SnT 2025
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O2.1-752

Dynamic GNNs for Spatio-Temporal Seismic Event Localization and Characterization with Multimodal Integration

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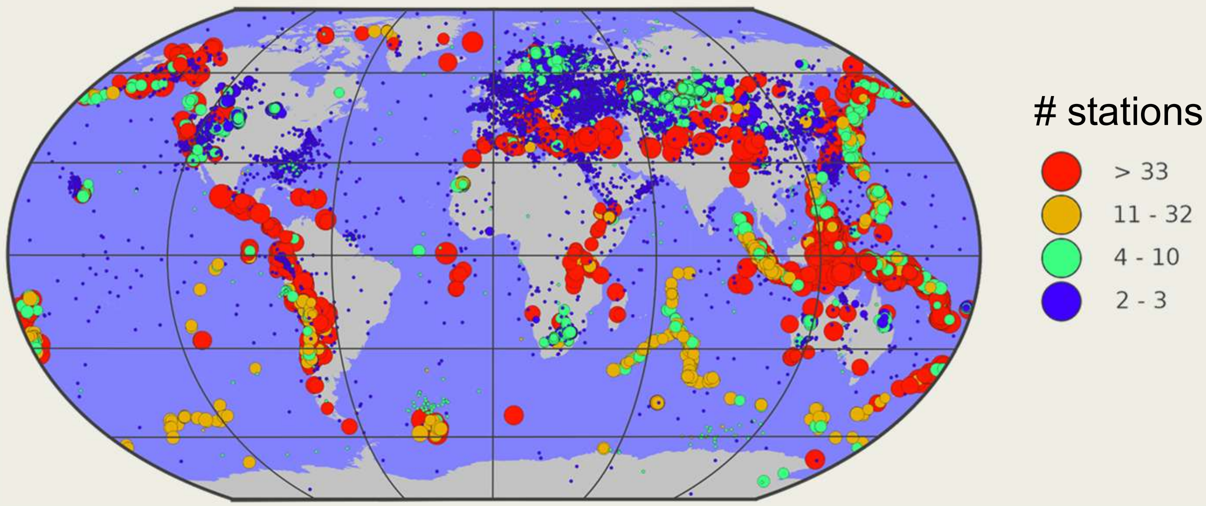
C. Millet, X. Cassagnou, M. Mougeot

I
Preliminaries



Map of seismic events (2014 – 2024) associated with at least one infrasound detection (REB), courtesy of H. Fauvel, CEA.

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I – Preliminaries

●○○○ ***Characterization without graphs***

Using full-wave modelling[1]

1. 10 seismic signals (▲): $1 - 1.5$ kt TNT.
2. 1 infrasound signal (▲): $0.1 - 0.25$ kt TNT.
3. 10^2 videos of blast waves: ~ 0.25 kt TNT.

Based on empirical laws

- Local magnitude (ML): 3.3 (USGS) or 3.8 ± 0.1 (CEA) ⇨ $0.1 - 0.6$ kt TNT.
- Multi-technique analysis[2] : $0.13 - 2$ kt TNT.

Based on AI? ⇨P2.1-716 (Noëlé, CM, Lehmann).

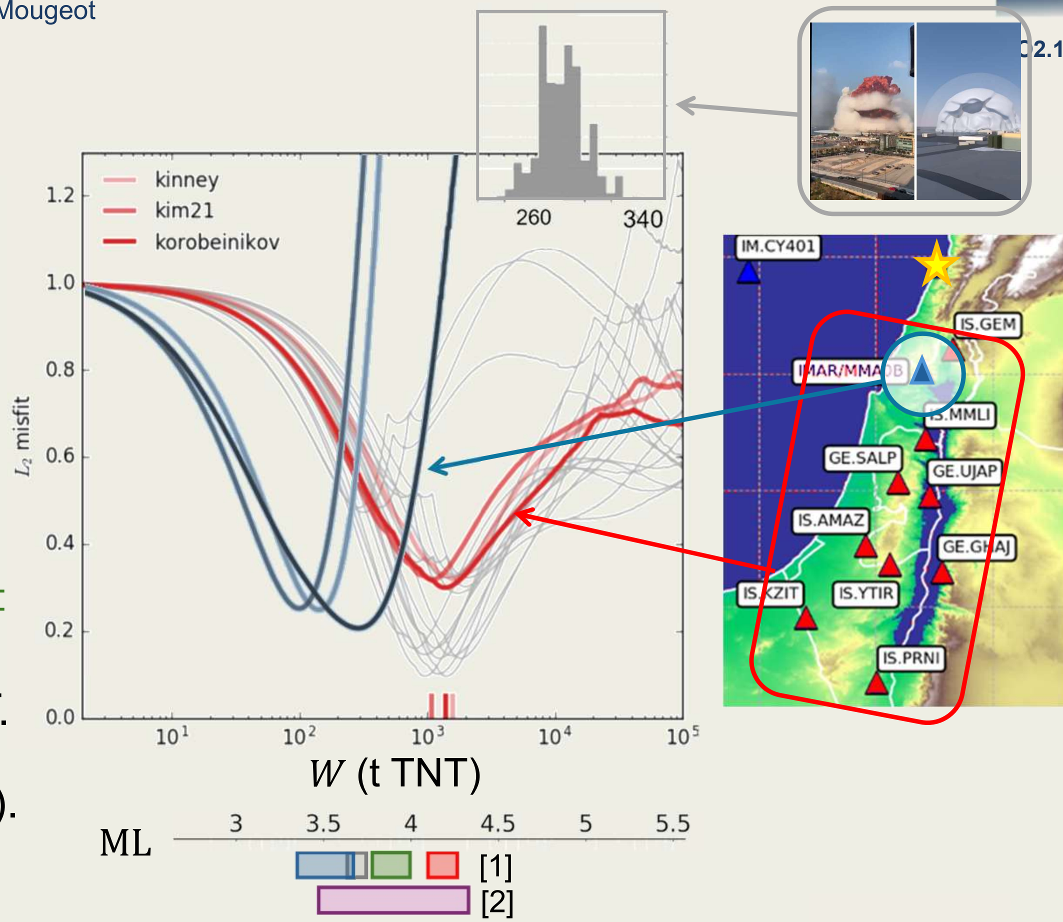

Fig. : Yield vs ML, Beirut (2020).

[1] Millet *et al.*, *ITW*, 2023.
[2] Pilger *et al.*, *Scientific Reports*, 2021.

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I – Preliminaries

○●○○ *Graphs*[3] *are everywhere*

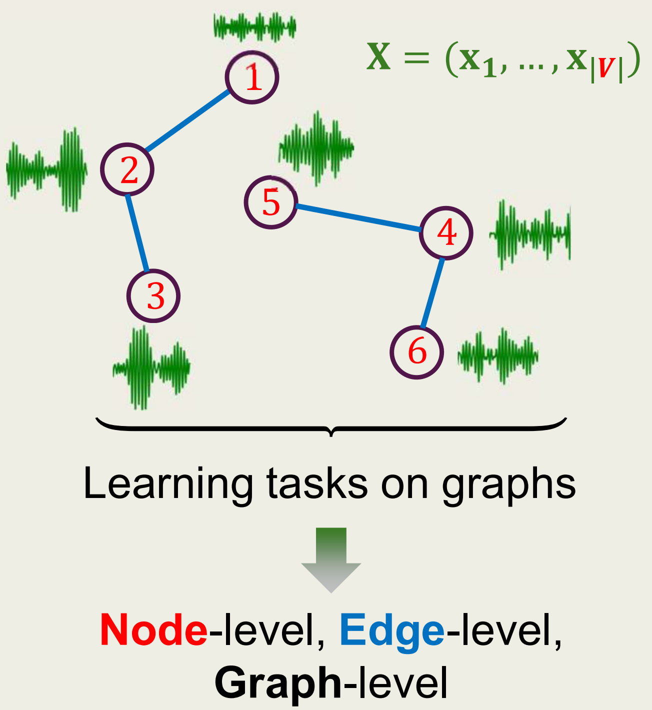
Graph = (vertices, edges) = (V, E)

- Universal representation for structured data.
- Social networks (people, messages), biology (atoms/proteins, chemical bonds), sensor networks (stations, geodesic), recommendation (users/items, ratings), transportation (cities, roads/flights), ...

