COMUNICAÇÃO TÉCNICA

Nº 179797

Detecting geological features in seismic data using segment anything model 2 across multiple datasets

Gustavo Torres Custodio
Thiago Yuji Aoyagi
Hugo Ferreira Saar
Cristina Maria Ferreira da Silva
Ney Ferreira de Souza Guerra
Aline Fernandes Heleno
Carlos Tadeu de Carvalho Gamba
Celso Luciano Alves da Silva
Denis Bruno Virissimo
Elisa Morande Sale
Felipe Silva Silles
Leonides Guireli Netto
Otavio Coaracy Brasil Gandolfo
Rafael Andrello Rubo

Palestra apresentada no AMERICAN ASSOCIATION PETROLEUM GEOLOGISTS IMAGE'25: INTERNATIONAL MEETING FOR APPLIED GEOSCIENCE & ENERGY, 2025, Texas. 30 slides

Detecting Geological Features in Seismic Data Using Segment Anything Model 2 Across Multiple Datasets

Gustavo Torres Custodio,
Thiago Yuji Aoyagi*,
et al.

Institute for Technological Research (IPT)
São Paulo, Brazil

27
AUG
2025

INSTITUTO DE
PESQUISAS
TECNOLÓGICAS

PETROBRAS

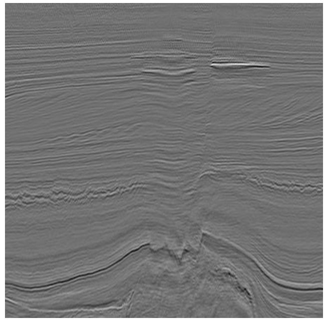
SEG | AAPG

International Meeting for Applied Geoscience & Energy

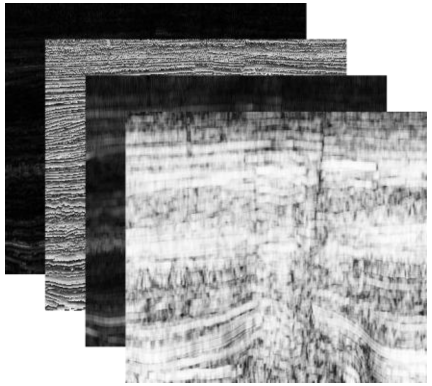
A bit of context: seismic interpretation with machine learning

Interpretation with machine/deep learning

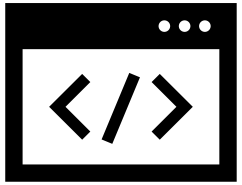
- Automated interpretation: ML can capture complex patterns



