Seismic and infrasound monitoring of military conflicts using machine learning

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Quentin Brissaud, Erik Myklebust, Ben Dando, Bettina Goertz-Allmann, Andreas Köhler, Johannes Schweitzer, and Tormod Kvaerna

Sandia National Laboratories

NORSAR
Exploring the Earth

Information sources

- Hard to get **objective data from ongoing military conflicts** for peace monitoring purposes
- **Existing technologies suffer from cost/biases**:
  - Satellite imagery – expensive and/or lack temporal resolution
  - Videos/Photographs – hard to authenticate
  - Reporters – expensive, dangerous, and limited temporal/spatial resolution
- Alternative to complement existing data streams: **seismo-acoustic monitoring?**

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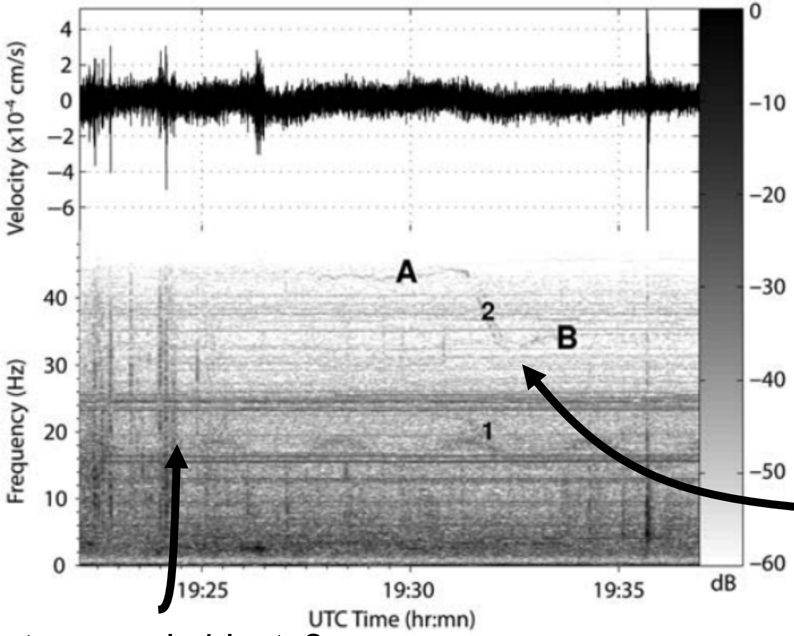
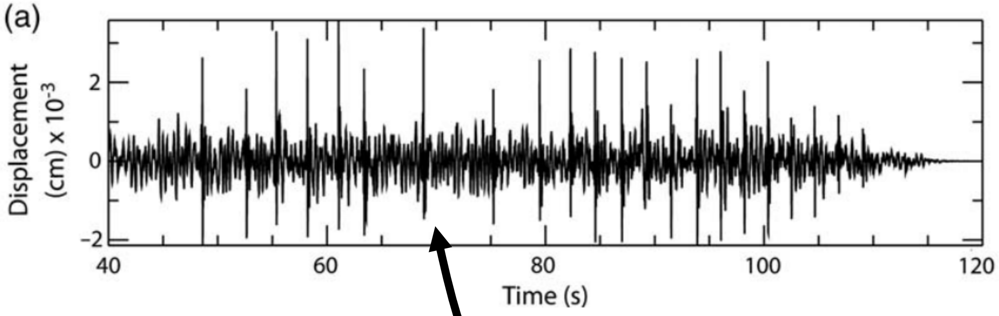
Seismo-acoustic signature of military activity

- There is **a limited number of studies investigating the signature of military activity** such as firearms, vehicles, artillery, and mortar
- For instance, (Aleqbi, 2015) showed example seismic signatures from military attacks
- However, a **methodology to locate events in time/space is absent from the literature**



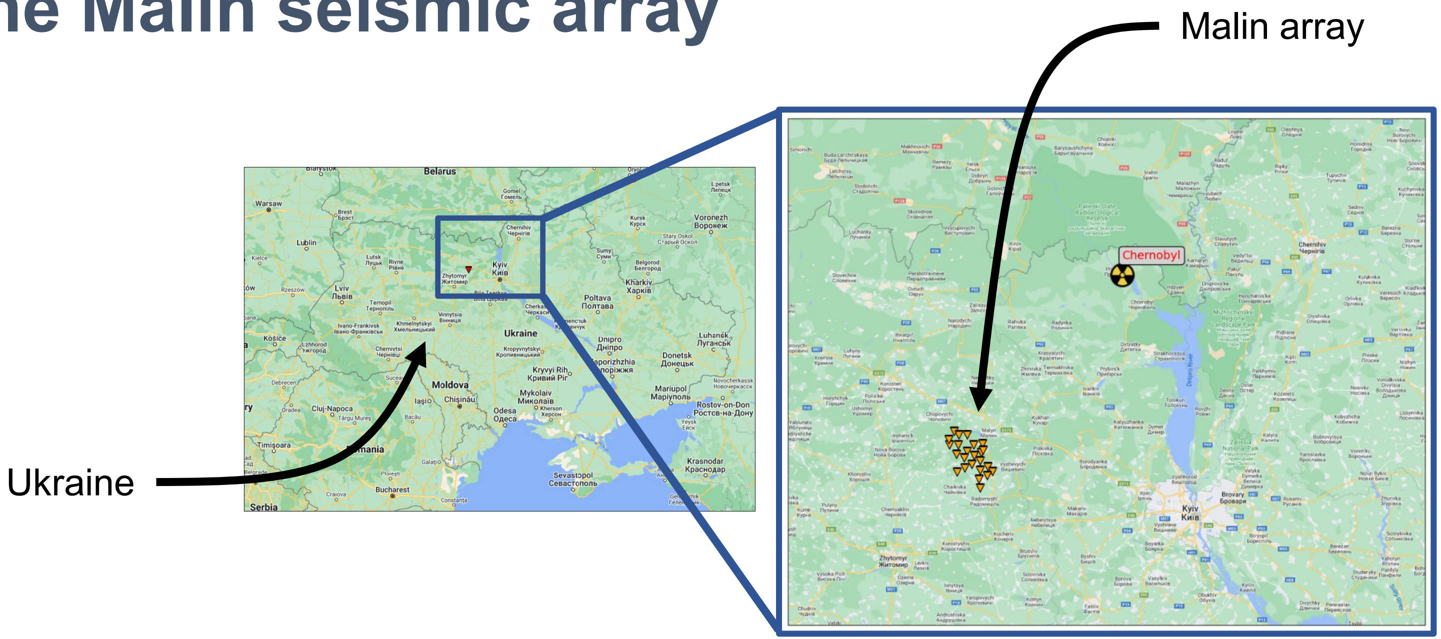


Military rounds?

Helicopter

Mortar muzzle blasts?

