

End-to-end PGA estimation for earthquake early warning using transformer networks

Jannes Münchmeyer^{1,2}, Dino Bindi¹, Frederik Tilmann^{1,3}, Ulf Leser²

¹ GFZ German Research Centre for Geosciences, Potsdam, Germany

² Institut für Informatik, Humboldt-Universität Berlin, Berlin, Germany

³ Institut für geologische Wissenschaften, Freie Universität Berlin, Berlin, Germany

Overview

We analyze prototypical early warning systems in terms of their alert performance. We show practical and theoretical limitations of both source-estimation based and propagation based early warning methods. To overcome these limitations, we propose a hybrid warning method based on deep learning, the transformer network model (TNM). We show the strong performance of our method on two early warning data sets from Japan and Italy.

Earthquake early warning

Early warning algorithms should issue a warning if a certain ground motion threshold will be exceeded during an event. There are four cases:

- Warning is issued, threshold is exceeded (true positive - TP)
- Warning is issued, threshold is not exceeded (false positive - FP)
- Warning is not issued, threshold is not exceeded (true negative - TN)
- Warning is not issued, threshold is exceeded (false negative - FN)

We investigate two summary statistics:

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

Baseline methods

Estimated point source (EPS):

- Estimates the event magnitude from the peak displacement in the first seconds after the onset
- Predicts the shaking using a GMPE

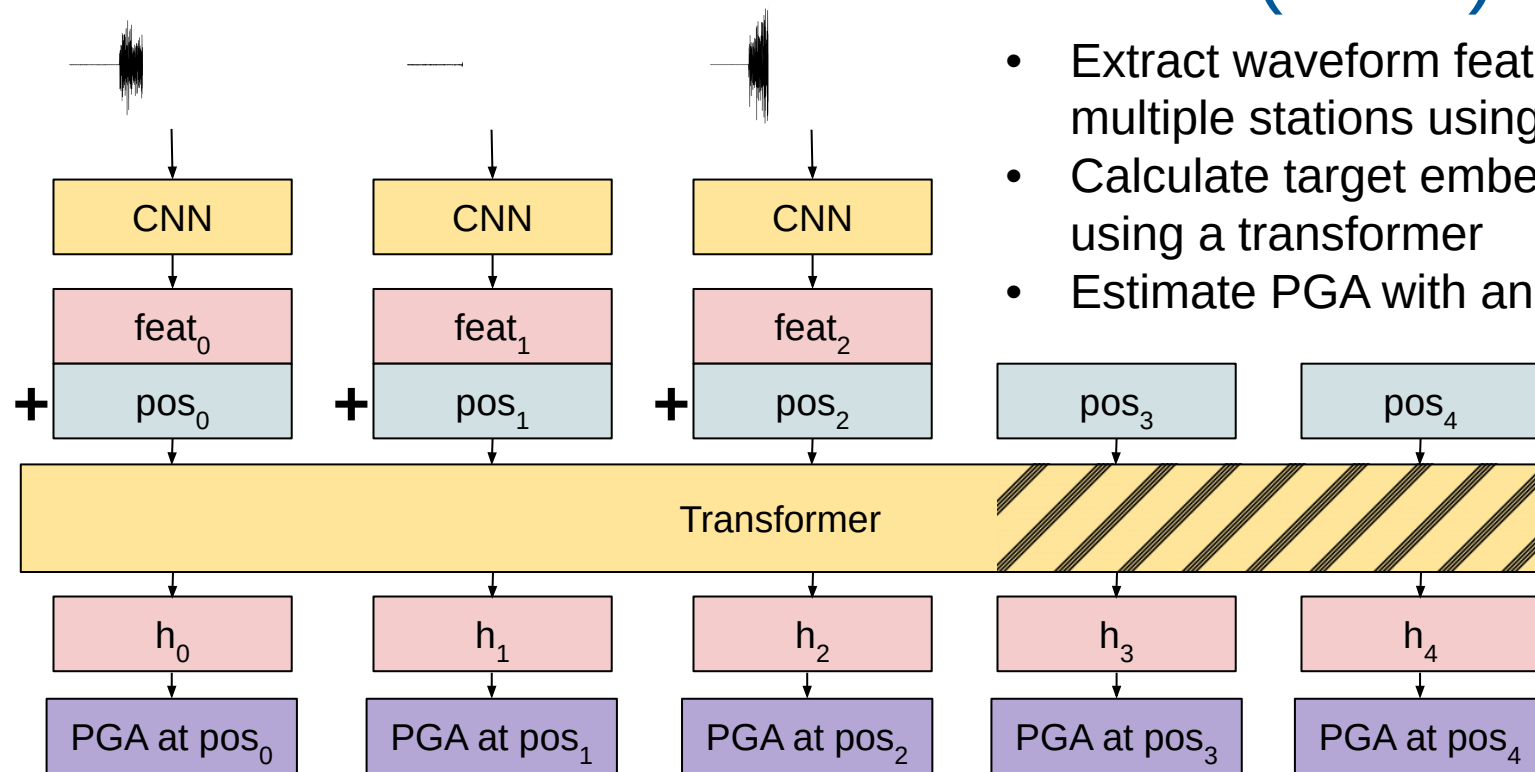
Ground motion prediction equation (GMPE):

