ML4Seismic Partners Meeting 2023

Modeling Fault Label Uncertainty in 3D Seismic Volumes for Machine Learning Workflows

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Publications Code Preprint

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Introduction

How Visual Attention Works to Drive Perception in the Human Brain

What objects do you notice first looking at this picture?

Introduction

How Visual Attention Works to Drive Perception in the Human Brain

Abrupt changes in properties such as texture, color, shape, contrast, intensity etc., unconsciously register in the human brain as it examines a visual scene.

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Introduction

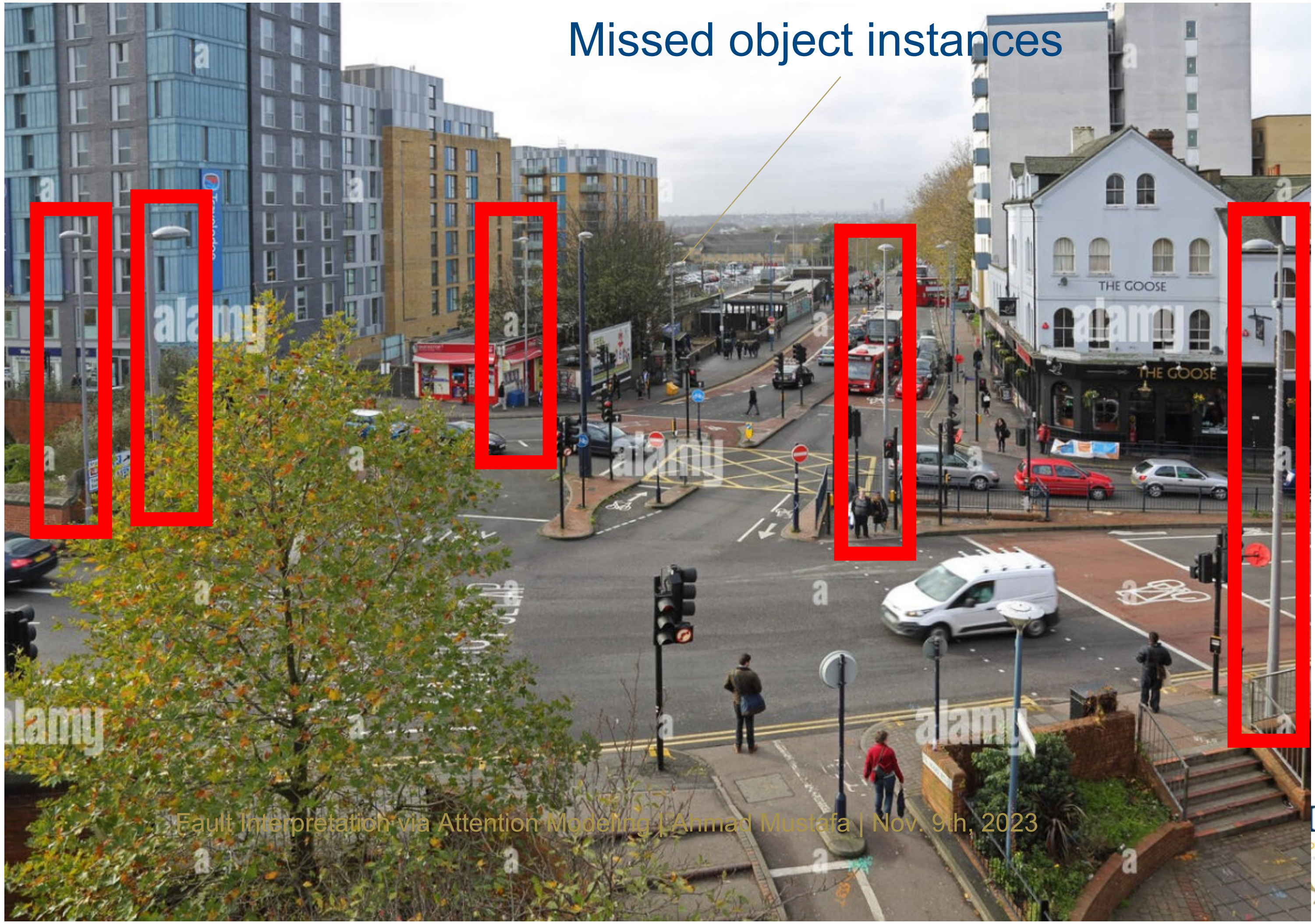
How Visual Attention Works to Drive Perception in the Human Brain

Can you find all of the street lamps in the image?

Introduction

How Visual Attention Works to Drive Perception in the Human Brain

Prior knowledge and expectations about the expected shape, color, appearance etc., of the object influences the way human brain searches the image

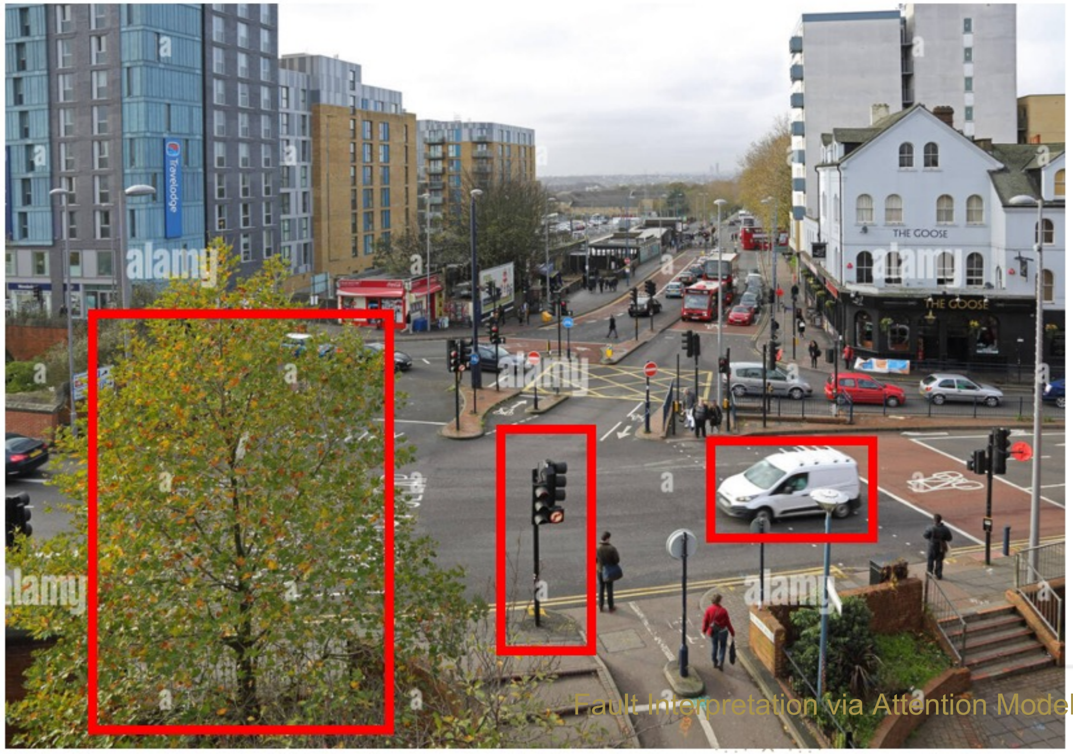


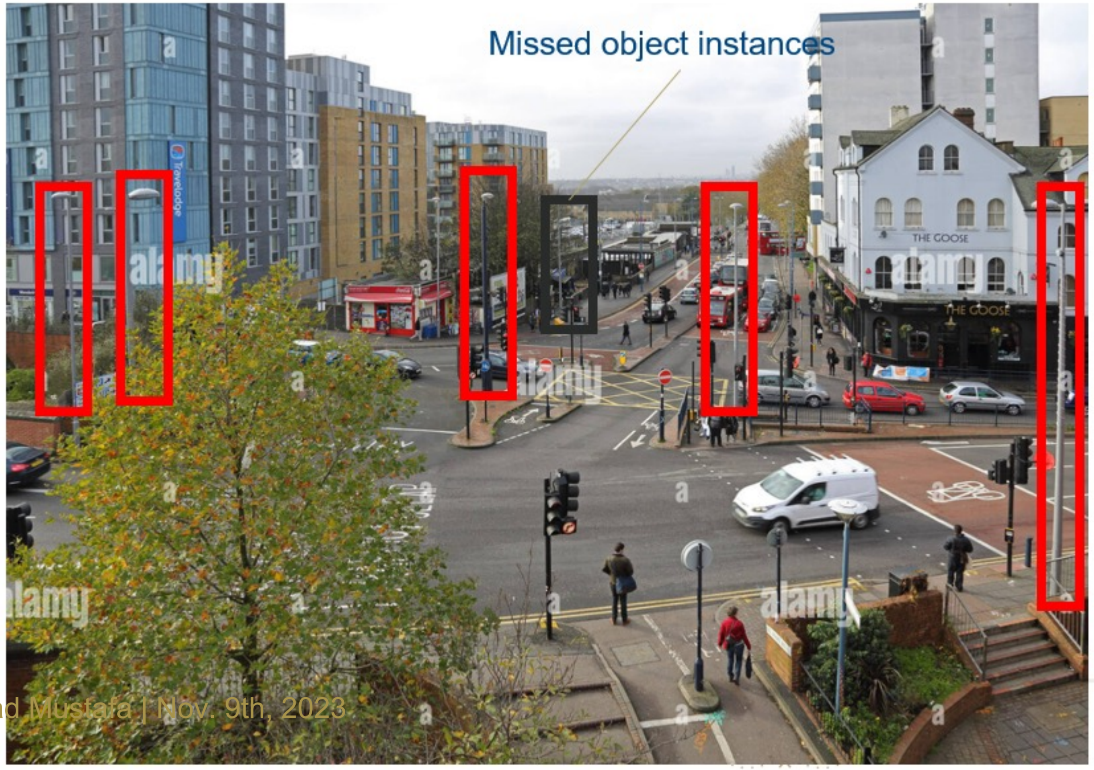
Introduction
Bottom-up vs Top-down Visual Attention

Human perception is a product of both bottom-up and top-down attentional mechanisms

Bottom-up Attention
- **Unconsciously** registers in the human brain
- Guided by **changes in object's appearance** with respect to its surroundings

Top-down Attention
- Objects are searched for in a **conscious** manner
- Guided by one's **prior knowledge, goals, and expectations** regarding the object in question



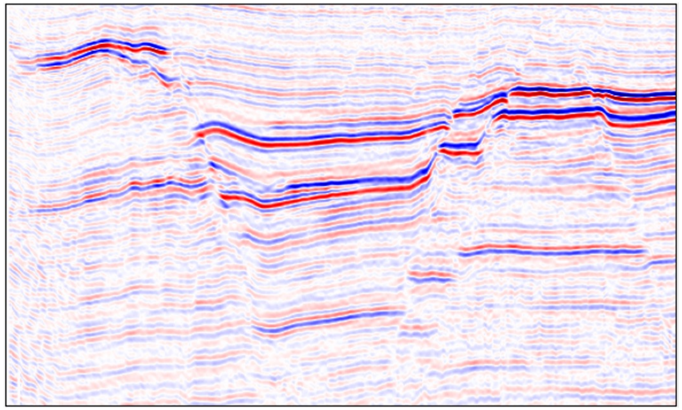


Introduction

The Role of Visual Attention in Seismic Fault Interpretation

Seismic interpretation is influenced by both bottom-up and top-down attentional mechanisms