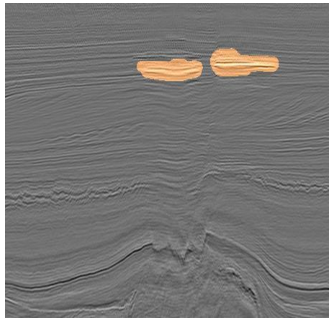
Seismic Data



Seismic Attributes



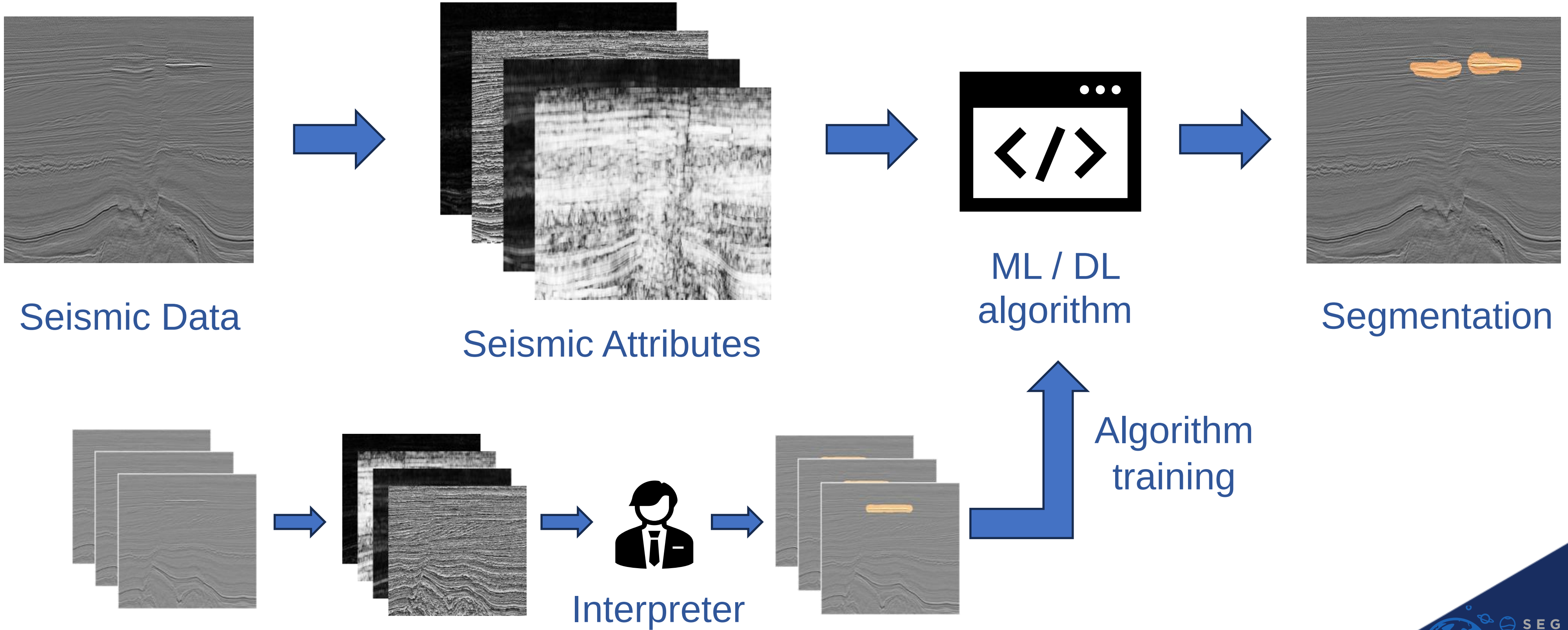
ML / DL algorithm



Segmentation

Interpretation with machine/deep learning

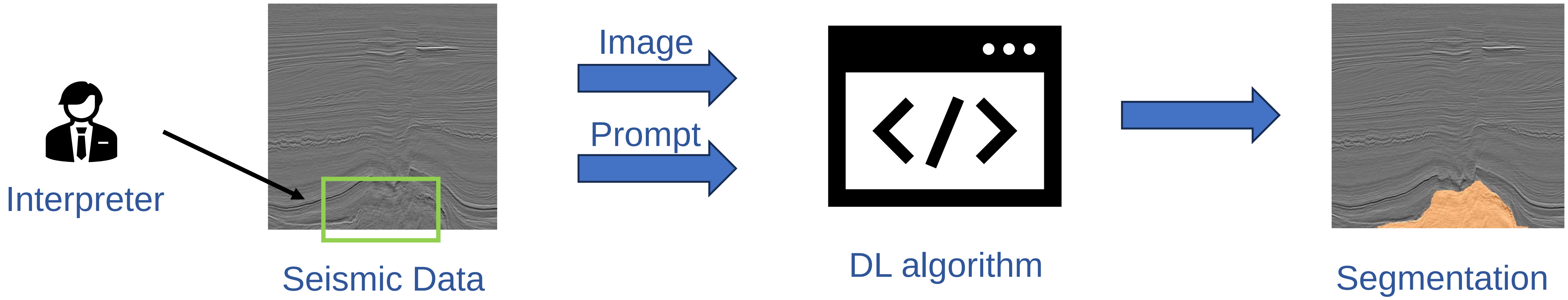
- Automated interpretation: ML can capture complex patterns



This work: Interpretation with promptable DL

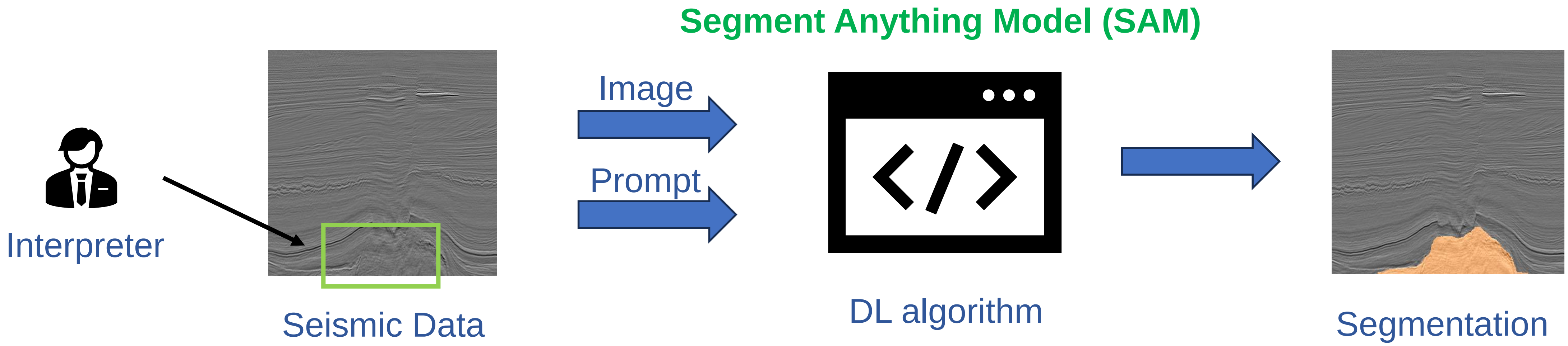
This work: interpretation with promptable DL