The Malin seismic array

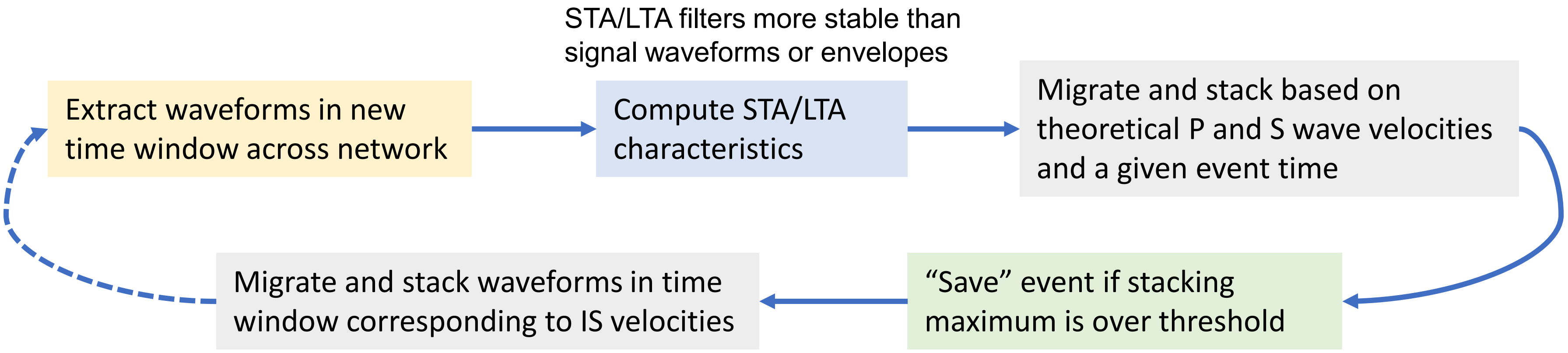


- NORSAR has real-time access to the Malin seismic array (24 sensors) in Ukraine (IMS station AKASG)
- The **Malin array spans over ~27 km with 2 km between each sensor**
- Beamforming challenging at high frequencies but … the **large network aperture can be used to locate non-planar waves**
- **Manual screening, arrival picking, and localization needed** which is slow → Needs automation!

Methodology

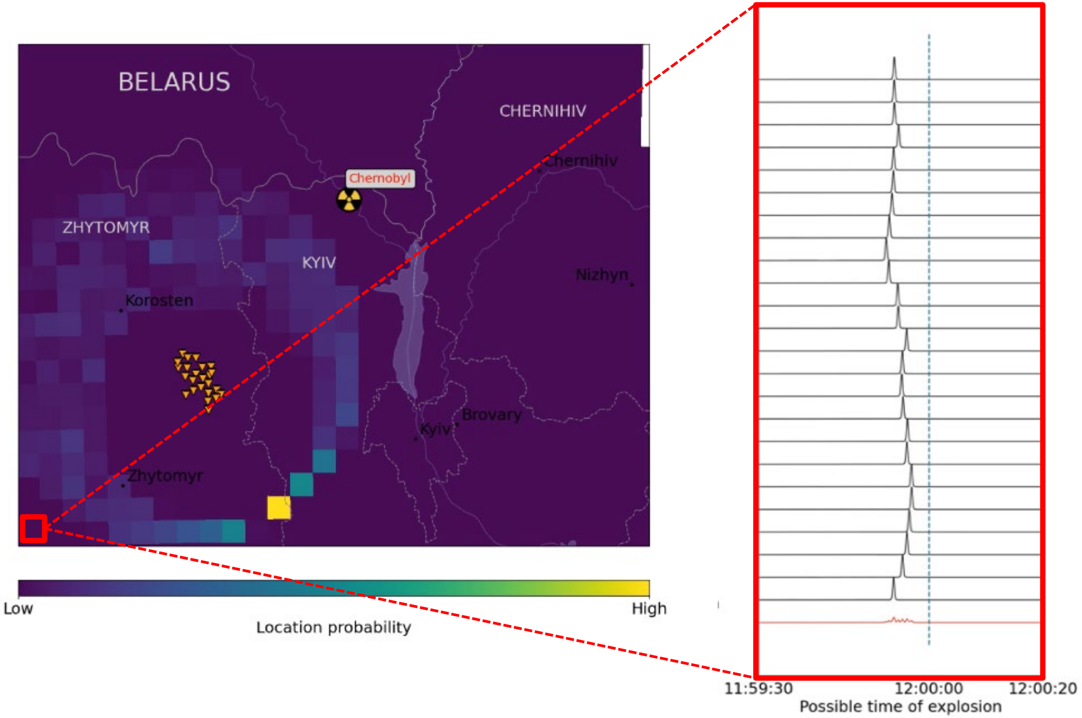
- **Arrival-time based inversions are challenging** because no tailored phase picking procedure exists for ground and atmospheric explosions

- **Solution**: **Migrating + stacking signals in time based on theoretical moveouts**
  - “Detection” and localization performed simultaneously
  - Inversion does not require picks!
  - Fast and adapted to real time applications
  - IS phases were added ad-hoc from detected events



Automatic real-time monitoring of Kyiv region

Low stacking value → low detection likelihood



- For a given origin time and location all signals will stack coherently
- High location precision close to the stations: ~1 km.
- High detectability: magnitudes <0.1 (<5 kg TNT)
- Runs in ~10 minutes behind real-time

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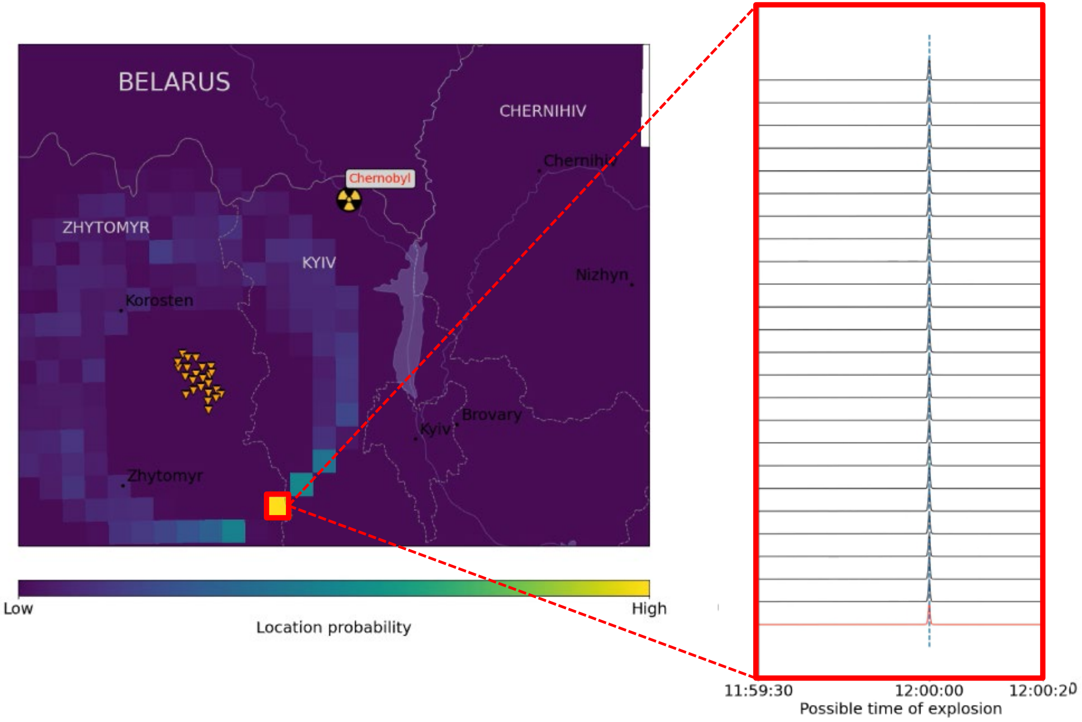
Automatic real-time monitoring of Kyiv region