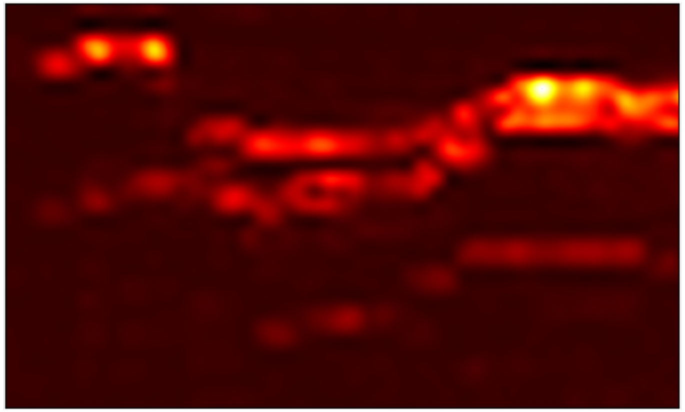
Seismic Image



Bottom-up Attention

- Intensity Contrast
- Color Contrast
- Texture Contrast
- ⋮

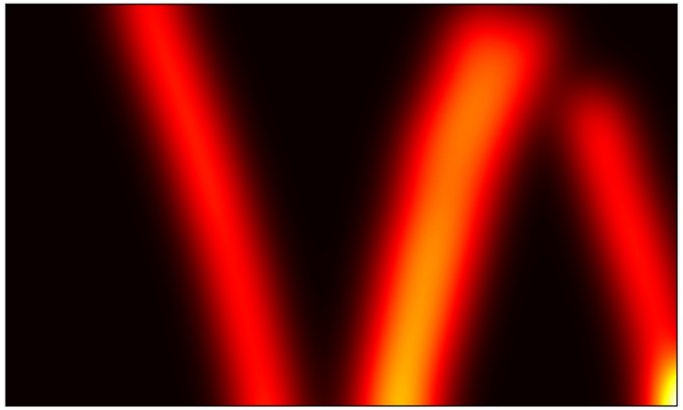
Low level cues in the seismic image draw interpreter's attention



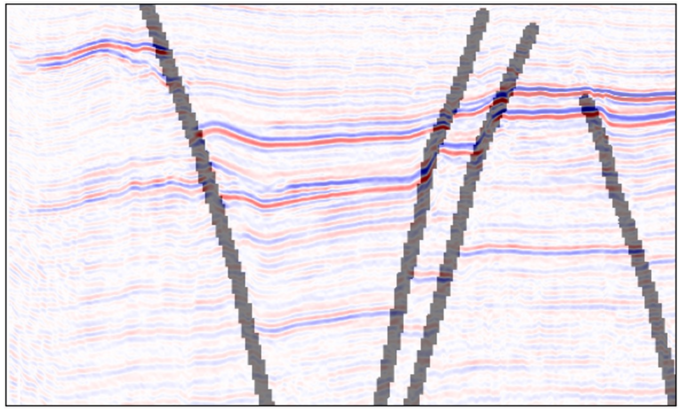
Top-down Attention

- Expected Fault Shape, Geometry, Size etc.,
- Prior Knowledge about Target Region
- Time and priority for annotations
- ⋮

Attentional focus is refined based on high level cues from the brain



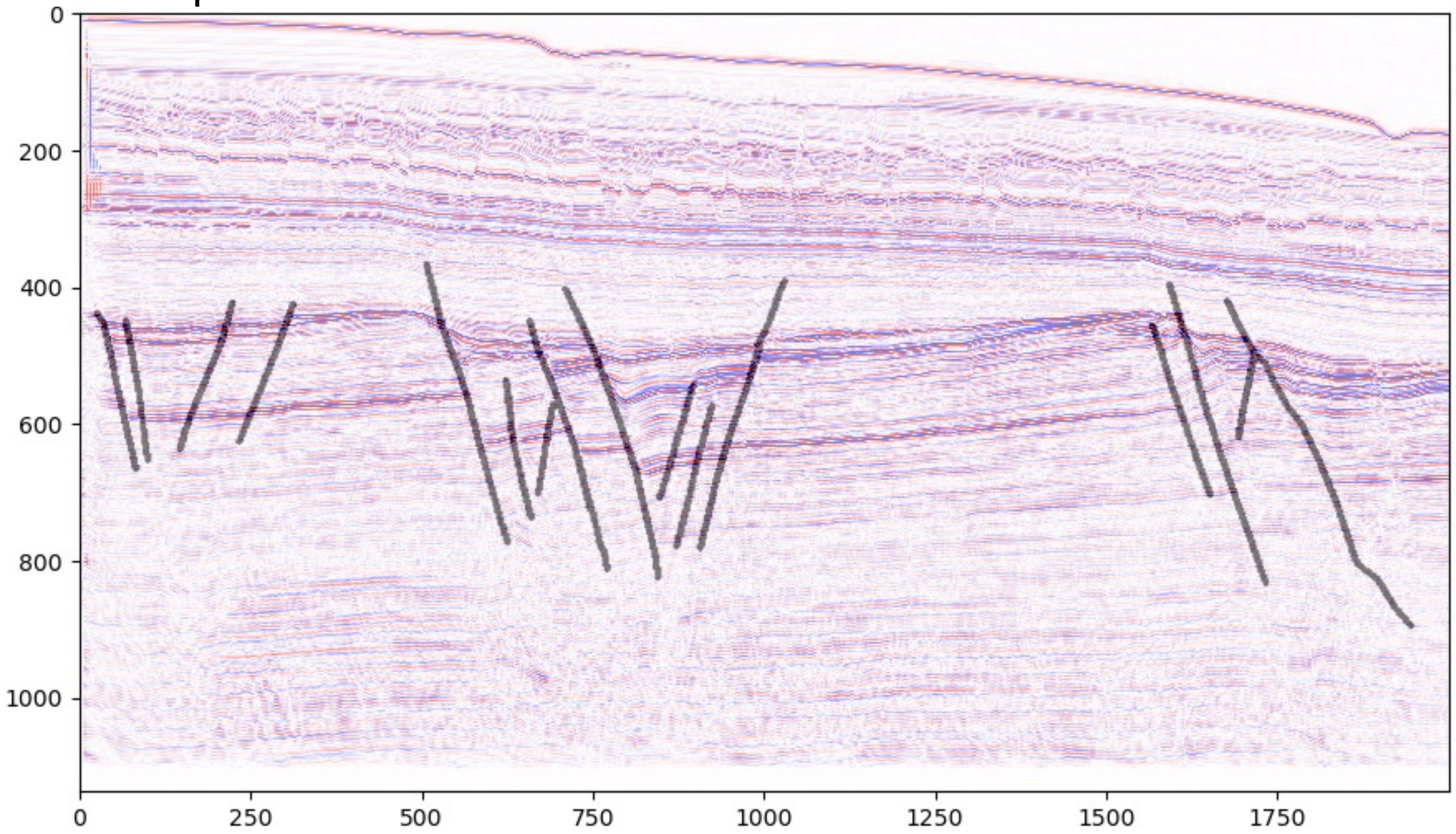
The final labels are created as a consequence of the attention map



Introduction
Modeling Visual Attention to Train Deep Networks for Interpretation

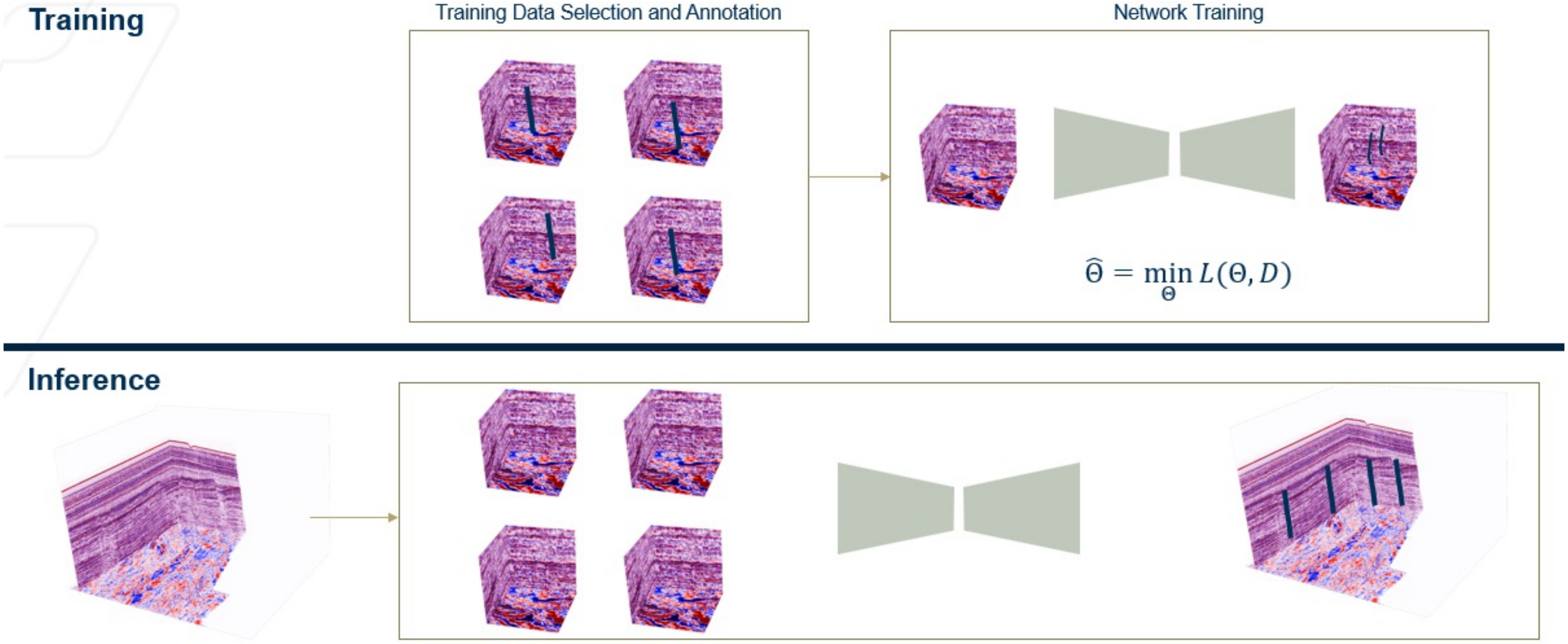
Biological attention selectivity result in missed fault annotations

- **Incomplete fault annotations** arising as a result of biological attention selectivity result in **suboptimal learning for the network**, resulting in **poor performance on unlabeled faults**
- We propose a training paradigm whereby **visual attention is modeled** and **incorporated** into training of deep networks for interpretation



Prior Work
Pretrained 3D CNNs for Fault Detection

Pretraining 3D CNNs on synthetic fault models is an effective method to detect faults on real data

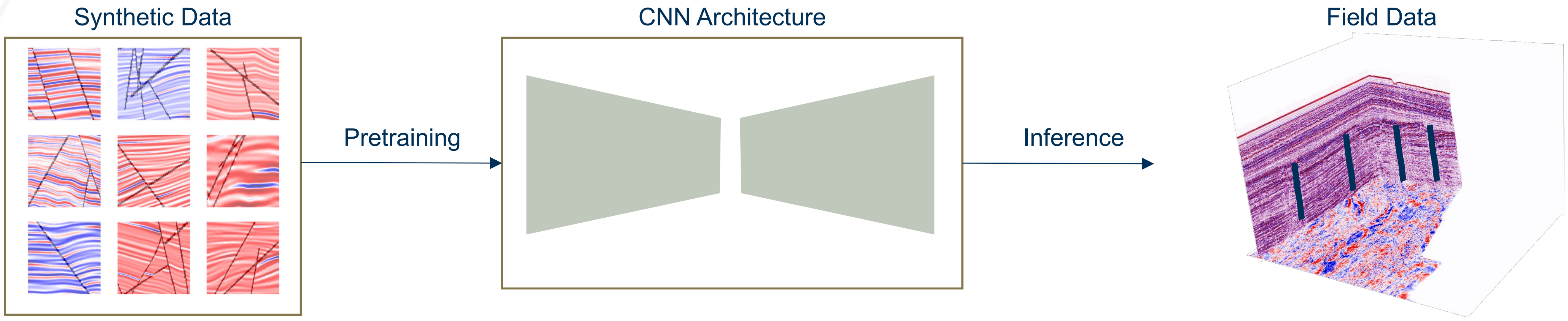


[1] Wu, Xinming, et al. "FaultSeg3D: Using synthetic data sets to train an end-to-end convolutional neural network for 3D seismic fault segmentation." *Geophysics* 84.3 (2019): IM35-IM45.

