ML4Seismic Partners Meeting 2023

On the Feedback between Experts and Machines in Seismic Annotation Workflows

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Motivation

Lots of Data is Collected During Seismic Acquisition Processes

Exploration
2D/3D Subsurface Images

Reservoir Engineering
Fluid Pressure
Temperature
Acoustic
Downhole Gauges
Strain Sensors
Carbon Sequestration Data

Health and Safety
Marine Environment Data

Massive Quantity of Data

Drilling
Logging while Drilling (LWD)
Measurement while Drilling (MWD)

Refining
Gas Compressor Optimization
Chemicals for Slickwater Treatment

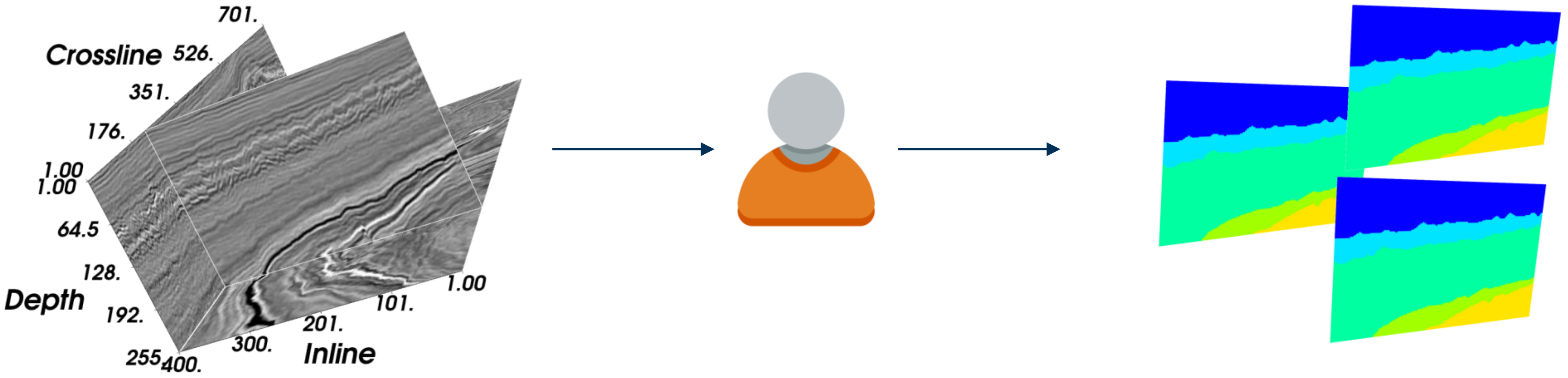
Transportation
Propulsion power information

Mohammadpoor, M., & Torabi, F. (2020). Big Data analytics in oil and gas industry: An emerging trend. *Petroleum*, *6*(4), 321-328.

Motivation

Interpretation of this Data is Time Consuming and Expensive

Data Annotation Pipeline for a typical Machine Learning-based Interpretation Workflow

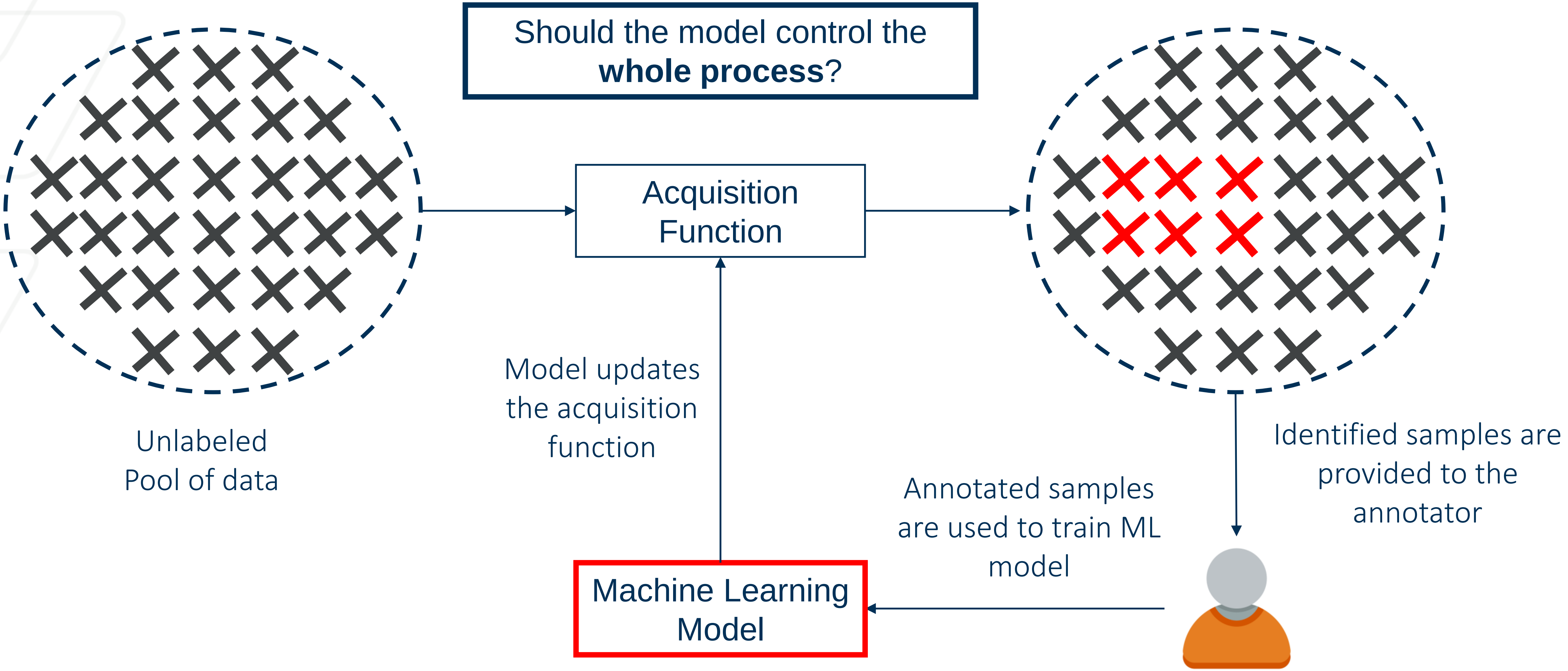


Challenges

Size and Resolution	Multidimensional Viewing	Multivolume Interpretation	Label Subjectivity
Seismic data can be **several thousand samples in resolution** in each dimension, making it difficult to interpret	Interpretation can be performed over **any (or all) dimension** in the volume.	**Multiple vintages of the same seismic** volume may need to be interpreted	It may not always be clear as to **what label a specific region** in the data should take