High stacking value → high detection likelihood



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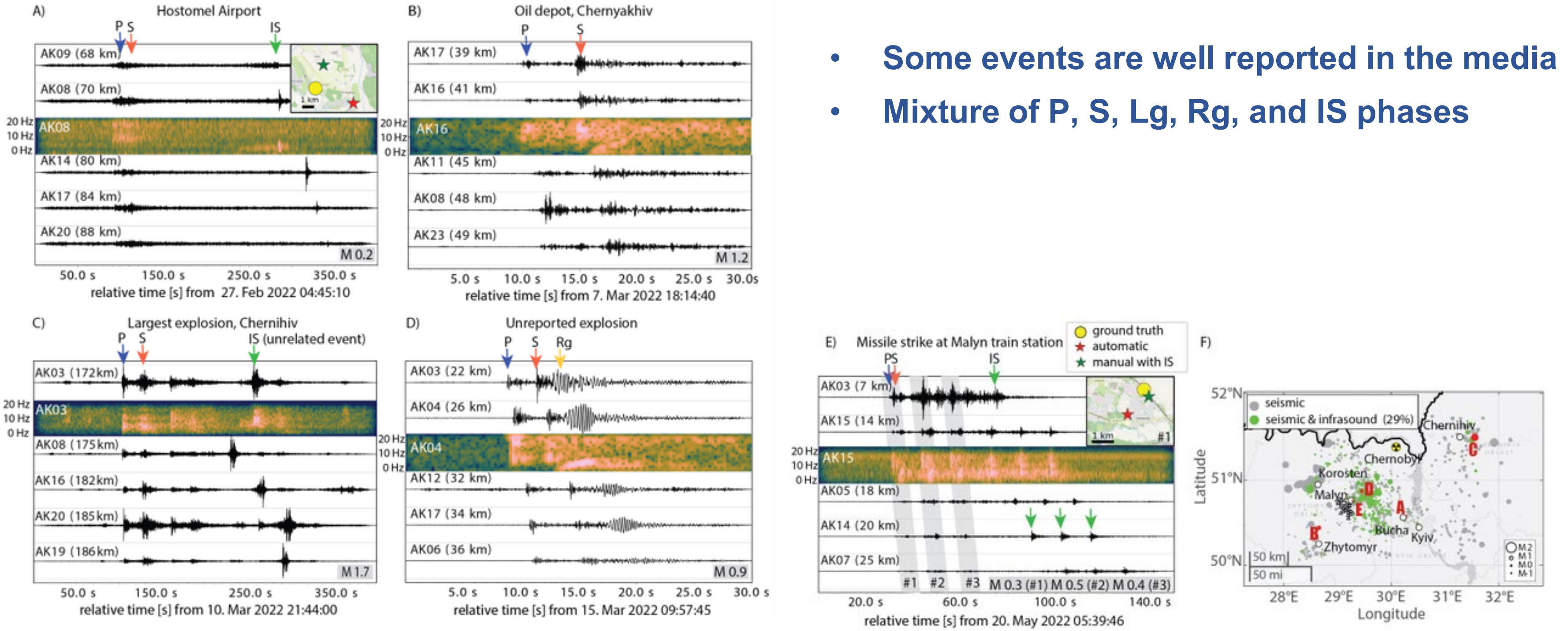
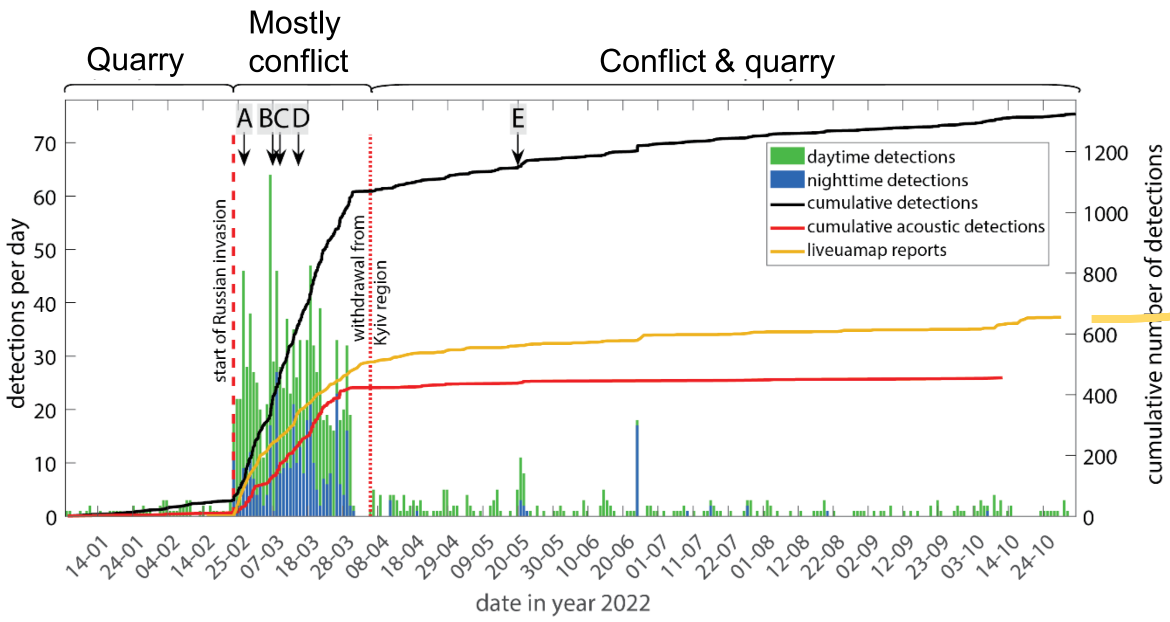
Examples of detected events



- **Some events are well reported in the media**
- **Mixture of P, S, Lg, Rg, and IS phases**