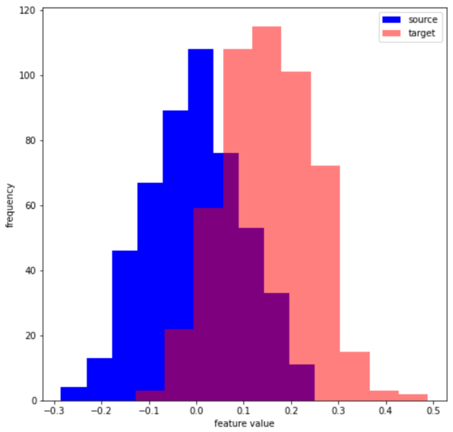
Prior Work

Domain Shift Leads to Poor Performance on Test Data

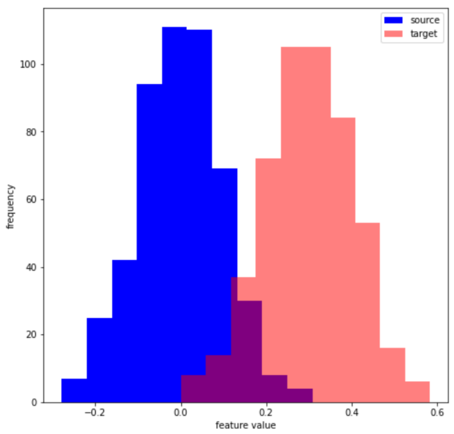
Domain shift between real and training data distributions caused suboptimal performance



Source and Target distributions match.

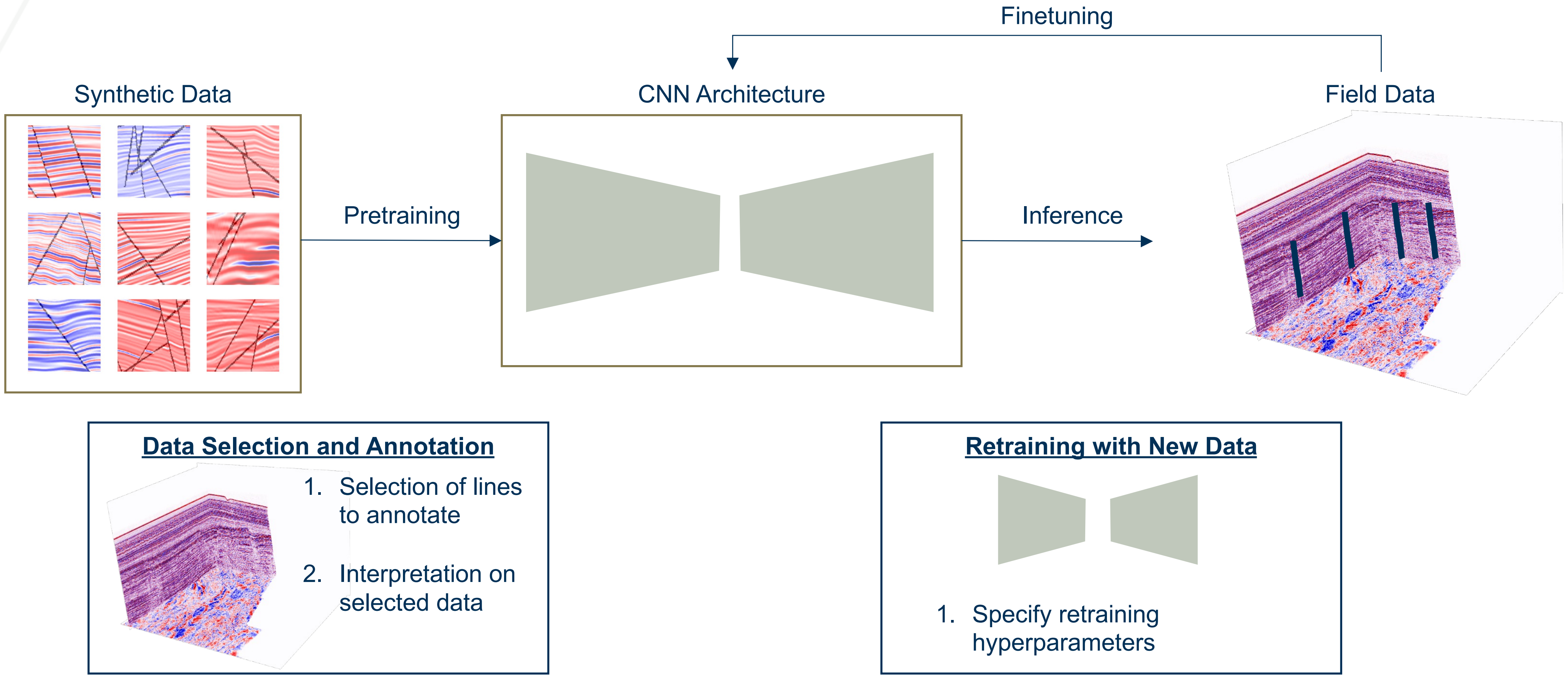


Source and Target distributions don't match.



Prior Work
Finetuning Pretrained Models for Real Data Adaptation

Domain shift can be addressed by finetuning model on labeled samples obtained from the real survey of interest



[1] Cunha, Augusto, et al. "Seismic fault detection in real data using transfer learning from a convolutional neural network pre-trained with synthetic seismic data." *Computers & Geosciences* 135 (2020): 104344.
[2] Zhu, Donglin, et al. "3D fault detection: Using human reasoning to improve performance of convolutional neural networks." *Geophysics* 87.4 (2022): IM143-IM156.

Prior Work

Comparison of Proposed Method to Existing Approaches

Prior works do not address the problem of visual attention leading to missed fault labels in real data used for finetuning

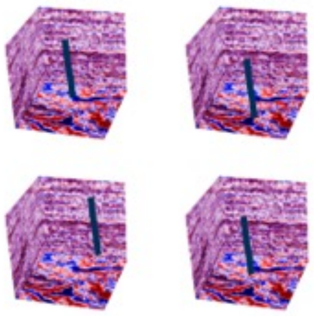
	3D CNNs	Uses Finetuning	Models Visual Attention
Wu et al.	✓	✗	✗
Cunha et al.	✗	✓	✗
Zhu et al.	✓	✓	✗
Dou et al.	✓	✓	✗
Proposed	✓	✓	✓

[1] Wu, Xinming, et al. "FaultSeg3D: Using synthetic data sets to train an end-to-end convolutional neural network for 3D seismic fault segmentation." *Geophysics* 84.3 (2019): IM35-IM45.
[2] Cunha, Augusto, et al. "Seismic fault detection in real data using transfer learning from a convolutional neural network pre-trained with synthetic seismic data." *Computers & Geosciences* 135 (2020): 104344.
[3] Zhu, Donglin, et al. "3D fault detection: Using human reasoning to improve performance of convolutional neural networks." *Geophysics* 87.4 (2022): IM143-IM156.

Methodology
Pretraining 3D CNN on Synthetic data

3D UNet Architecture is trained on synthetic fault models

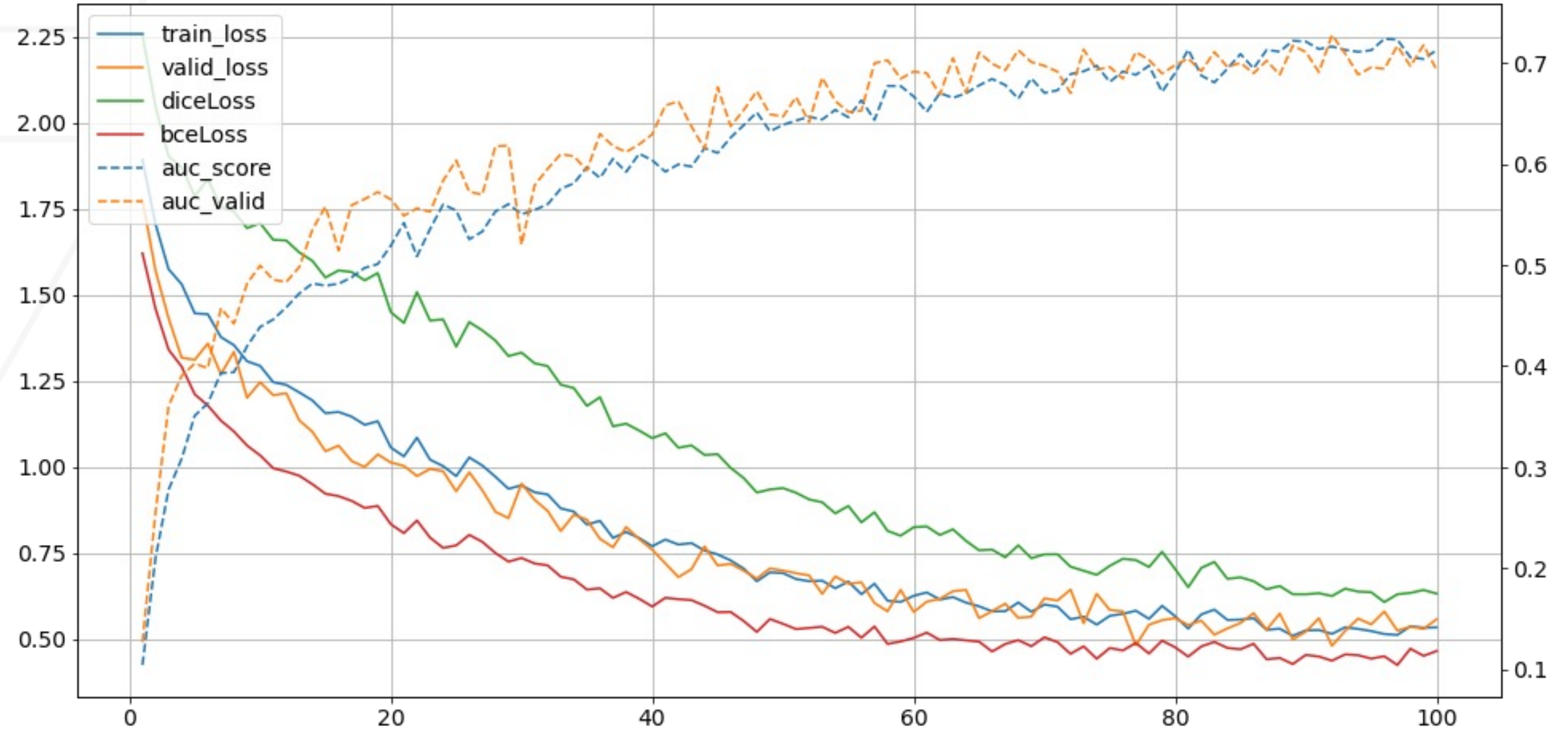
Synthetic Data Pretraining



Methodology
Pretraining 3D CNN on Synthetic data

Network is trained to convergence until it can predict faults on synthetic test samples with good accuracy