- A GMPE using the cataloged magnitude and location
- Provides an upper bound on the performance of source based early warning

Propagation of local undamped motion (PLUM):

- Issues a warning if the threshold is exceeded at a neighboring station

Transformer network model (TNM)

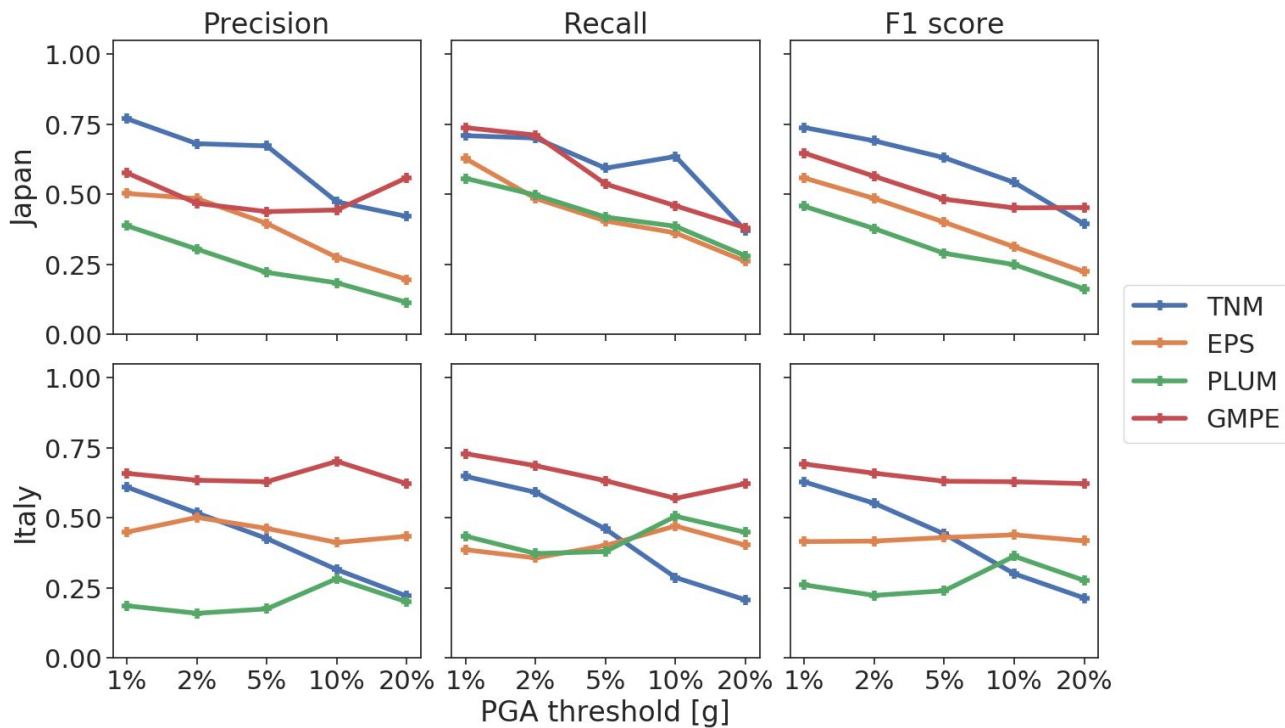


- Extract waveform features at multiple stations using CNNs
- Calculate target embeddings using a transformer
- Estimate PGA with an MLP