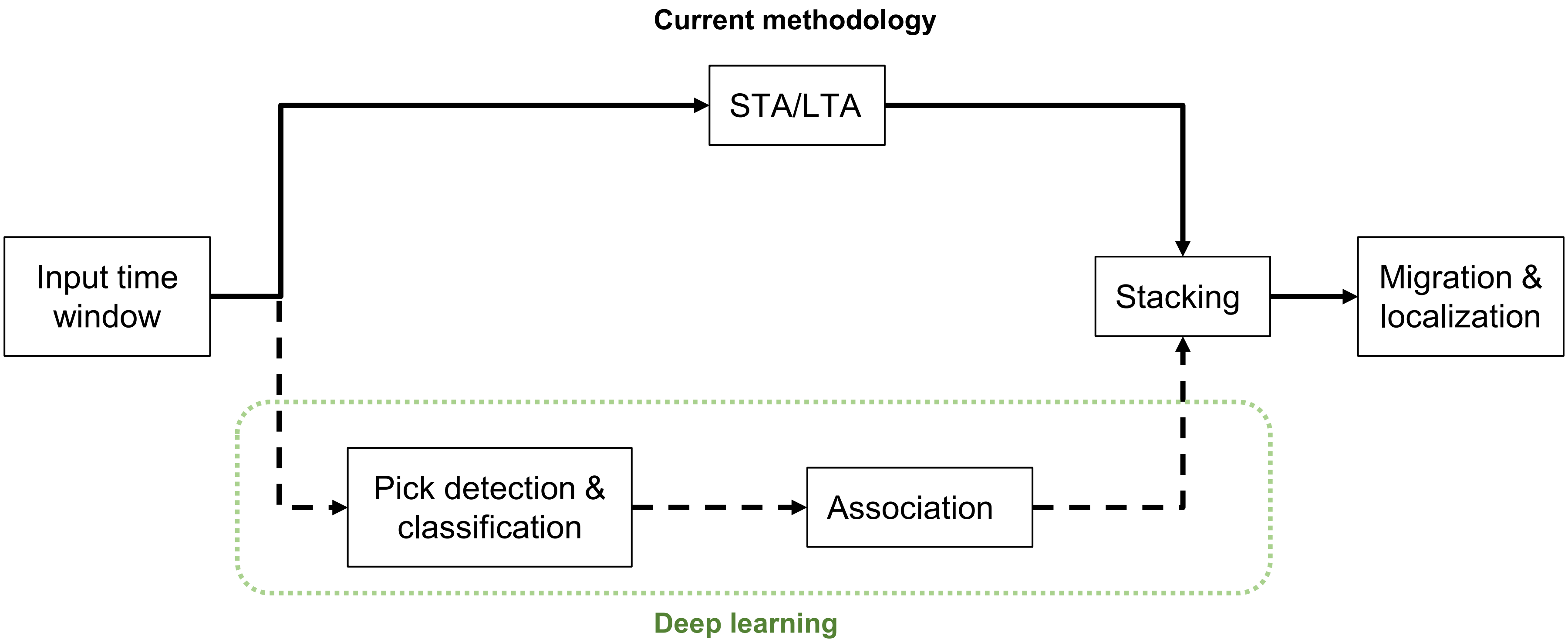
Event catalog

- **Event catalog** here: http://dx.doi.org/10.21203/rs.3.rs-2613796/v1
- Detection confirmed for high stacking values after **migration-stacking** of STA/LTA characteristics
- Yet, **STA/LTA filters** not informed by explosion signal characteristics → **large number of false positives**
- **…But we have a lot of data**



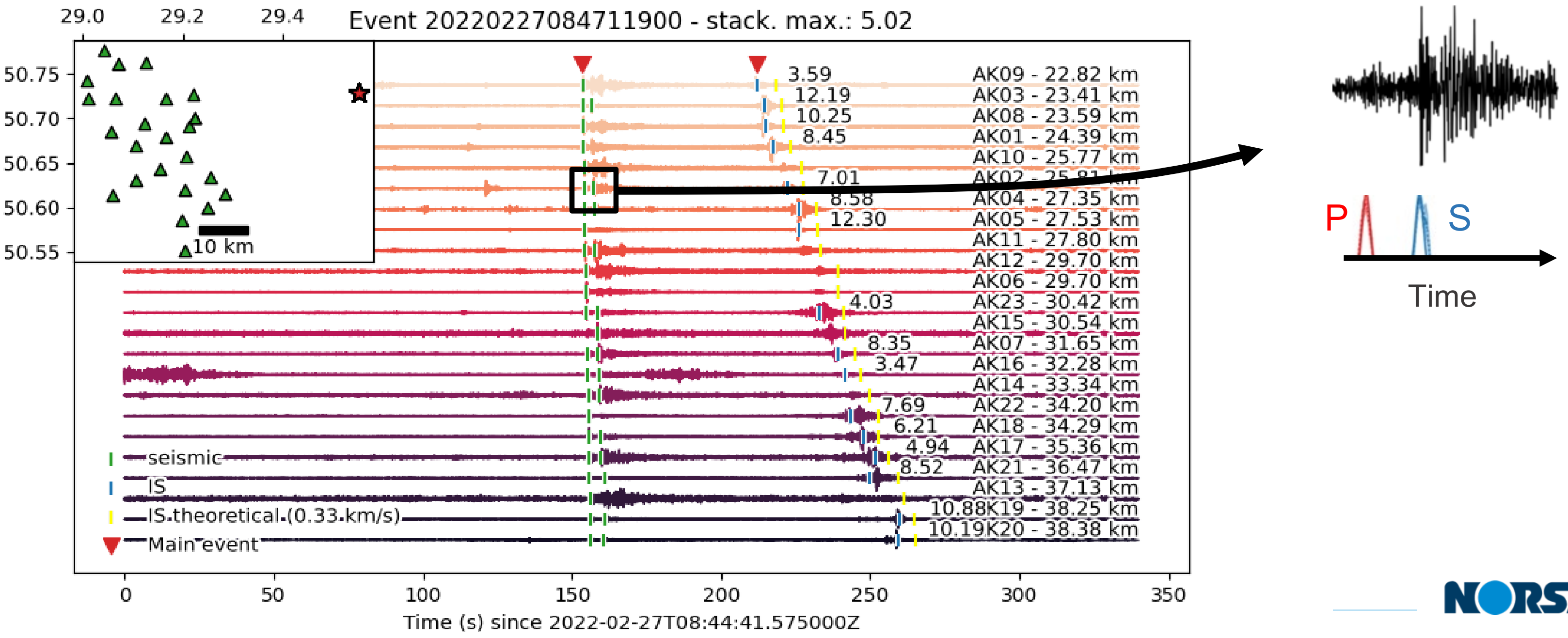
Live Universal Awareness Map
AI-based event extraction from social media

Building a “context”-informed detection methodology



From event catalog to picks & detection probabilities

- Picks were extracted in narrow theoretical arrival time window for each event using STA/LTA filters
- Phase **pick probabilities were built as gaussian functions centered around the STA/LTA pick** with standard deviation varying from 0.5 (P and S) to 1.5 s (IS)



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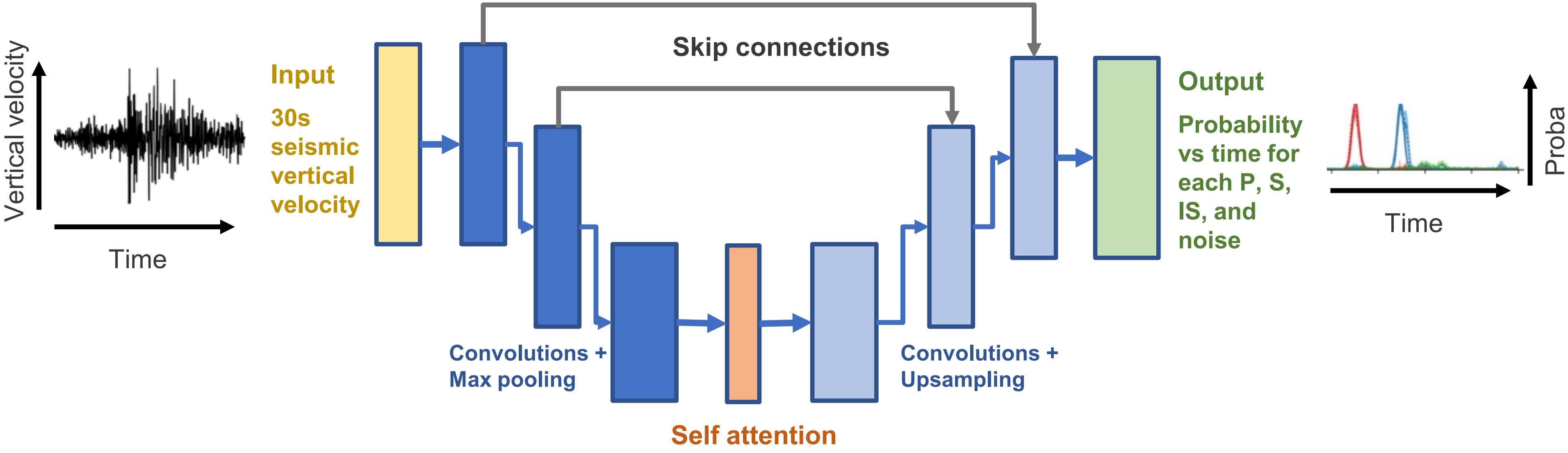
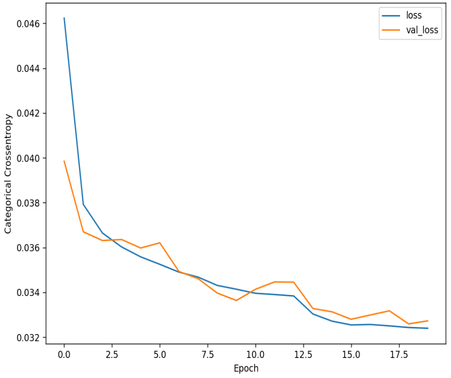
Learning from the data

