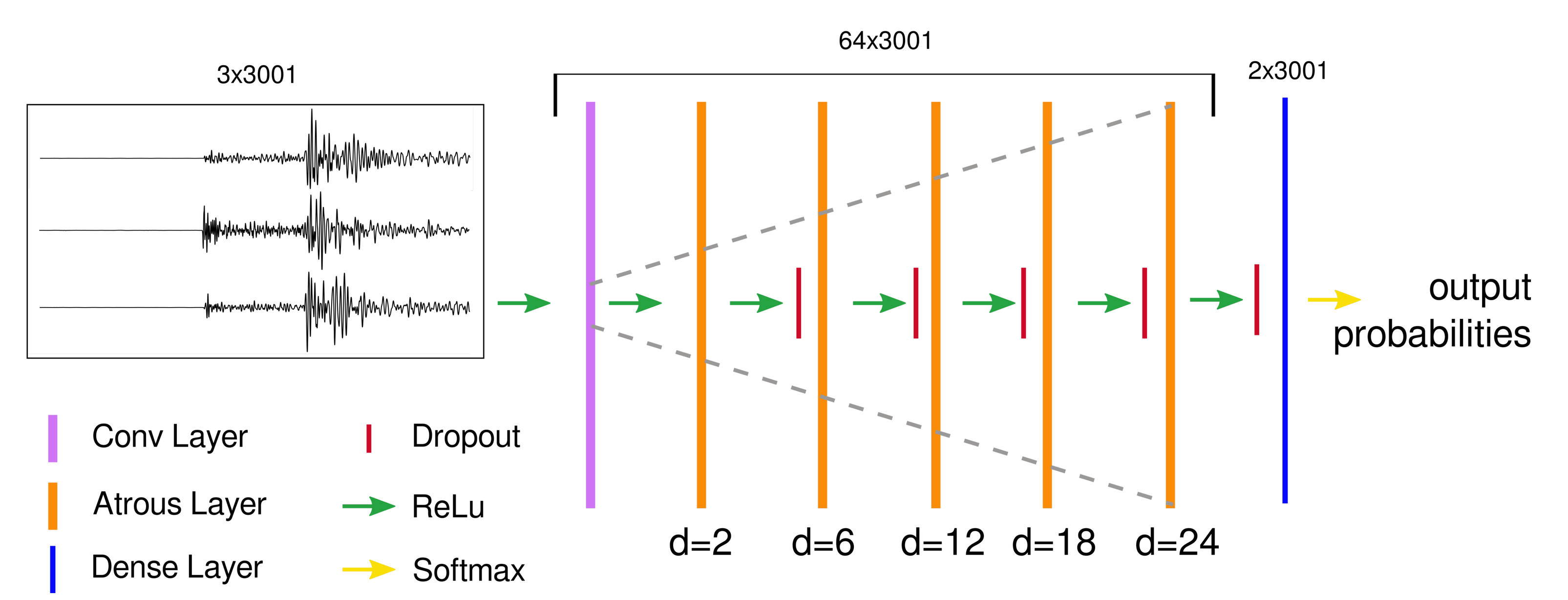

Figure 3. The architecture with atrous layers (orange), the grey dotted line represents how the field of view for the network increases as the kernel dilation, d, increases.

Conclusions

Table 1 shows that introducing atrous convolutional layers increases model performance. Additionally, using a spectrogram gave nominal improvements. Our precisions and time differences (figure 5) show worse performance than PhaseNet [3] and EQTransformer [2]. Because our simple straight CNN might not be able to capture the complexity needed for this problem, our next step would be to introduce a more involved architecture such as U-nets.