Motivation

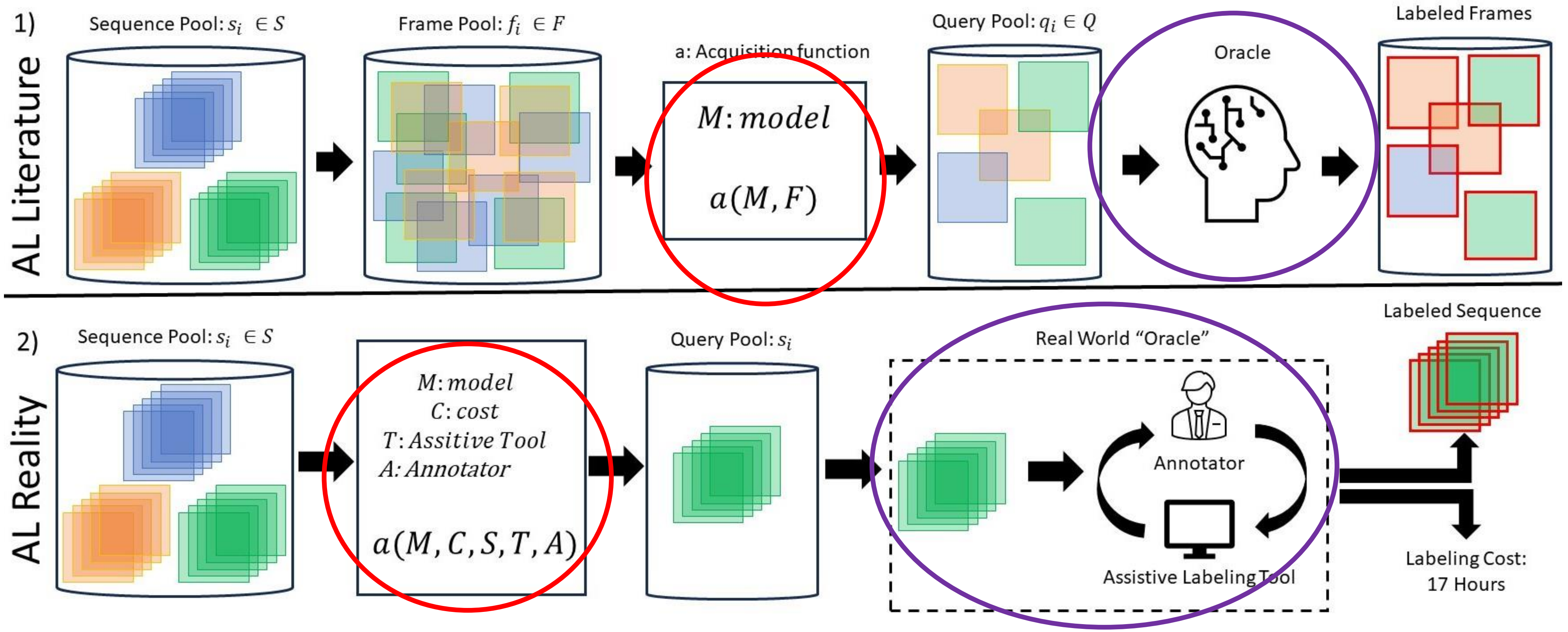
Annotation Workflows like Active Learning can Mitigate this Labeling Problem



Introduction
Why should we Question Traditional Active Learning Setups?

Active learning literature does not reflect many **influencing factors** that exist in **real-world annotation setups**.

Understanding how **humans fit into annotation process** can model proper deployment of these algorithms.



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K. Kokilepersaud*, Y. Logan*, R. Benkert, C. Zhou, M. Prabhushankar, G. AlRegib, E. Corona, K. Singh, A. Parchami,, "FOCAL: A Cost-Aware, Video Dataset for Active Learning," in *IEEE Conference on Big Data 2023*, Sorento, Italy, Dec. 15-18, 2023.

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Introduction

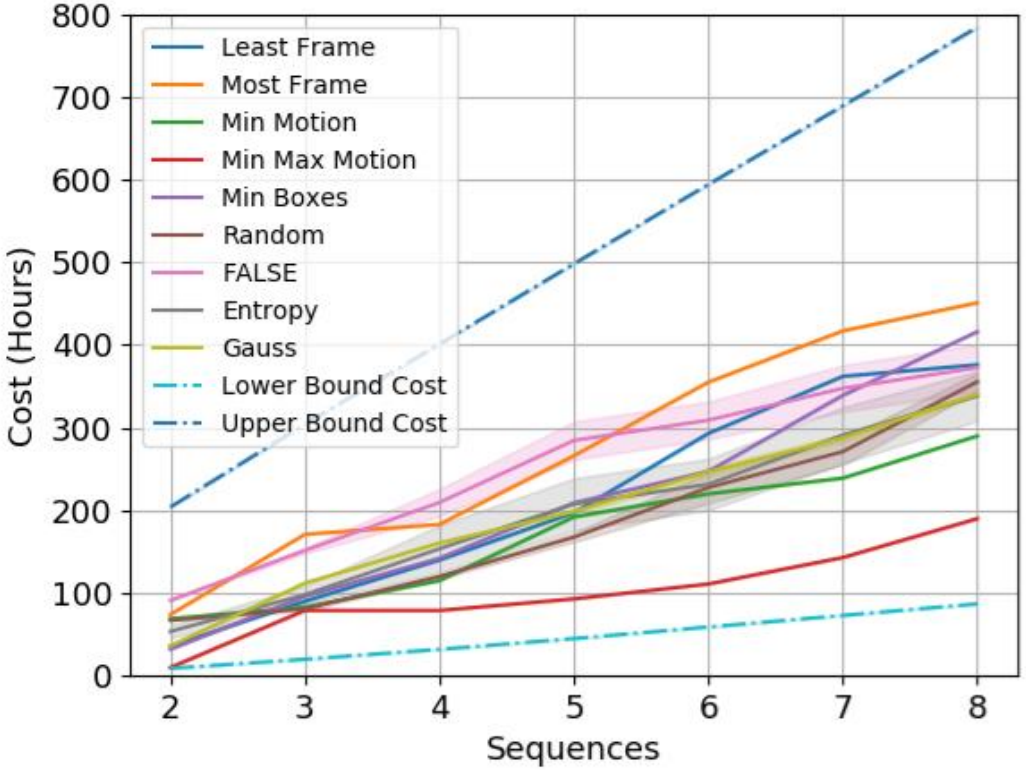
The Domain Influences the Annotation Process

Understanding of **human influence on annotation process can reveal pitfalls** in active learning literature

FOCAL Main Contribution: Understanding of **Annotation Cost** is wrong

FOCAL Dataset Statistical Correlation with Cost

Statistic	Total Dataset			Most Costly			Least Costly		
	P	K	S	P	K	S	P	K	S
Sequence Length	0.21	0.22	0.31	-0.27	-0.10	-0.17	0.26	0.25	0.34
Number of Objects	0.31	0.34	0.46	-0.37	-0.03	-0.05	0.25	0.26	0.35
Occlusion Severity	0.25	0.26	0.37	0.05	0.021	0.12	0.14	0.18	0.23
Motion	0.21	0.17	0.24	-0.14	0.00	-0.04	0.14	0.06	0.12
Season	0.07	0.07	0.09	0.24	0.20	0.25	0.17	0.08	0.12
Time of Day	0.11	0.07	0.10	0.17	0.15	0.21	0.15	0.15	0.26
Number of Cars	0.17	0.21	0.30	-0.48	-0.04	-0.02	0.12	0.26	0.36
Number of Pedestrians	0.26	0.28	0.39	-0.15	-0.17	-0.23	0.03	0.08	0.16