Nodes and edges can carry information $\mathbf{X} \in \mathbb{R}^{|V| \times C}$

- Node **features** $(\mathbf{x}_j \in \mathbb{R}^C)$: age/interests, charge/position, waveform/noise level, traffic load/delay at airport, ...
- Edge **features** $(\mathbf{e}_{ij})$: distances, correlations, similarities, ...

Fig. : Example of (V, E).



[3] https://ecoles-cea-edf-inria.fr/files/2025/06/GNN_2025_SummerSchoolCEAEDFINRIA_Millet.pdf

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I – Preliminaries

○○●○ *An example of distributed data*

What we know

- **Vertices (△):** French seismological network*.
- **Features:** Station waveforms, positions of stations.
- **Data set**: $n \sim 10^5$ seismic events (REB) recorded during 1995 – 2024.

What we don't know (and want to predict)

- **Edges**, **relevant stations**.
- **Characteristics** $\mathbf{y}$ of new earthquakes (magnitude ML, depth, location, $\ldots$), i.e. $\mathbf{y} = f(V, E, \mathbf{X})$.
- **A way to adapt!** Depending on the data available, relevant stations and **edges** can change.

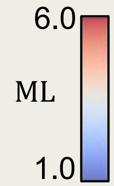
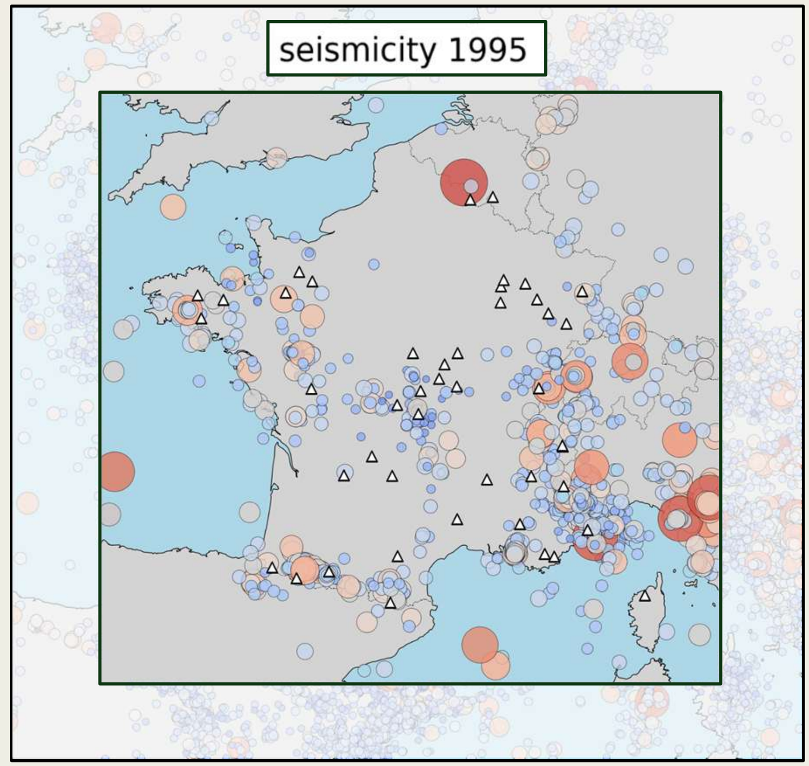


Fig. : EQ, FSN*, 1995 – 2024



*FSN: French Seismic Network.

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I – Preliminaries

○○○● f = Graph Neural Networks (GNNs)

Dynamic GNNs

- **Idea:** learn the **edges** implicitly during the training process using Graph Convolution (GC) layers:

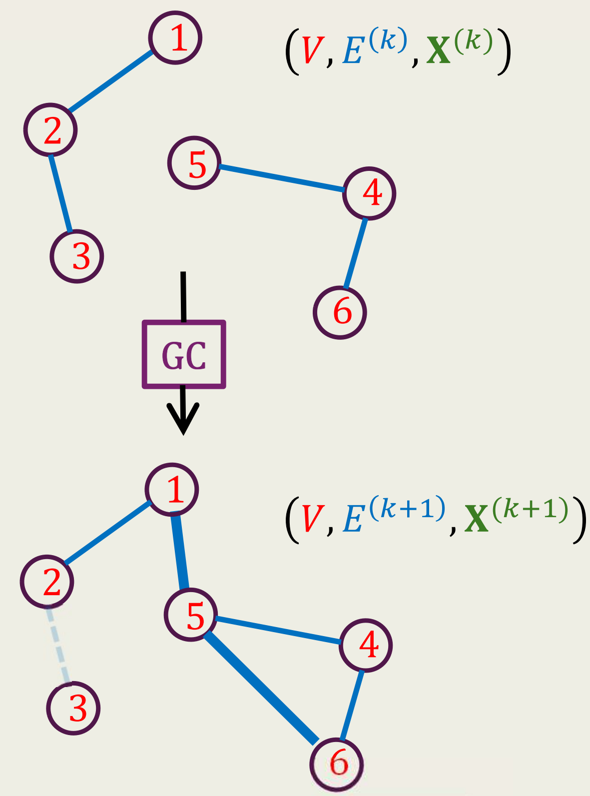
$$\boxed{(V, \emptyset, \mathbf{X}) \to \cdots \to \left(V, E^{(k)}, \mathbf{X}^{(k)}\right) \to \cdots \to \left(V, E^{(N)}, \mathbf{X}^{(N)}\right)}$$

- **Interpretability**: learning $E^{(N)}$ offers a data-driven way to assess station relevance for each prediction (y_i).

Other advantages of GNNs

- Do not require a **fixed** input: **stations** can be added/removed, or repositioned over time; **recording quality** may change.
- Can handle graphs with **different** sets of **vertices** → *transfer* learning from one region to another.

Fig. : Dynamic graphs and Graph Convolution.



