

ML4Seismic Partners Meeting 2023

Effective Data Selection for Seismic Interpretation through Disagreement

Ryan Benkert, Mohit Prabhushankar, and Ghassan AlRegib

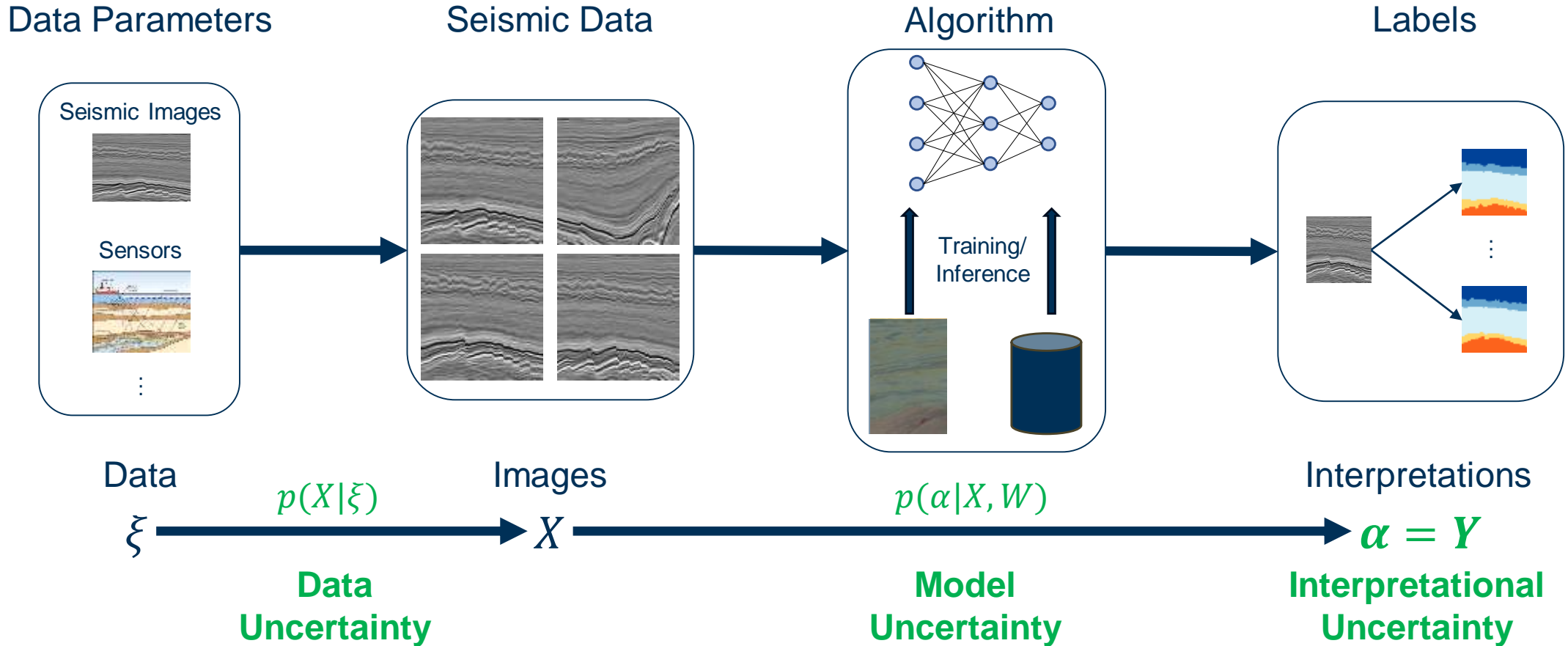
Nov. 7th – Nov. 9th



Proposed Uncertainty Framework

Our Framework Reflects the Processing Steps of the Entire Interpretation Pipeline

Proposed Uncertainty Framework



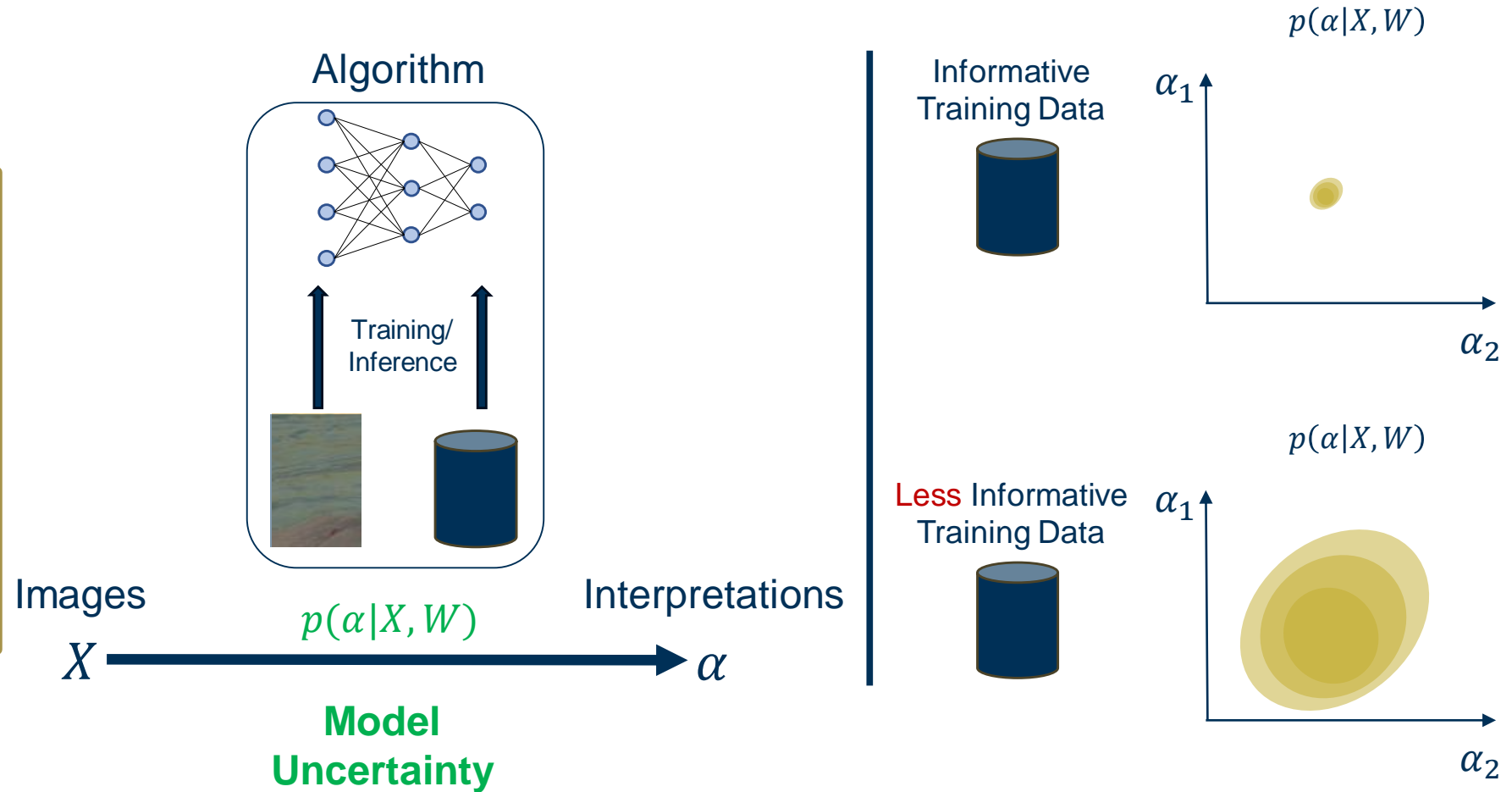
Proposed Uncertainty Framework

Our Framework Reflects the Processing Steps of the Entire Interpretation Pipeline

Proposed Uncertainty Framework

Model Uncertainty:

- Uncertainty in the **model parameters**
- Depends on the **information content** of the training data
- Heavily influenced by training **data selection**

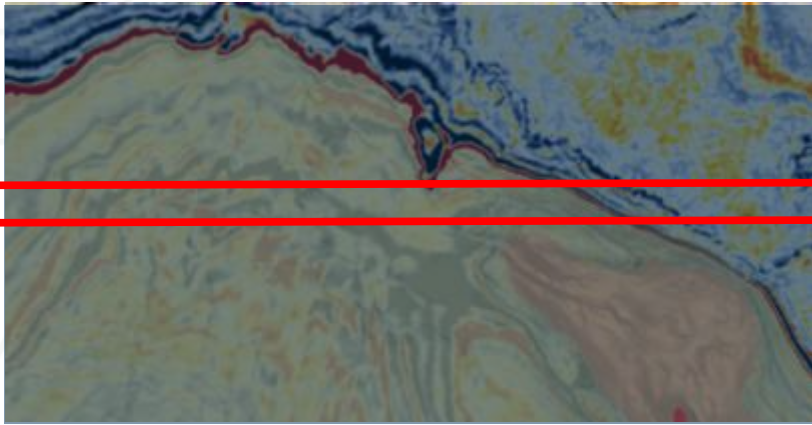


Dataset Selection for Seismic Interpretation

Training Set Selection Severely Impacts the Performance of Deep Neural Networks

Automated Seismic Interpretation Workflow

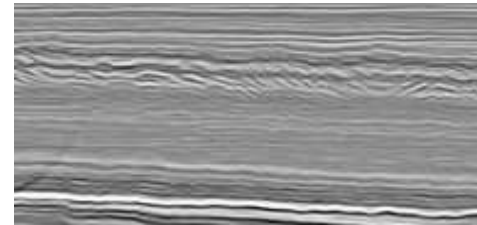
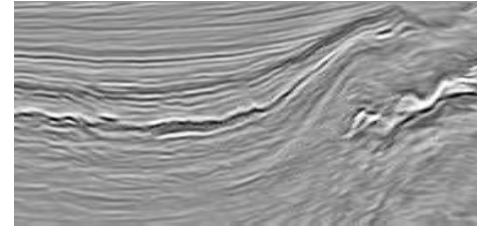
Unlabeled Volume