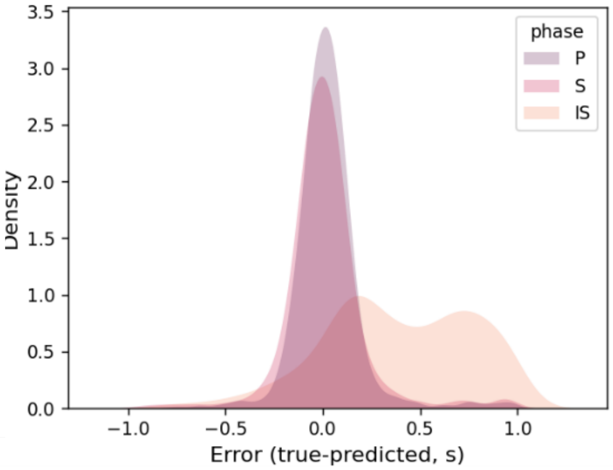
- **Sequence-to-sequence** architecture (U-net)
  - **Input**: vertical seismic records
  - **Output**: probability of given data point to be P, S, IS, or noise
- About **20000 waveforms in training** dataset + augmentation (time shift, random noise, event overlap)

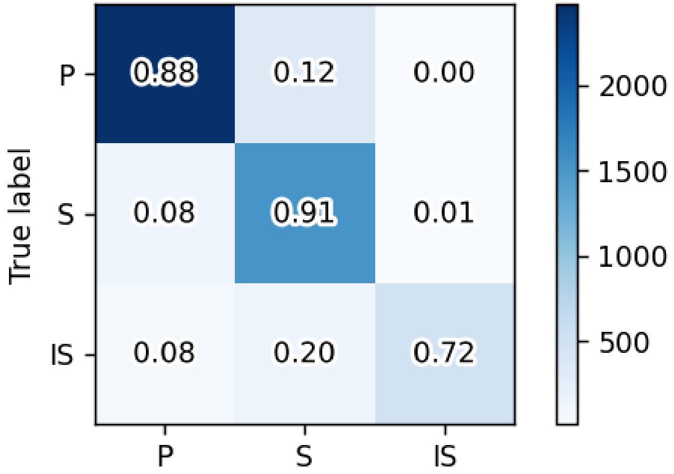


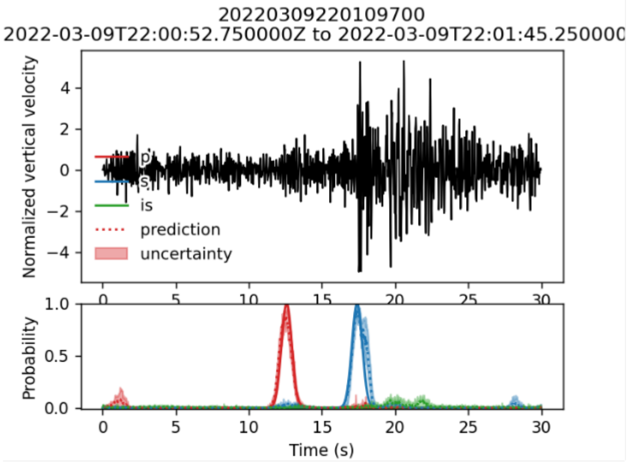
Accuracy assessment

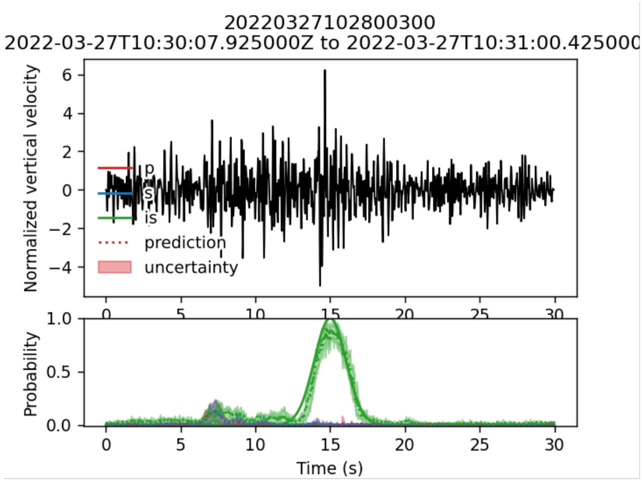
- Errors generally within 0.5s for seismic and 1s for IS
- Asymmetric error distributions for IS
- Misclassifications particularly bad between IS and S





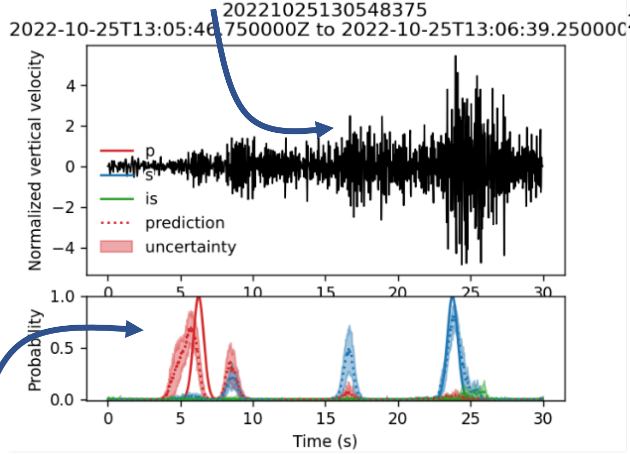


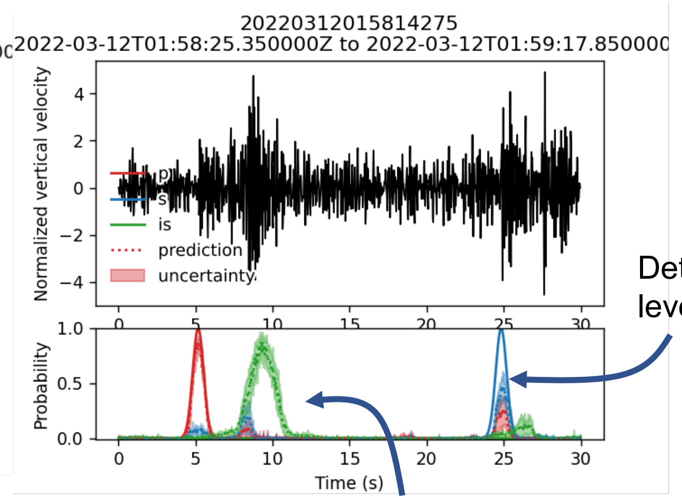




- **More consistent than automatically extracted peaks** + new phases
- Uncertainty provided by dropout at inference stage
- Some phases are misclassified especially S and IS
- The **pick quality can be low in the dataset** which leads to misclassifications