Loss Curves

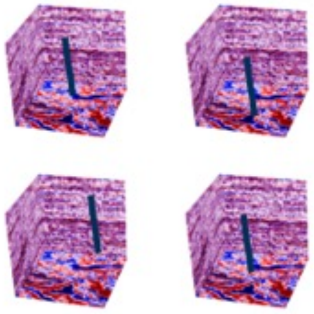


Synthetic Data Predictions

Methodology
Preparing Real Data for Finetuning

3D seismic cubes are sampled from the from the labeled seismic lines and labels processed to finetune 3D CNN

Synthetic Data Pretraining



Real Data Preparation

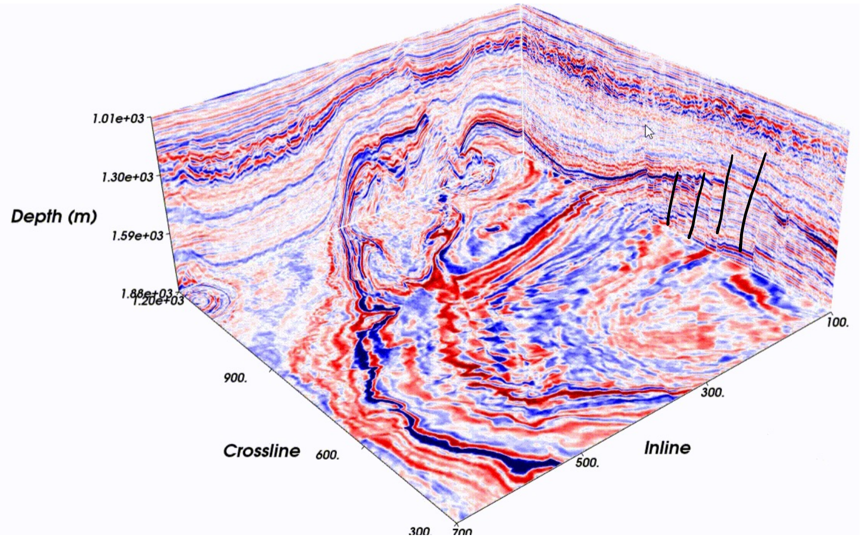
Attention-based Stochastic Sampling of Seismic Cubes

Label Expansion for 3D CNN Training

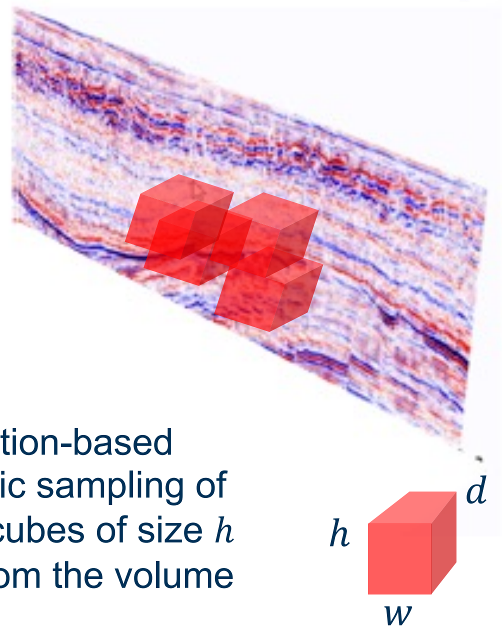
Methodology

Preparing Real Data for Finetuning

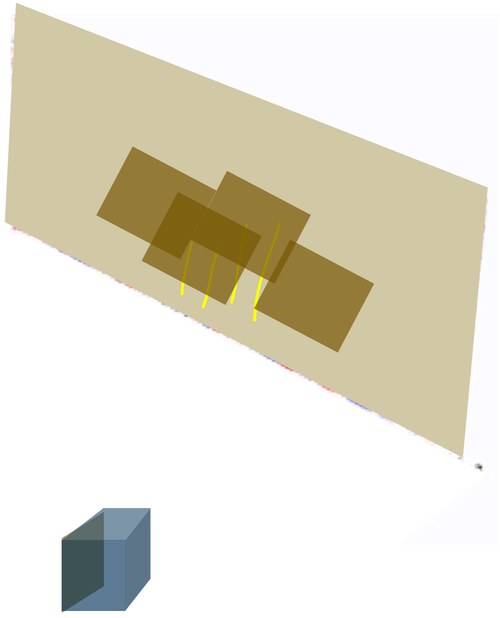
3D seismic cubes are sampled from the from the labeled seismic lines and labels processed to finetune 3D CNN



Seismic volume along with labeled fault section(s) is provided



Attention-based stochastic sampling of seismic cubes of size $h \times w \times d$ from the volume

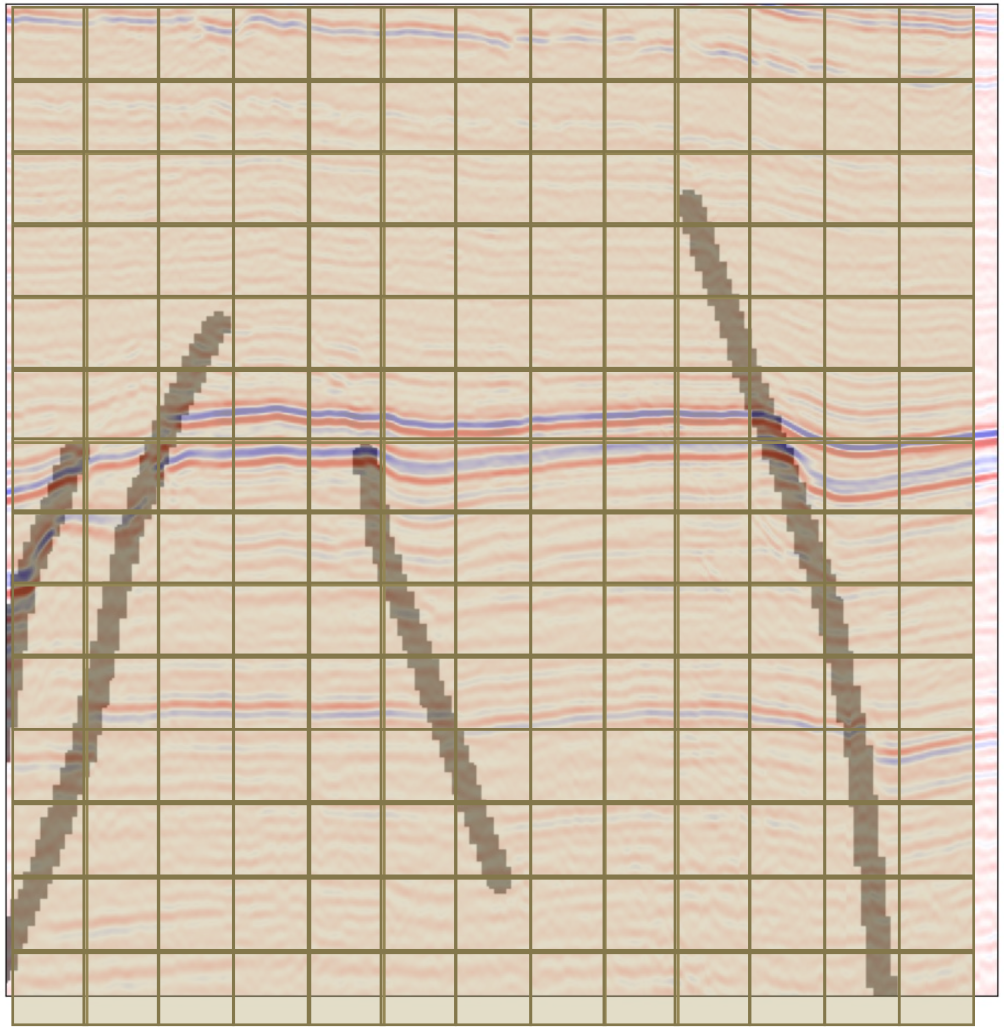


A block of zeroes is appended to the corresponding label squares to match seismic dimensions

Methodology – Data Sampling Strategy

Conventional Strategies Sample from a Uniform Grid

Strategies that sample cubes from a uniform grid lead to class imbalance problem



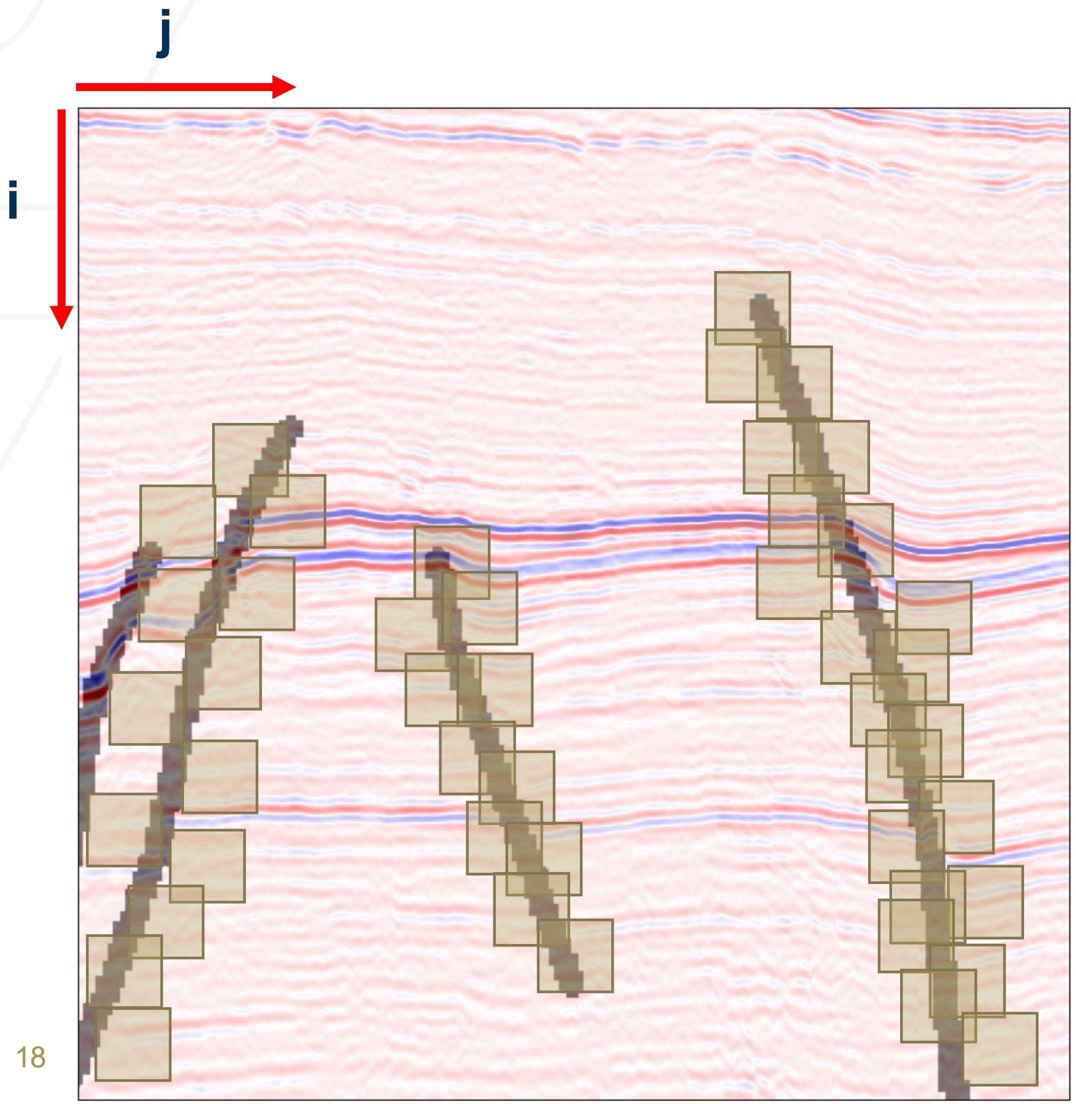
- Due to **sparse annotations**, number of cubes with faults << number of cubes without faults.
    - Leads to **a class imbalance problem** and subsequent poor performance on faults in test data.