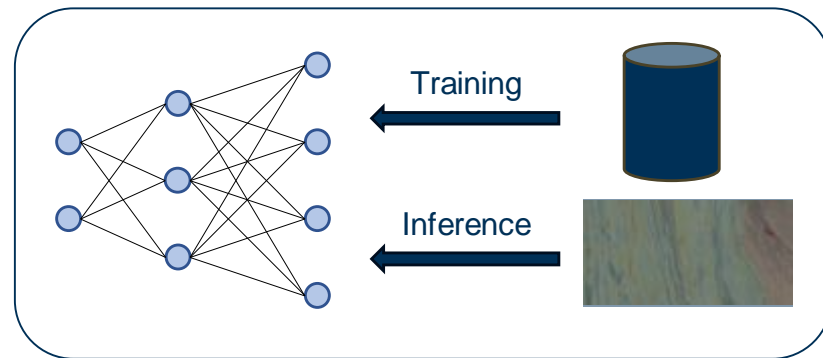
Training Set Selection



Section Labeling



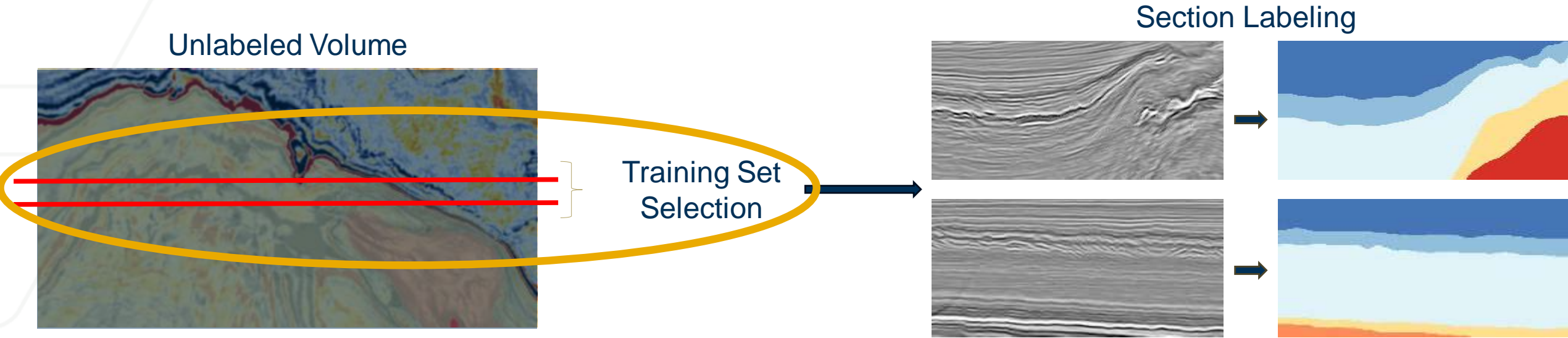
Neural Network Training/Inference



Dataset Selection for Seismic Interpretation

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Automated Seismic Interpretation Workflow



Which samples must be labeled to maximize the interpretation performance?

Dataset Selection for Seismic Interpretation

Training Set Selection Severely Impacts the Performance of Deep Neural Networks

Training Set Selection is a Paramount Factor in Prediction Performance

Selected Training Samples (Toy)

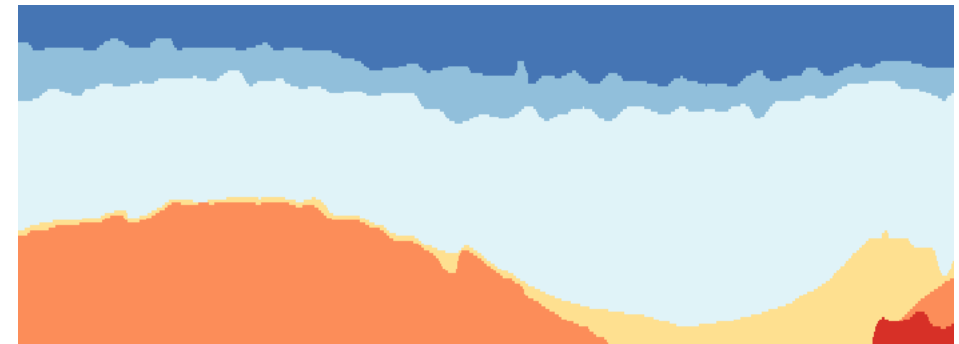


- **Annotations are limited** in seismic datasets
- **Naively** selected training sets can result in **poor performance**

Test Set Prediction



Manual Interpretation

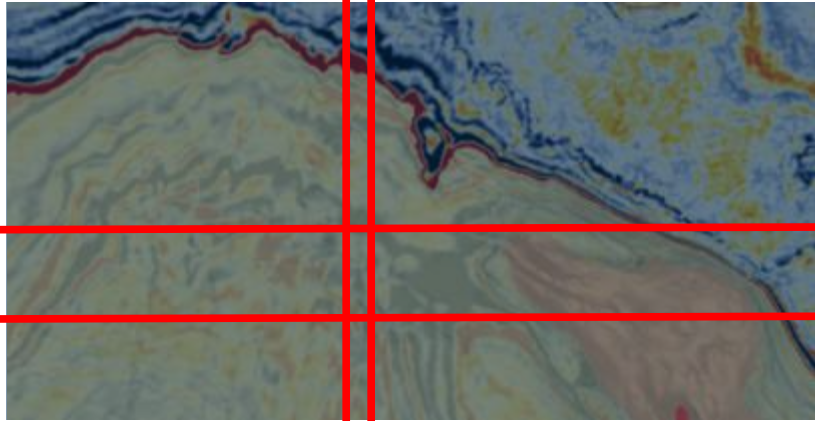


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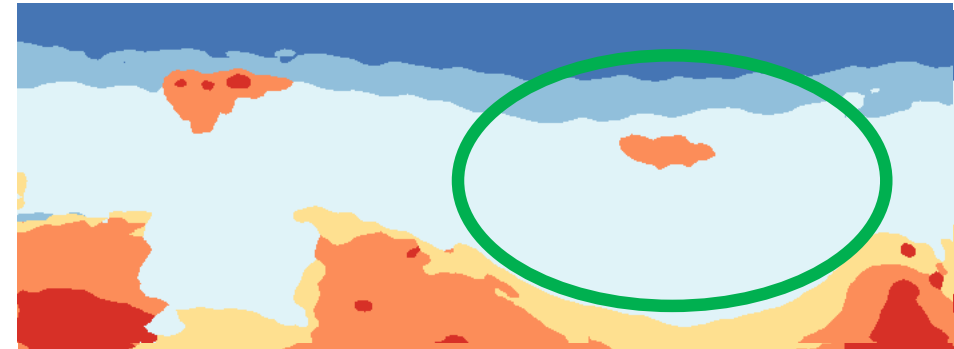
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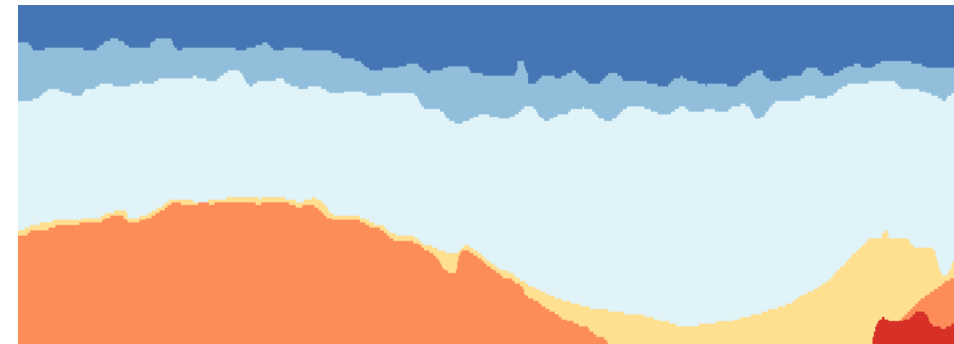


- **Annotations are limited** in seismic datasets
- **Selecting efficiently increases generalization**

Test Set Prediction



Manual Interpretation

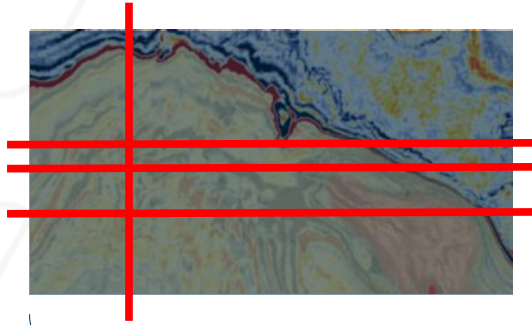


Contributions: Disagreement for Dataset Selection

We Integrate Disagreement into Data-Selection for Seismic Interpretation

Contributions: Integrating Disagreement in Data-Selection for Seismic Interpretation

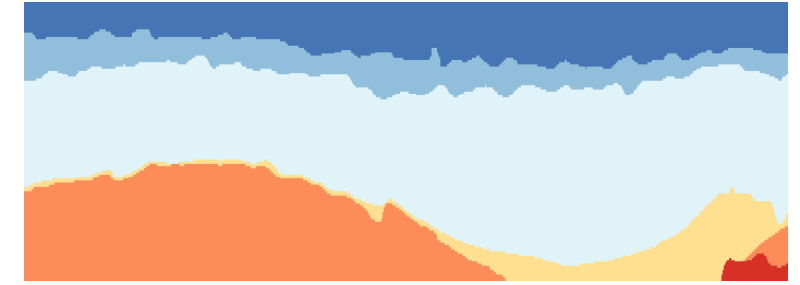
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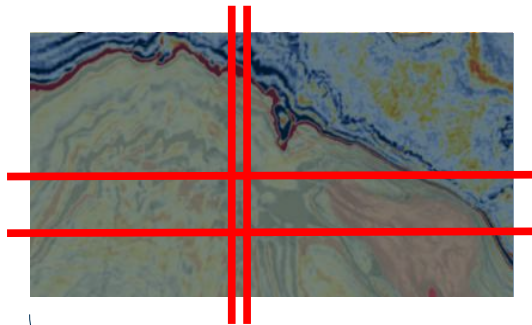
Test Set Prediction



Manual Interpretation



Baseline



Ours

Contributions:

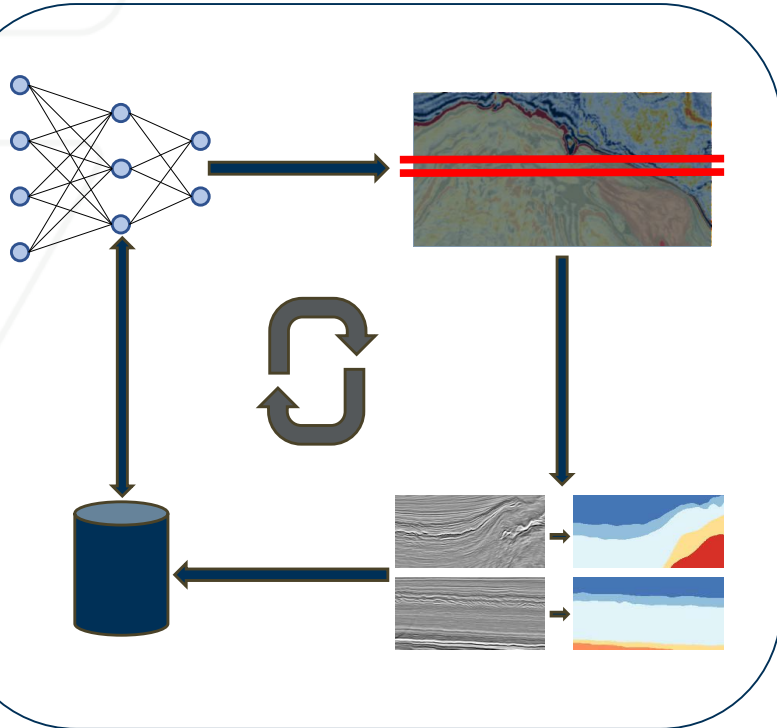
- Discuss **disagreement** as a method to **reduce model uncertainty**
- A theoretically grounded **definition** of disagreement **for neural networks**
- An **automated selection framework** for seismic interpretation

Presentation Structure and Outline

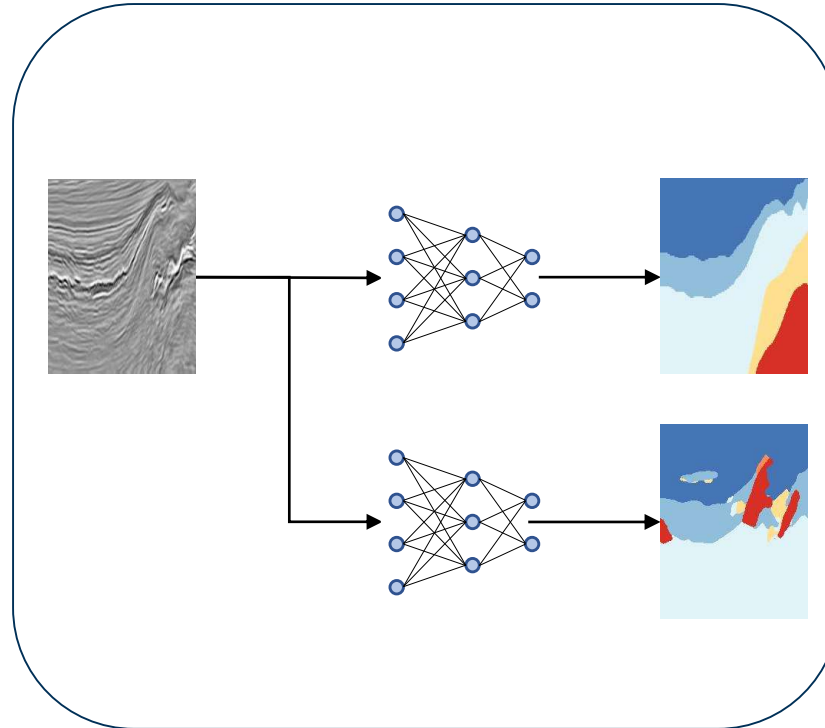
Discussion Topics are Active Learning, ATLAS, and Results

Contributions: Integrating Disagreement in Data-Selection for Seismic Interpretation