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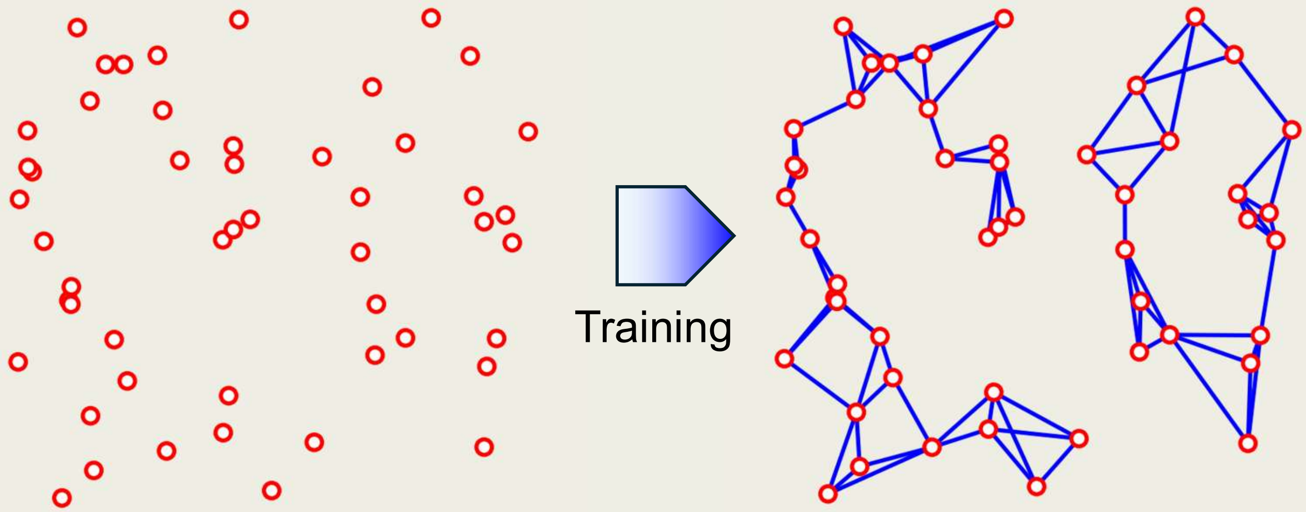
II
Graph Neural Networks



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II – Graph Neural Networks

●○○ *How can we build edges? Theory*

The **Message Passing (MP)** paradigm:

$$\mathbf{x}_j^{(k)} \xrightarrow[\text{AG + UP}]{} \mathbf{x}_j^{(k+1)}.$$

- The **AG**regate step over the κ-hop neighbors controls the receptive field at each layer: $\mathrm{AG} = \max(.), \sum(.), \ldots$
- The **UP**date step refines the aggregated message by combining it with the node's current state.

Who are the neighbors $\boxed{i \in \mathcal{N}_j\textbf{?}}$

- **Fixed**, through κ-nearest neighbors graph constructed from the geographic distances $\mathbf{p}_i - \mathbf{p}_j$.
- **Adapted**, using similarities $\mathbf{x}_j$ between features.

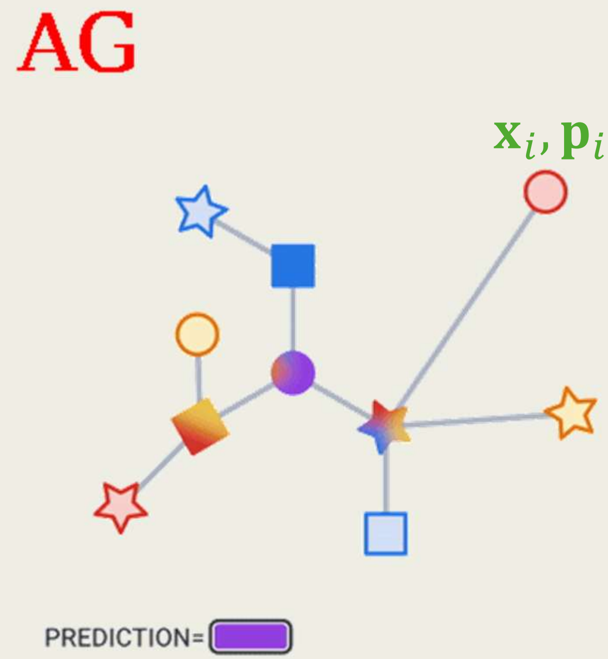

Fig. : Scheme of MP (Google Research Blog. 2024).

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II – Graph Neural Networks

○●○ *The Spatio-Temporal GC block - Practice*

Edge generation: each node j is connected to $i \in \mathcal{N}_j$ which show maximum similarity

- Geographic proximity: nearby stations often observe similar signals $\to \mathcal{N}_{\text{geo}}$.
- Feature similarity: distant stations can exhibit similar waveform characteristics $\to \mathcal{N}_{\text{sig}}$.

Feature update: max pooling along the edges ji

$$\mathbf{x}_j^{(k)} \to \underbrace{f\left(\mathbf{x}_j^{(k)}\right)}_{\text{global}} + \underbrace{g(\mathbf{x}_i^{(k)} - \mathbf{x}_j^{(k)})}_{\text{local}} \to \mathbf{x}_j^{(k+1)}.$$

⇨4 neural networks $(f, g) \times 2$ neighbors.

Multi-scale embedding: features produced by each STGC layer are concatenated.

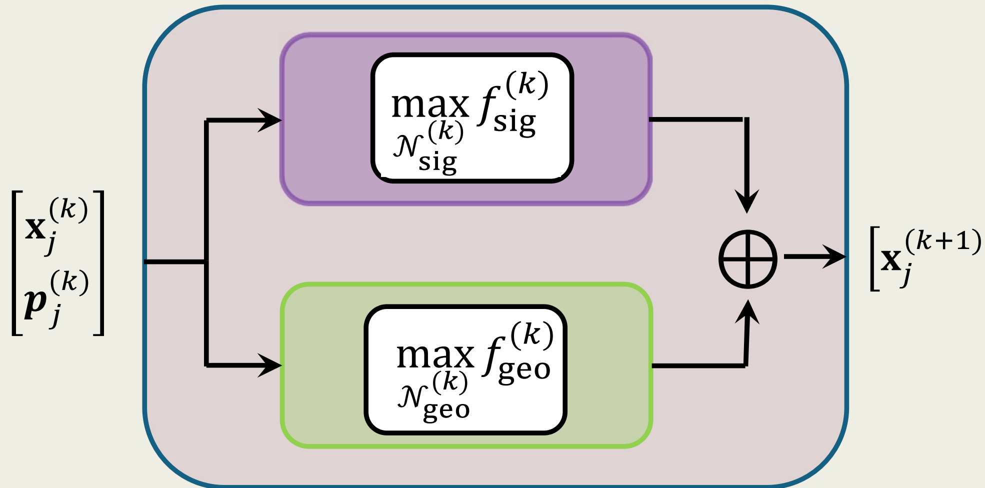

Fig. : STGC Block.

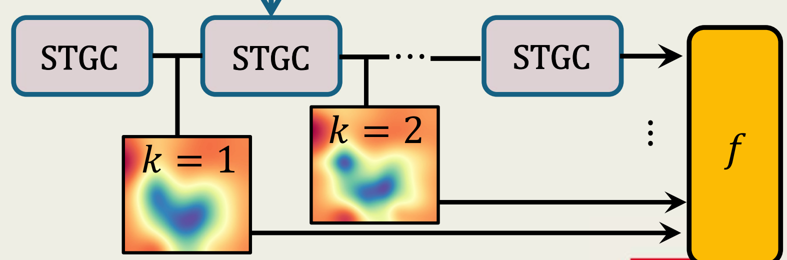

Fig. : multi-scale embedding.

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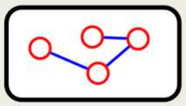
II – Graph Neural Networks

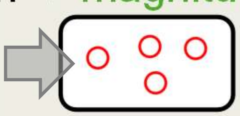
○○● *Overview of the architecture*

Dynamic-GNN



1. **Convolutional Encoding**: extraction of features using a CNN-based encoder ⇨ dim. reduction ⇒ $\mathbf{x}_i$.
2. **Spatial feature fusion** through N steps of STGC ⇨ perceptive field is gradually enlarged.
3. **Aggregation**: condenses the information into a single fixed-size vector: $\mathbf{z} = \max_j \mathbf{x}_j$.
4. **Prediction**: extraction of graph-level seismic information ⇨ magnitude, depth, location ($= \mathbf{y}$).