- **Regular sampling** leads to **redundancy** in the training cubes presented to the network.
    - Network may **overfit** to only the perspective seen during training

Methodology – Data Sampling Strategy

Proposed Attention-based Sampling Strategy

Proposed strategy addresses problems of label imbalance and missed faults treated as no-faults



- Cubes are sampled in **the neighborhood of annotated fault pixels**
    - **Less likely** to sample cubes with **missed fault labels**

- **Stochastic sampling** of cubes to result in diverse data samples for the network
- Let $\mathrm{P} = \{(i, j)\}$ be the set of all annotated fault pixels in the image. Then the sampling indices i_s, j_s are obtained as

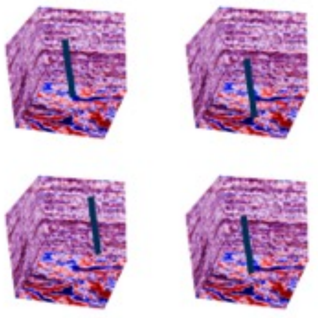
$$i_s, j_s = \mathrm{Poisson}(i), \mathrm{Poisson}(j)$$

- Network is exposed to **multiple, new perspectives** on the same set of annotated faults

Methodology
Attention-based Finetuning

CNN is finetuned on labeled 2D lines from real data using attention-based modulation of the loss function

Synthetic Data Pretraining



Real Data Preparation

Attention-based Stochastic Sampling of Seismic Cubes

Label Expansion for 3D CNN Training

Finetuning

Network Prediction

Masking of Unlabeled Lines in the Unreduced Loss Tensor

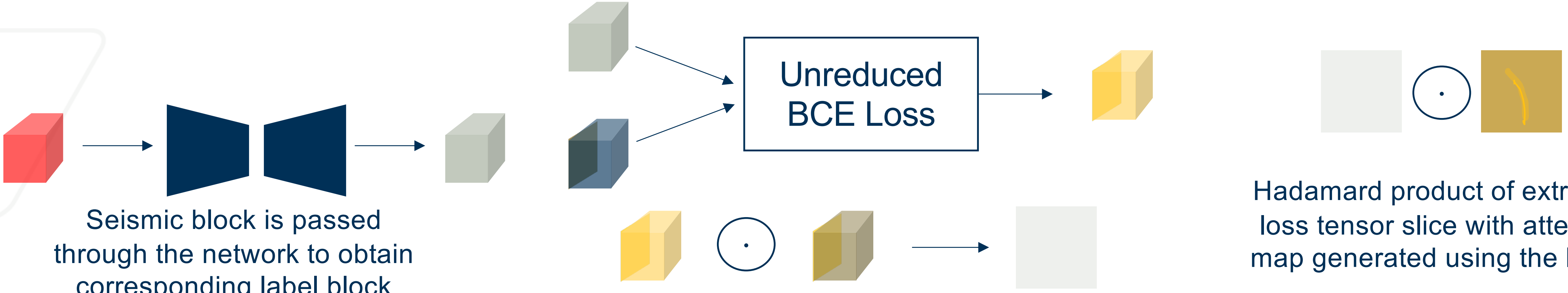
Modulation of Loss Tensor with Attention Map

Backpropagate

Methodology
Attention-based Finetuning

CNN is finetuned on labeled 2D lines from real data using attention-based modulation of the loss function

Network output and label array from before compared via BCE loss to produce loss tensor



Seismic block is passed through the network to obtain corresponding label block

Hadamard product of extracted loss tensor slice with attention map generated using the labels

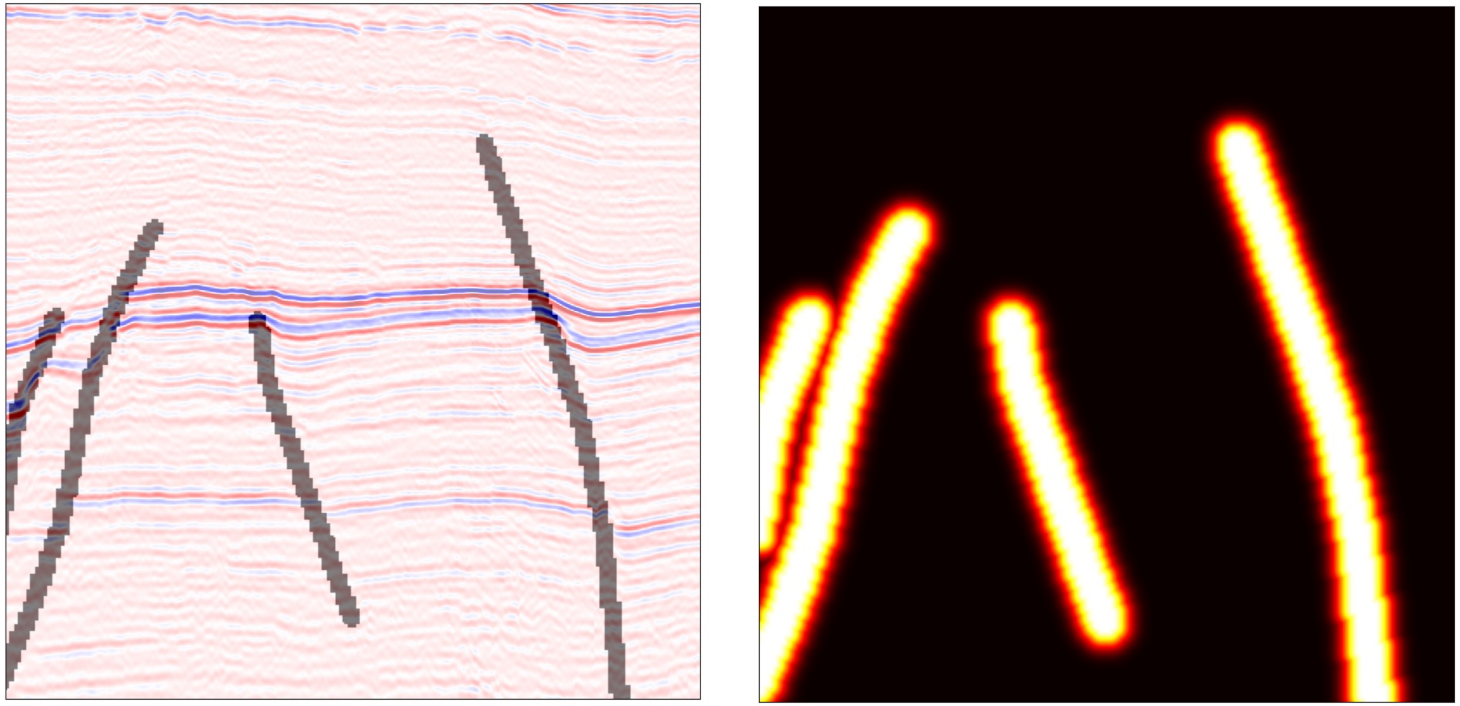
Hadamard product of loss tensor to mask all voxels except for those in labeled inline position

Methodology

Attention-based Modulation of the Loss Tensor

Per-pixel Loss values on annotated lines are modulated by the visual attention map

(a) Seismic Image and Fault Labels (b) Attention Mask



- Loss pixel values are modulated by the **visual attention map.**
- Pixels **further away** from the annotated faults **contribute less** to the aggregated loss.
- Let $I = \{(i, j)\}$ be set of all pixels in the image and $P = \{(i_f, j_f)\}$ be the set of all annotated fault pixels

$$\text{mask}[\mathrm{i}, \mathrm{j}] = \min_{i_f, j_f \in P} \left(i - i_f\right)^2 + \left(j - j_f\right)^2$$

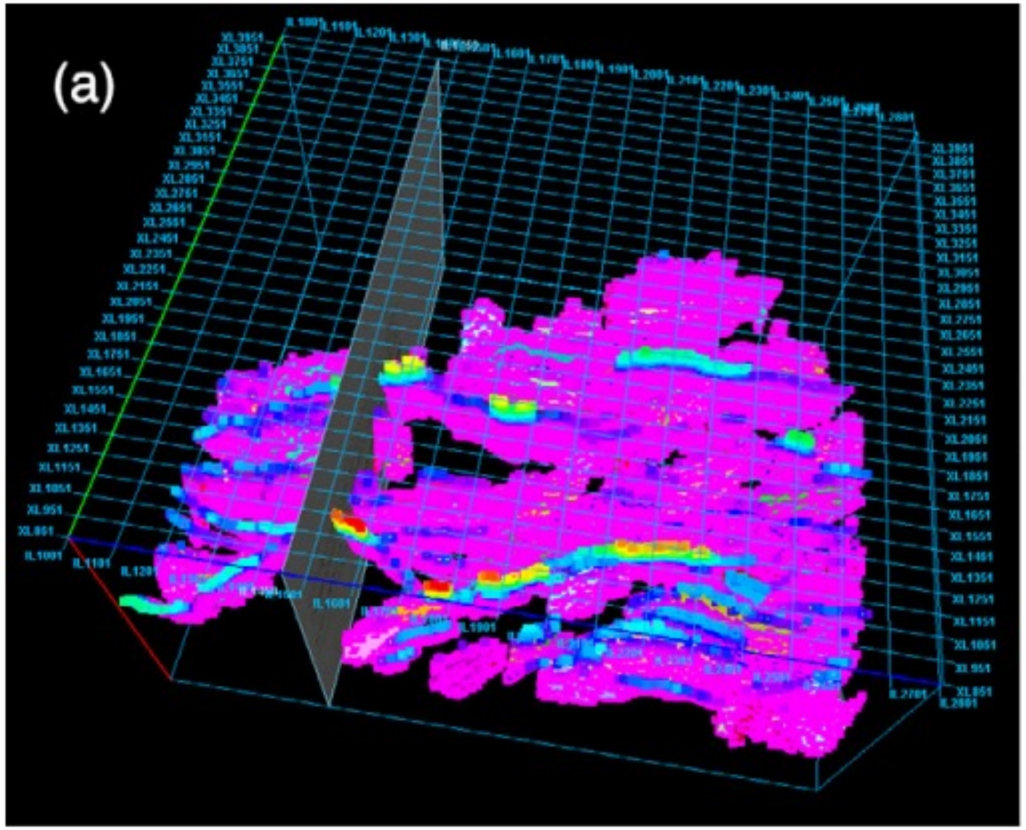
$$\text{attention}[\mathrm{i}, \mathrm{j}] = \alpha \times \exp^{-\gamma \times mask[i,j]}$$