- Different paradigm: automatic segmentation subject to prompts from user



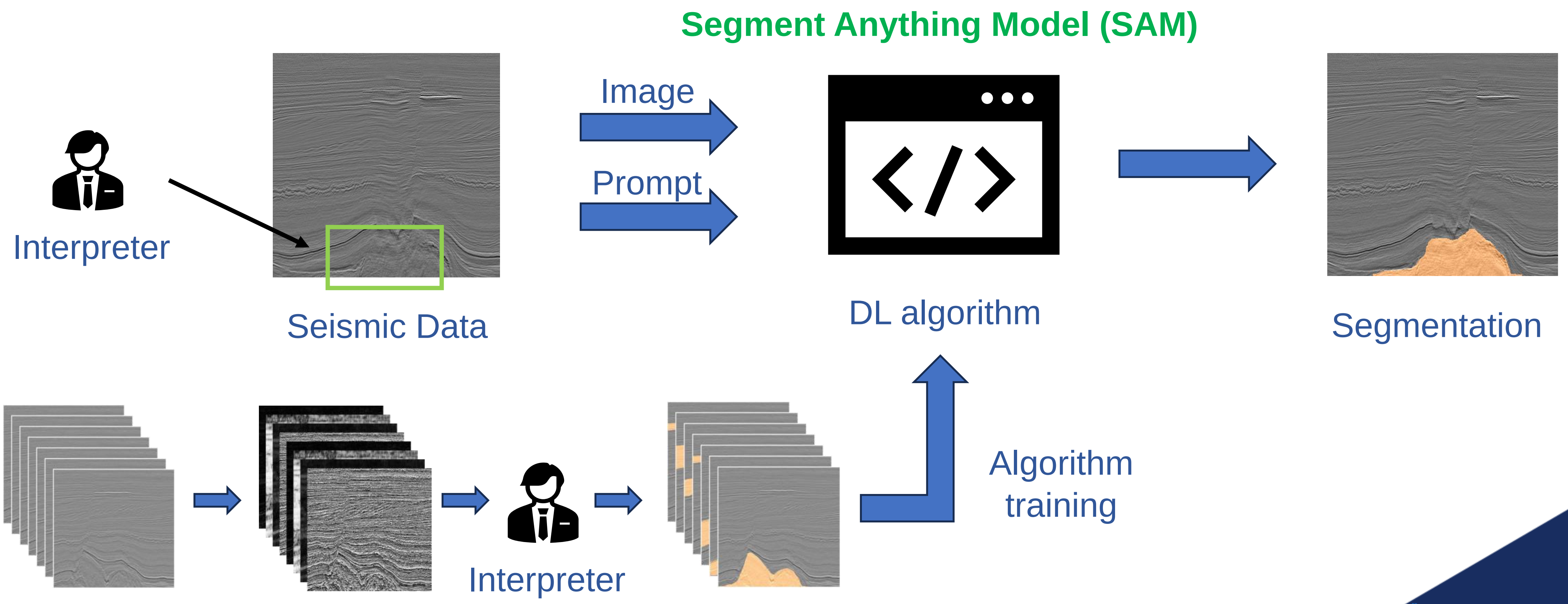
This work: interpretation with promptable DL

- Different paradigm: automatic segmentation subject to prompts from user



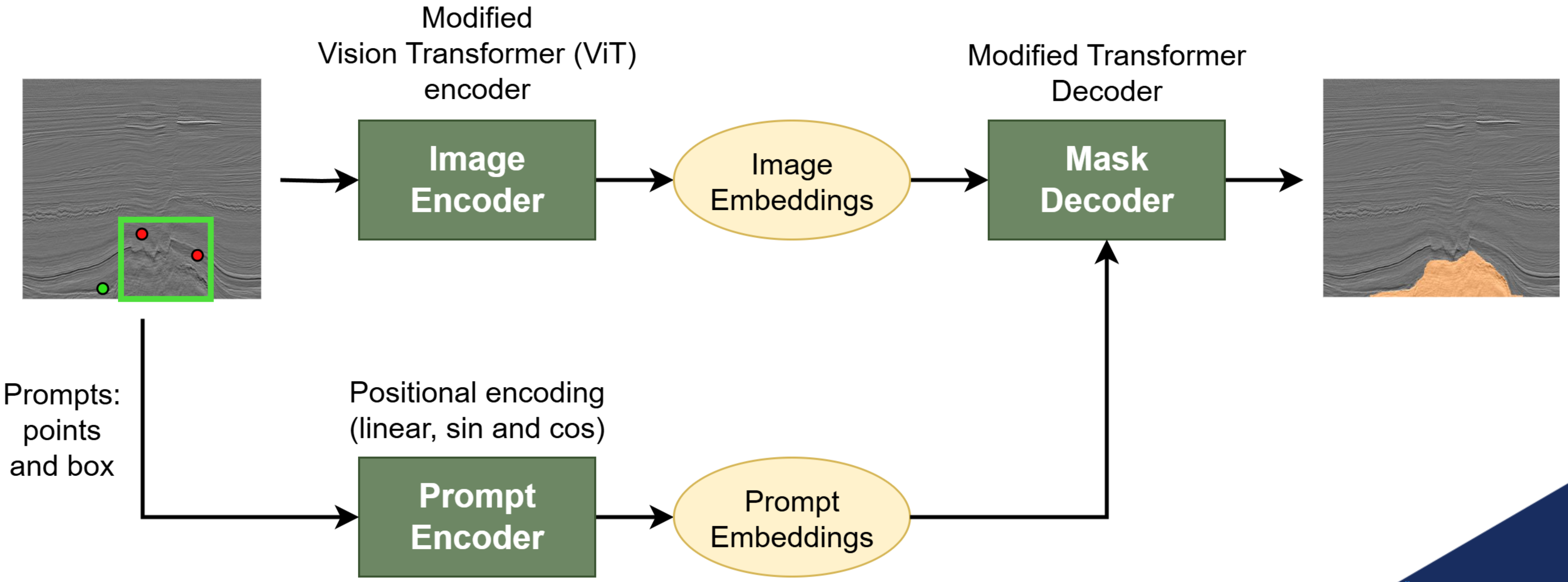
This work: interpretation with promptable DL

- Different paradigm: automatic segmentation subject to prompts from user



This work: interpretation with promptable DL

- SAM/SAM2 architecture



This work: interpretation with promptable DL

- **Proposition:** We apply SAM and SAM2 (Meta AI) to segment geological facies in 2D seismic images

- SAM and SAM2 are originally trained on natural images
  - We finetune SAM/SAM2 with seismic images to increase performance