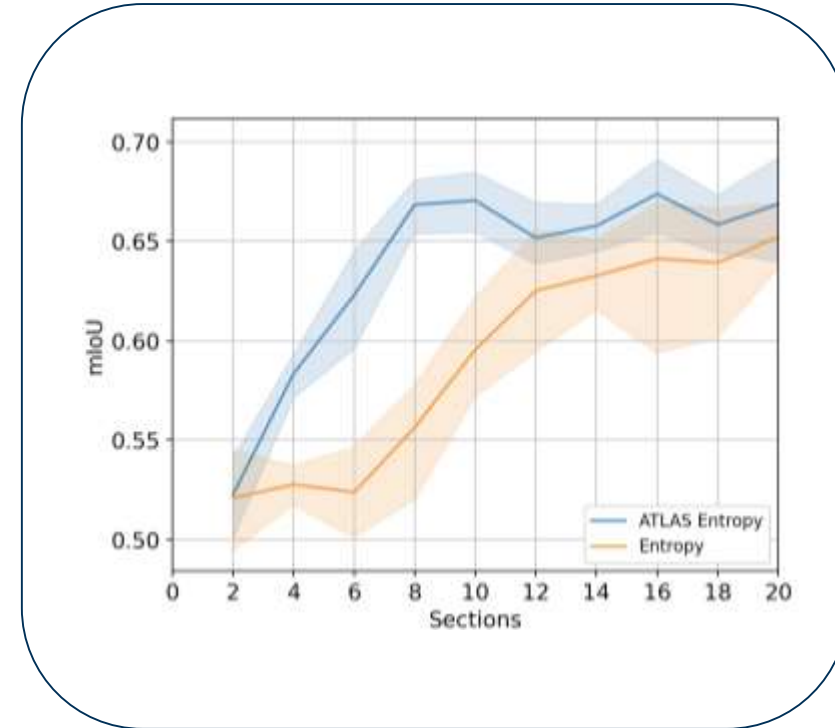
Background: Active Learning



Method: Disagreement



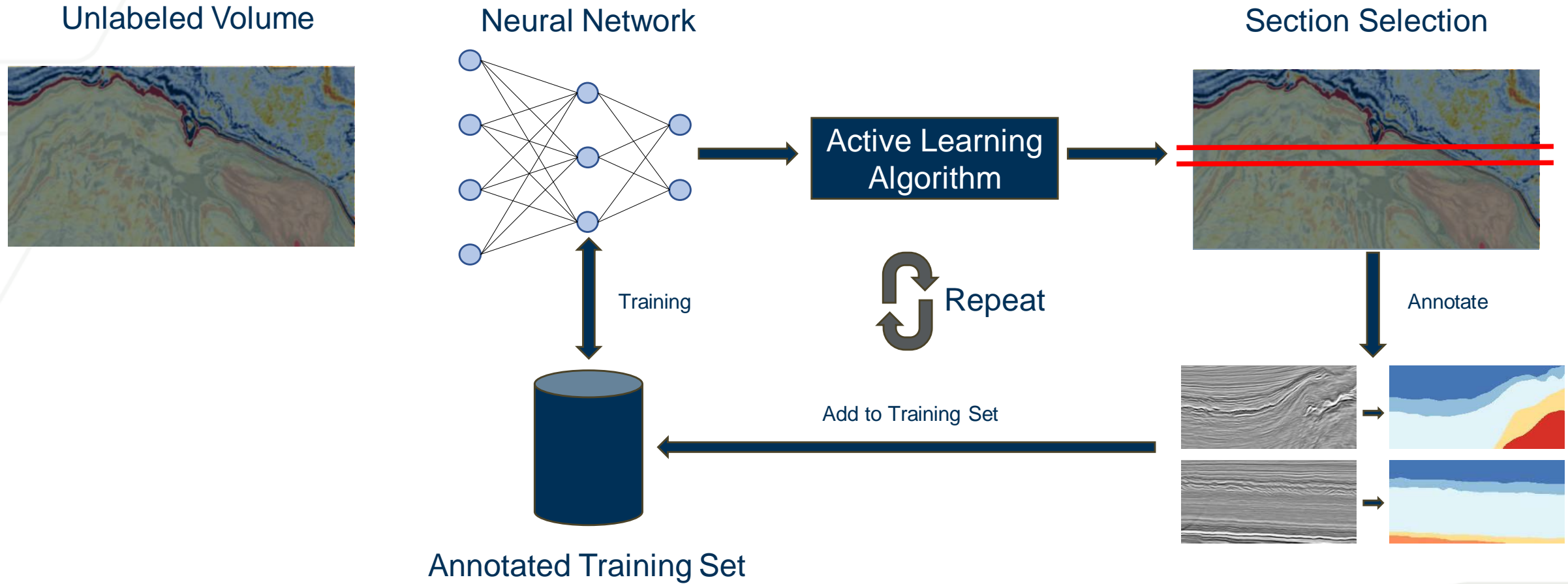
Results: Disagreement



Background: Active Learning

Active Learning is a Machine Learning Paradigm for Efficient Data Selection

Conventional Active Learning Workflow



Background: Active Learning

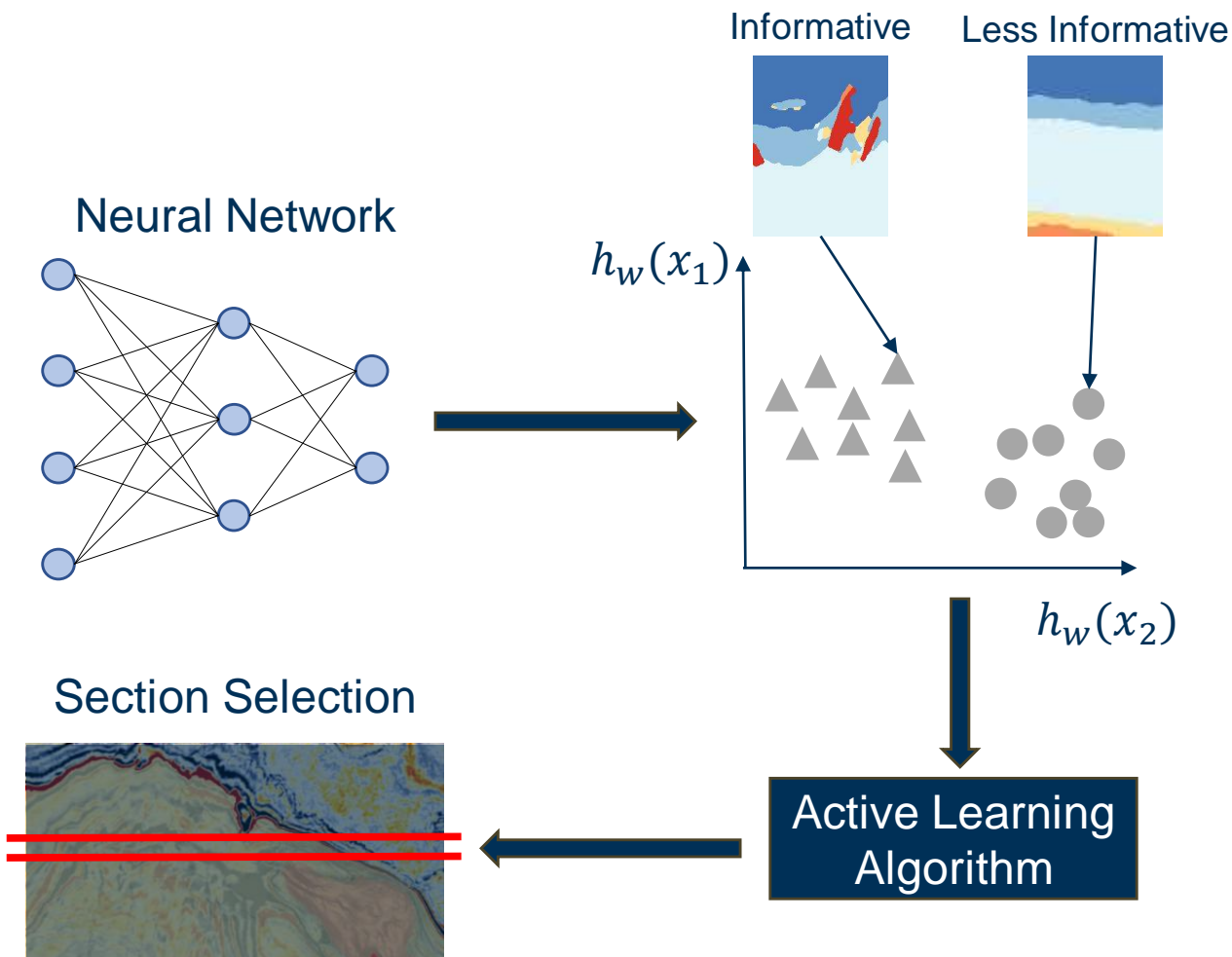
Active Learning is a Machine Learning Paradigm for Efficient Data Selection

Conventional Active Learning Workflow

- Active learning selects samples using an acquisition function to rank representations

$$\operatorname{argmax}_{x_1, \dots, x_b \in D_{pool}} a(x_1, \dots, x_b | h_w)$$

- For an effective selection, the input **representations must be separable** based on their information content
- Interesting geological** regions are frequently **underrepresented** and **collapse** to single data-points



Background: Active Learning

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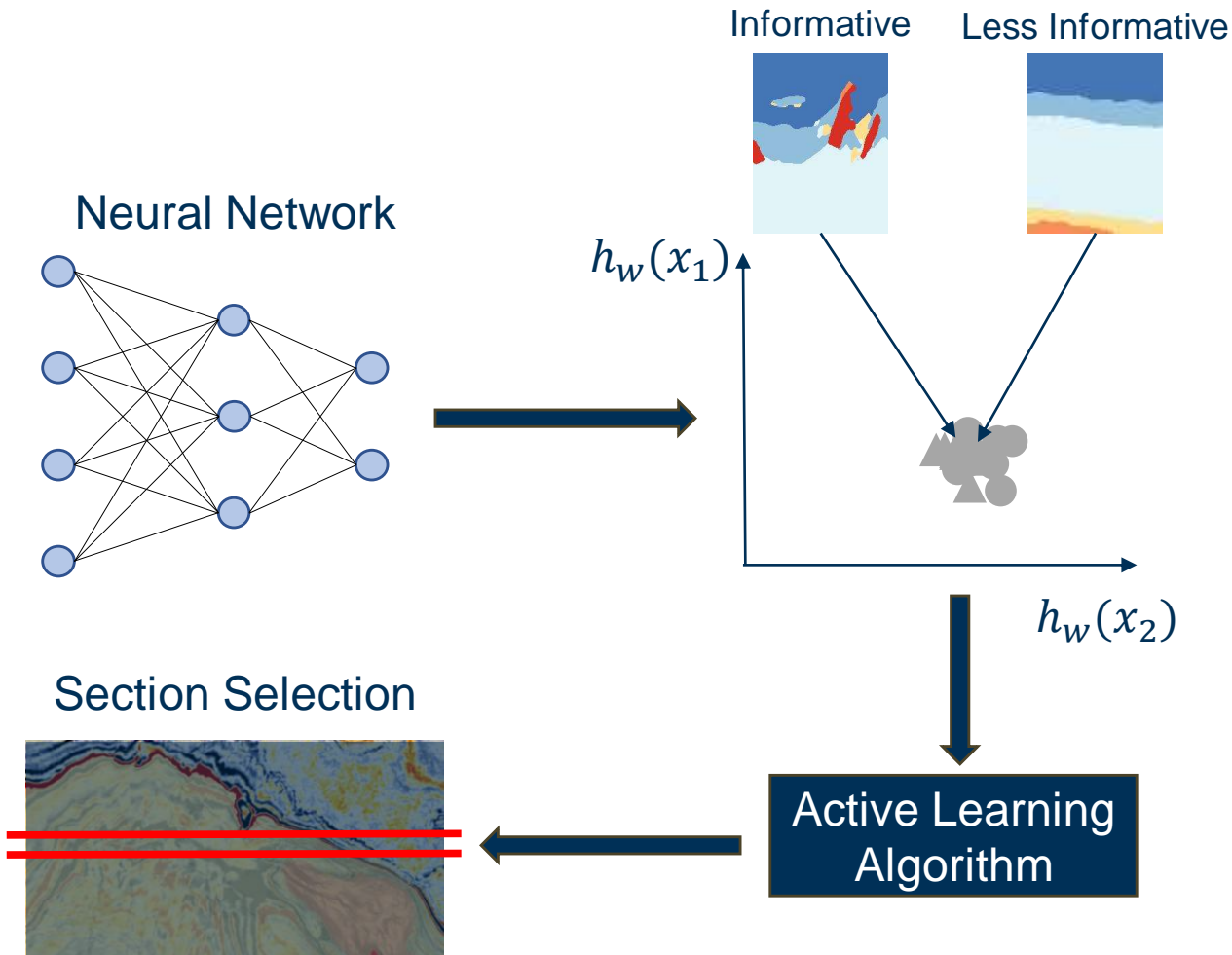
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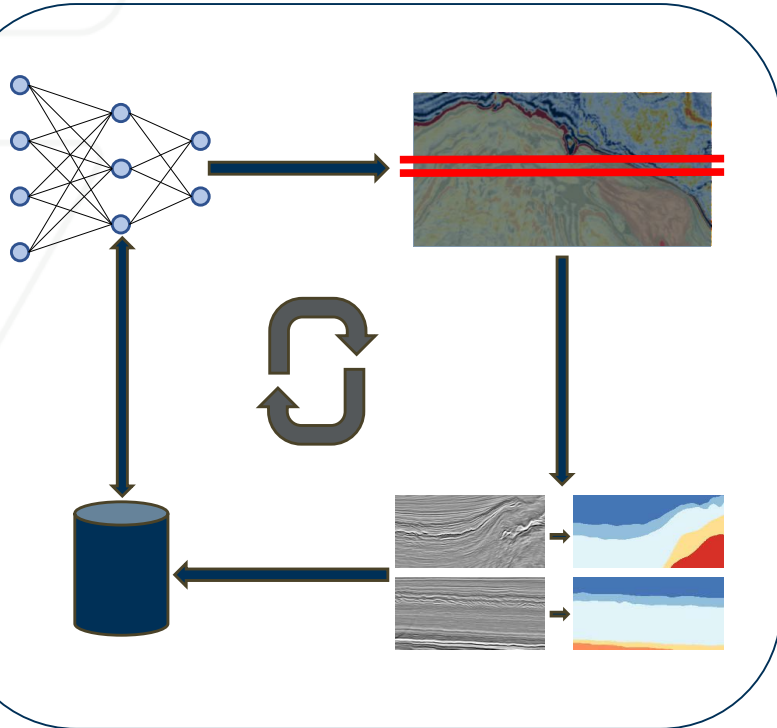