Dataset

Annotated Seismic Dataset from Thebe Gas Basin, NW Australia

Dataset contains some annotated faults and many other missed faults

3D view of the annotated fault planes



A crossline through the volume annotated for faults

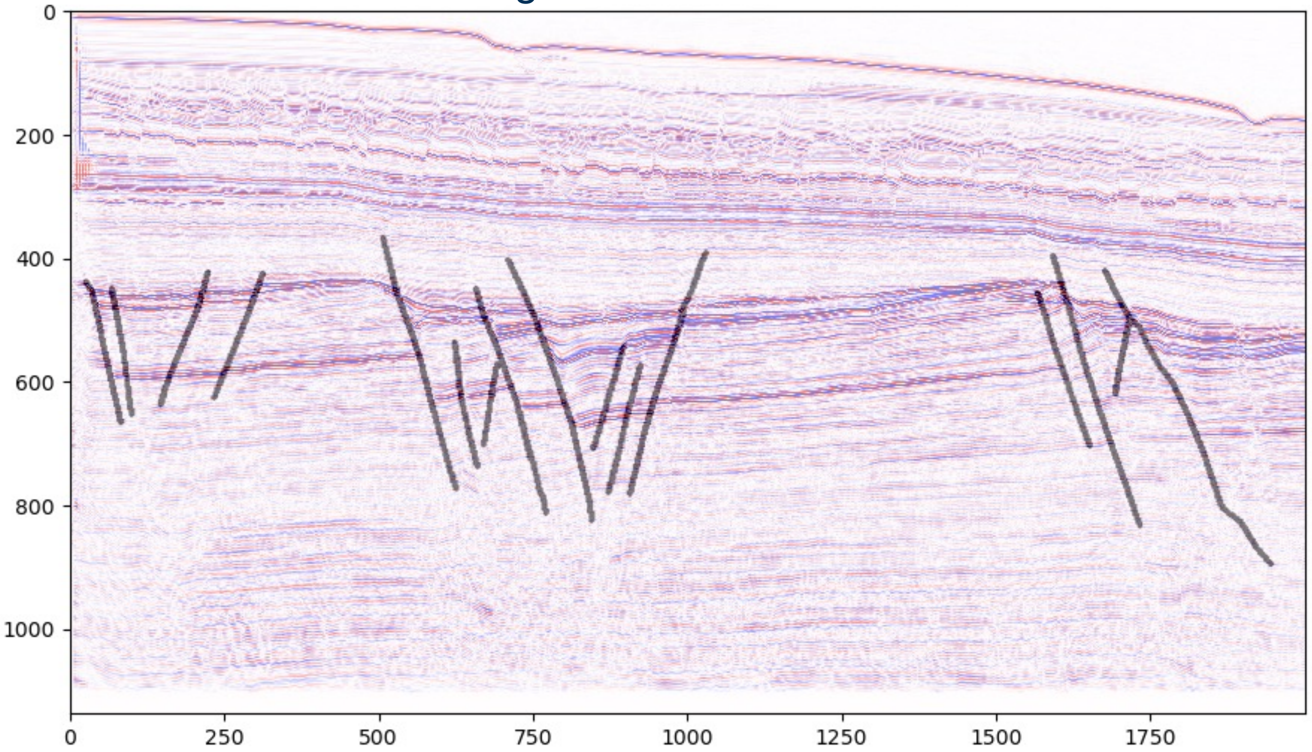


Figure borrowed from [1]. The complete seismic volume contains 1807 crosslines, 3174 inlines, and 1537 samples. Only faults greater than 20m in extent and falling in a certain depth range were annotated.

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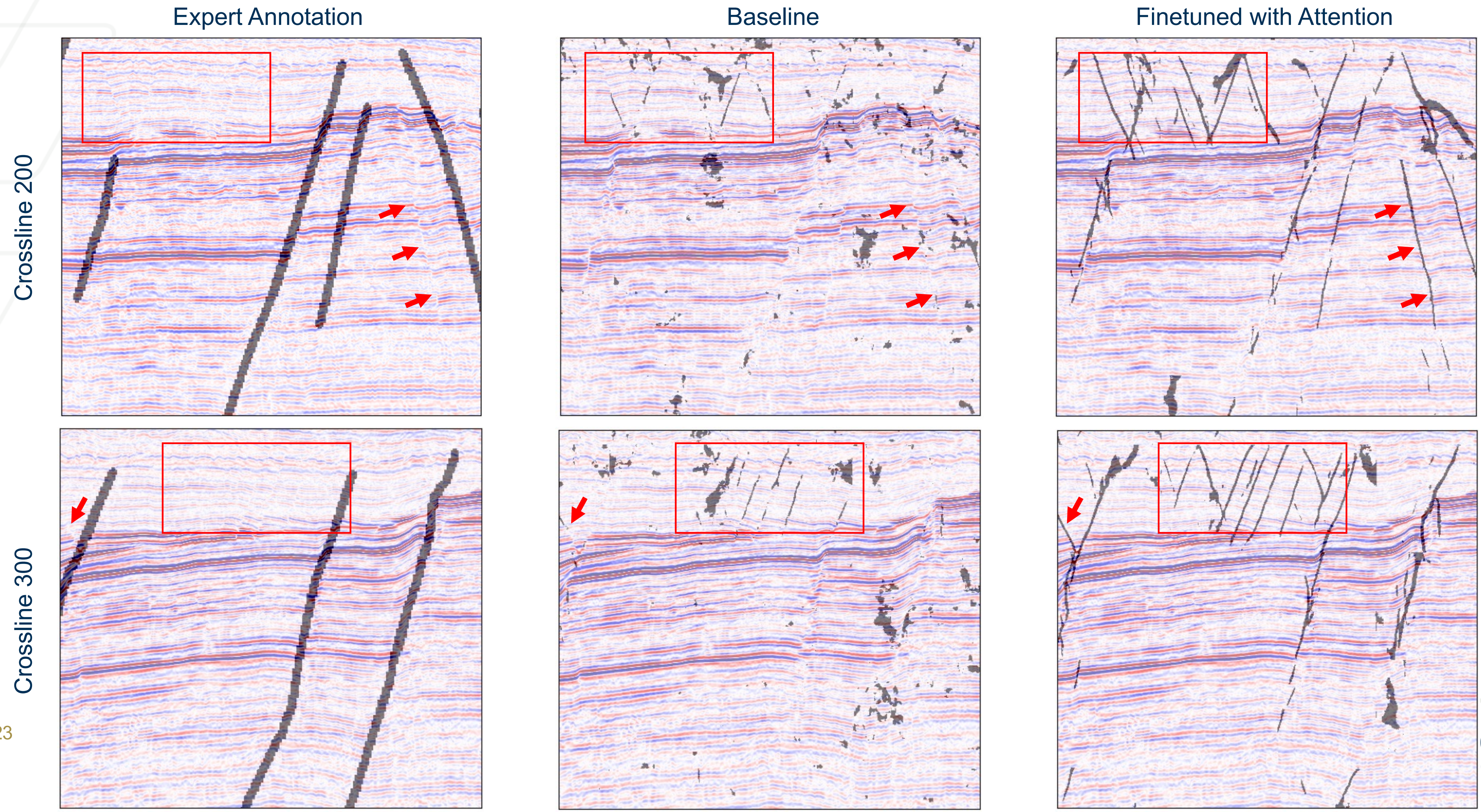
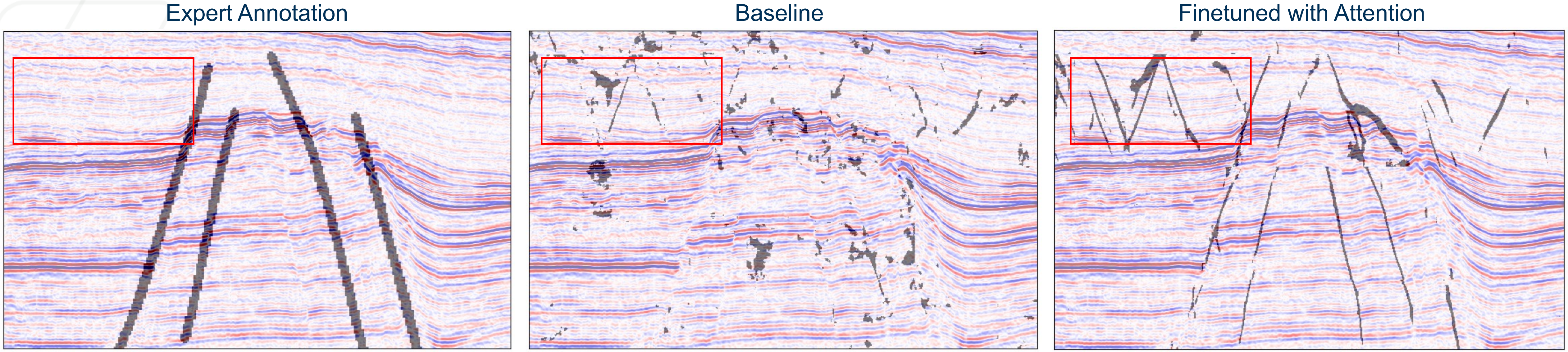
[1] An, Yu, et al. "A gigabyte interpreted seismic dataset for automatic fault recognition." *Data in Brief* 37 (2021): 107219.

Results – Crossline View
Pretrained vs Proposed Finetuning Approach with Attention

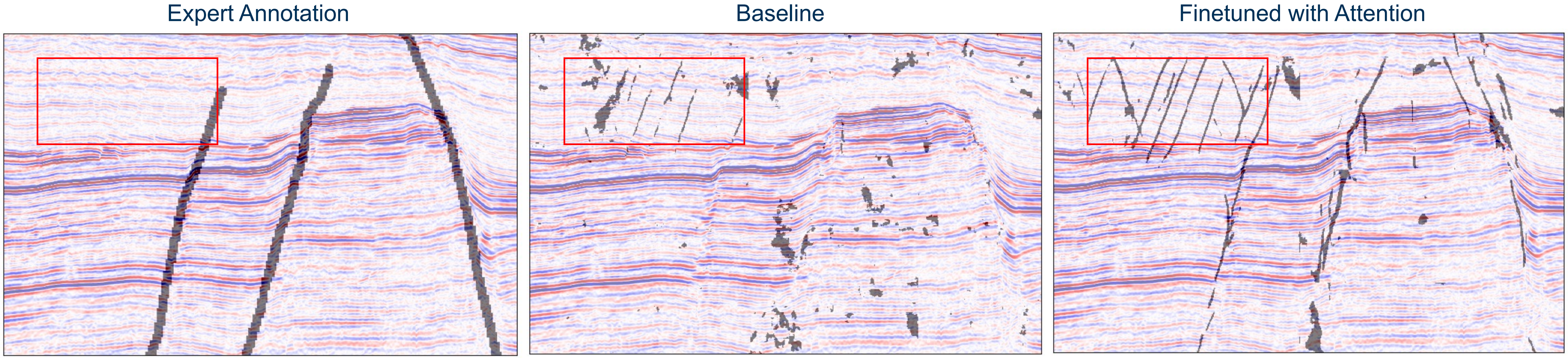


Results – Crossline View
Pretrained vs Proposed Finetuning Approach with Attention