Edgeless-GNN



② STGC are substituted to a MLP with $\mathbf{X}||\mathbf{P}$[4] as input.

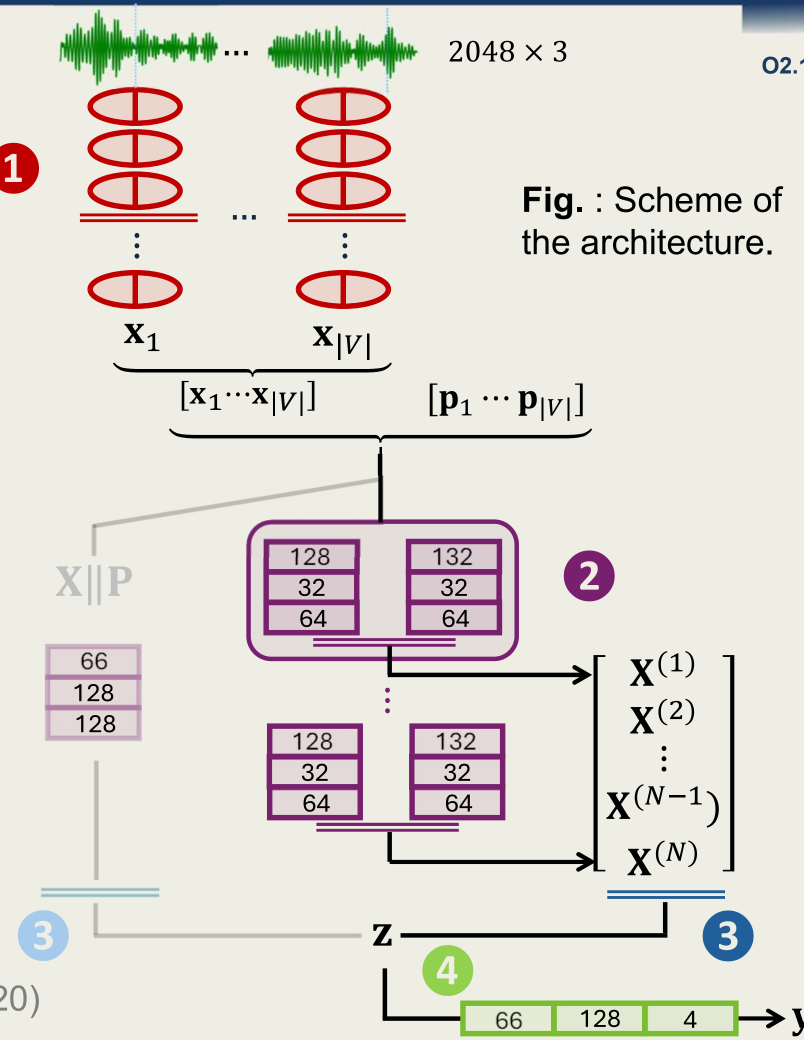


Fig. : Scheme of the architecture.

[4] van den Ende & Ampuero (2020)

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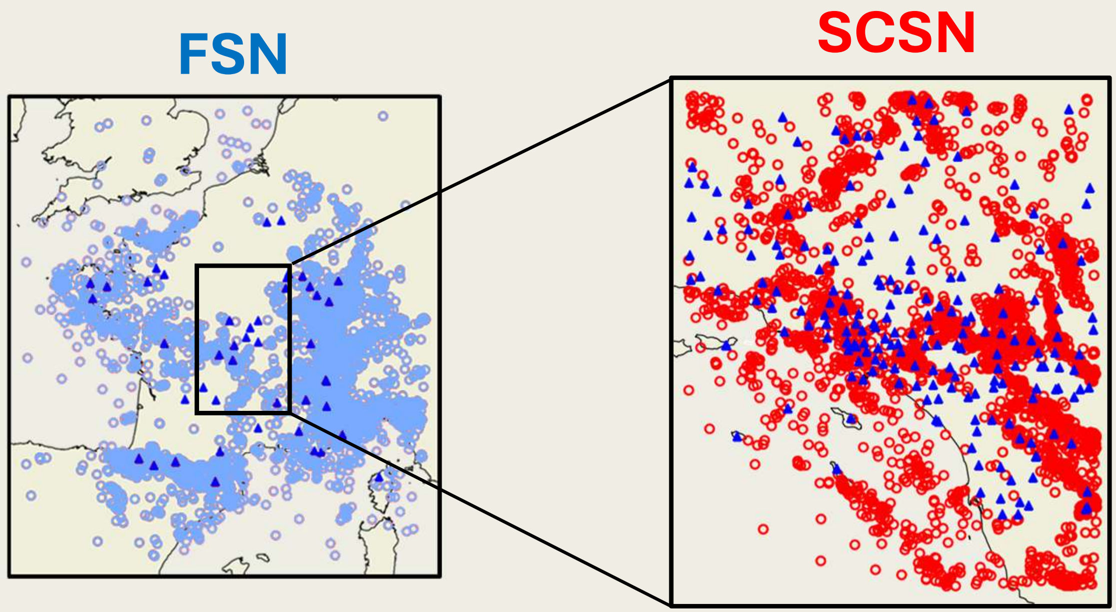
III
Numerical results



III – Numerical results

●○○○○ Datasets & processing

Datasets:

- **FSN[5]** (France): 2019–12/2021; $|V| = 42$.
- **SCSN[6]** (USA, CA): 2000–06/2019; $|V| = 72$.
- $\mathrm{ML} > 2.5 \Rightarrow$ **small** datasets ($\sim 1\mathrm{k}$ events).

Processing of signals $\mathbf{s}_j^{[.]} \in \mathbb{R}^{C\times P}$ (= features)

- # of components $C = 1[z]$ or $C = 3[x,y,z]$, time samples $P = 2048$, time windows 200 s or 100 s.
- Band-pass: $1 - 8$ Hz or $1 - 1.5$ Hz.

[5] https://renass.unistra.fr/
[6] https://www.fdsn.org

Fig.: # of events, SCSN vs FSN.