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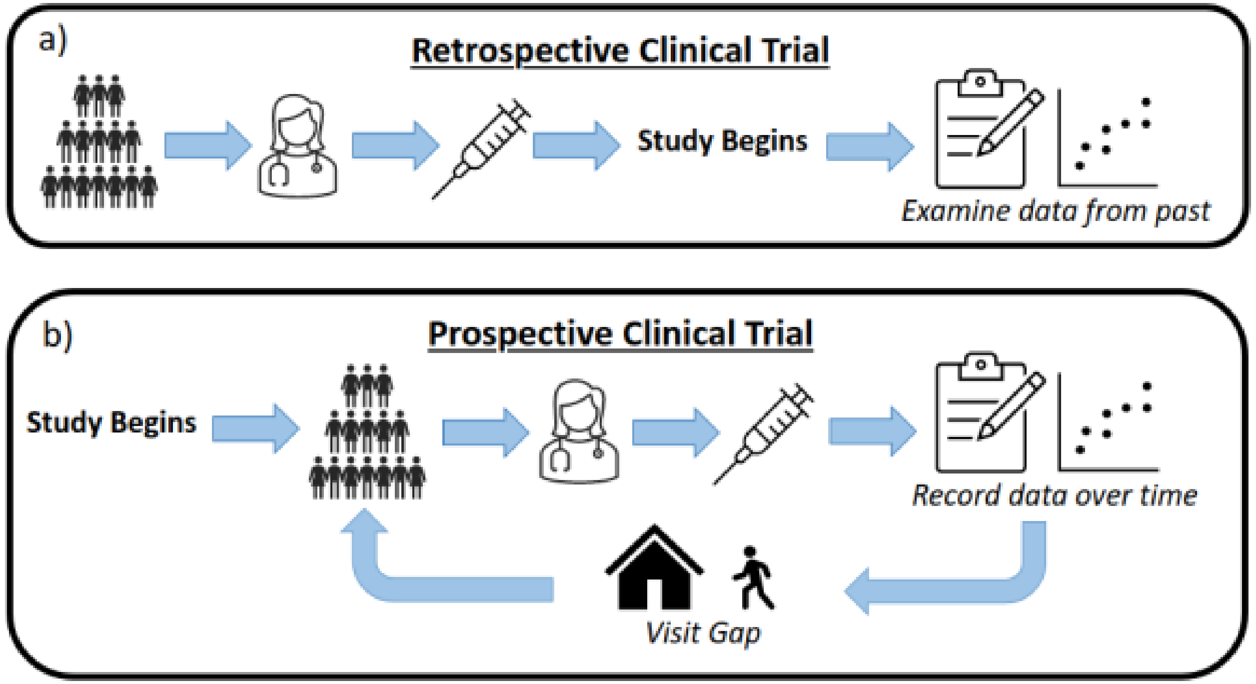
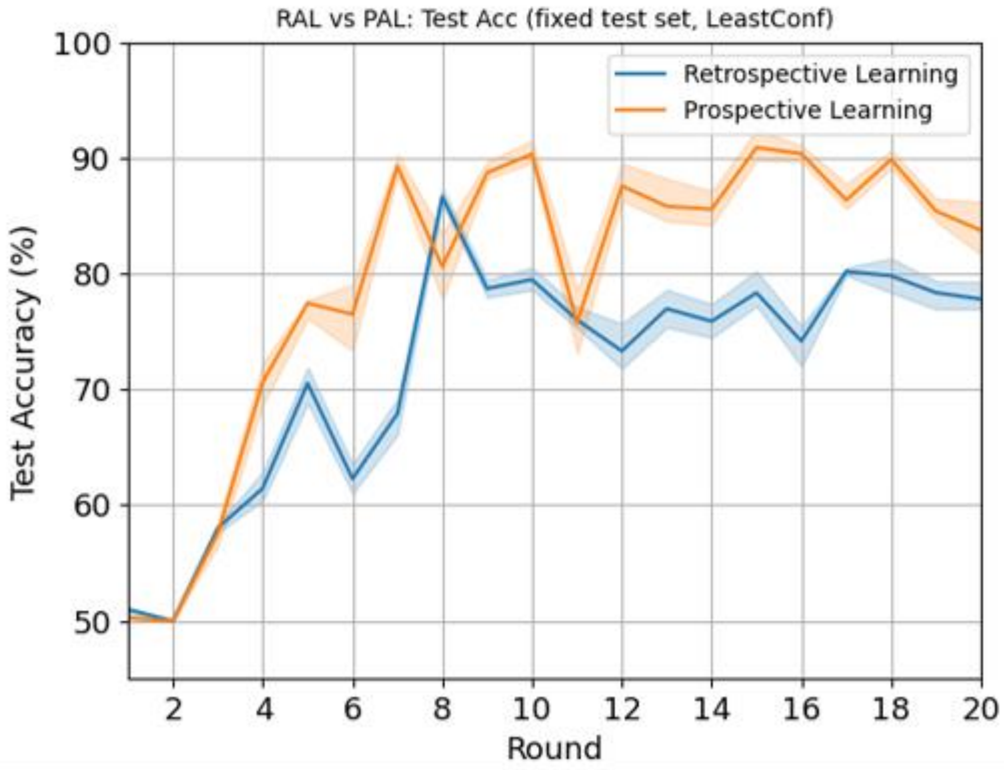
Introduction

Traditional Active Learning does not Work for Clinical Trial Data

Clinical Trials involve **sequentially acquired** data undergoing **treatment interventions**.

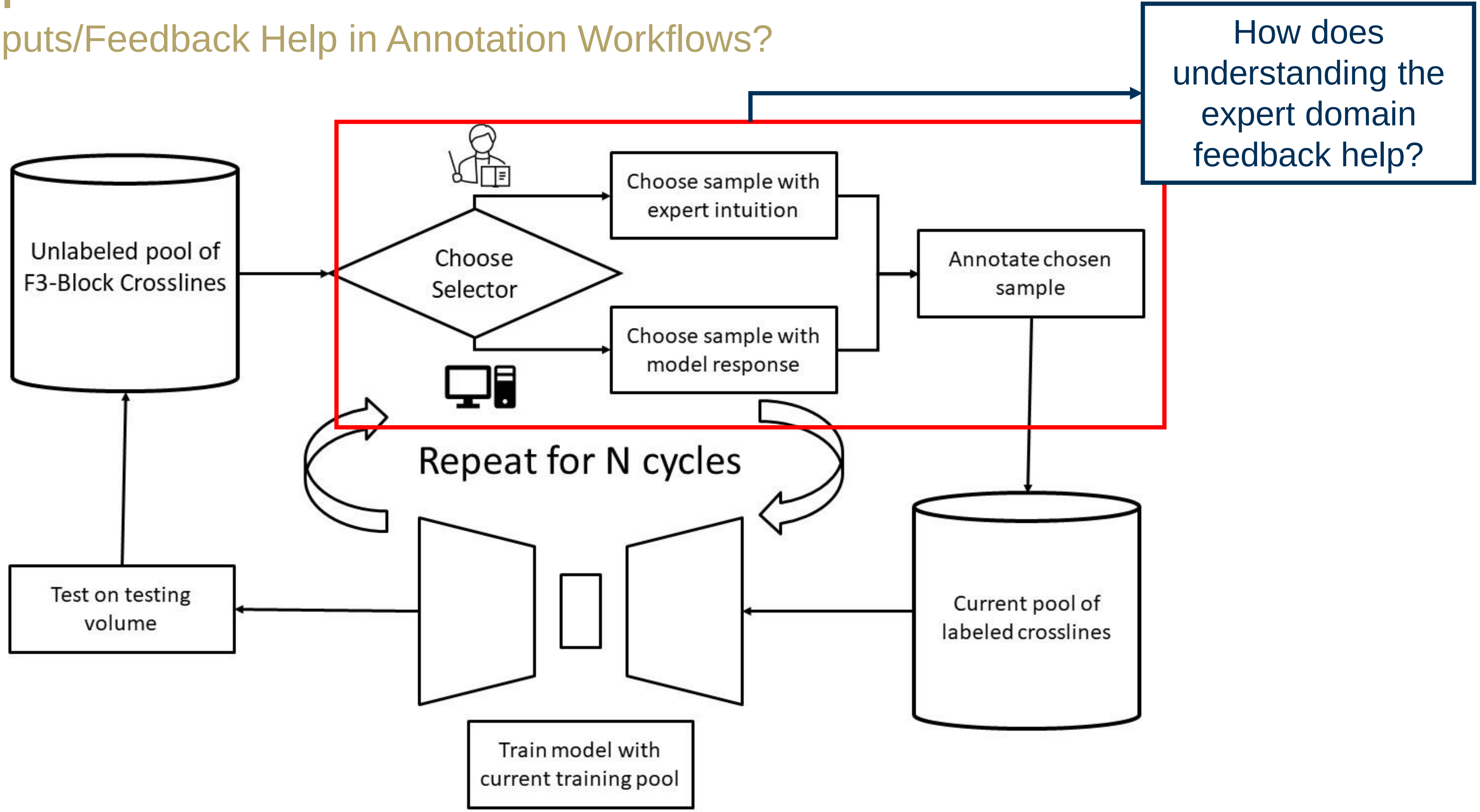
Active Learning must be modified to account for these domain-specific considerations.





Introduction

Can Expert Inputs/Feedback Help in Annotation Workflows?

