Bridging the Acoustic–Elastic Gap in Seismic Inversion via Robust Summary Statistics

SLIM
ML4Seismic

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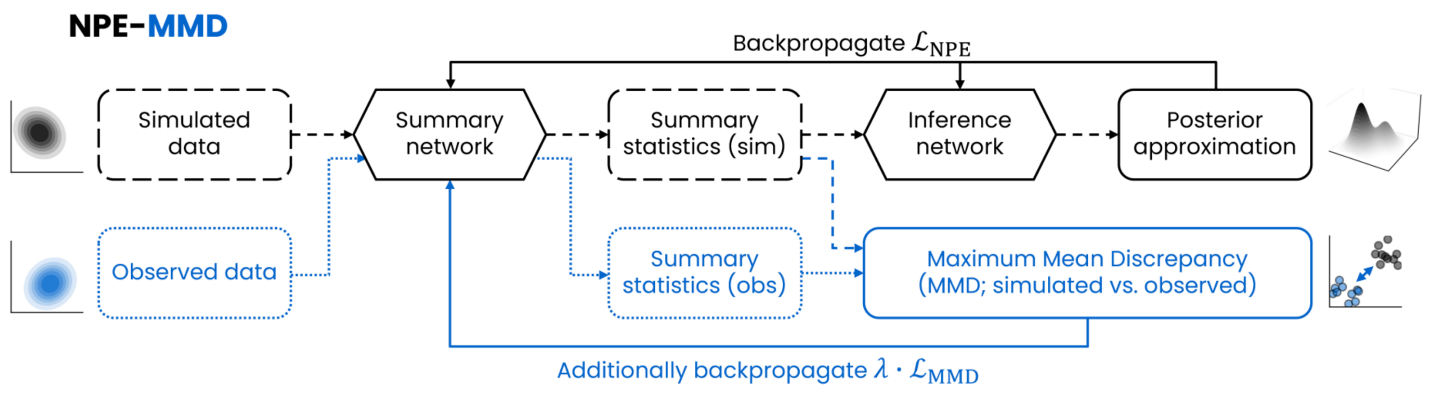
Motivation

- Simulation-based inference (SBI) delivers full posteriors for seismic inversion, but relies on an accurate simulator, noise model, and prior.
- Real seismic data involve elastic wave propagation; large-scale training simulations are often acoustic because of computational constraints.
- This acoustic–elastic mismatch is a form of model misspecification: posteriors become biased and uncertainty is underestimated.

Goal: develop robust SBI that remains reliable under the acoustic–elastic gap — learning from abundant acoustic simulations plus a few unpaired elastic observations.

ElasNet: MMD-Regularized Neural Posterior Estimation



- *Acoustically* imaged common-image gathers (CIGs) act as physics-informed summary statistics; a learned summary network h_ψ further compresses them.
- **Maximum mean discrepancy (MMD)** aligns summary features of simulated (acoustic) and observed (elastic) CIGs — *unpaired* data, no adversarial training.
- A **conditional normalizing flow** f_θ learns the posterior of velocity models; λ balances the flow loss and the MMD alignment.

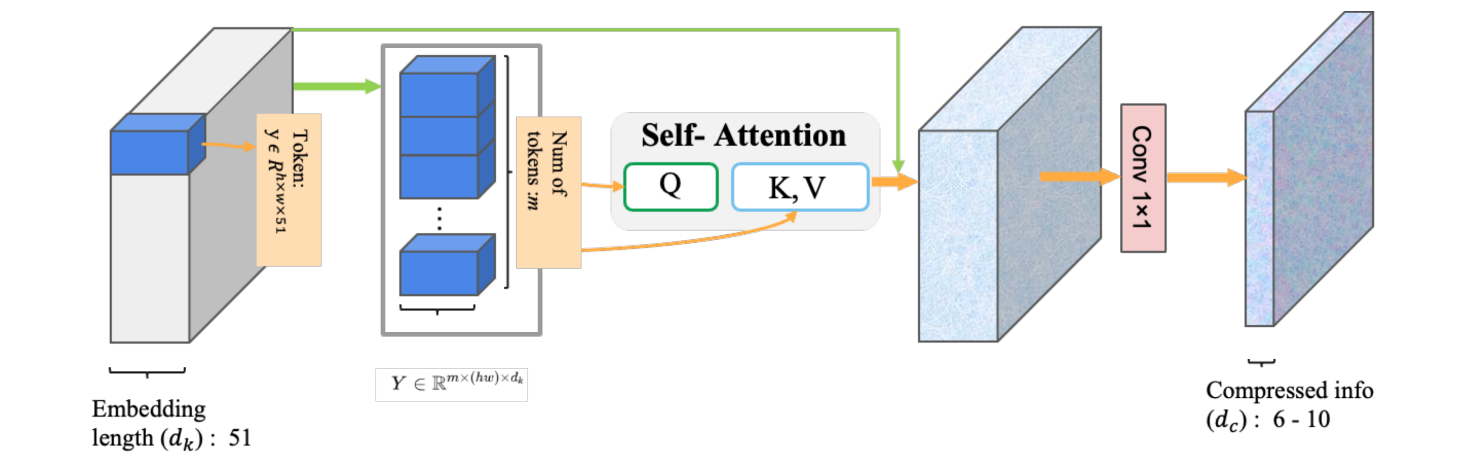
$$\mathscr{L}_{\text{total}} = \underbrace{-\mathbb{E}_{(\mathbf{x},\mathbf{y}_{\text{sim}})}\left[\log p_Z\big(f_\theta(\mathbf{x}; h_\psi(\mathbf{y}_{\text{sim}}))\big) + \log\left|\det \frac{\partial f_\theta}{\partial \mathbf{x}}(\mathbf{x}; h_\psi(\mathbf{y}_{\text{sim}}))\right|\right]}_{\text{Conditional normalizing flow loss}} + \underbrace{\lambda \cdot \mathrm{MMD}^2\big[\, h_\psi(\mathbf{y}_{\text{sim}}) \,\|\, h_\psi(\mathbf{y}_{\text{obs}}) \big]}_{\text{MMD loss}}$$