New S phase

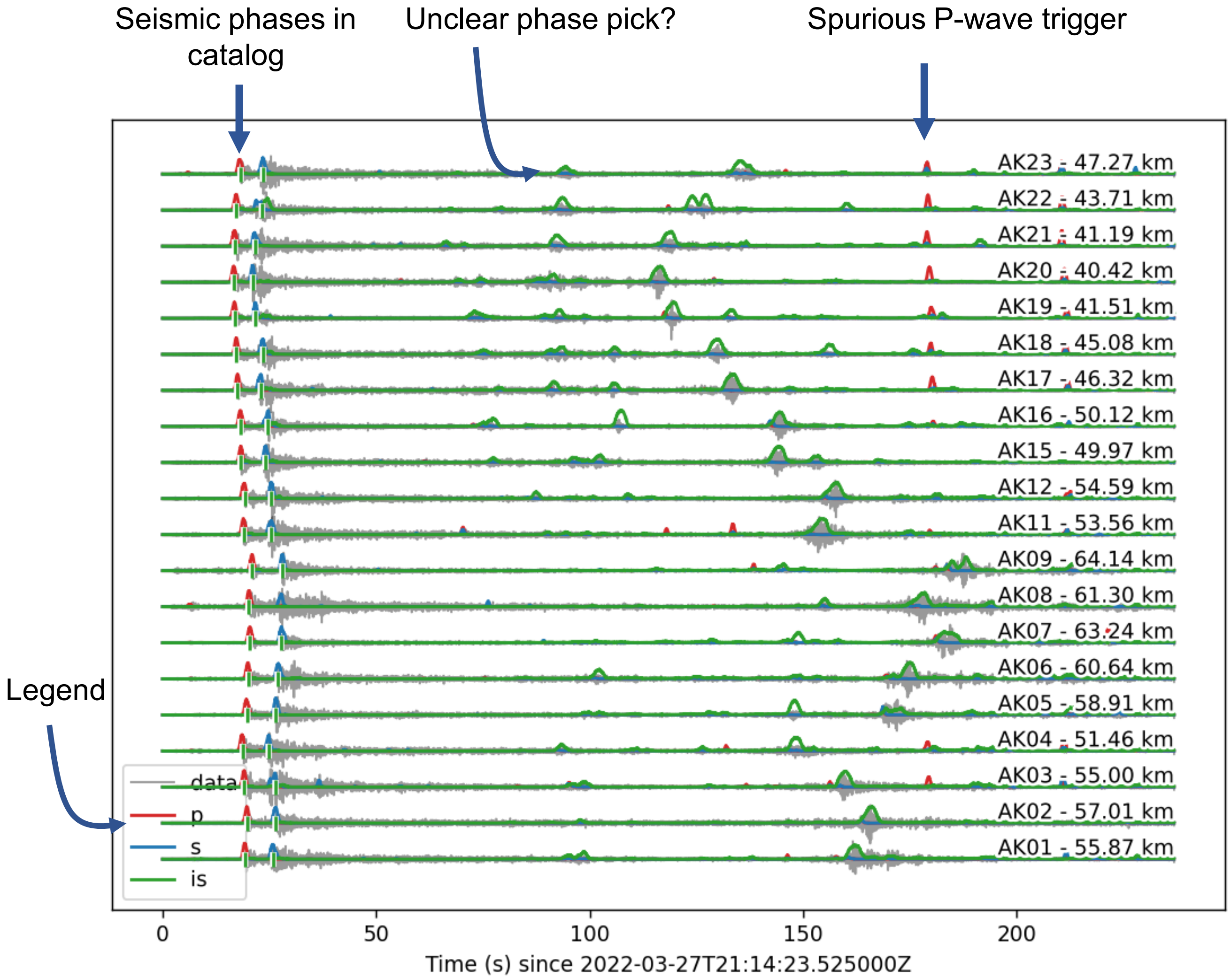




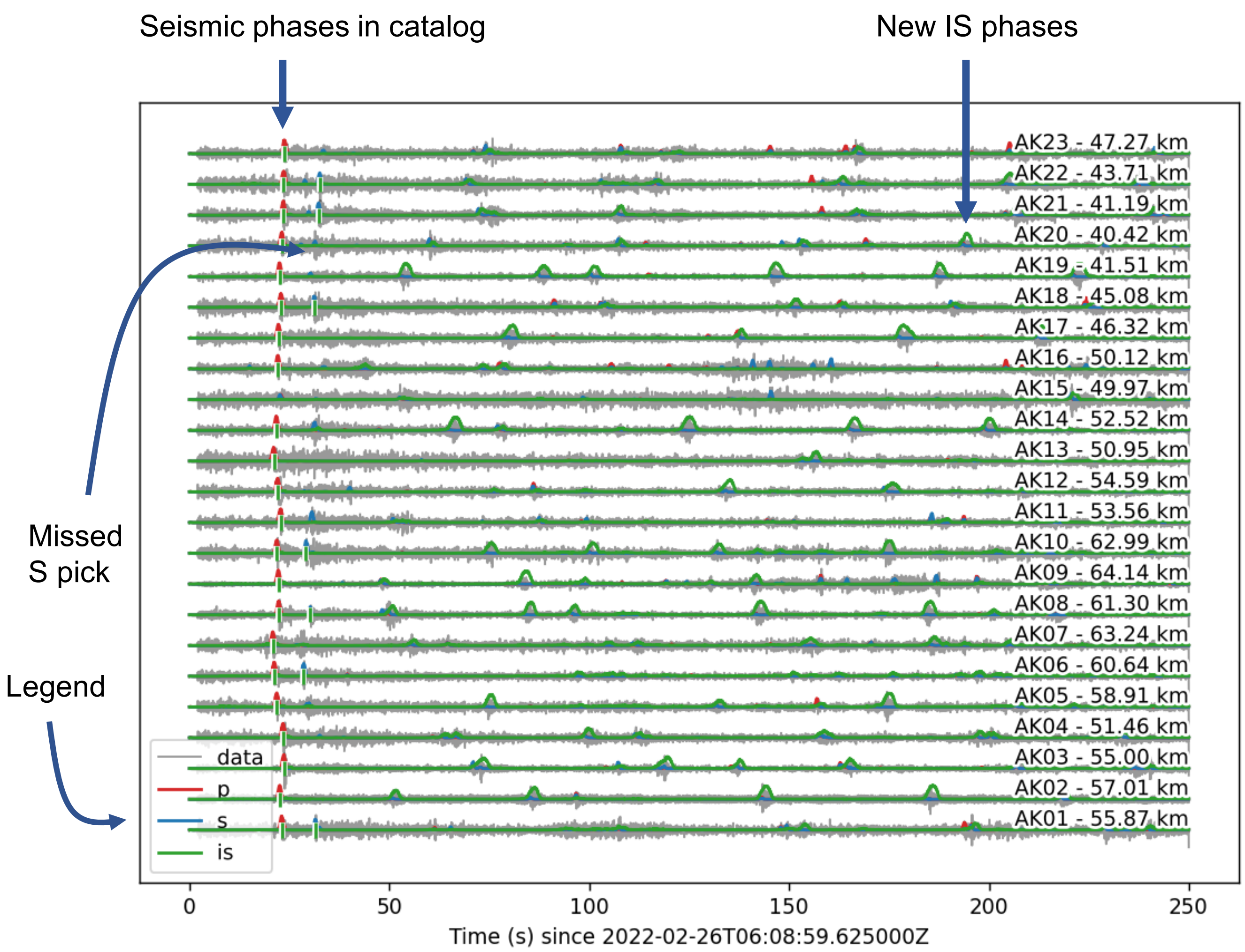
Detection with high level of confusion

Better P phase pick

Probably S pick



- **Phases for events in catalog + phases from new events are detected**
- Some spurious triggers at the transition between moving time windows
- Some picked phases are challenging to confirm