Presentation Structure and Outline

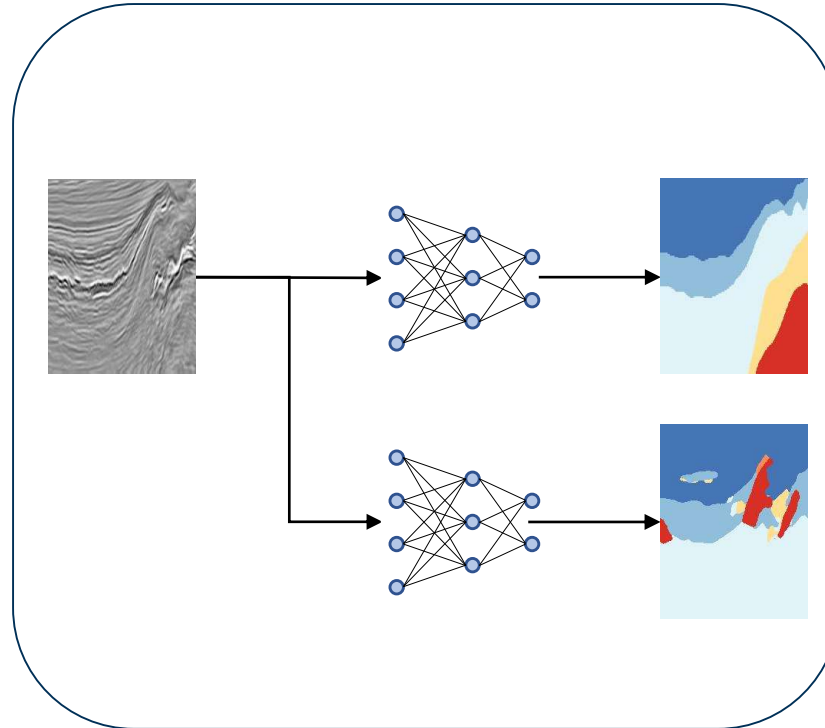
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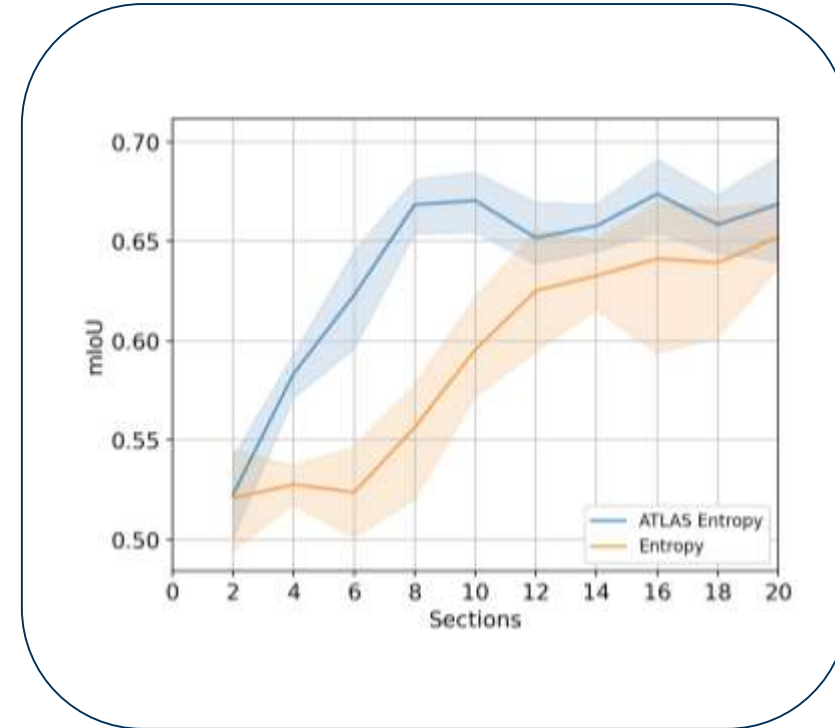
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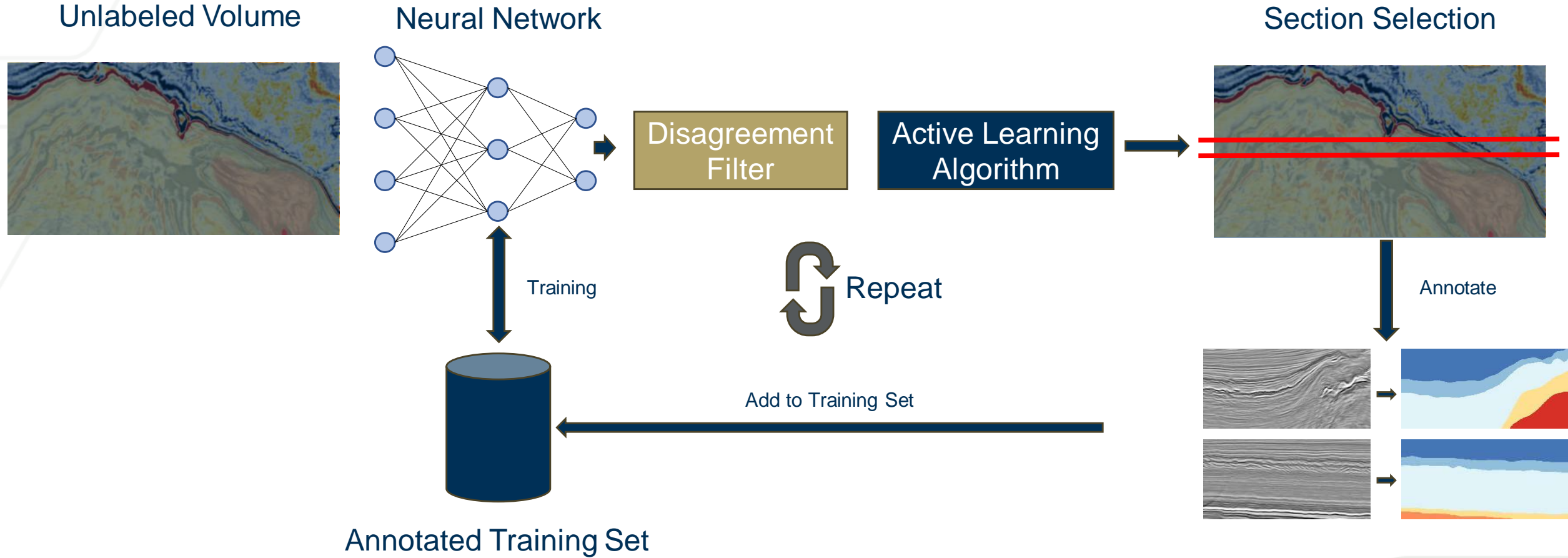
Results: Disagreement



Method: Spatially-Aware Active Learning

Seismic Interpretation Requires Spatial Awareness in Data Selection

Spatially-Aware Active Learning Workflow



Method: Spatially-Aware Active Learning

Active Learning is a Machine Learning Paradigm for Efficient Data Selection

Spatially-Aware Active Learning Workflow

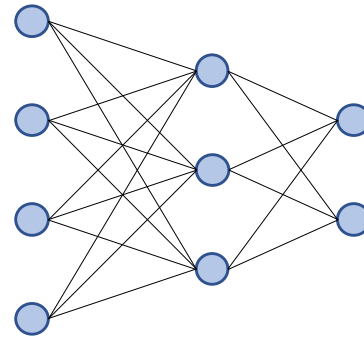
- **Spatially-Aware Active Learning** uses a modified acquisition function

$$\operatorname{argmax}_{x_1, \dots, x_b \in D_{pool}} a(\phi(x_1, h_w), \dots, \phi(x_b, h_w) | h_w)$$

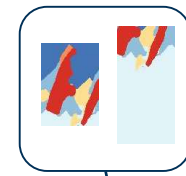
where the input is a mask filter

$$\phi(x, h_w) = x * m(x, h_w)$$

Neural Network



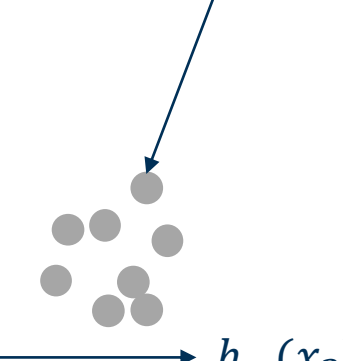
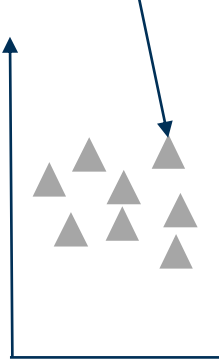
Informative



Less Informative



$h_w(x_1)$



$h_w(x_2)$

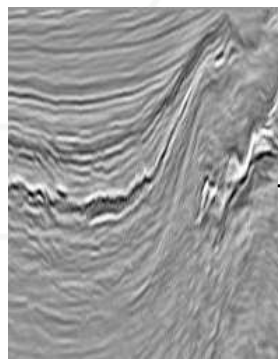


Method: Active Transfer Learning for Attention Sensitivity (ATLAS)

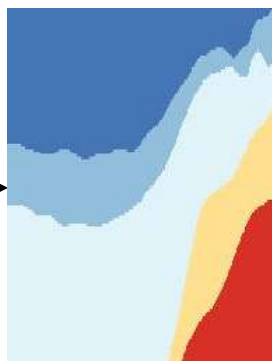
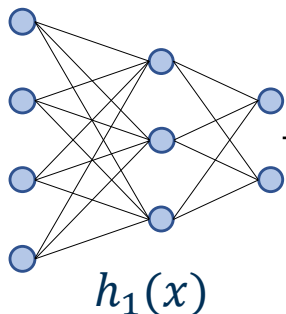
ATLAS is a Simple Implementation of Spatially-Aware Active Learning with Prediction Switches

ATLAS Workflow

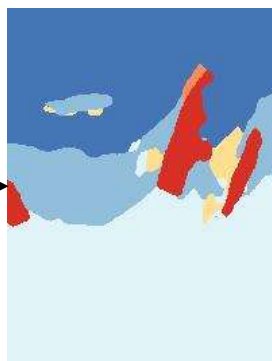
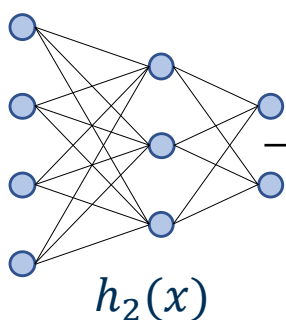
Unlabeled Section



Network at Round N



Network at Round N - 1



Prediction Difference

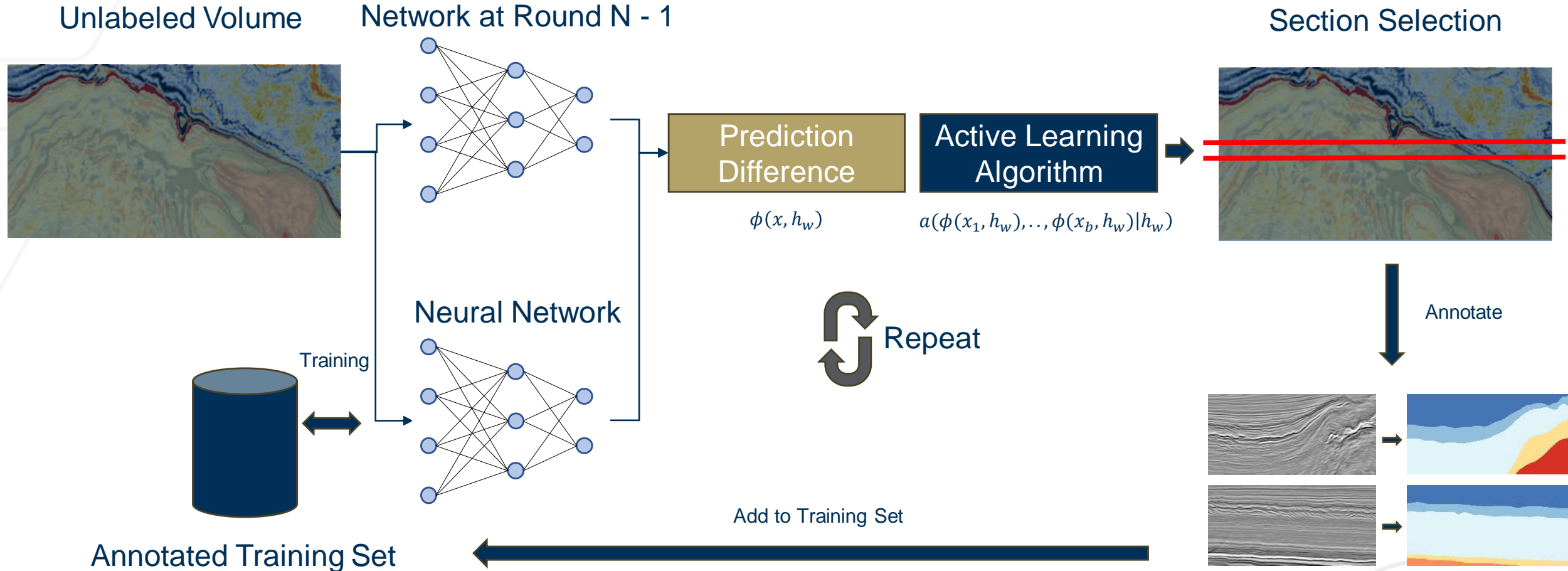


Active Learning Algorithm

Method: ATLAS – Full Workflow

ATLAS is a Simple Implementation of Spatially-Aware Active Learning with Prediction Switches