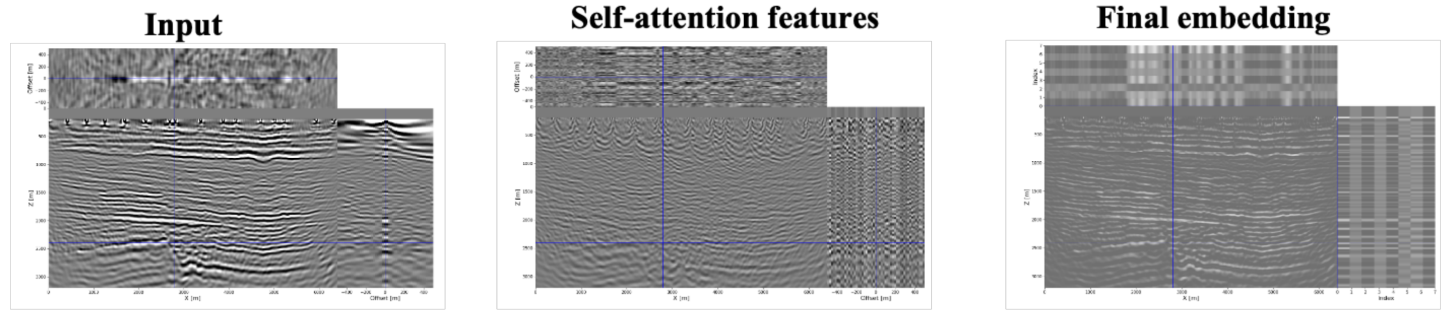
Total training objective: conditional normalizing-flow loss + λ · MMD² between acoustic and elastic summary features.

Note: The observed field data does not need to be paired with the simulated data during training.