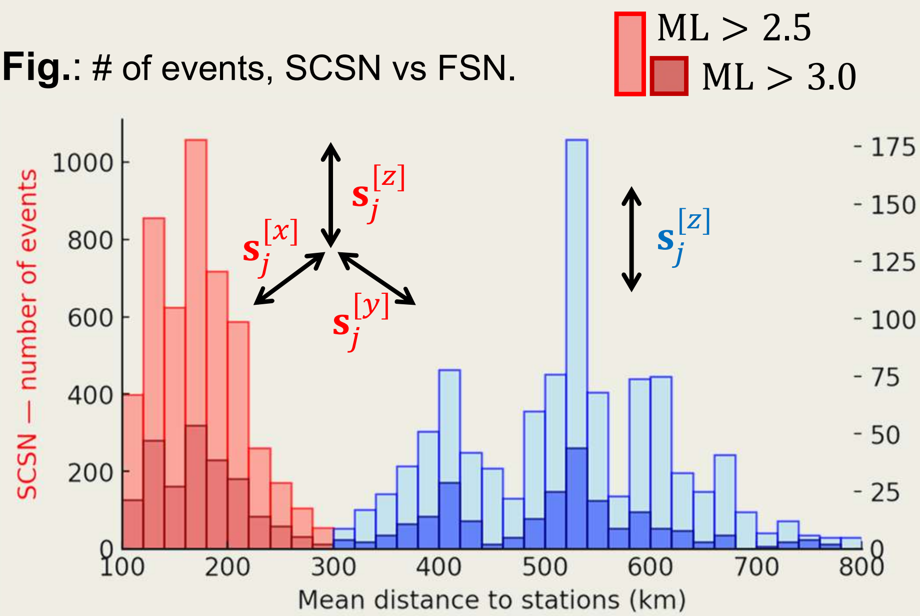
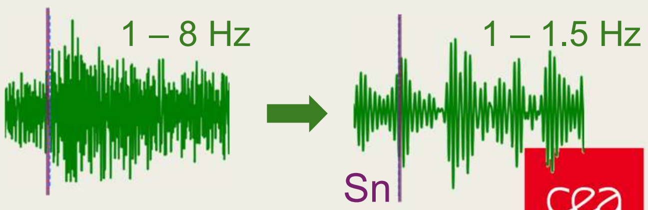


Fig.: 2021/01/02, ML ≃ 3.3 (**FSN**)



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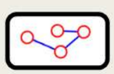
○●○○○ Error metrics

Separating data vs training variability

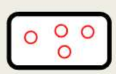
- **k-fold cross validation:** test sensitivity to dataset splits (90% - 10%) → *data variability.*
- **Random seeds:** repeat training with different initializations → *optimization variability.*

Not a single training…

- 100 trainings per model (folds × seeds) ⇒ 100 RMSEs; $\sigma^2 = \sigma^2_{\mathrm{opt}} + \sigma^2_{\mathrm{dat}}$.
- × **10's of GNN variants**[7] ⇒ 10^3's of models, but today only the best one:

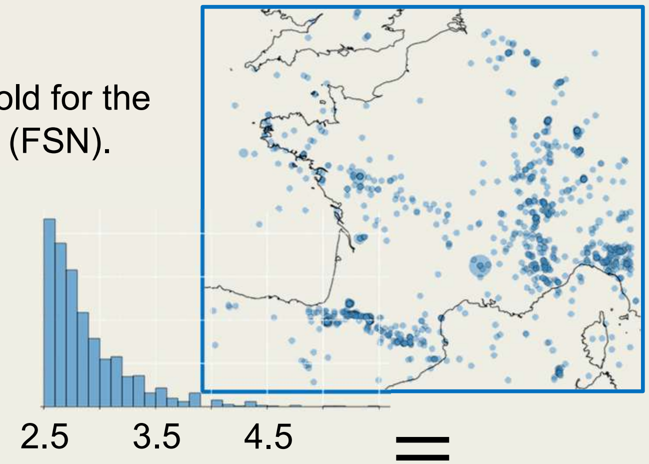


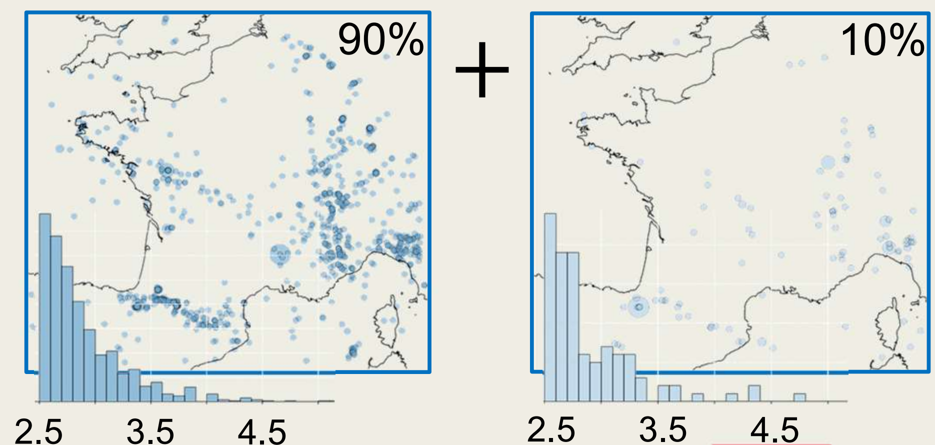
vs



w/ STGC w/o STGC

Fig.: Ex. of k-fold for the French dataset (FSN).





[7] see arxiv2025.

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III – Numerical results

○○●○○ Impact of STGC* on performance

Learned uncertainty

- Uncertainty learned: $\pm\mathbf{0.02}$ vs ± 0.3 in most available bulletins (for $\mathrm{ML} \geq 2.5$).
- STGC reduces variance and bias compared to baseline (edgeless-GNN).
- Most variability comes from large magnitudes variability ($\sigma \simeq 0.14$ for $\mathrm{ML} > 3.75 \leftrightarrow$ 42 events!), but stays below operational benchmarks (± 0.3).

*Spatio-Temporal Graph Convolution
SCSN: Southern California Seismic Network
FSN: French Seismic Network.

Fig.: RMSE for SCSN and FSN (best model).

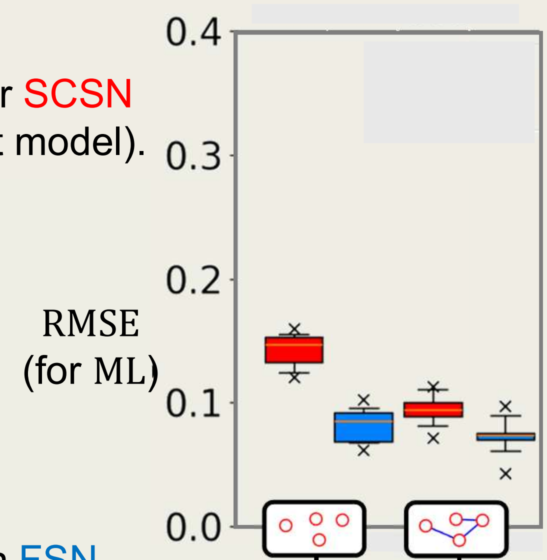
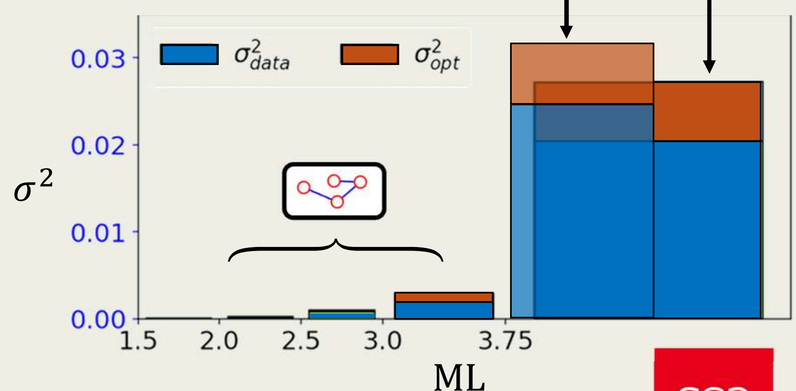


Fig.: Variance decomposition FSN.