Spatially-Aware Active Learning Workflow

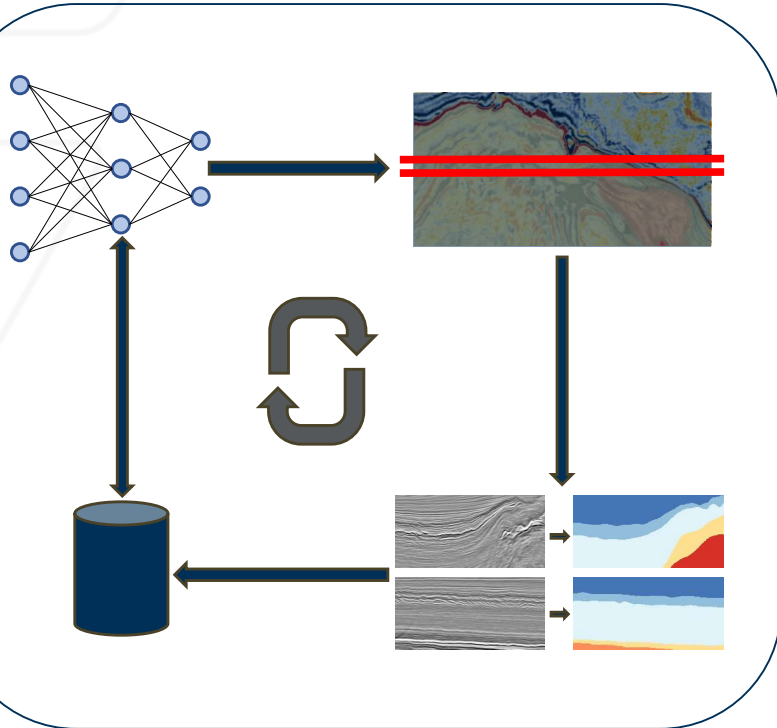


Presentation Structure and Outline

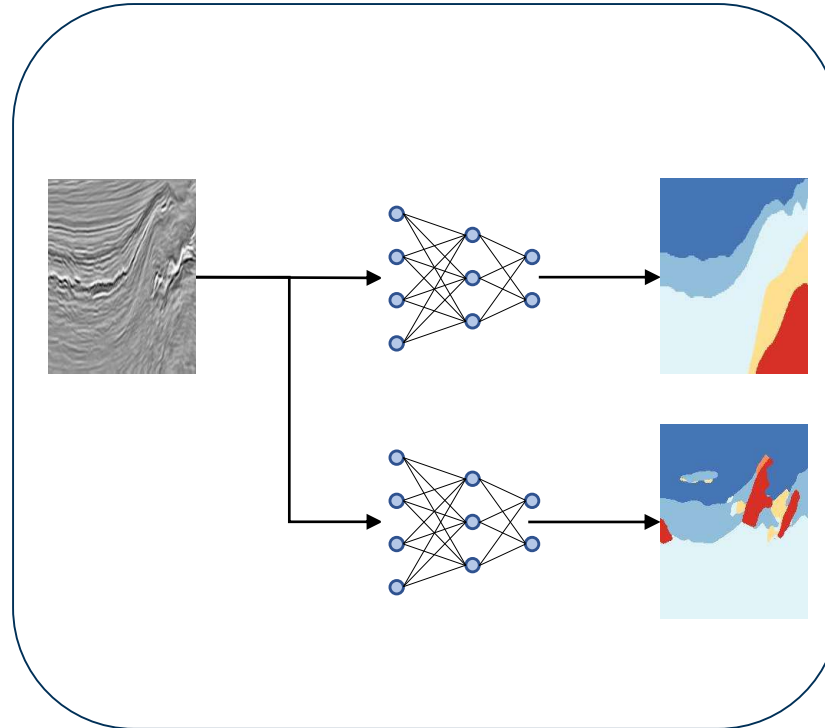
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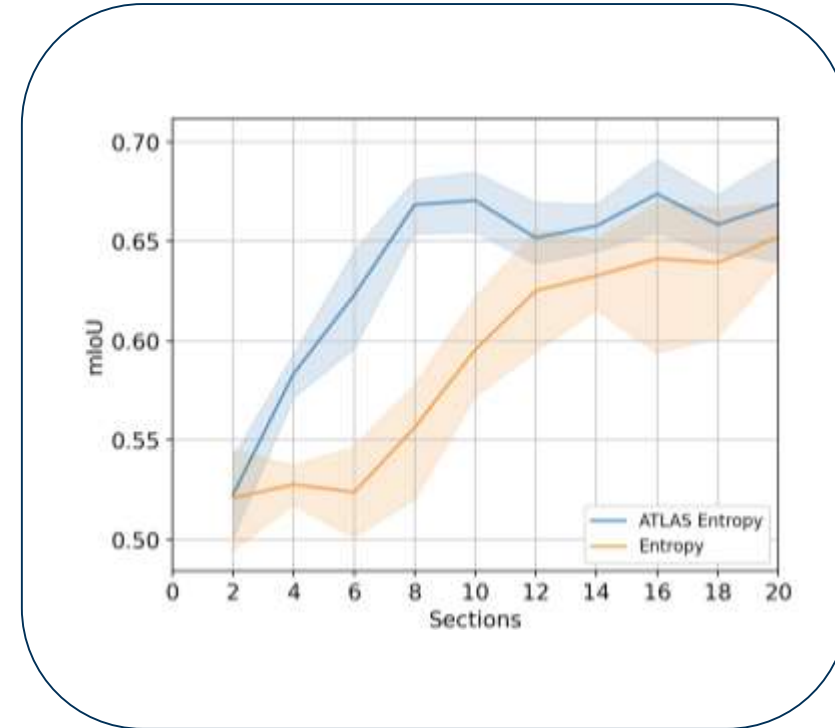
Background: Active Learning



Method: Disagreement



Results: Disagreement

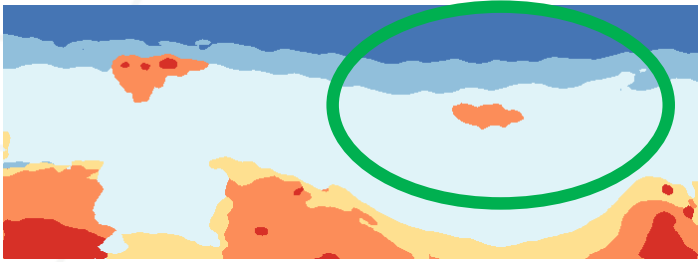


Results: ATLAS – Qualitative Results

ATLAS Matches or Outperforms the Baseline

Qualitative Results – Least Confidence Predictions with or without ATLAS

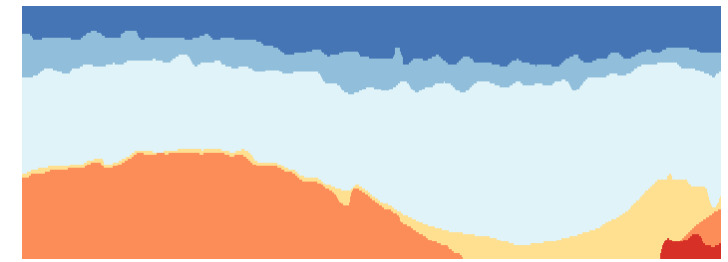
ATLAS Least Confidence



Least Confidence



Manual Interpretation



ATLAS matches or improves over conventional Active Learning.

Results: ATLAS – Qualitative Results

ATLAS Matches or Outperforms the Baseline

Qualitative Results – Areas ATLAS Focuses On

Filtered Regions Across All Rounds

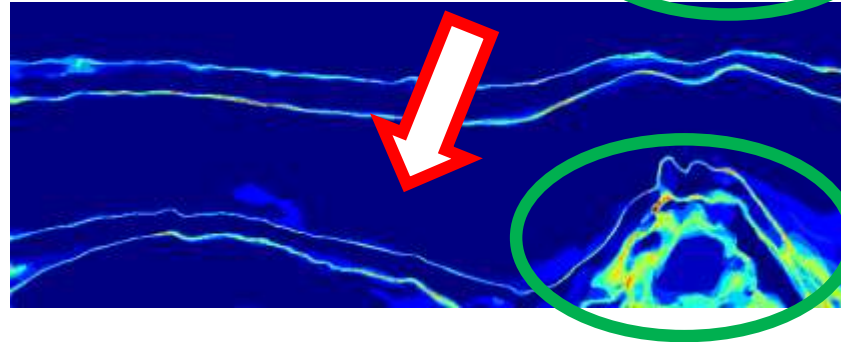
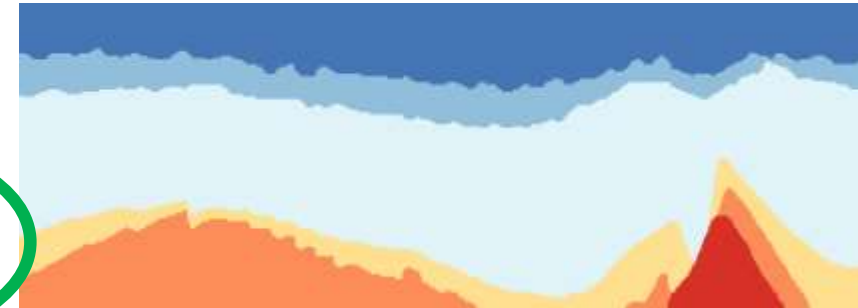
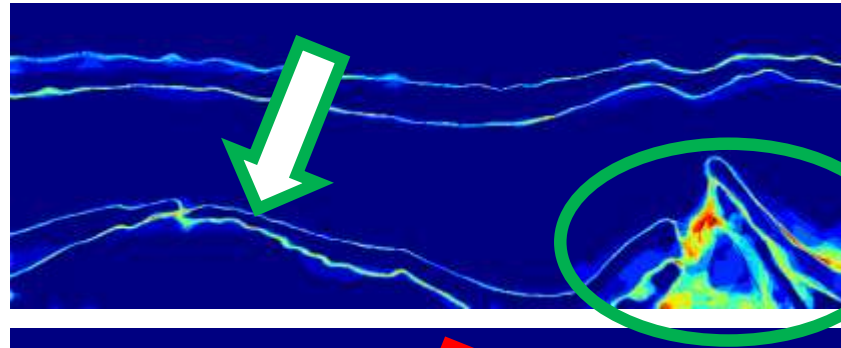
Manual Interpretation

Regions ATLAS Filters:

- Class boundaries
- Difficult structures
- Underrepresented classes
- ...