- We segment 3D geobodies by slice-to-slice propagation

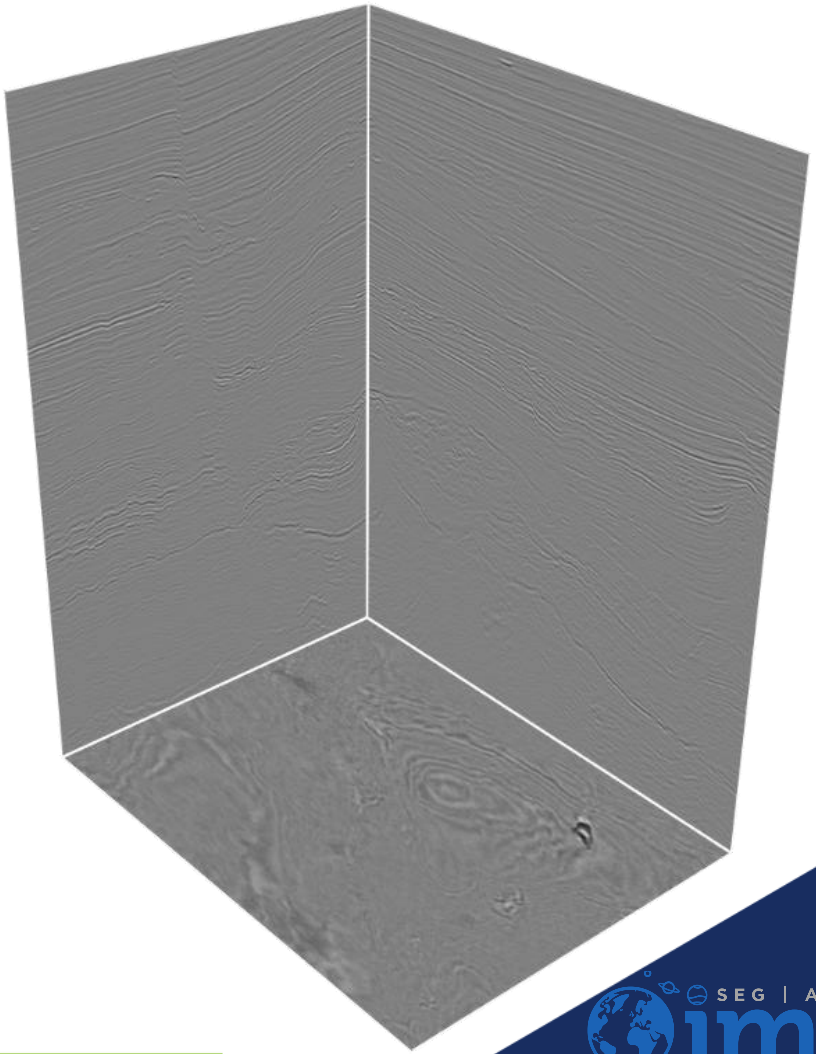
Data Preparation

Model Training

Results

Data Preparation

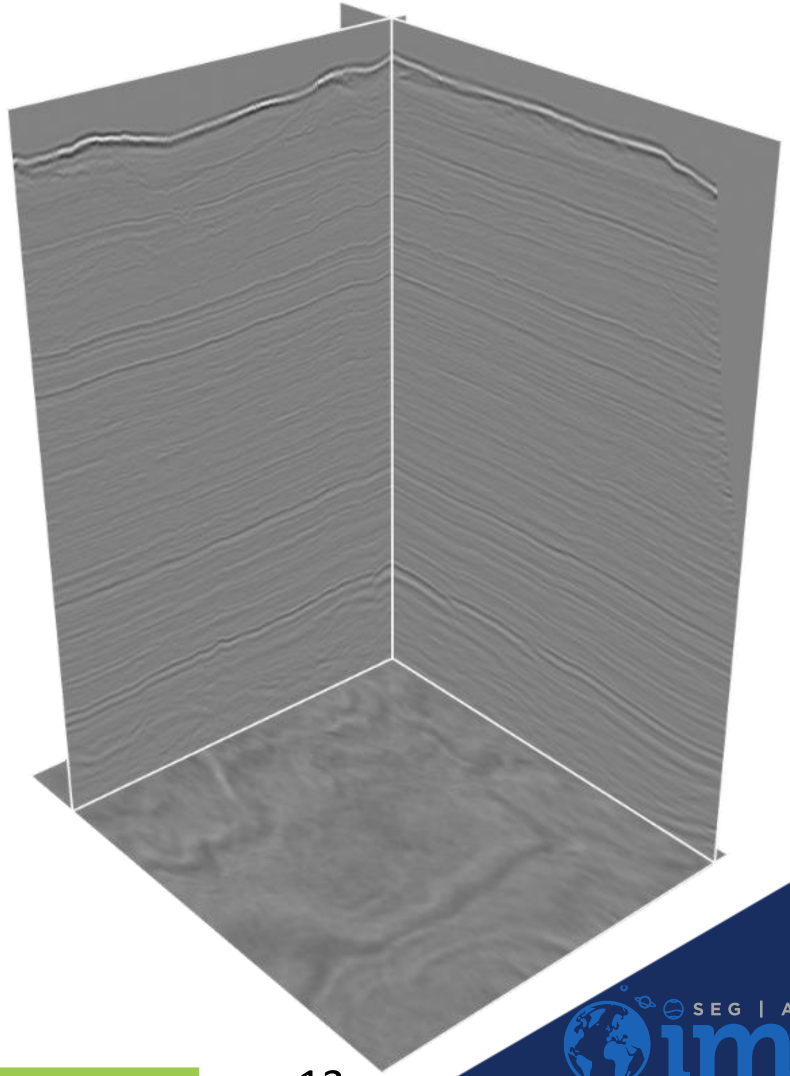
- Public data gathered for model training
  - **Parihaka (AIcrowd / SEAM)**
  - Penobscot (TerraNubis)
  - Netherlands F3 (TerraNubis)



Labels/Annotations: Facies (mudstone, MTD, etc)