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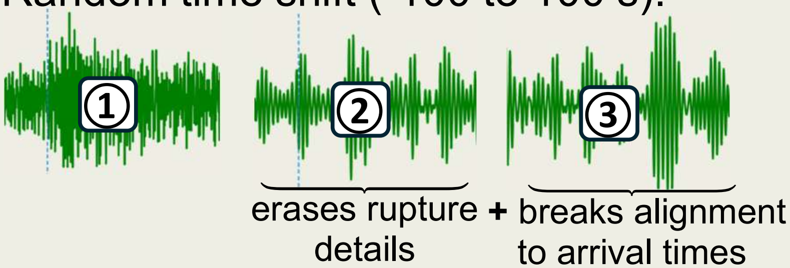
III – Numerical results

○○○●○ Impact of STGC on Robustness

Signal degradation steps

- Waveforms are degraded to mimic more realistic, noisy conditions: ① ⊃ ② ⊃ ③.
- ① Full spectrum (1-8 Hz).
- ② Narrow band (1-1.5 Hz).
- ③ Random time shift (-100 to 100 s).



Results

- STGC enhances robustness.
- **Multi-scale embedding** stabilizes learning for deeper architectures.

Fig.: RMSE for magnitude, showing robustness as inputs are degraded.

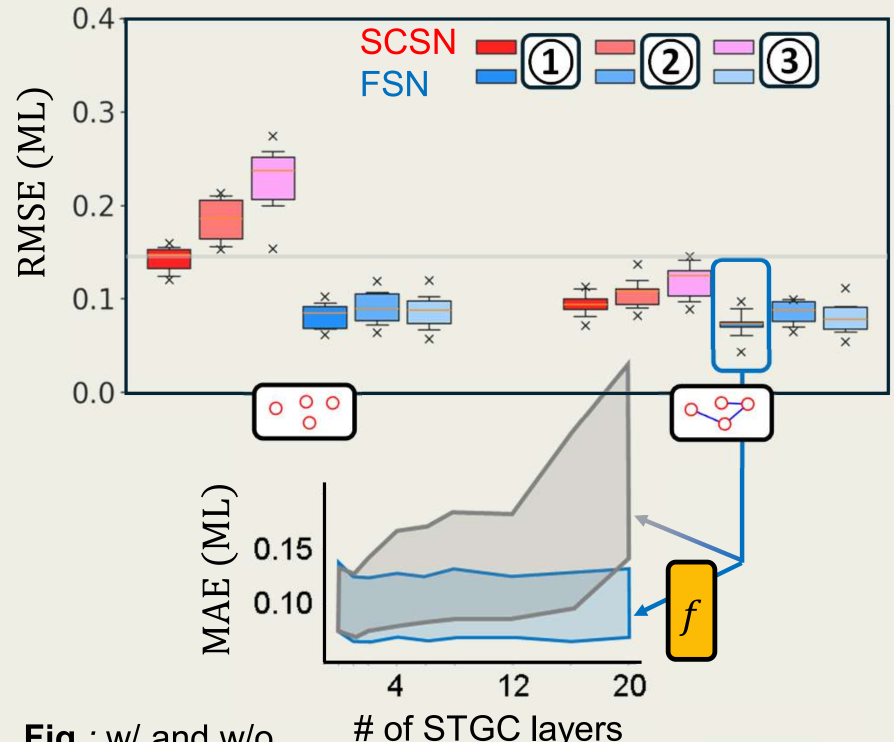


Fig.: w/ and w/o embedding.

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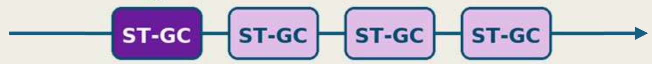
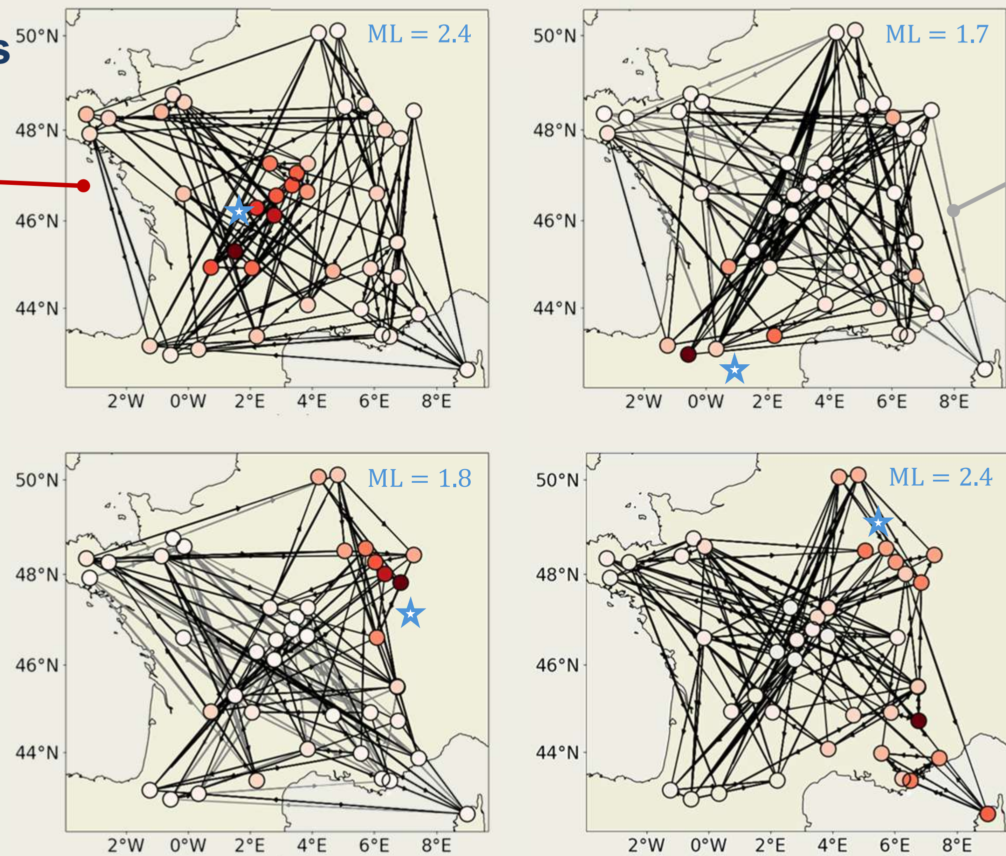


III – Numerical results

○○○○○● Interpretability of graphs

Color $\propto \|\mathbf{s}_j\|$
with $\mathbf{s}_j \sim \nabla_{\mathbf{x}_j} y_j$.



ij grayed out
if $\|\mathbf{s}_j\| < 1\%$

Not a black-box:

- STGC (2) learns spatial **attention** mechanism.
- Max pooling (3) condenses and reveals key stations.

Fig. : Scores (ML) across STGC layers for new events.