Regions ATLAS Ignores:

- Well-represented facies
- Monotonous structures
- ...



Results: ATLAS – Qualitative Results

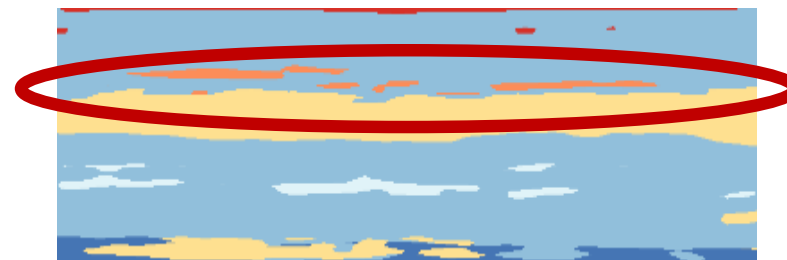
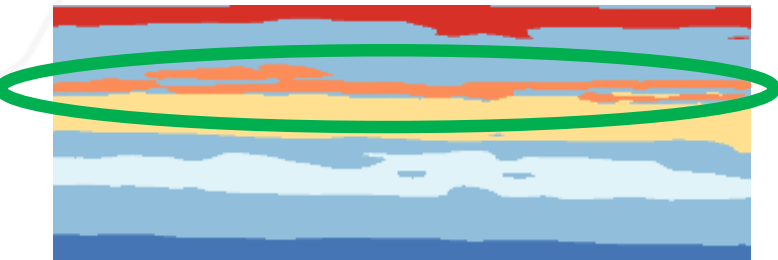
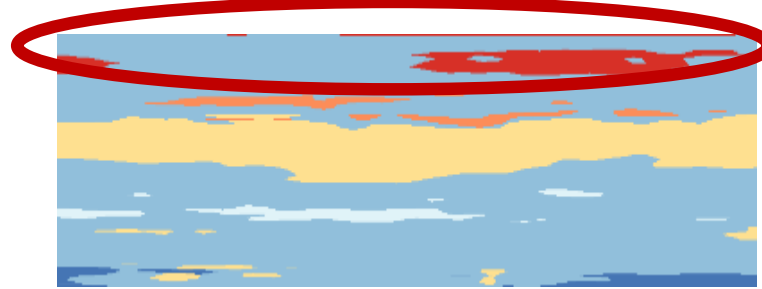
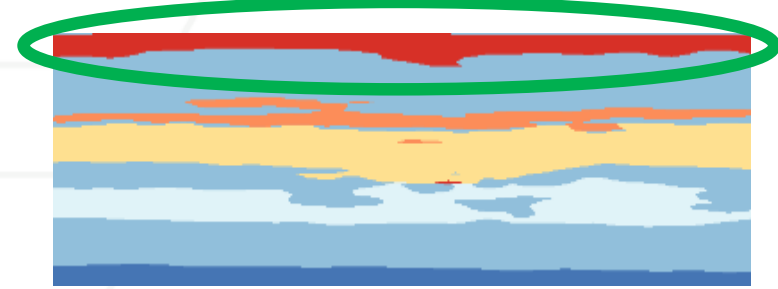
ATLAS Matches or Outperforms the Baseline

Qualitative Results – Least Confidence Predictions with or without ATLAS

ATLAS Least Confidence

Least Confidence

Manual Interpretation



ATLAS performs especially well on class boundaries

Results: ATLAS – Numerical Results

ATLAS Matches or Outperforms the Baseline

Experimental Details:

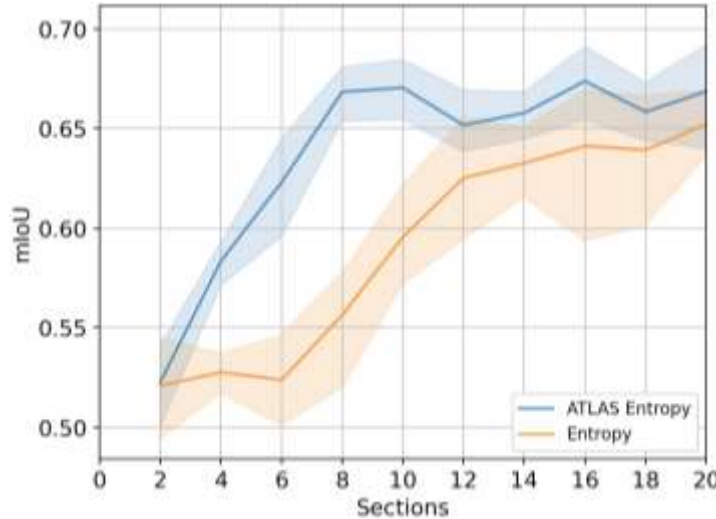
Dataset: F3 block

Initial training size: 2 Sections

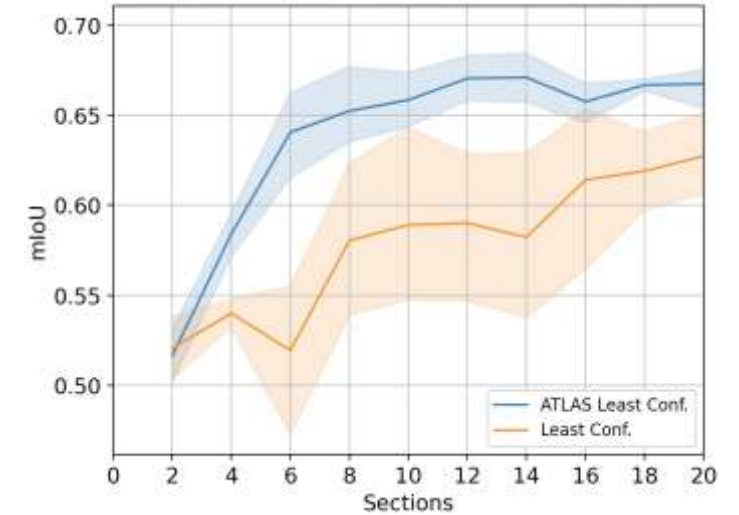
Query Size: 2 Sections

Numerical Results

Entropy



Least Confidence



Algorithm	mIoU	Upper N.S.	Mid. N.S.	Lower N.S.	Chalk	Scruff	Zechstein
Entropy	0.591	0.975	0.846	0.950	0.636	0.373	0.461
ATLAS Entropy	0.620	0.976	0.872	0.957	0.651	0.495	0.417
Least Conf.	0.575	0.970	0.808	0.944	0.637	0.388	0.430
ATLAS Least Conf.	0.619	0.974	0.869	0.956	0.653	0.480	0.459

Thanks for Listening
Questions?

ML4SEISMIC



Publications



Code



Method: Spatially-Aware Active Learning

Active Learning is a Machine Learning Paradigm for Efficient Data Selection

Spatially-Aware Active Learning Workflow

- **Spatially-Aware Active Learning** uses a modified acquisition function

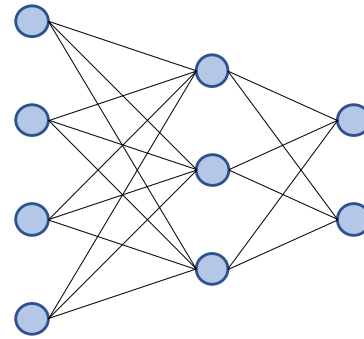
$$\operatorname{argmax}_{x_1, \dots, x_b \in D_{pool}} a(\phi(x_1, h_w), \dots, \phi(x_b, h_w) | h_w)$$

where the input is a mask filter

$$\phi(x, h_w) = x * m(x, h_w)$$

We model geological interest as interpretation disagreement.