Data Preparation

- Public data gathered for model training
    - Parihaka (AIcrowd / SEAM)
    - **Penobscot (TerraNubis)**
    - Netherlands F3 (TerraNubis)

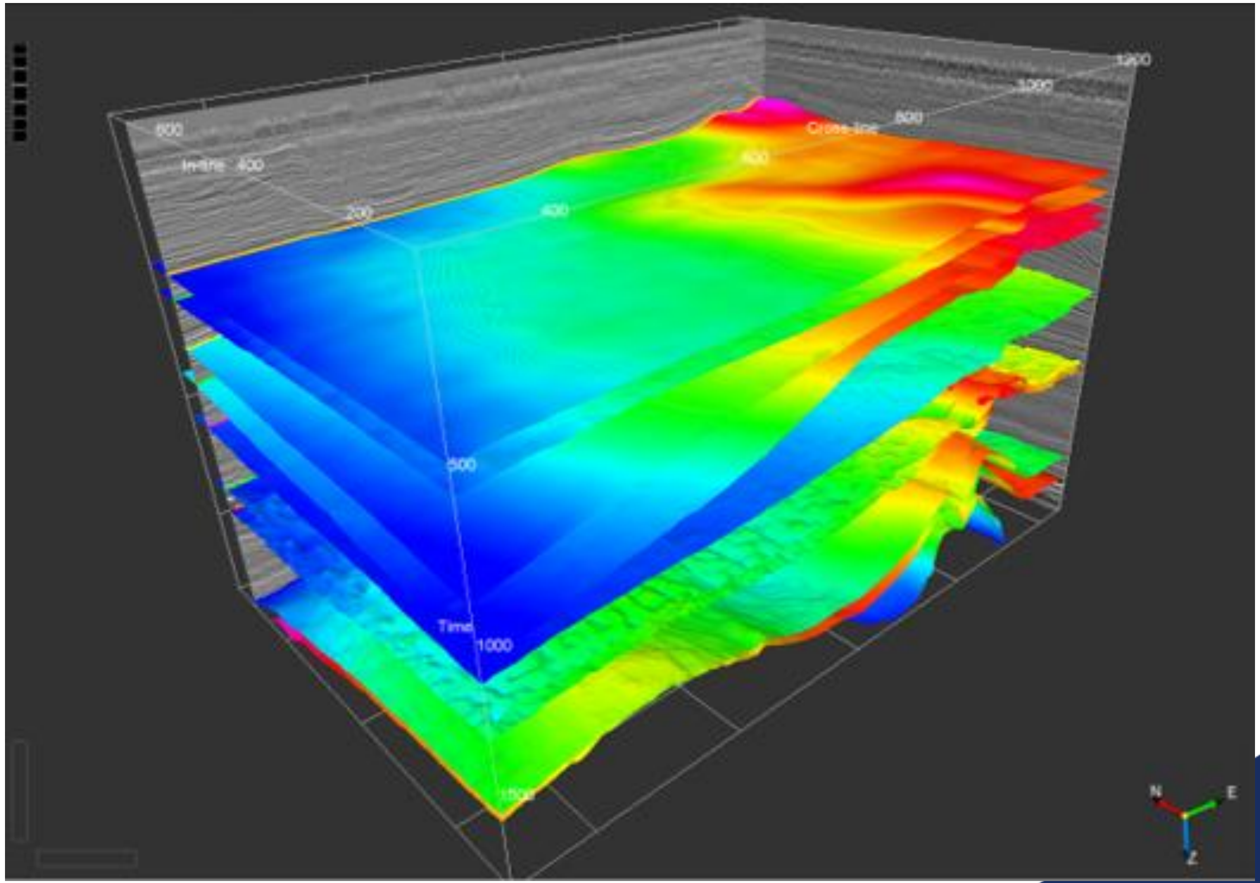


Labels/Annotations: Horizons (used to obtain facies)

Data Preparation

- Public data gathered for model training
    - Parihaka (AIcrowd / SEAM)
    - Penobscot (TerraNubis)
    - **Netherlands F3 (TerraNubis)**

- Our annotations
    - 9 horizons → 10 facies
    - Bright spots
    - Channels



Data Preparation

- Dataset
  - Extract iline/xline slices
  - Each image contains multiple facies instances