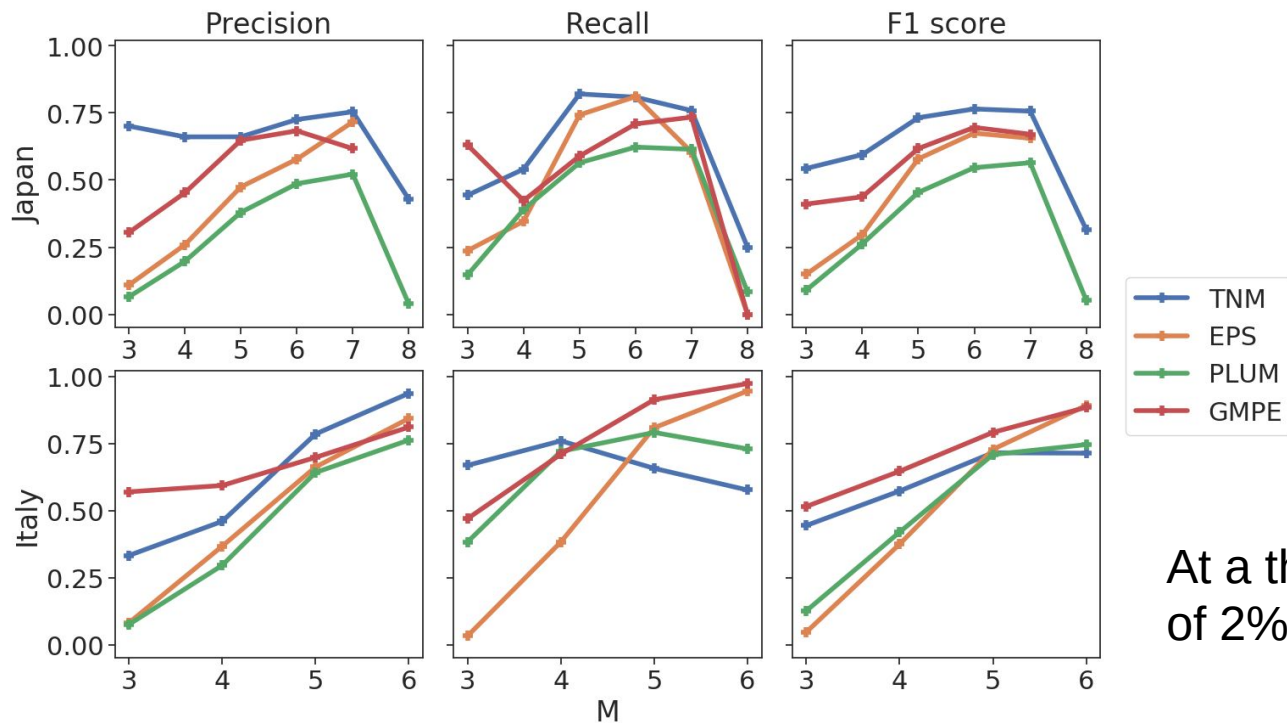
Data

	Japan					Italy				
Years	1997 - 2018					2008 - 2019				
Magnitudes	2.7 - 9.0					2.7 - 6.5				
Events	13,512					7,055				
Unique stations	697					1,080				
Traces	372,661					494,183				
Traces per event	27.6					70.3				
PGA [g]	1%	2%	5%	10%	20%	1%	2%	5%	10%	20%
Traces exceeding	55,618	24,396	6,802	2,223	631	6,379	2,921	888	330	107
Events exceeding	8,761	5,324	2,026	782	238	1,841	1,013	348	120	40

Performance across PGA thresholds



Performance across magnitudes



At a threshold
of 2%g

Results

- All methods suffer degraded performance for smaller magnitude, but degradation is lowest for the TNM.
 - Small events are harder to warn for, as they occur often, but rarely cause stronger shaking.
- The TNM outperforms the baselines clearly, except for the highest thresholds in Italy.
 - Degraded performance for Italy is likely caused by the very small number of training examples with these high levels of PGA in the data set.
- For Japan, the TNM consistently outperforms the GMPE.
 - With the hybrid approach between ground motion modelling and the source estimation, the TNM can constrain the aleatoric variability of the ground motion better than the GMPE using only magnitude and location.