Crossline 200



Crossline 300

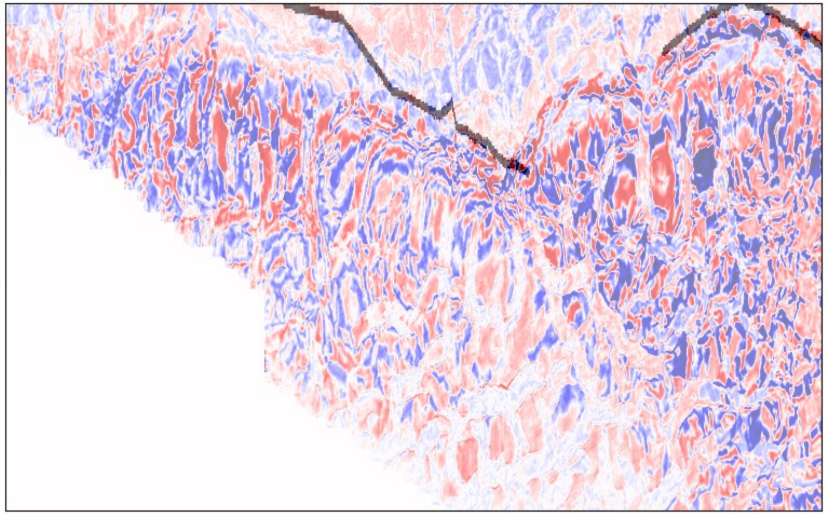


Results – Depth Slice View

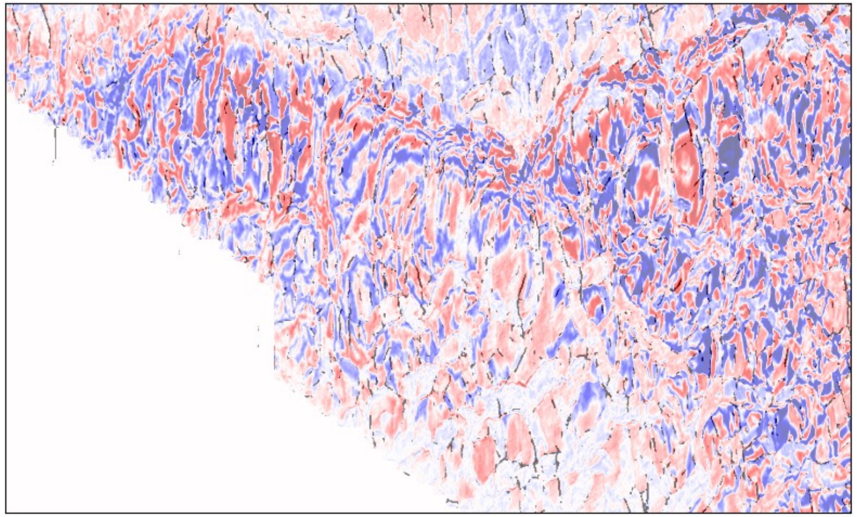
Pretrained vs Proposed Finetuning Approach with Attention