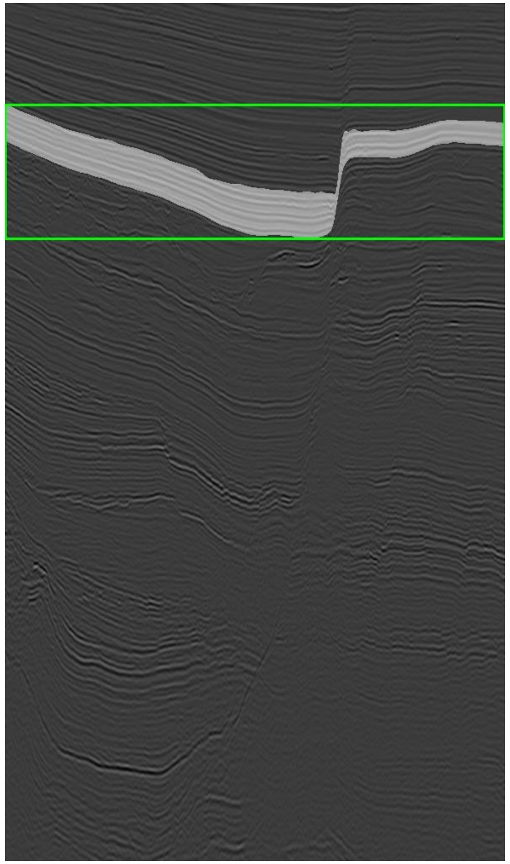
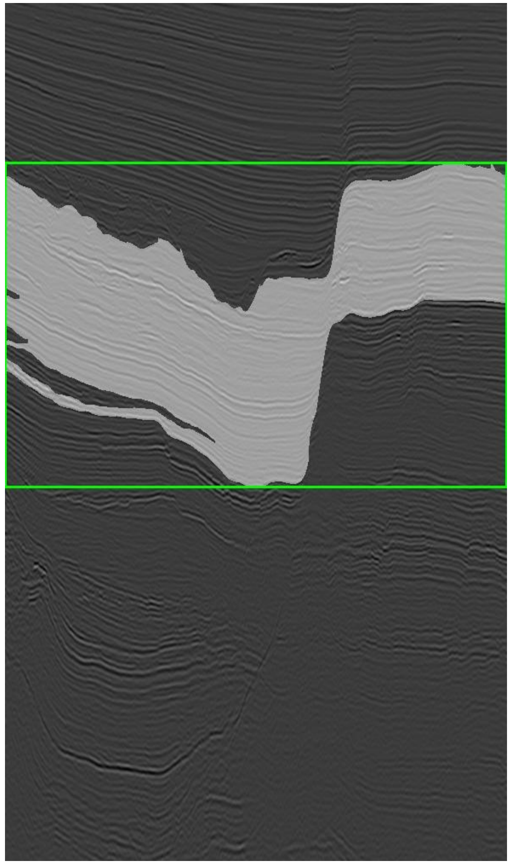
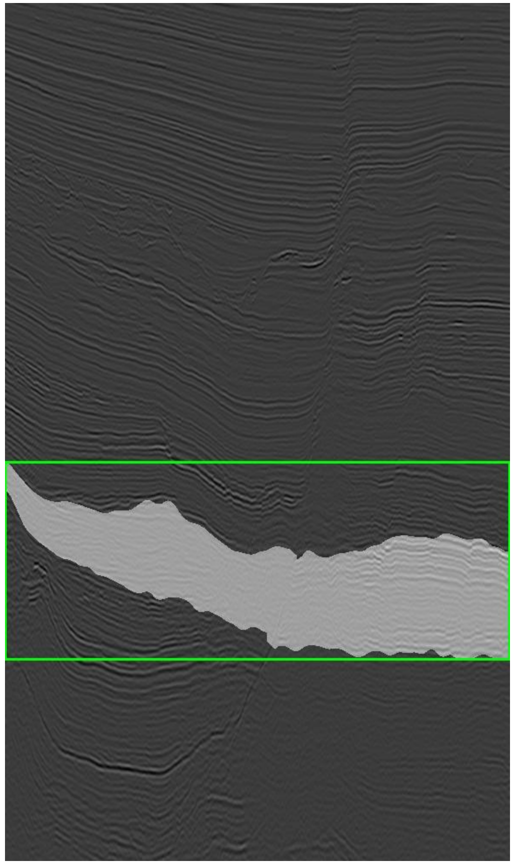
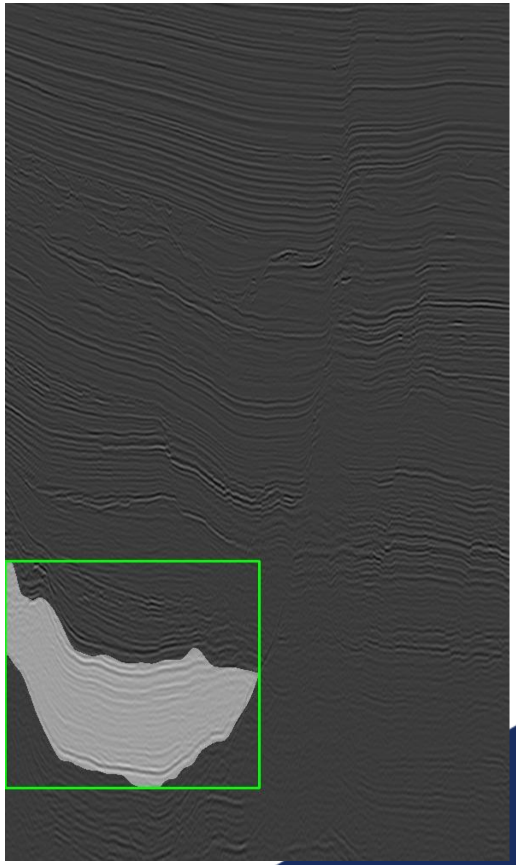
Dataset	Num. Images (ilines/xlines)	Num. Facies
Parihaka	68	1191
Penobscot	72	386
F3 Netherlands	80	1315
Total	220	2892

- Train/Test Split
  - Train 80%
  - Test 20%

Dataset	Train	Test
Parihaka	54	14
Penobscot	58	14
F3 Netherlands	64	16
Total	176	44