Neural Network

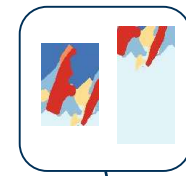


Mask filter



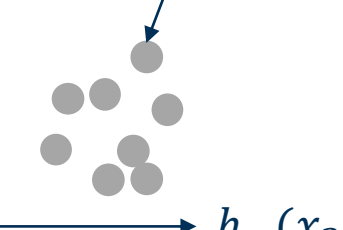
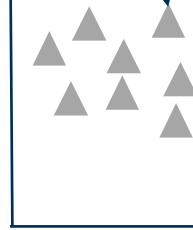
Informative

Less Informative



$h_w(x_1)$

Active Learning Algorithm

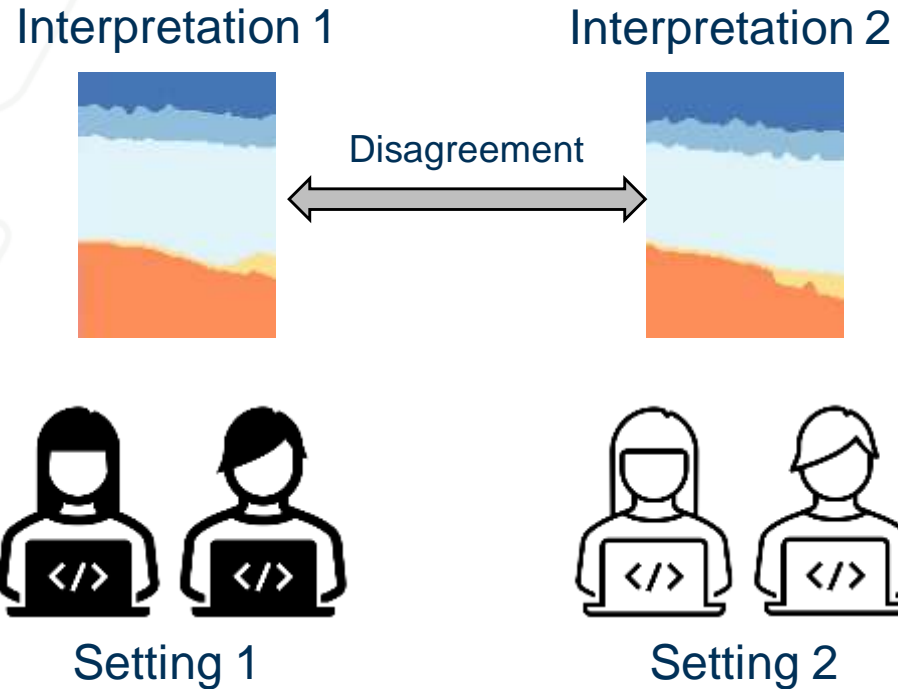


$h_w(x_2)$

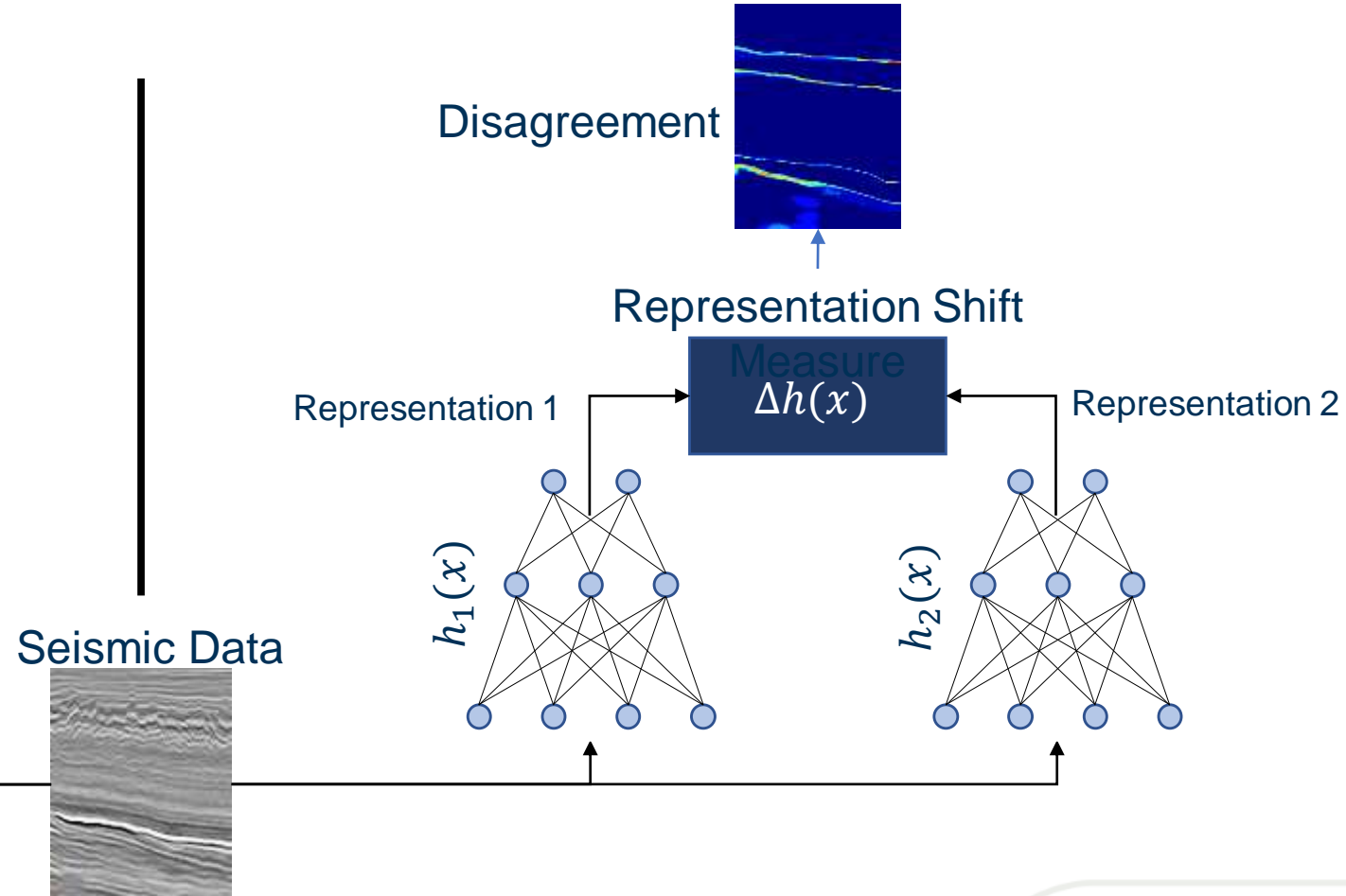
Method: Geological Interest as Disagreement

Disagreement Mimics the Manual Interpretation Process and is Beneficial for Data Selection

Interpretation Disagreement



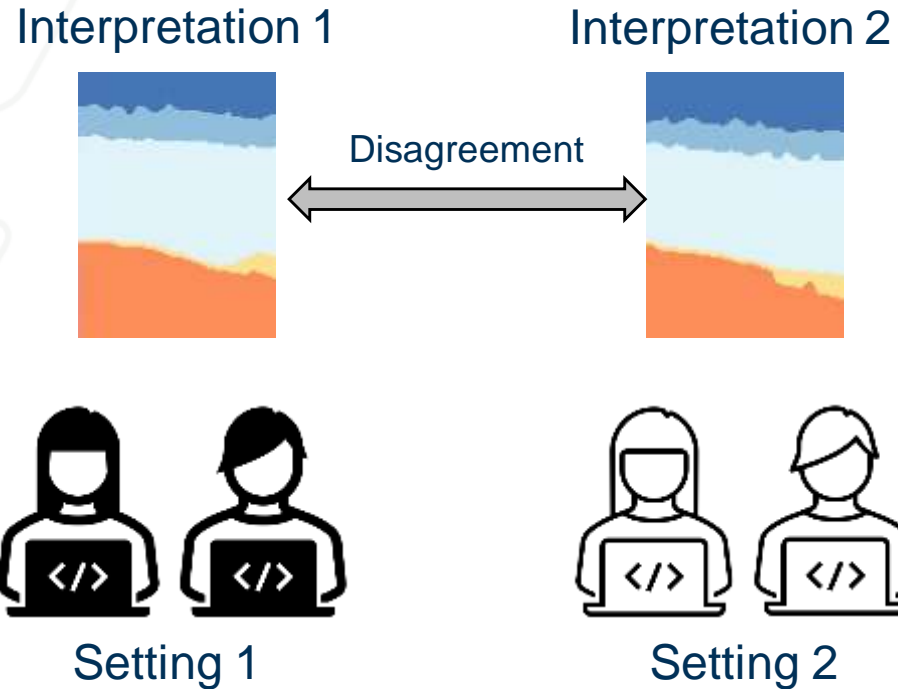
Representation Disagreement



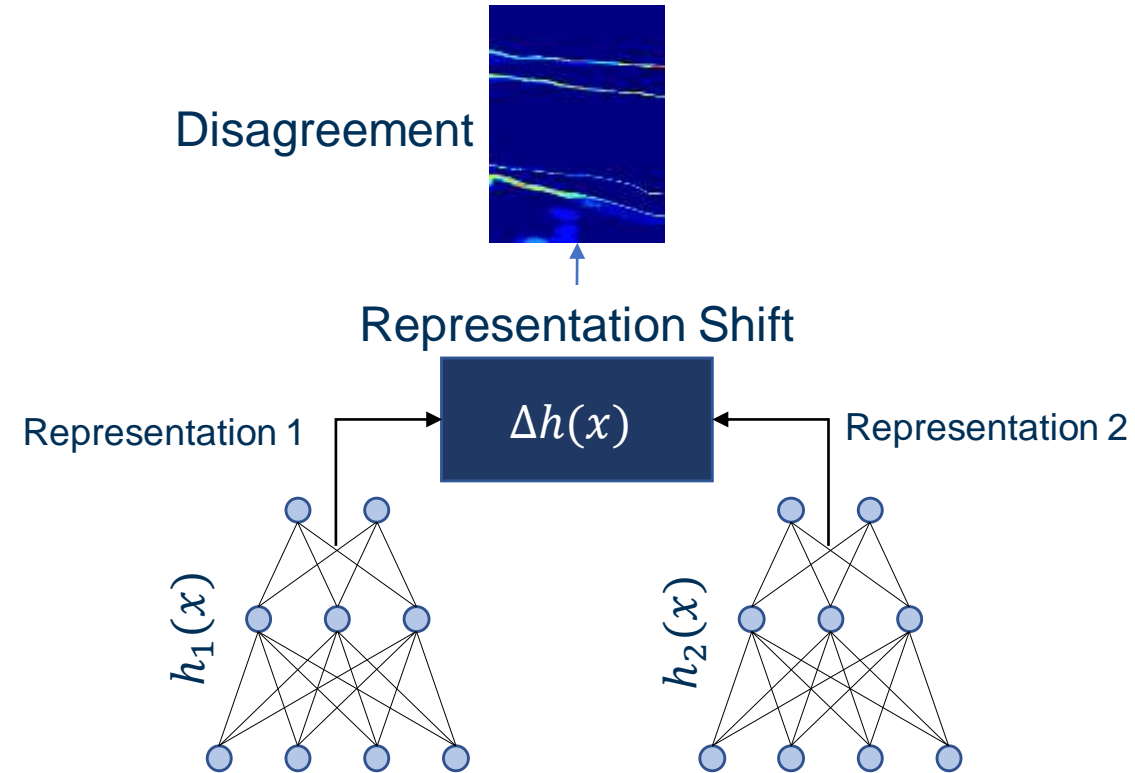
Method: Geological Interest as Disagreement

Disagreement Mimics the Manual Interpretation Process and Measures Information Content

Interpretation Disagreement



Representation Disagreement



Disagreement mimics manual interpretation and measures information content of a section