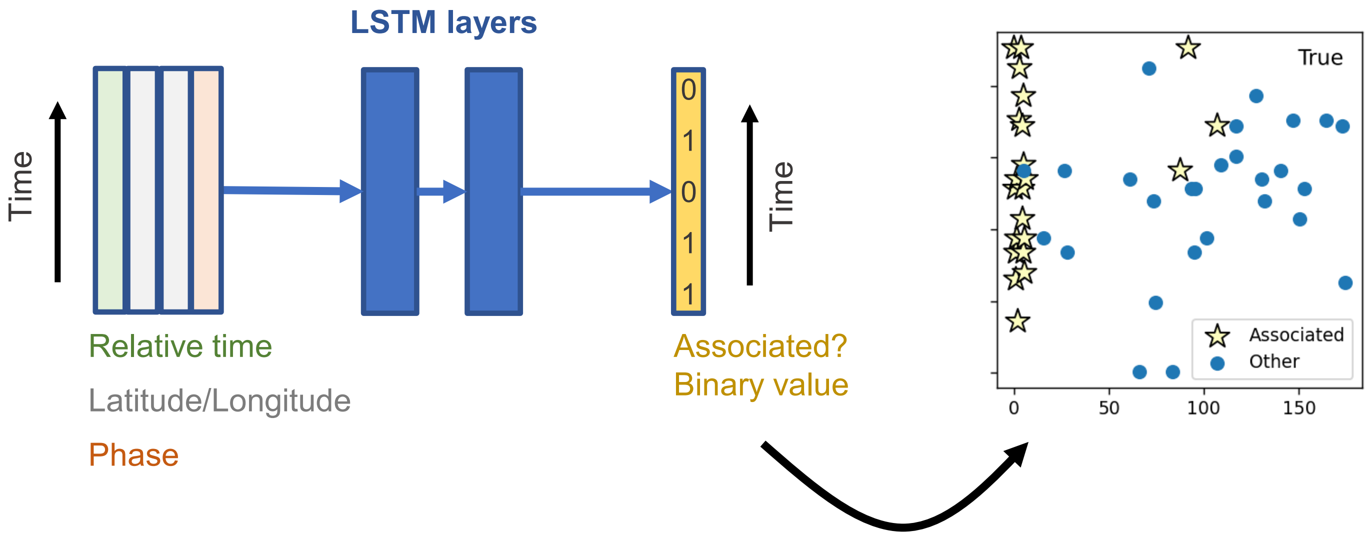


- ➢ **Phases for events in catalog + phases from new events are detected**
- ➢ Some seemingly obvious phases are missed → **inaccuracy in training picks**

- Once phases are detected, we need to **associate them to a specific event** → ongoing work
- Comparisons between stacking migration of STA/LTA vs deep learning ongoing
- **Single-station approach** → how to improve to leverage moveout across network

Associating arrivals

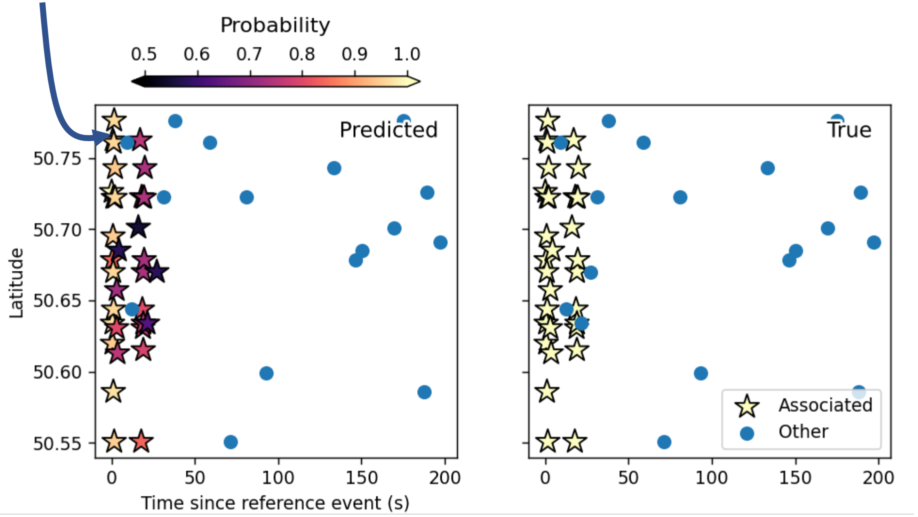
- **Sequence-to-sequence** architecture
  - **Input**: list of relative arrival times, location, and phase
  - **Output**: likelihood of each arrival to be associated with first arrival in time window
- A **lot of augmentation**: fake picks, random phase swap in arrivals, event overlap, noise in arrival time

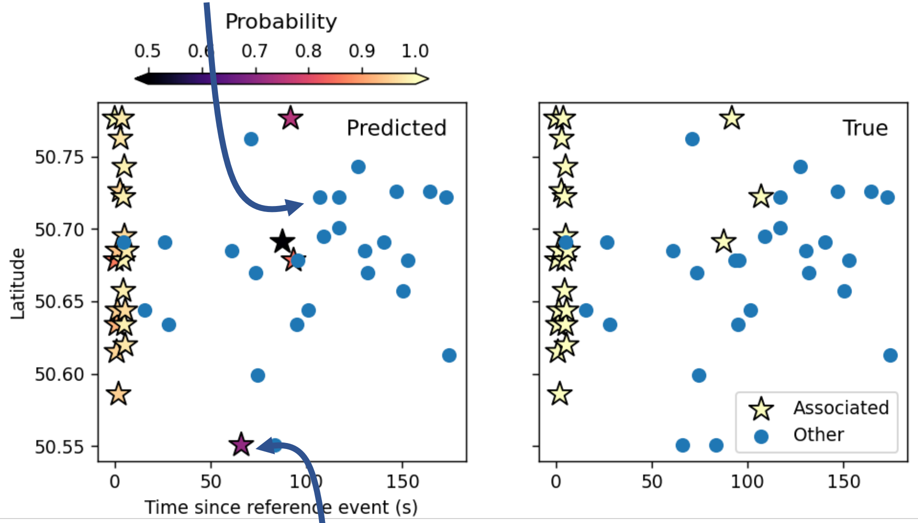


Preliminary results

The larger the time between P and S, the lower the likelihood

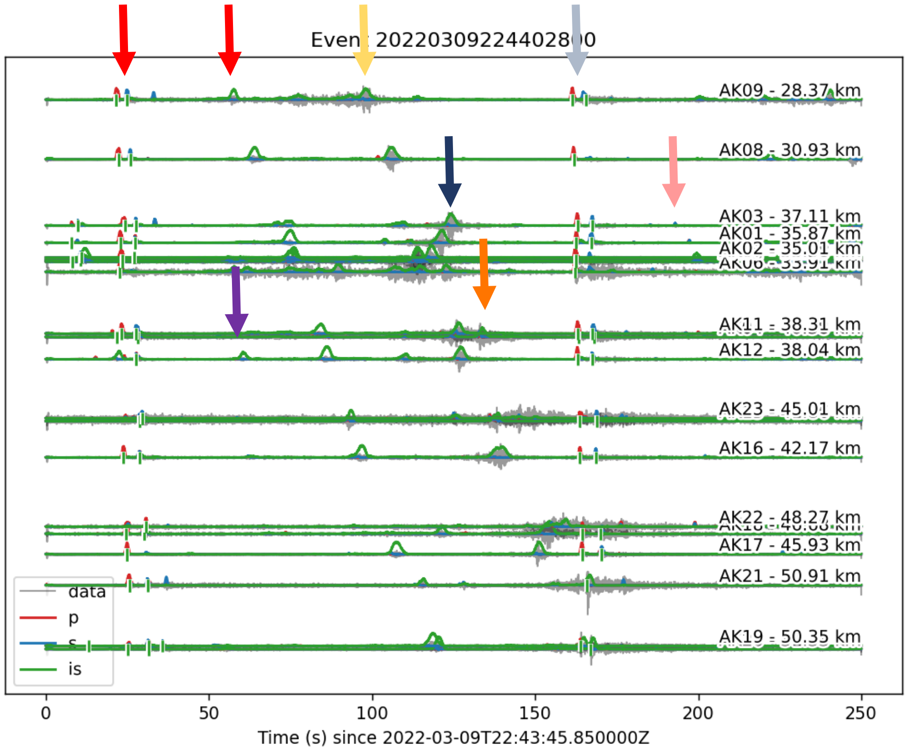
Challenging to capture all IS when numerous events present