Key Results

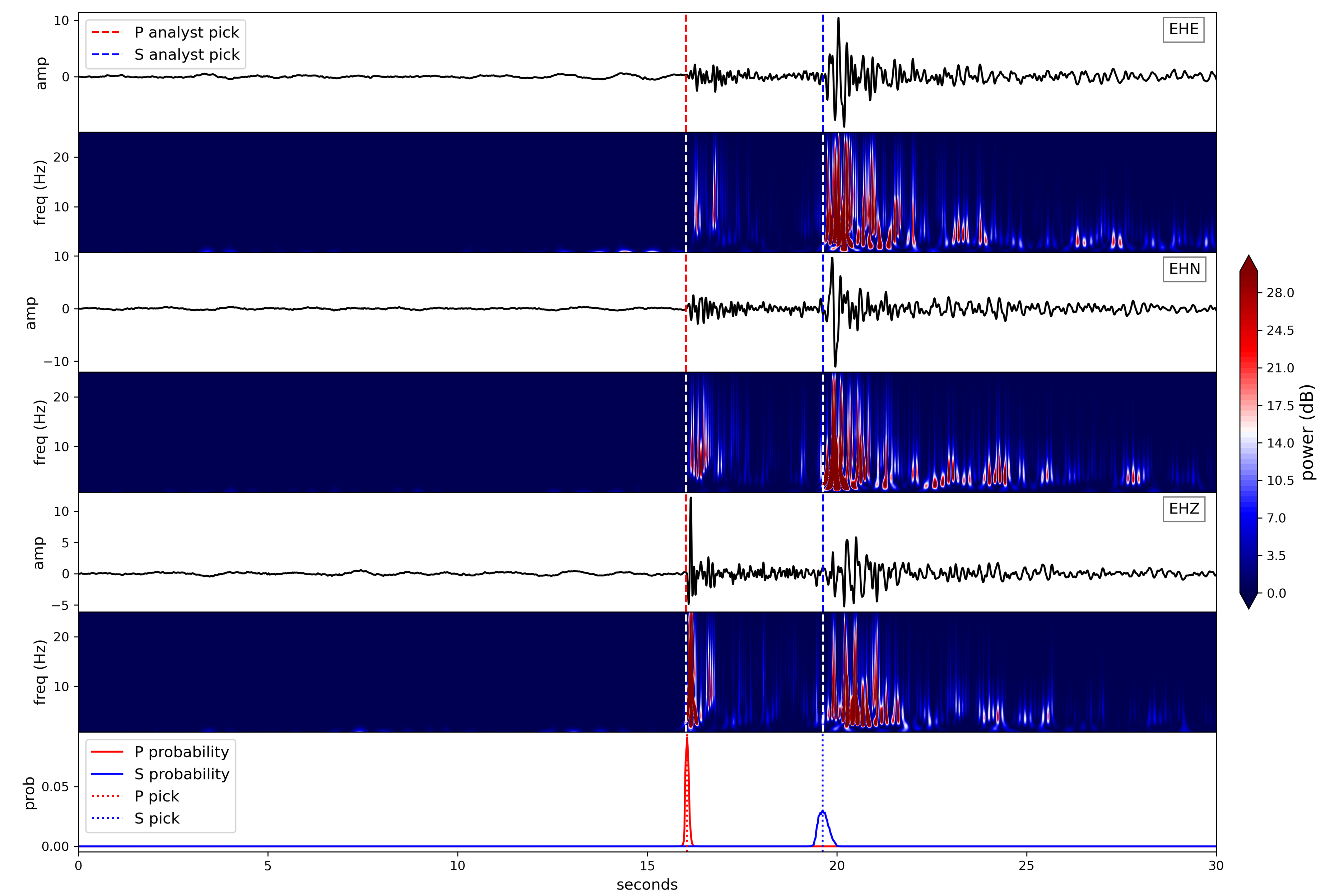

Figure 4. Waveforms with analyst picks (dashed line), calculated spectrograms and model output softmax probabilites with model picks (dotted lines).

model type + input	P-wave .1s	S-wave .1s	P-wave .5s	S-wave .5s
CNN no atrous + waveform	.85	.42	.94	.85
CNN w atrous + waveform	.86	.51	.98	.95
CNN w atrous + spectro	.88	.49	.99	.96

Table 1. Precision for models and input for P and S waves within .1 and .5 seconds.

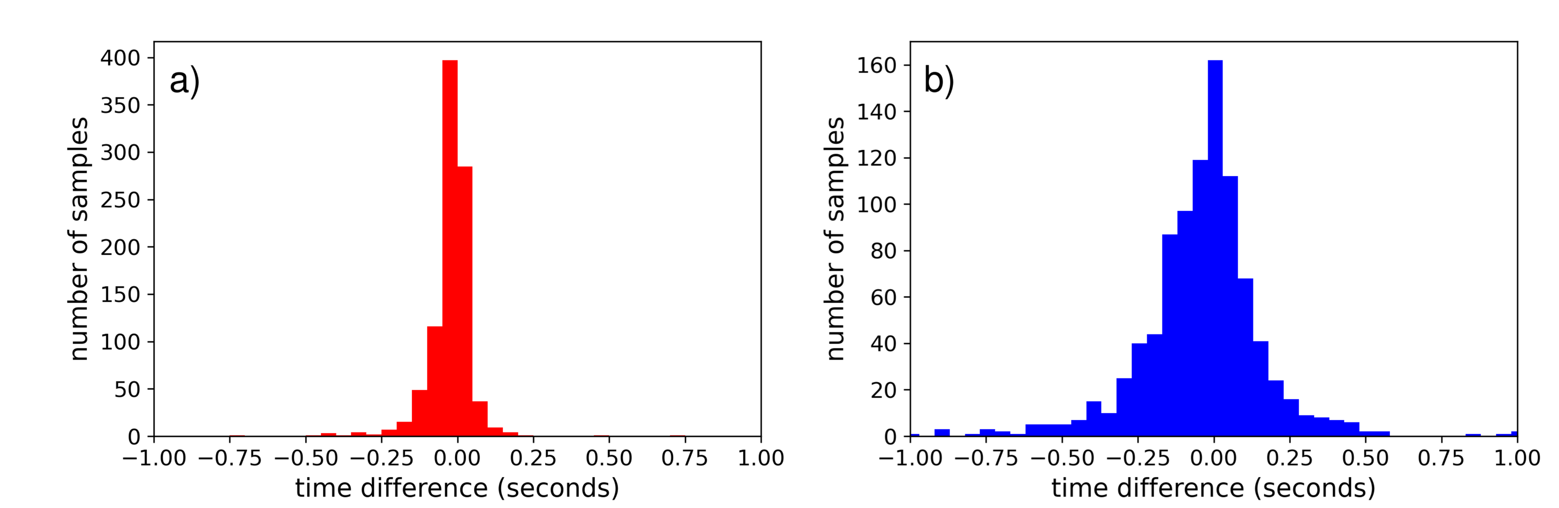

Figure 5. Time differences between analyst picks and model picks for a) P-waves and b) S-waves.