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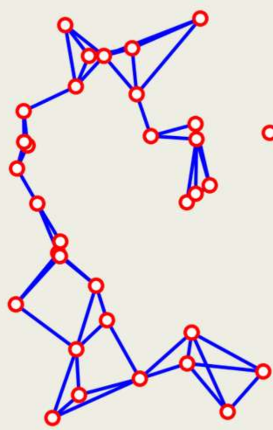
IV
Multimodal integration



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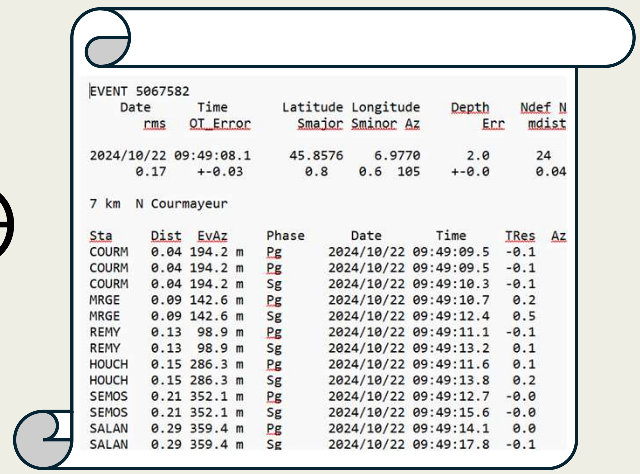

```
EVENT 5067582
    Date       Time        Latitude Longitude    Depth    Ndef N
         rms    OT_Error     Smajor Sminor Az       Err    mdist

2024/10/22 09:49:08.1     45.8576    6.9770      2.0       24
      0.17    +-0.03        0.8     0.6  105    +-0.0      0.04

7 km  N Courmayeur

Sta     Dist  EvAz     Phase      Date       Time     TRes  Az
COURM   0.04 194.2 m   Pg      2024/10/22 09:49:09.5  -0.1
COURM   0.04 194.2 m   Pg      2024/10/22 09:49:09.5  -0.1
COURM   0.04 194.2 m   Sg      2024/10/22 09:49:10.3  -0.1
MRGE    0.09 142.6 m   Pg      2024/10/22 09:49:10.7   0.2
MRGE    0.09 142.6 m   Sg      2024/10/22 09:49:12.4   0.5
REMY    0.13  98.9 m   Pg      2024/10/22 09:49:11.1  -0.1
REMY    0.13  98.9 m   Sg      2024/10/22 09:49:13.2   0.1
HOUCH   0.15 286.3 m   Pg      2024/10/22 09:49:11.6   0.1
HOUCH   0.15 286.3 m   Sg      2024/10/22 09:49:13.8   0.2
SEMOS   0.21 352.1 m   Pg      2024/10/22 09:49:12.7  -0.0
SEMOS   0.21 352.1 m   Sg      2024/10/22 09:49:15.6  -0.0
SALAN   0.29 359.4 m   Pg      2024/10/22 09:49:14.1   0.0
SALAN   0.29 359.4 m   Sg      2024/10/22 09:49:17.8  -0.1
```

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IV – Multimodal integration

●○ Principle

Architecture: 2 pretrained modality-specific models:

- **Dynamic-GNN** processes data from stations to produce embedding **+ Proj head.**
- **Text encoder** fined-tuned* to the technical language of bulletins ("expurged" of the predicted values) **+ Proj head.**

Hybrid loss: $l_{\mathrm{I}} + \lambda l_{\mathrm{II}} + \mu l_{\mathrm{III}}$

I. **Alignment:** InfoNCE (contrastive objective).

II. **Regularization:** KL, Gutenberg–Richter.

III. **Supervised head (lightweight)** $\tilde{\mathbf{x}} \mapsto \mathbf{y}$ to ensure calibration while reducing bias.

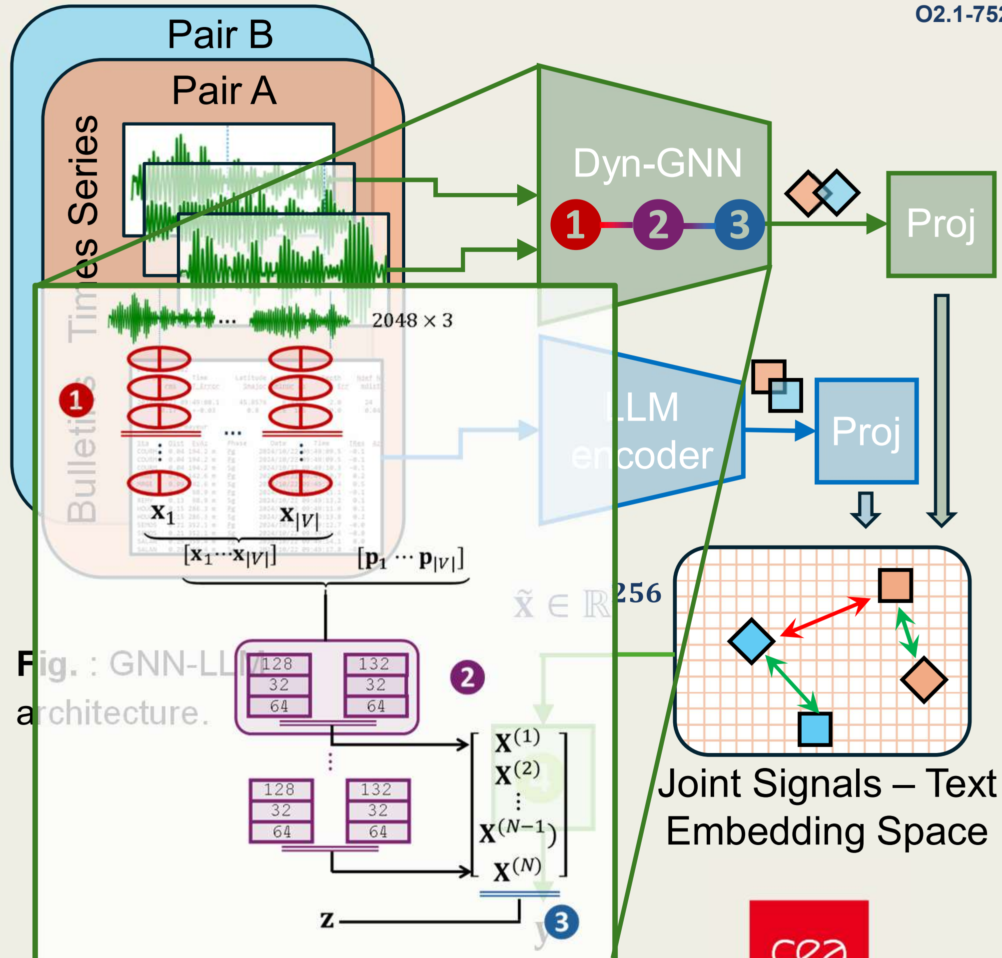

Fig. : GNN-LLM architecture.

* LLaMA-3 (Meta) + LoRA/QLoRA, persp.: "SeismoBERT".

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IV – Multimodal integration
○● First results

Training & validation:

- Training on **FSN catalogue** (waveforms + derived bulletins*, 2019–2021) for ML>1.5.
- Validation against **external agencies** (ETHZ MLv, EMSC/EPOS) via ML(Pred)-MLv(ETHZ).

First trends

- GNN-only: **systematic bias** +0.3 vs MLv (ETHZ), and -0.2 vs ML (RMSE~0.14).
- GNN+LLM reduces the bias (+0.1 vs 0.3) but so far only on the common dataset FSN ∩ ETHZ**.**

* **Without** predicted ML, depth, loc.

Tab.: Pred. ML – ML (FSN).