Depth Slice at Index 300

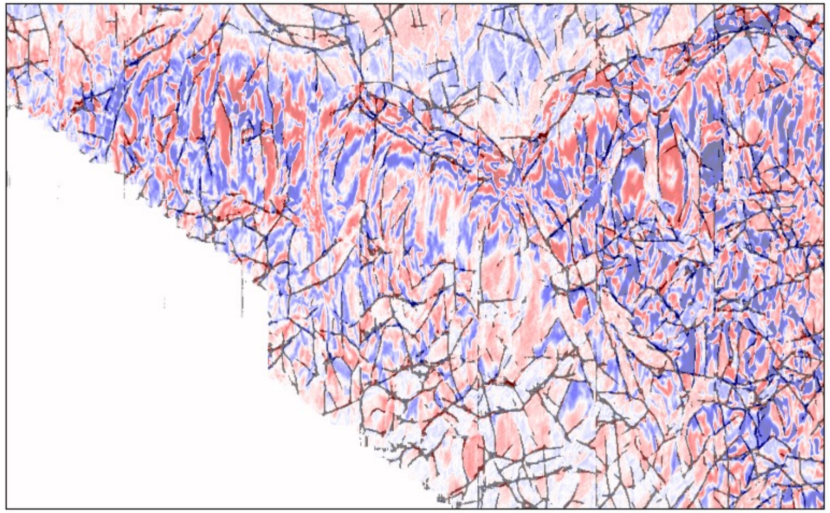
Expert Annotation



Baseline

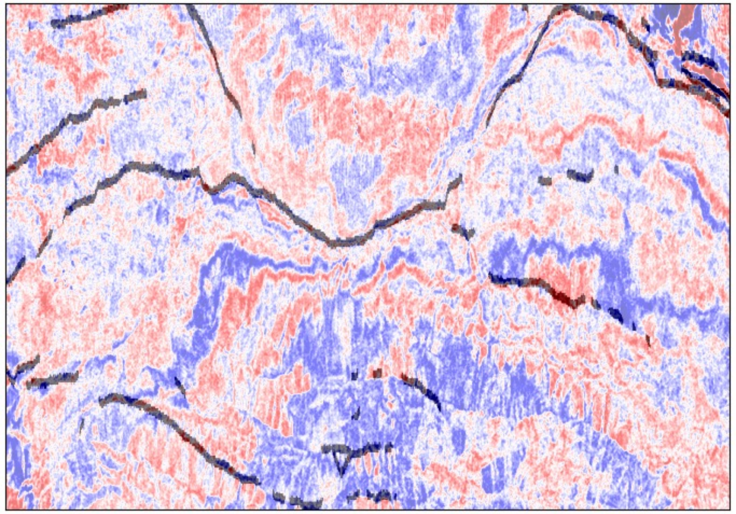


Finetuned with Attention

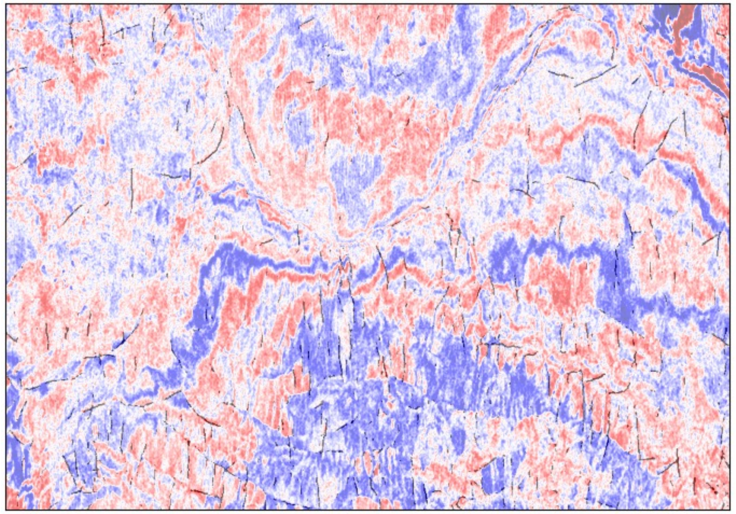


Depth Slice at Index 400

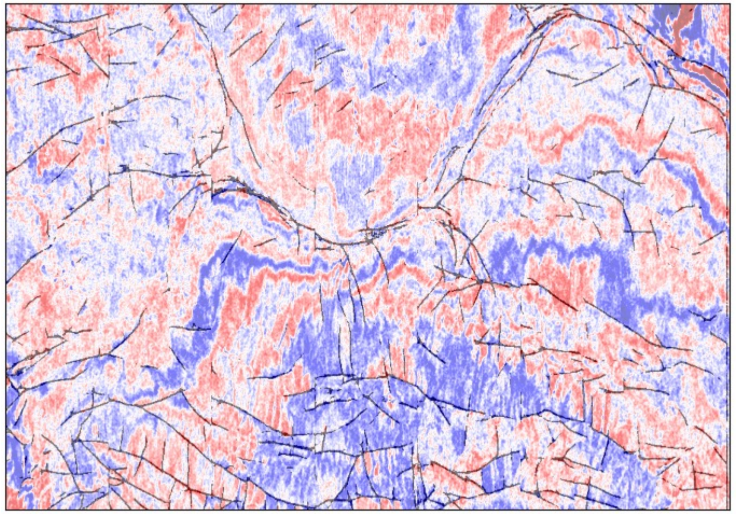
Expert Annotation



Baseline

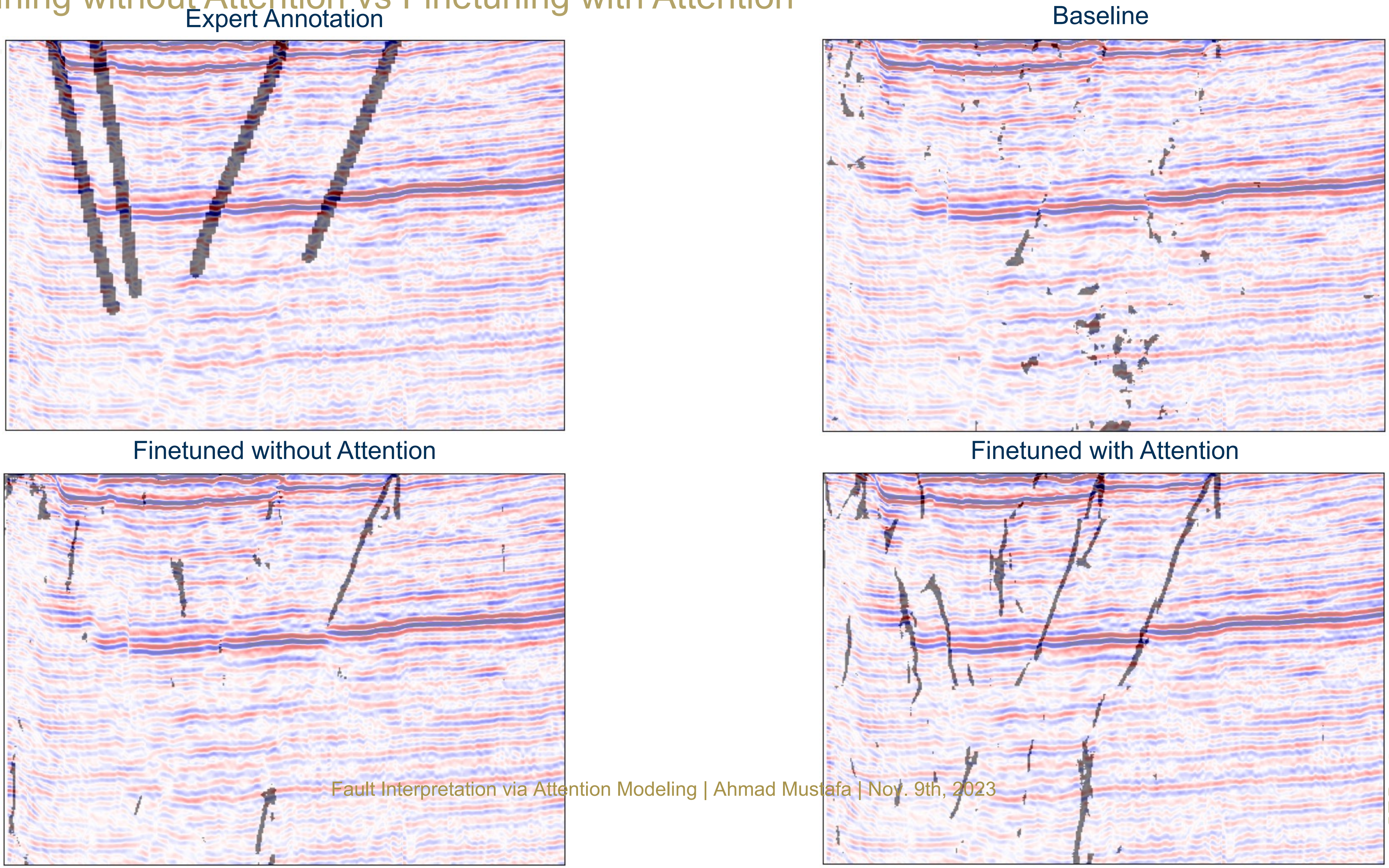


Finetuned with Attention



Results – Crossline View

Finetuning without Attention vs Finetuning with Attention



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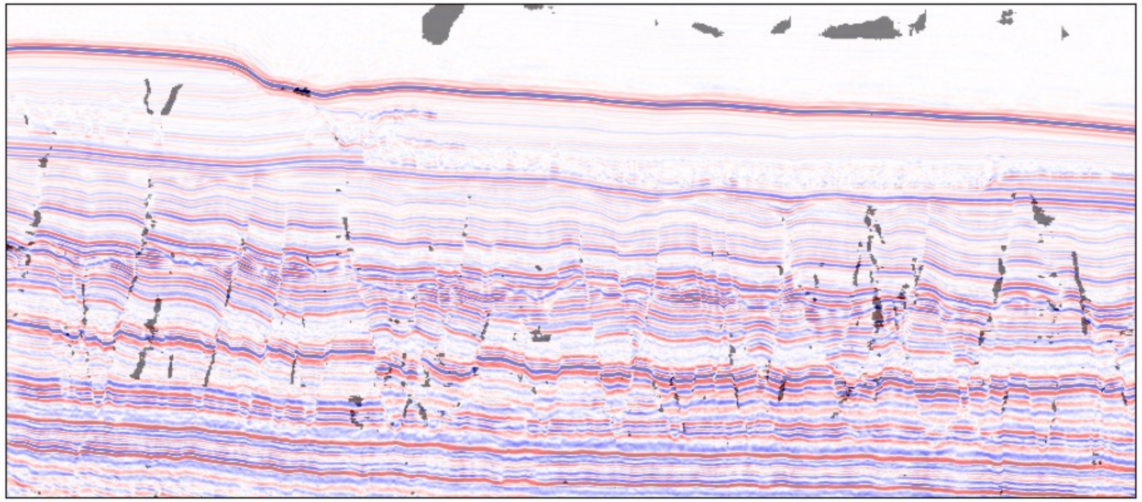
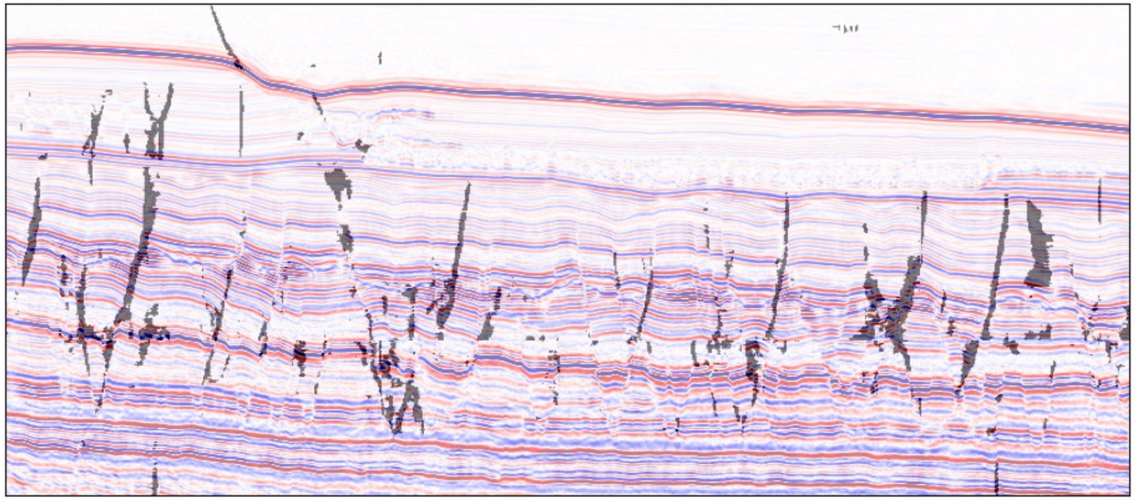
Results – Crossline View

Finetuning without Attention vs Finetuning with Attention

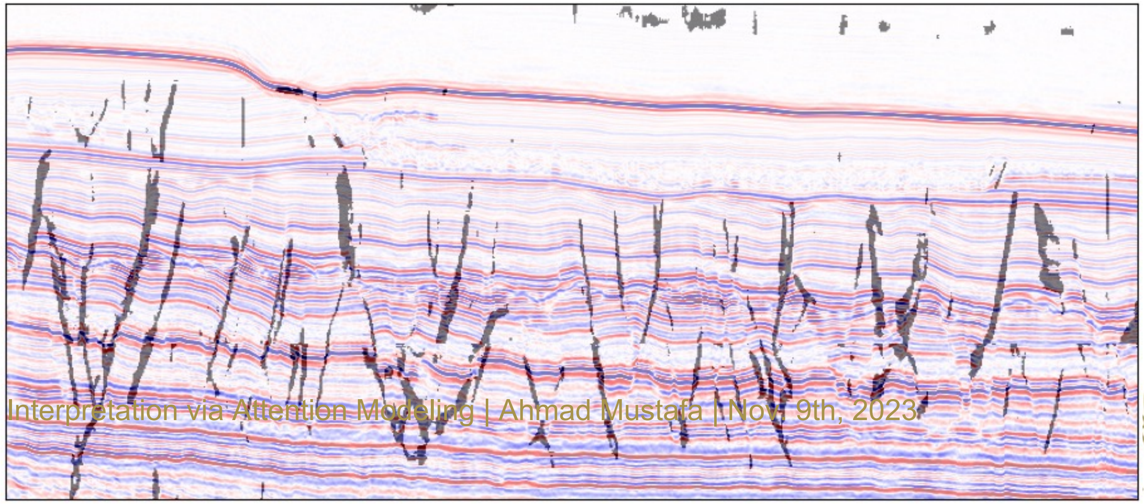
Baseline



Finetuned without Attention



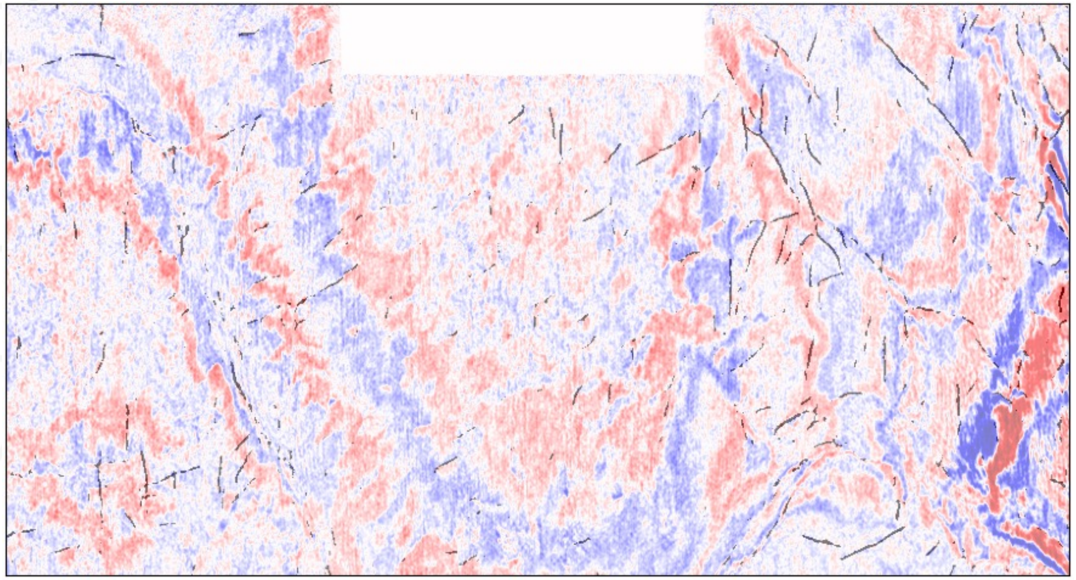
Finetuned with Attention



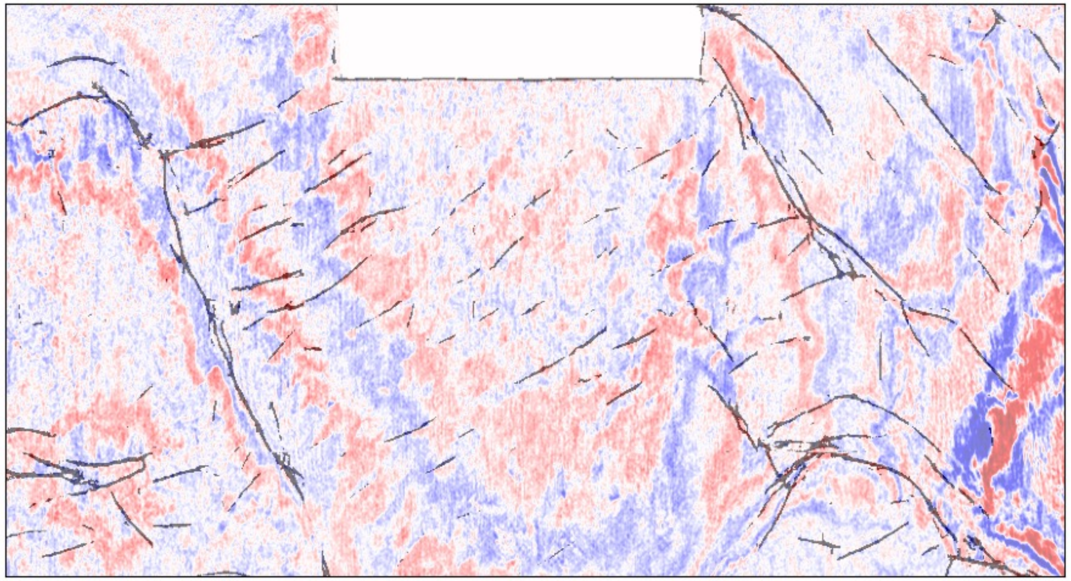
Results – Depth Slice View

Finetuning without Attention vs Finetuning with Attention

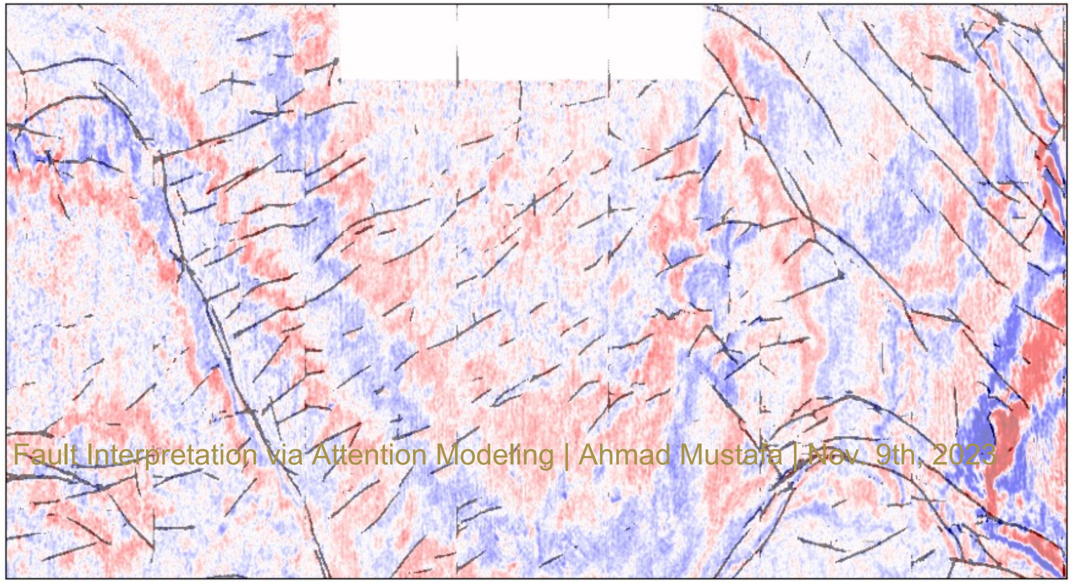
Baseline



Finetuned without Attention



Finetuned with Attention



Conclusion

Modeling Visual Attention to Extract the Best Value from Human Labels

- **Attention selectivity** in biological perception caused by **bottom-up and top-down attention mechanisms** limits focus of perception while annotating seismic images, leading to **incomplete fault labels**
- Missing labels in annotated seismic section can lead to network **learning to predict unlabeled faults as non-faults**, leading to suboptimal learning and test performance
- **Modeling visual attention during network training** can improve network's performance on both **labeled and unlabeled faults**
- Proposed method can be used a **plug-in approach** on top of any existing network architecture and loss function

Acknowledgements

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Publications Code Preprint

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