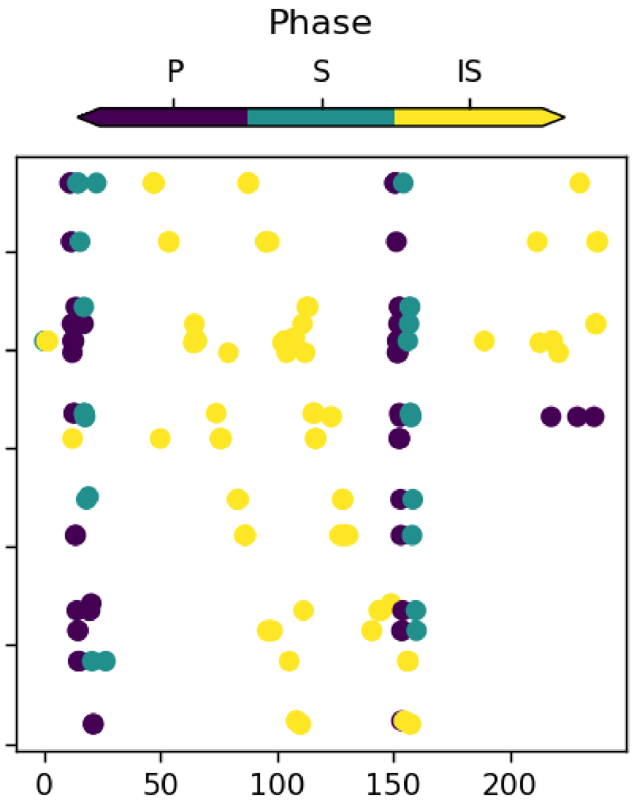




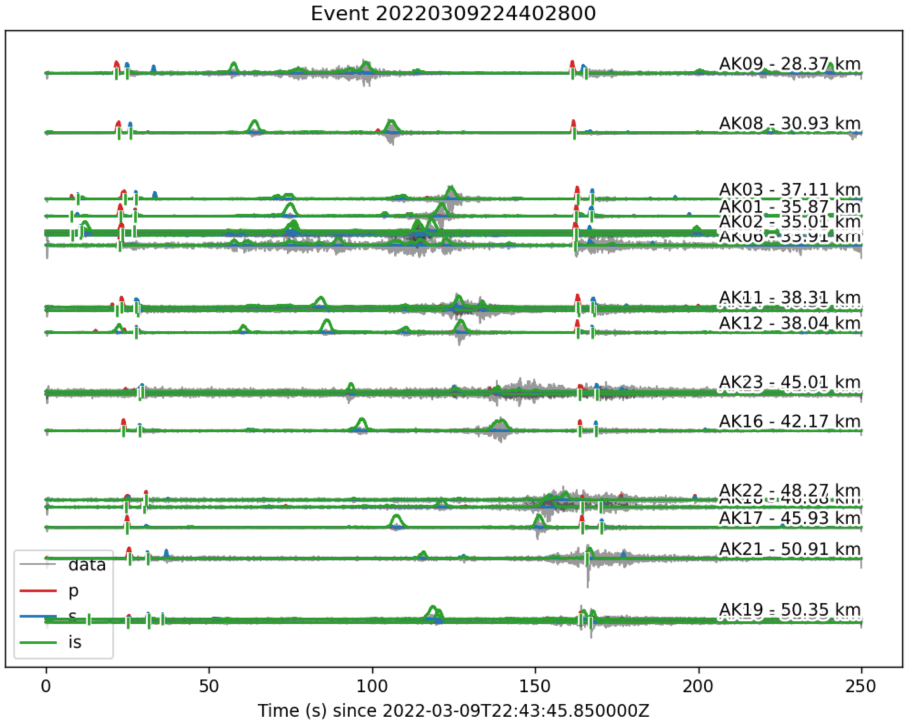
Increased likelihood of false associations

Preliminary results

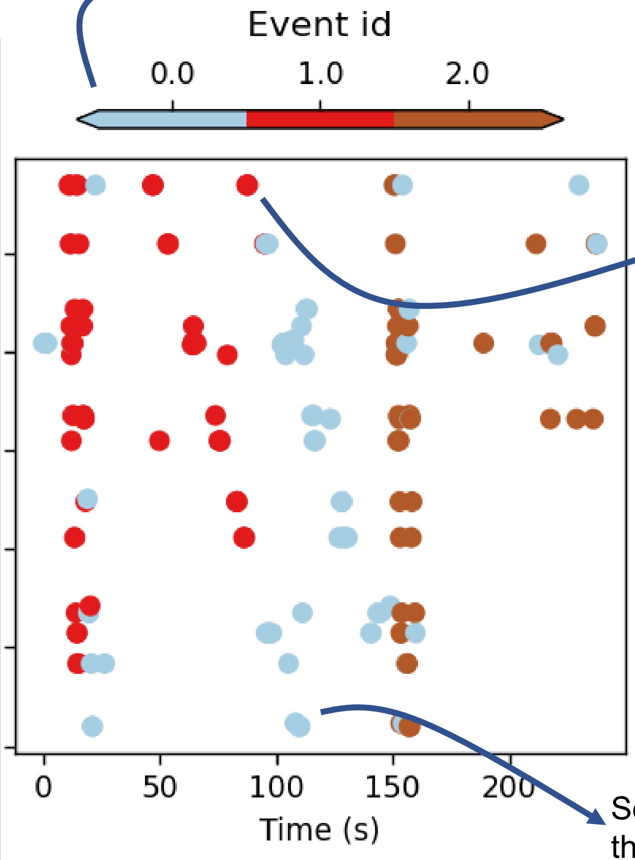




Preliminary results



First cluster corresponds here to "Others"



Need physics to remove outliers

Some of the later phases missed

Perspectives

- Unique and **extensive event catalog from (mostly) conflict-related explosions**
- **Deep learning** approaches might provide an alternative to limit false positives in dataset in real time
- The **automatic extraction of picks introduce significant challenges to train a supervised model**!

- Iterative procedure to **clean up the dataset**: Human first labeling → machine assessment → Human review
- Comparisons **between localization results using STA/LTA vs deep learning**
- The latent space of the detector might inform us about specific source properties
- **Single-station approach** → how to improve to leverage moveout across network

Thank you

We thank the staff at the Ukrainian National Data Centre for the continued operation of the Malin seismic array and for allowing us to publish work based on its data.

How to assess the catalog’s reliability