# Events	RMSE ± σ
1011	0.140 ± 0.020
3435	0.140 ± 0.012
7030	0.136 ± 0.017

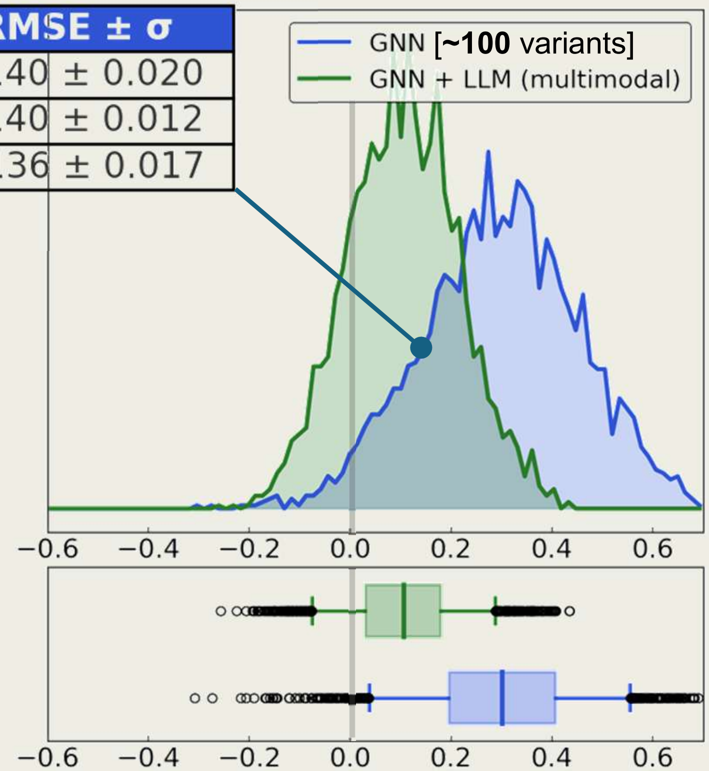

Fig.: Predicted ML – MLv (ETHZ).

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Key outcomes & perspectives

Dynamic-GNNs:

- **Accuracy/robustness:** ~1k events already yield near-expert performance, even with low spectral richness!
- **Interpretability:** Dynamic graphs reveal the key stations, that can be compared to that analysts rely on.
- **+ LLM**: **corrects bias**, links waveforms ↔ bulletins, classifies unseen events (**zero-shot classification**).

Limitation:

- Preliminary results on research datasets: **to be consolidated** on larger & diverse catalogs.
- Need for **global associator** to select waveforms — yet GNNs can self-associate (PLAN[8]).

[8]Phase picking, Location, and Association Net. (Xu Si et al., *Nature*, 2024).

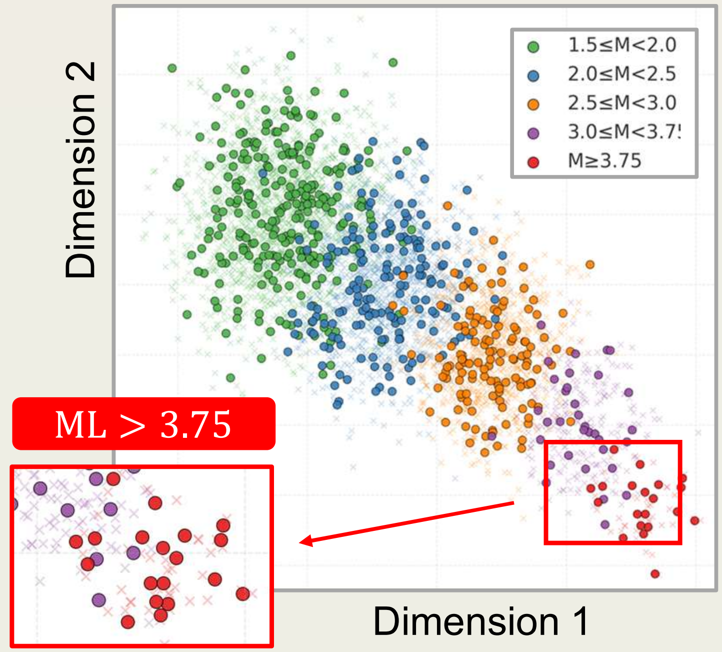
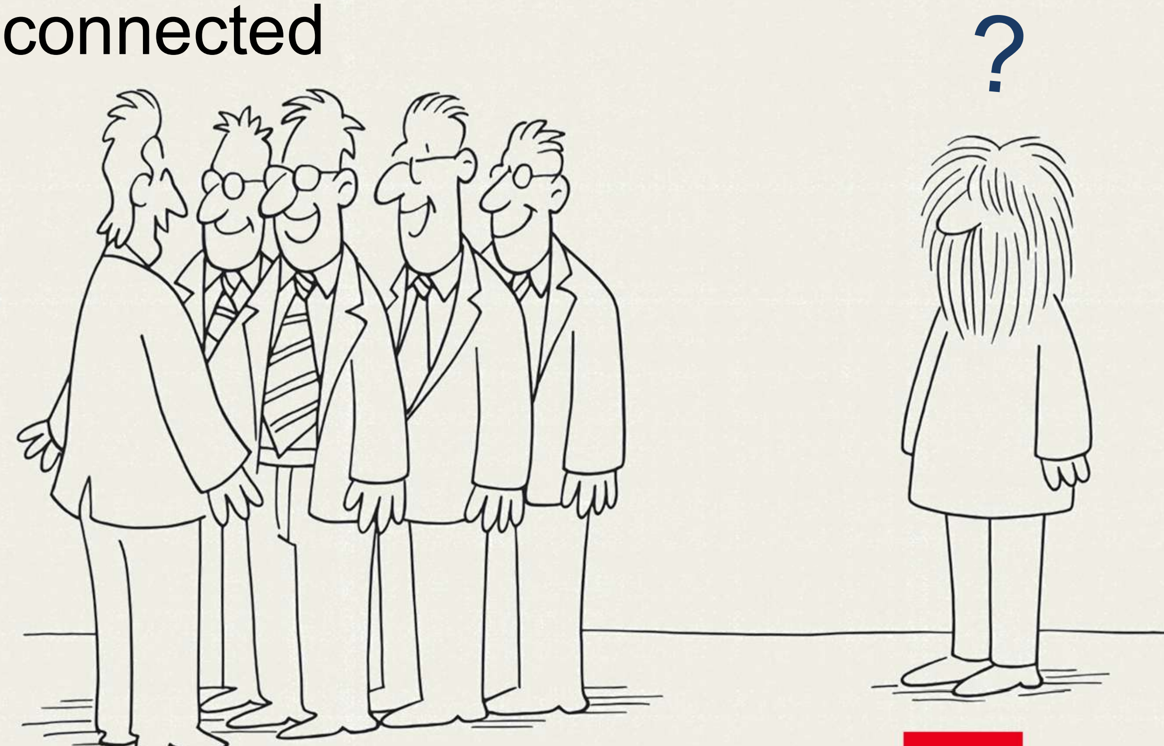


Fig. : Waveforms (**x**) and bulletins (●), visualized using PCA and t-SNE.

Thanks for attention!
And may your graphs stay connected



Special thanks to the invisible crowd of AI assistants (GPT-5, …) — still working on inclusivity too!

Paper: arxiv2025.

C. Millet, X. Cassagnou, M. Mougeot

What's next?

Robustness & trust:

- *Self-adaptive dyn-GNN* for the IMS ("I'm thinking" analogy).
- Scalable methods and confidence metrics for automatic detections and event characterization.
- Privacy, distillation & unlearning for sensitive data.

Graph Foundation Models:

- GFMs for multimodal IMS data (stations, signals, events).
- Breaking silos across seismic, infrasound, hydroacoustic & radionuclide networks.
- Integration of LLMs as ***graph nodes/agents*** → acting like analysts and interacting with databases, physical models...