Data Preparation

- Parihaka image samples

Data Preparation

Model Training

Results

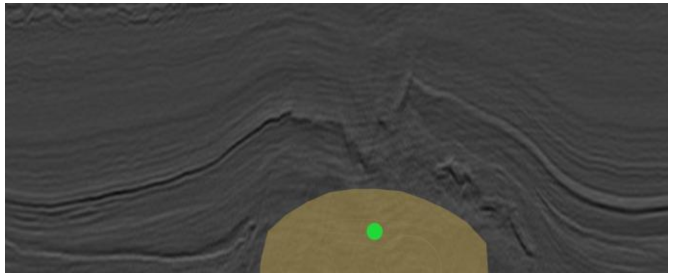
Model Training

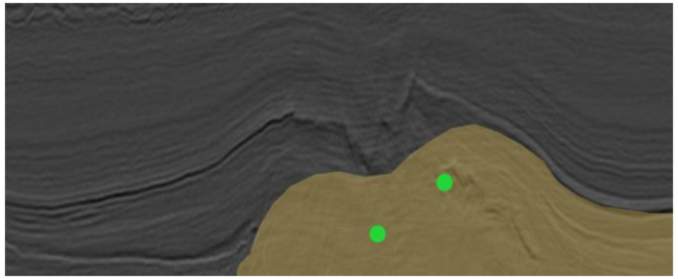
- Some training settings
    - Batch size 1
    - 300 epochs
    - AdamW optimizer with decreasing learning rate (1e-5 to 1e-7)

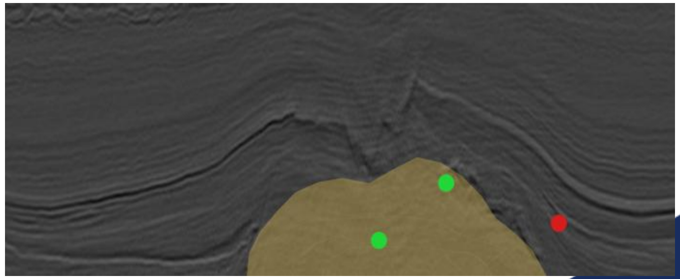
- Data Augmentation
    - Amplitude distortion (logarithmic)
    - Gaussian blur and gaussian noise
    - Cropping
    - Resizing with aspect ratio distortion

Model Training

- Loss function
  - $\underbrace{\text{Focal cross entropy}}_{\text{Pixelwise supervision}} + 0.05\ \underbrace{\text{Dice coefficient}}_{\text{Prediction/target area overlap}} + 0.05\ \underbrace{\text{Score loss}}_{\text{Score supervision}}$
- Two variations of training
  - single prompt (point or box)
  - multiple prompts (point/box + 7 points)







Data Preparation

Model Training

Results

Results

- Performance comparison among different models
  - SAM 1 Base
  - SAM 2 Tiny
  - SAM 2 Small
  - SAM 2 Base+
  - SAM 2 Large

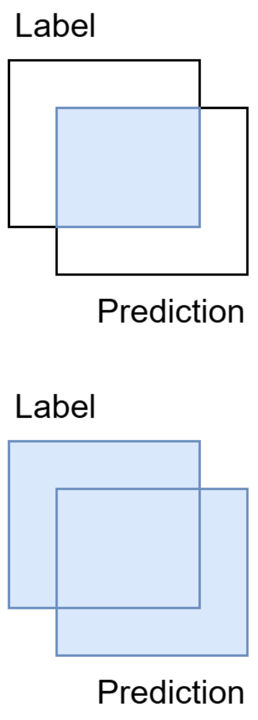
- Metrics (ranges from 0 to 1):
  - Precision
  - Recall
  - F1 score
  - Intersection Over Union (IoU)

Results

- Performance comparison among different models
  - SAM 1 Base
  - SAM 2 Tiny
  - SAM 2 Small
  - SAM 2 Base+
  - SAM 2 Large

- Metrics (ranges from 0 to 1):
  - Precision
  - Recall
  - F1 score
  - Intersection Over Union (IoU)

$$\textbf{IoU} = \frac{\text{Area of intersection}}{\text{Area of union}}$$



Results

- Baseline models
  - Zero-shot: trained by Meta AI, without retraining

Model	Loss	Precision	Recall	F1	IoU
SAM 1 Base	0.0868	0.6192	**0.7664**	**0.6062**	**0.5002**
SAM 2 Tiny	**0.0573**	**0.6489**	0.6903	0.5990	0.4851
SAM 2 Small	0.0611	0.5866	0.6550	0.5325	0.4300
SAM 2 Base+	0.0744	0.5745	0.7139	0.5453	0.4252
SAM 2 Large	0.0781	0.5319	0.7405	0.5280	0.4233

Results

- Finetuned models (single prompt)