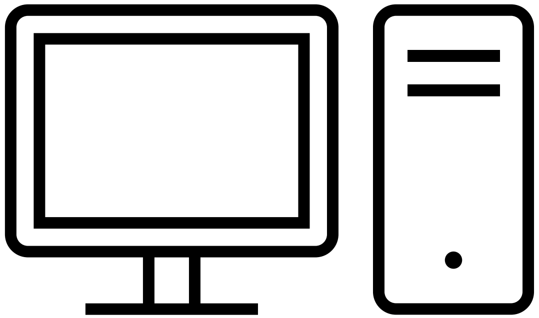


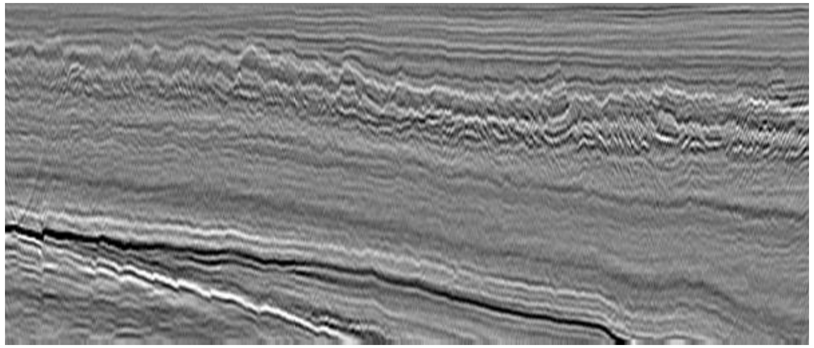
Introduction

Potential Issue is the Interaction between Experts and the Model

Setting: Round N of Training

Objective: Choose next informative sample to label based on own criterion



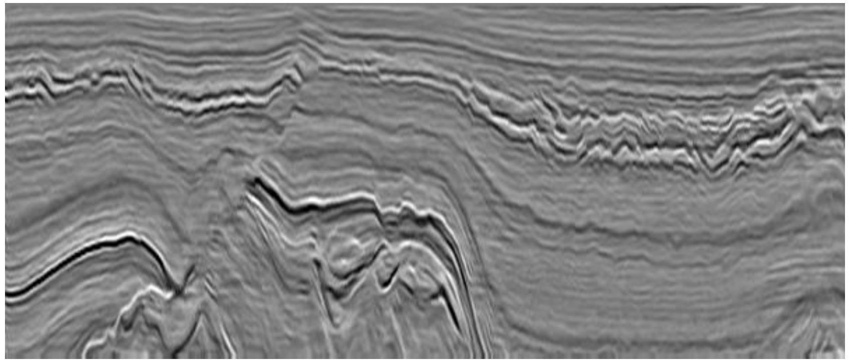


<u>Research Goal(s)</u>

What is the implication of this difference, and can we analyze it?

Can the expert **be integrated** into annotation workflow?

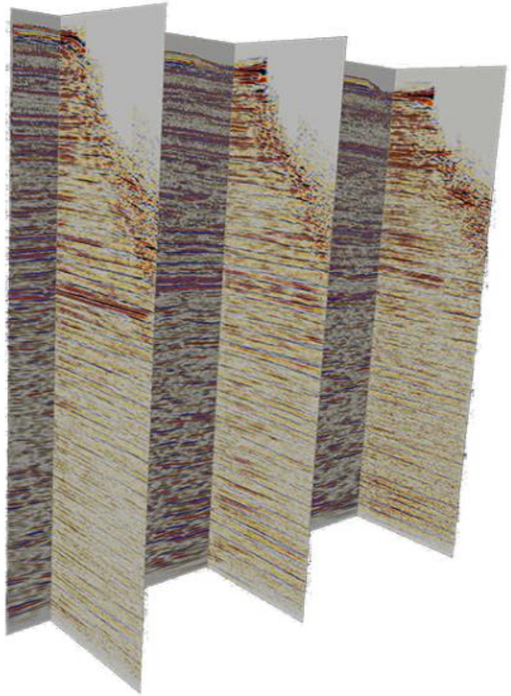
What insights can we get from **analyzing expert's interaction with models**?



Expert Selection

Expert Selection Requires a Precise Definition

Past → Open Dtect



- Basic interpolation software
- Hard to define informativeness

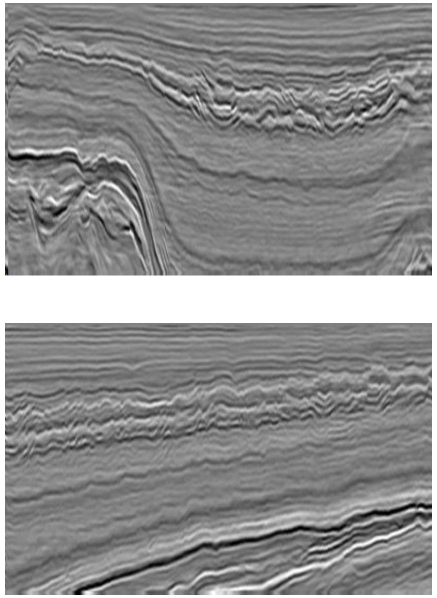
Modern → Prompting Analysis

- Segment Anything Model
- Prompting **approximates human annotation** process
- Define informativeness in terms of **statistics related to prompting**