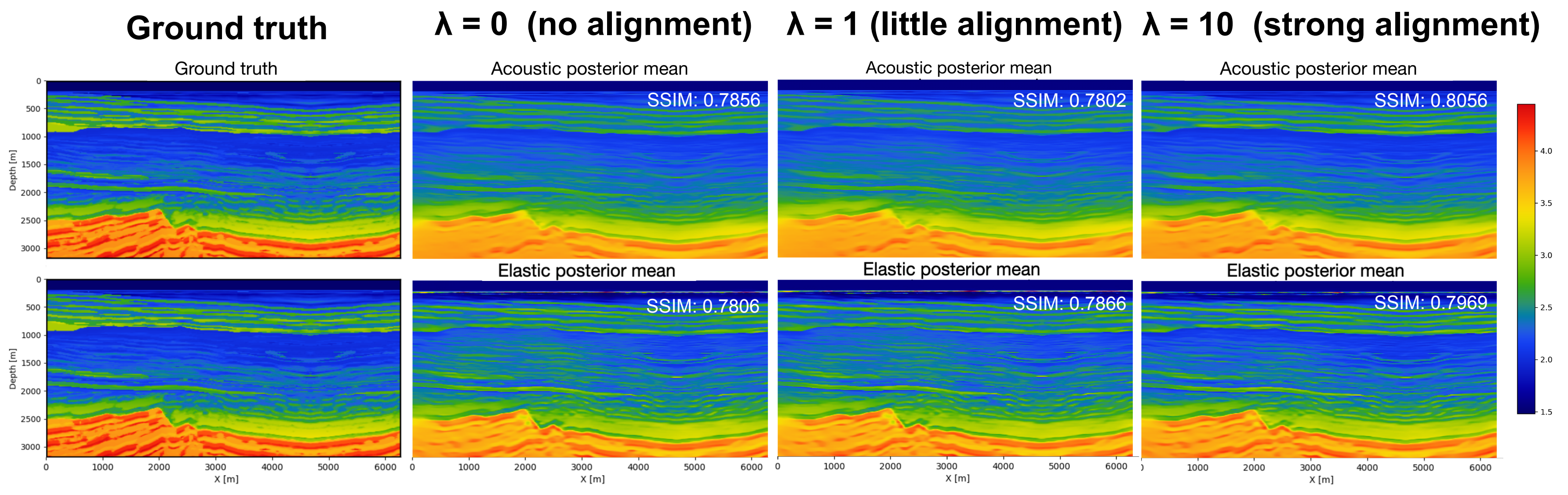
Attention-Based Summary Network h_ψ

Offset responses at each spatial location of a CIG (51 subsurface offsets) are treated as tokens. Self-attention within local 8×8 windows aggregates offset-dependent focusing information; a 1×1 convolution compresses features to dc ∈ [6, 10] channels.



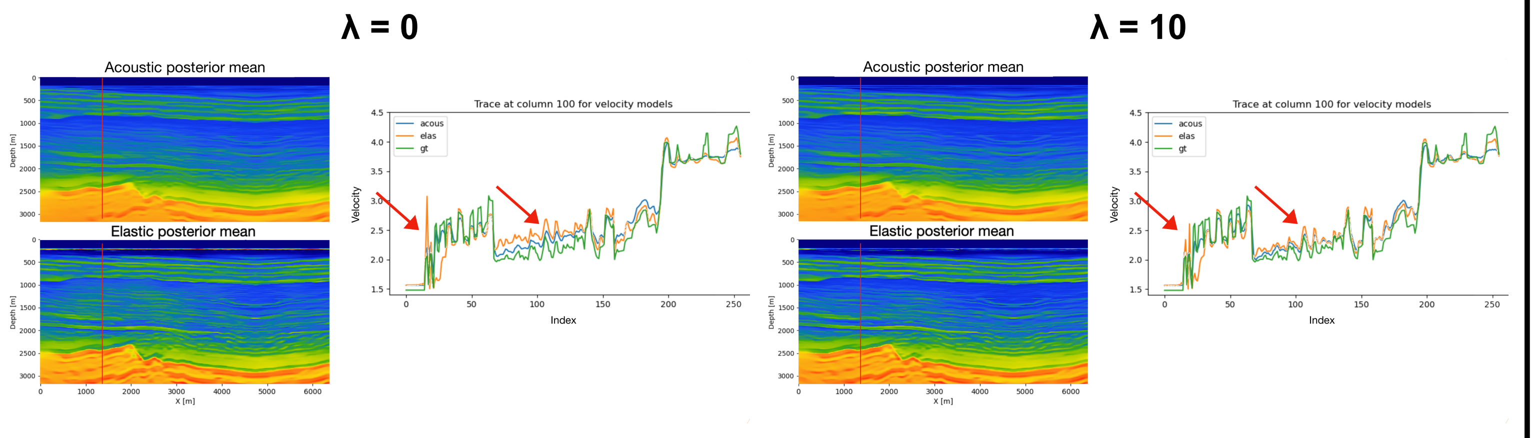


Posterior Means: Effect of MMD Alignment



Ground truth (left column) vs. acoustic (top) and elastic (bottom) posterior means with increasing MMD alignment strength. Strong alignment (λ = 10) suppresses the spurious water-bottom contrast and mid-depth bias in the elastic posterior, producing better agreement with the ground truth and the highest SSIM for both acoustic and elastic cases.

Traces at x = 1.4 km



Arrows: water-bottom contrast (≈200 m) and central region. With λ = 10 the elastic trace aligns with the acoustic one and approaches the ground truth.

Observations

- Acoustic and elastic posterior means both preserve the overall structure — the summary network captures the features needed to inform the posterior.
- Increasing the MMD weight pulls the elastic summary distribution closer to the acoustic one.
- The summary statistic learns to ignore elastic events that do not inform the posterior of acoustic properties.
- Elastic posterior means show finer details: PP-reflections carry contributions from both P- and S-wave velocities.

Conclusions

- ElasNet bridges acoustic simulations and elastic observations by combining robust CIG summaries with MMD distribution alignment.
- Trained almost entirely on inexpensive acoustic simulations; only ≈90 unpaired elastic examples are needed.
- Reduces acoustic–elastic posterior discrepancies and improves structural consistency and uncertainty calibration — a scalable path for SBI under realistic physics mismatch.

References

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