Expert Selection

Experiment Relies on Human Interaction with SAM Model

1. User **Exposed to ROI Exemplars** to learn generic structure

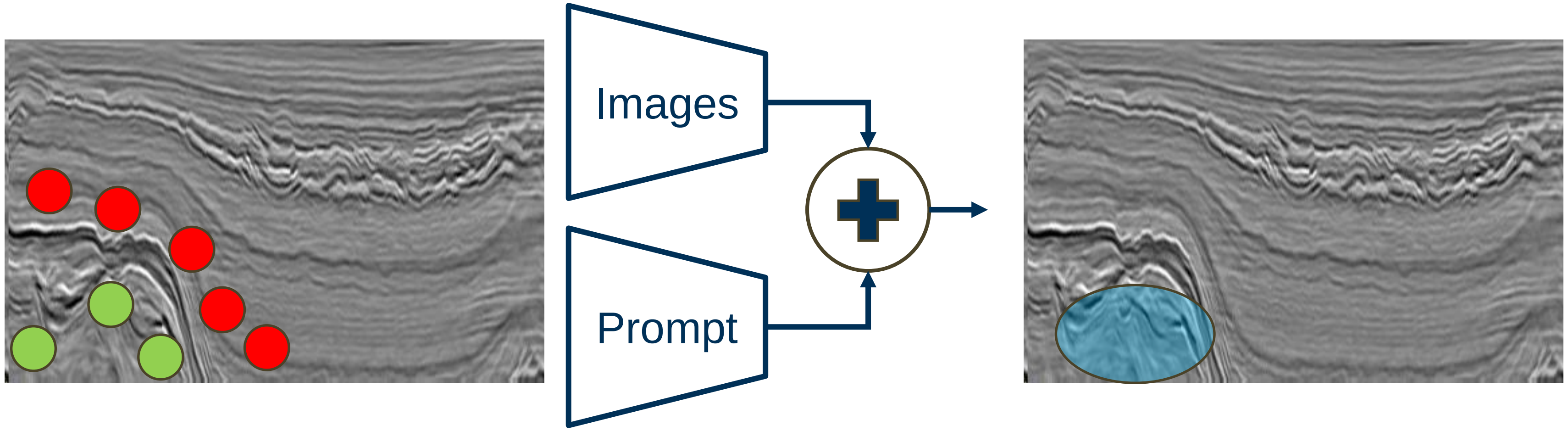


2. User provides **prompt points** to model

= Include ROI Region

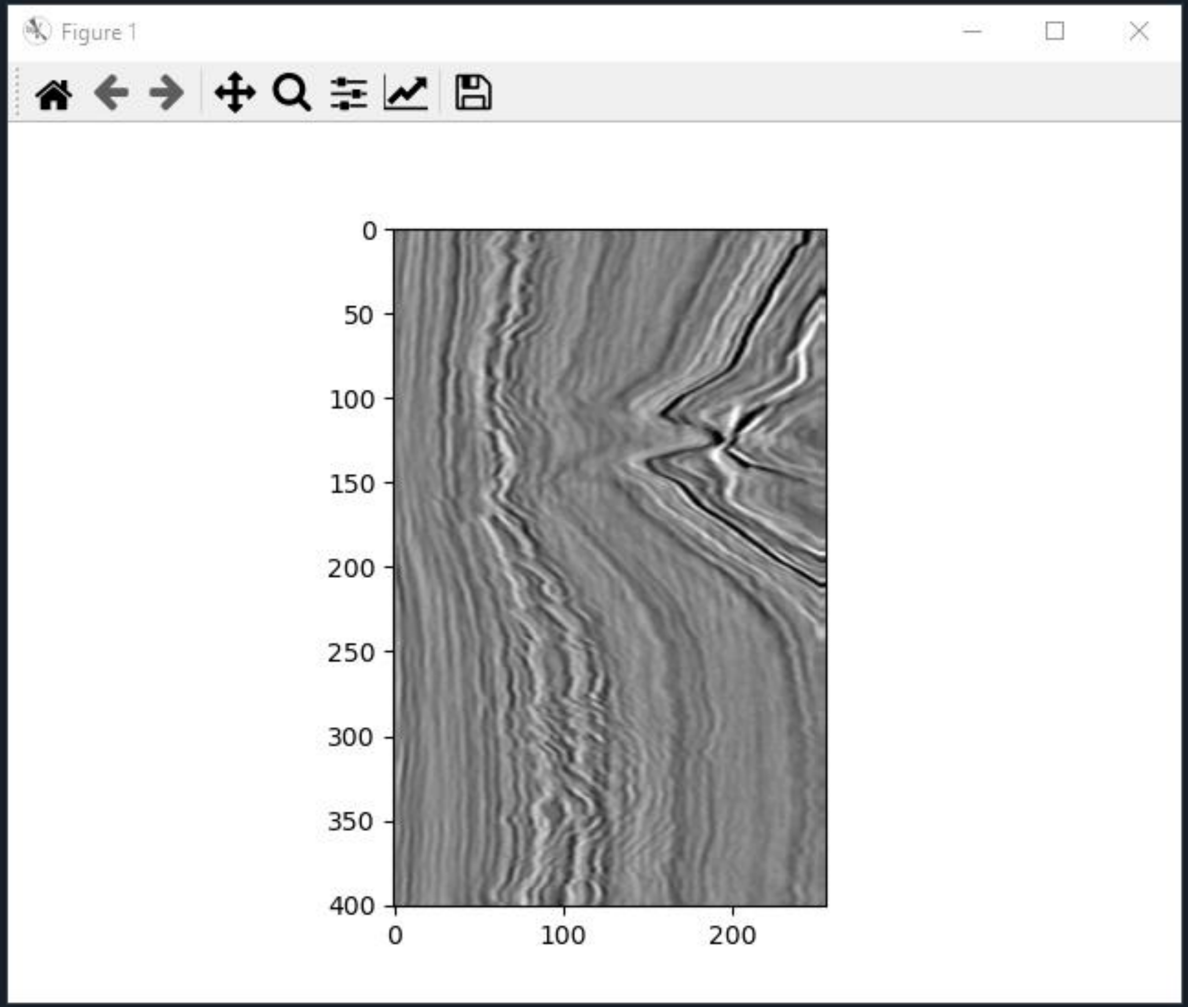
= Exclude ROI Region

3. User given **option to redo** prompting by observing output



- Users label 150 ROI structures on F3 Block Dataset
- Variety of statistics tracked during annotation

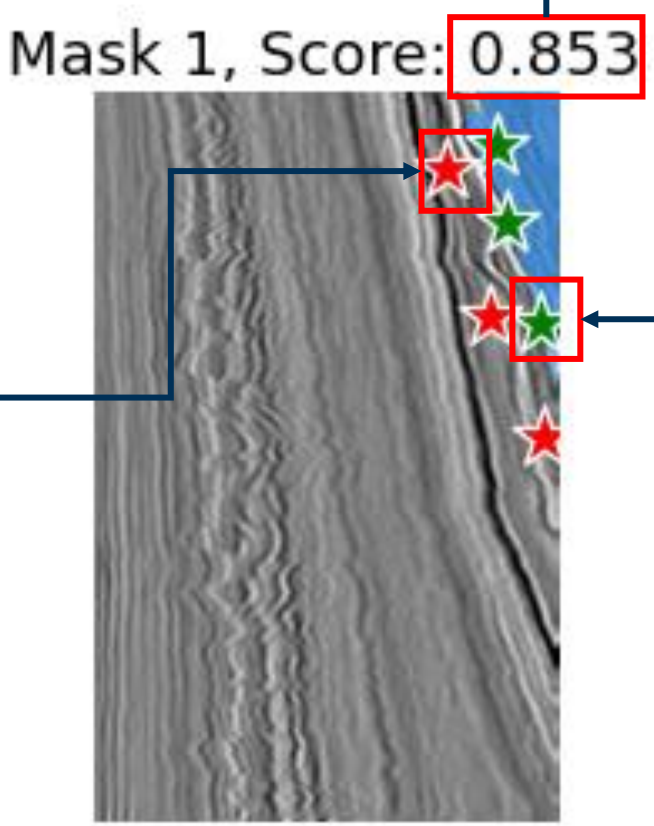
Expert Selection
Display of Prompting Setup



Statistical Analysis

What Statistics can we Gather?

Quality of ROI Output (IOU)



Number of Red Points

Number of Green Points

Location of Points

Statistical Analysis
What Variance Exists within the so-called Experts?

Variance exists due to **expert's training** on the annotation tool.

Novice
No previous experience with prompting

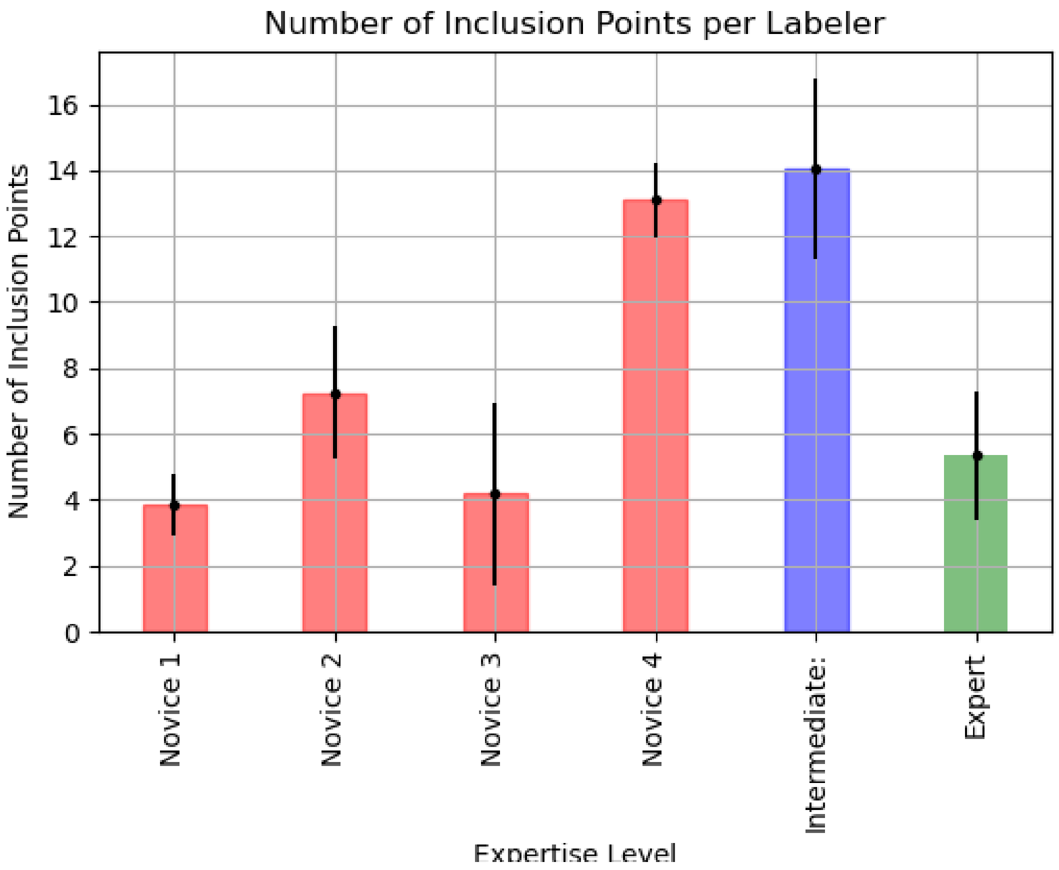
Intermediate
Experience with prompting in different domain

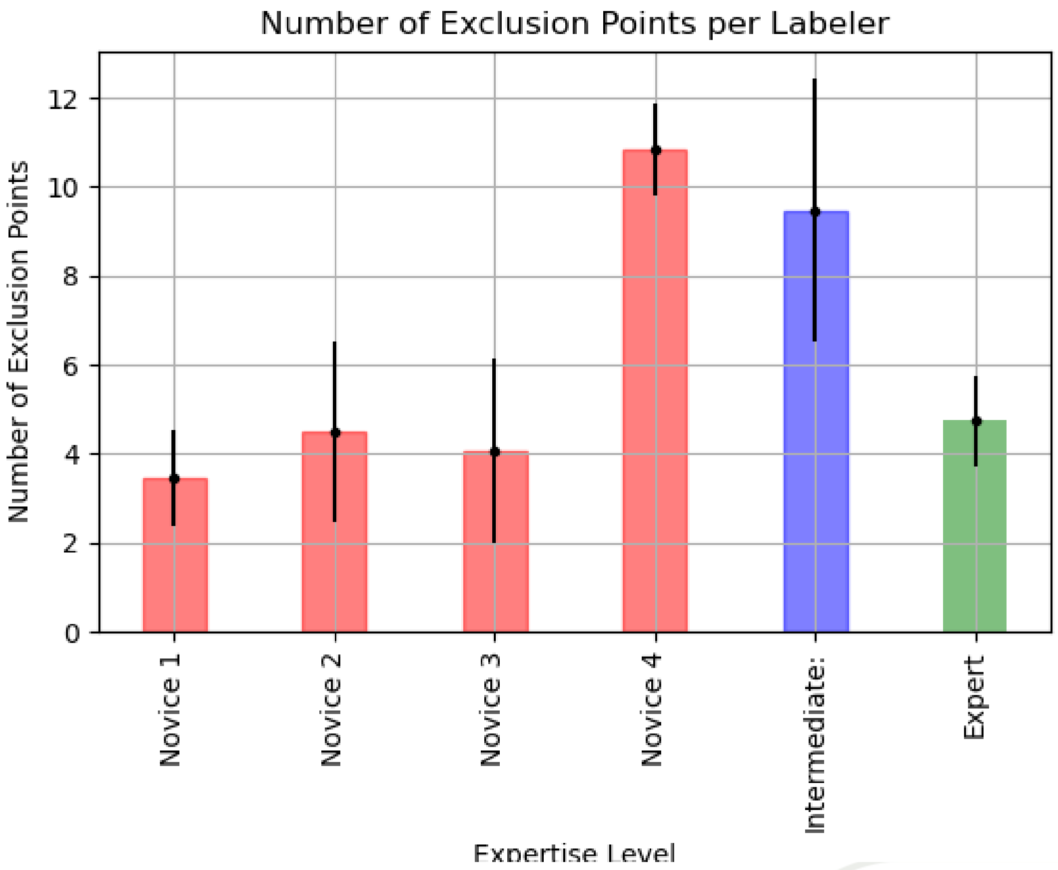
Expert
Experience with prompting in seismic

Statistical Analysis

How Often were Inclusion and Exclusion Points Used?

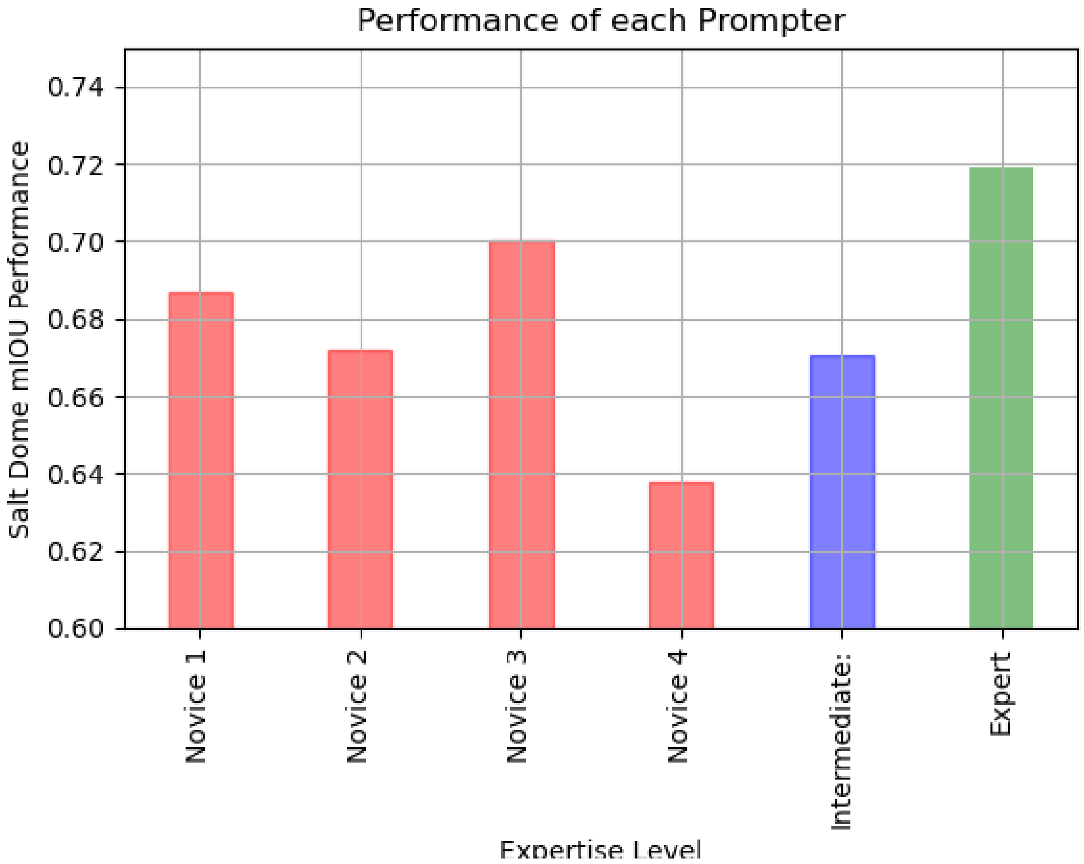
- Slight tendency to **use more inclusion points**
- Expertise didn't show correlation with **type of points** used

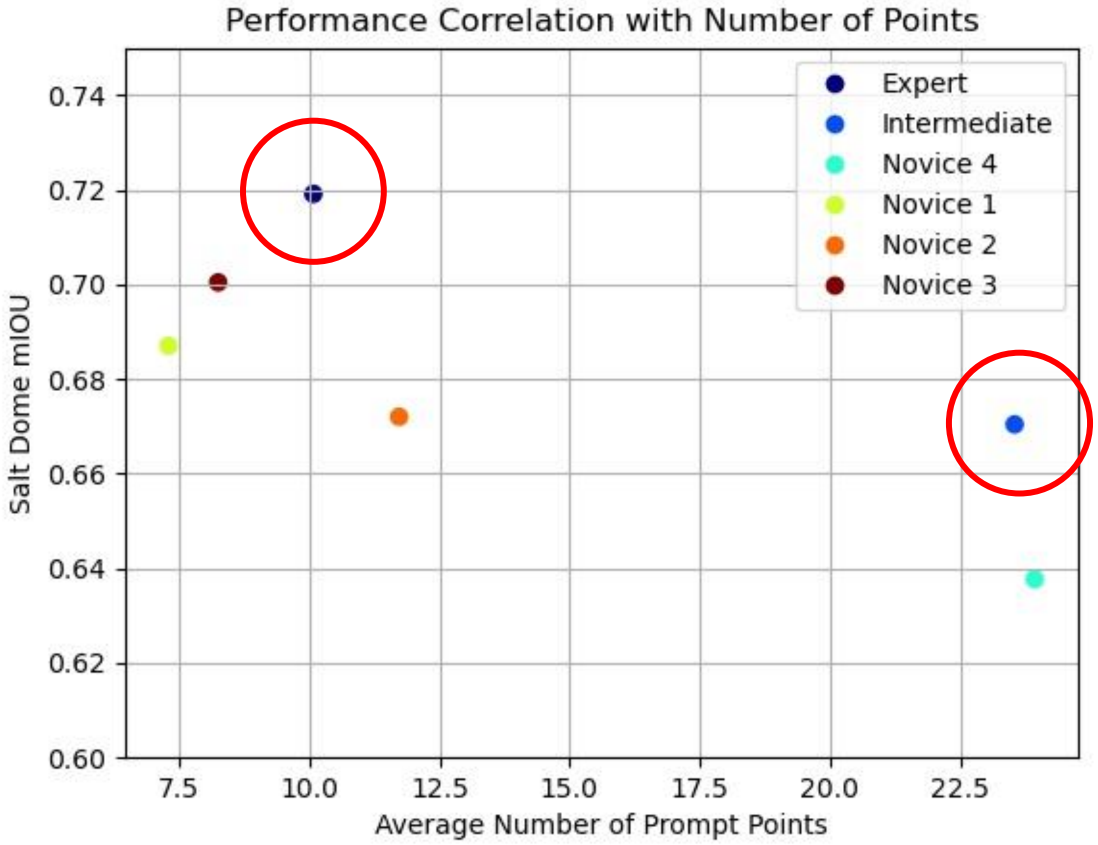




Statistical Analysis
How does Performance Vary?

- Expert knowledge of **domain and tool** is necessary for best performance
  - Optimal for **fewest number of points** that lead to best performance

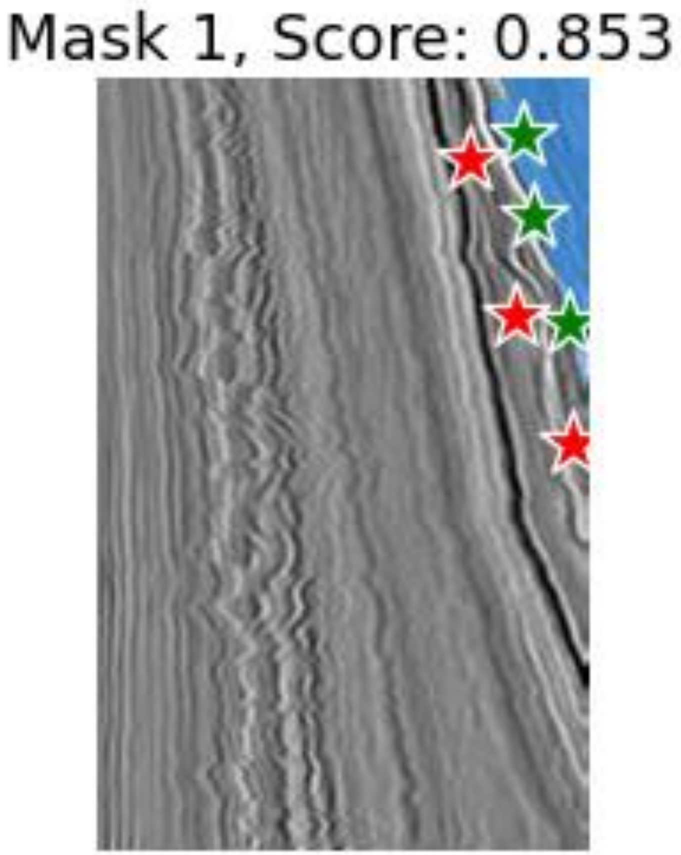


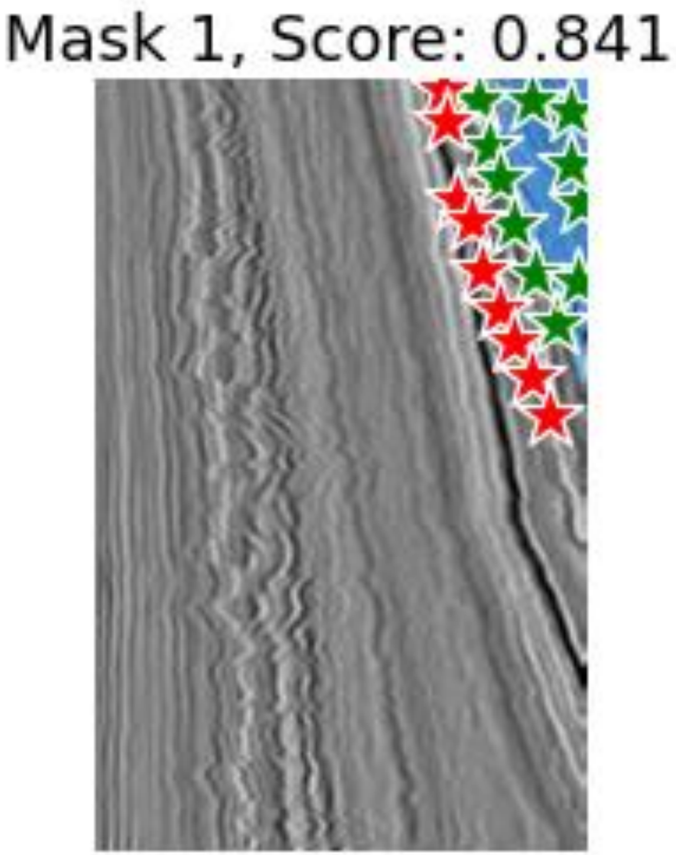


Expert Selection

Intelligent Selection of Points is Important

Better to select **informative points,** rather than more points.

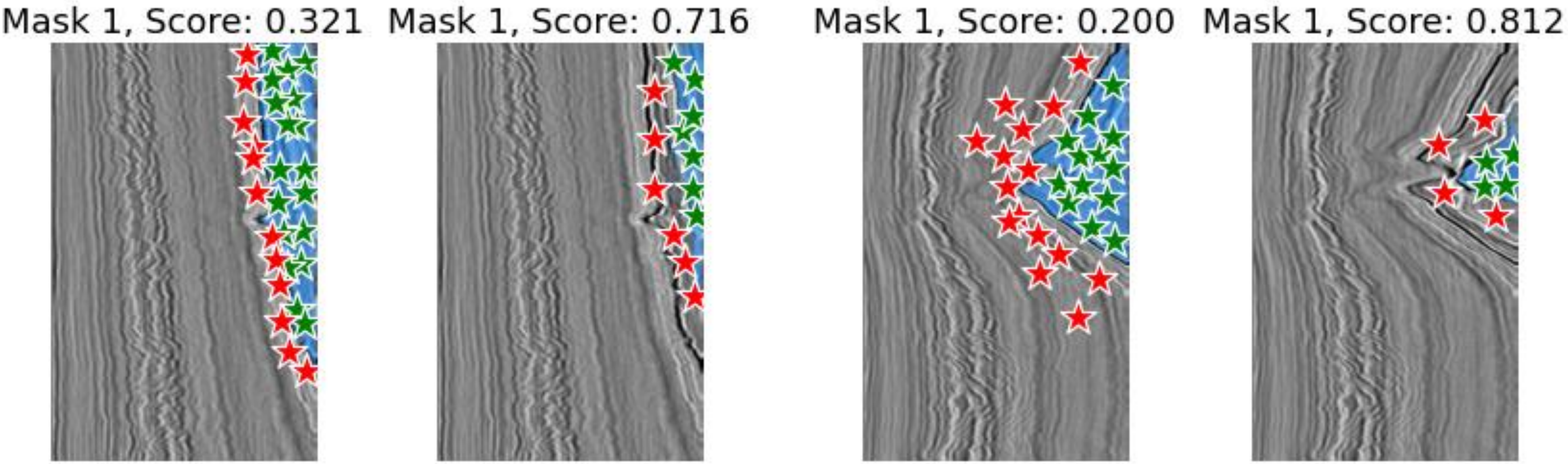




Expert Selection

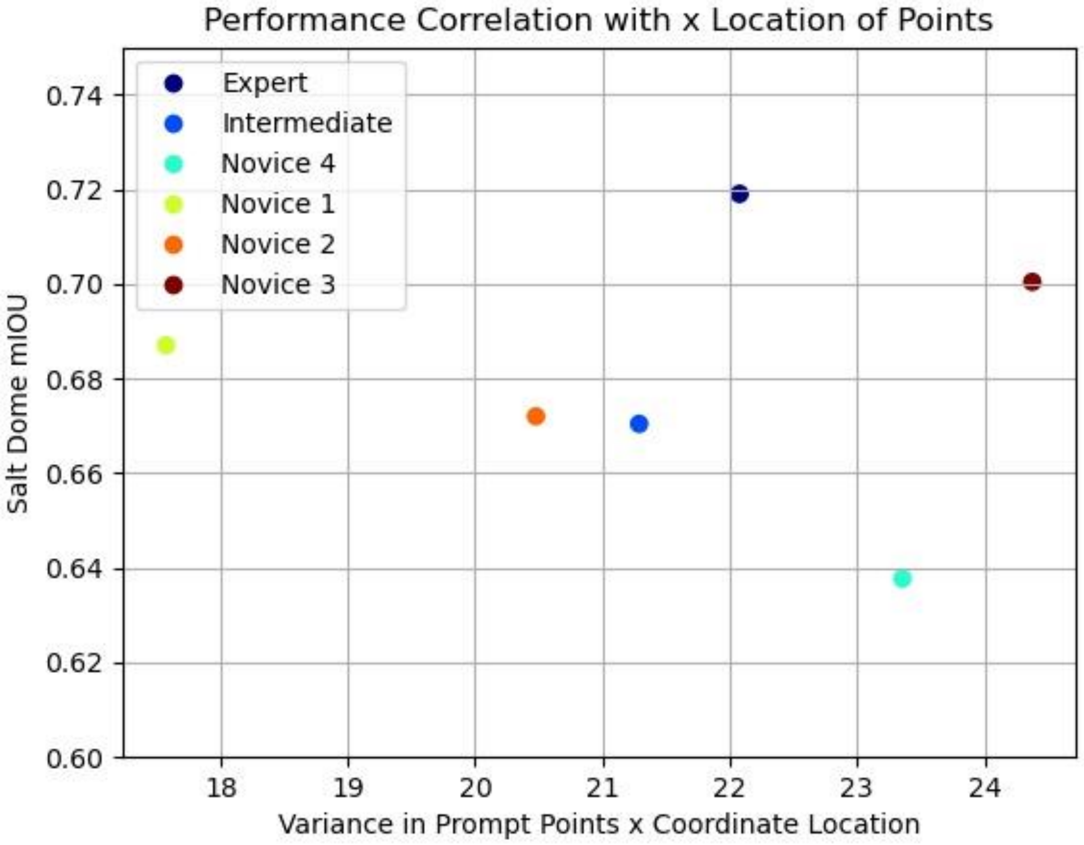
Expert Understanding of Seismic Matters

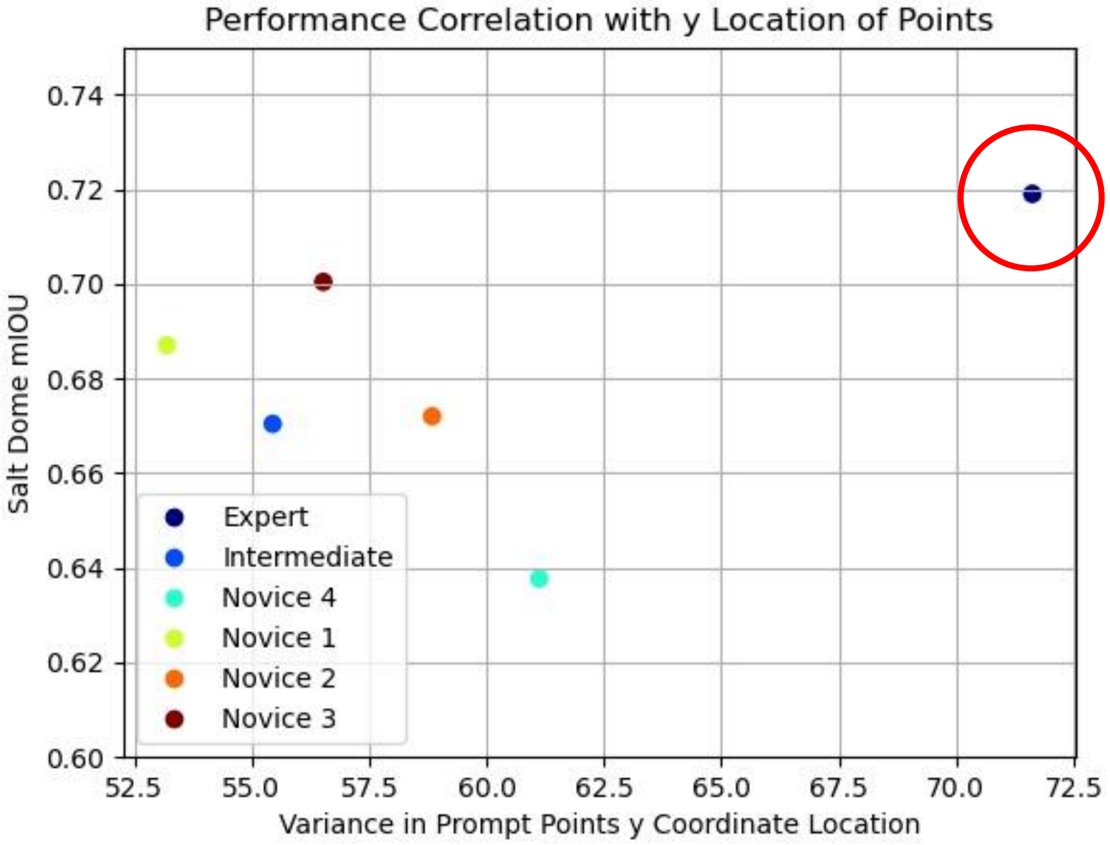
Inaccuracies also due to **seismic understanding** of expert.



Expert Selection

Manner in Selecting Points Influenced Performance to Some Degree





Conclusions

- Understanding the **interaction between the model and the expert** in process of annotation can produce active learning analyses that better reflect real-world practice.
- Prompting provides a **mechanism to assess and analyze expert interactions** during annotating
- This can potentially lead to understanding how to **integrate expert feedback** into annotation workflows.

Publications and Code

1. Mustafa, A., & AlRegib, G. (2023). Active learning with deep autoencoders for seismic facies interpretation. *Geophysics*, *88*(4), IM77-IM86.

2. R. Benkert, M. Prabhushankar, and G. AlRegib, "Effective Data Selection for Seismic Interpretation Through Disagreement," *IEEE Transactions on Geoscience and Remote Sensing (TGRS)*, submitted on Jul. 21, 2023.

3. R. Benkert, M. Prabhushankar, G. AlRegib, A. Parchami, and E. Corona, "Gaussian Switch Sampling: A Second Order Approach to Active Learning," in *IEEE Transactions on Artificial Intelligence (TAI)*, Feb. 05, 2023.

4. K. Kokilepersaud*, Y. Logan*, R. Benkert, C. Zhou, M. Prabhushankar, G. AlRegib, E. Corona, K. Singh, A. Parchami,, "FOCAL: A Cost-Aware, Video Dataset for Active Learning," in *IEEE Conference on Big Data 2023*, Sorento, Italy, Dec. 15-18, 2023.

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