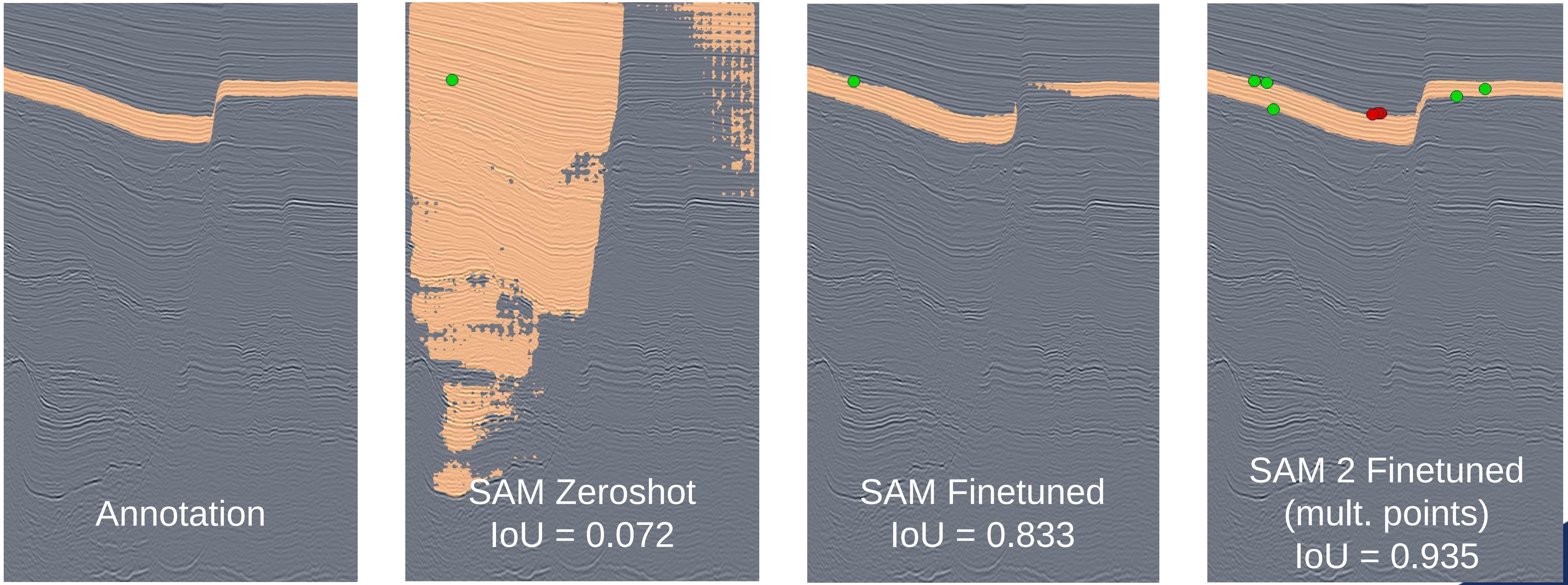
Model	Loss	Precision	Recall	F1	IoU
SAM 1 Base	0.0098	0.9283	0.9178	0.9178	0.8681
SAM 2 Tiny	0.0109	0.9166	0.9086	0.9062	0.8507
SAM 2 Small	0.0104	0.9293	0.9078	0.9122	0.8583
SAM 2 Base+	0.0090	0.9343	0.9227	0.9229	0.8742
SAM 2 Large	**0.0086**	**0.9386**	**0.9271**	**0.9286**	**0.8818**

- Finetuned models (multiple prompts)

Model	Loss	Precision	Recall	F1	IoU
SAM 1 Base	0.0085	0.9473	0.9296	0.9339	0.8899
SAM 2 Tiny	0.0078	0.9458	0.9323	0.9349	0.8902
SAM 2 Small	0.0073	0.9460	0.9369	0.9370	0.8941
SAM 2 Base+	**0.0064**	0.9536	0.9458	**0.9469**	0.9086
SAM 2 Large	0.0065	**0.9550**	**0.9459**	0.9468	**0.9106**

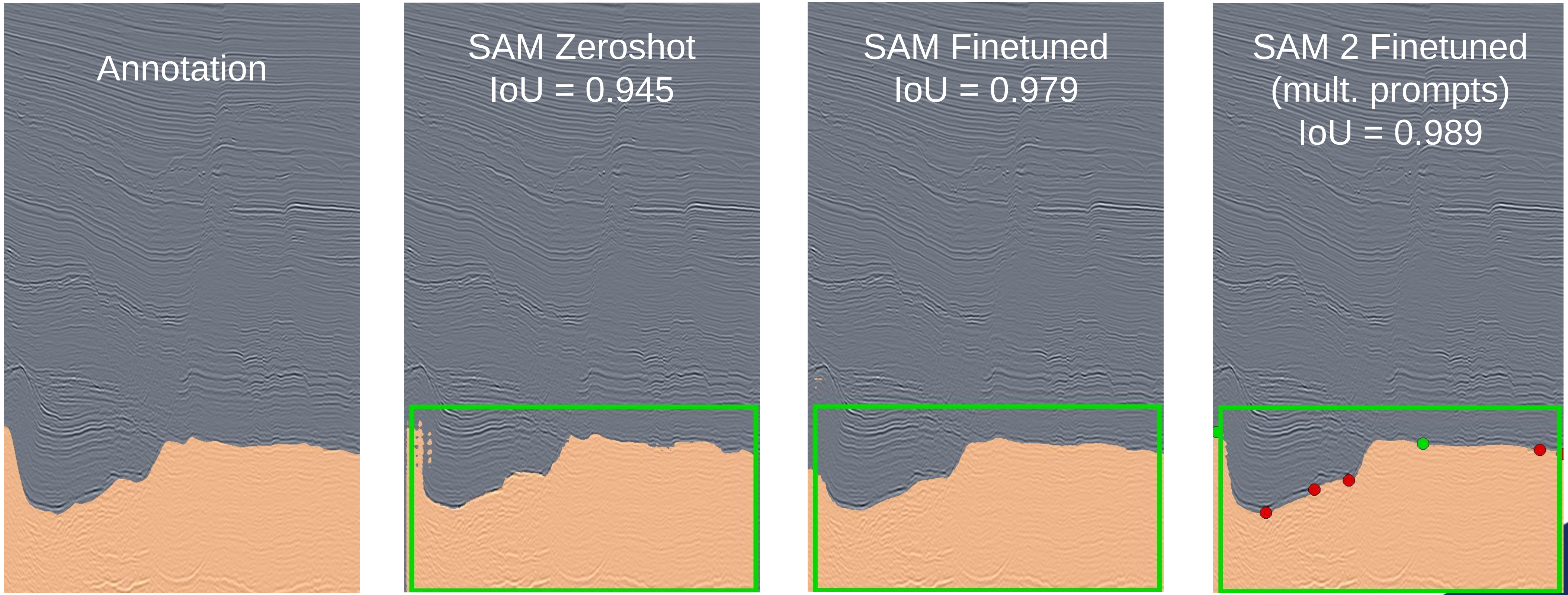
Results

- Segmentation sample results: Parihaka iline 78



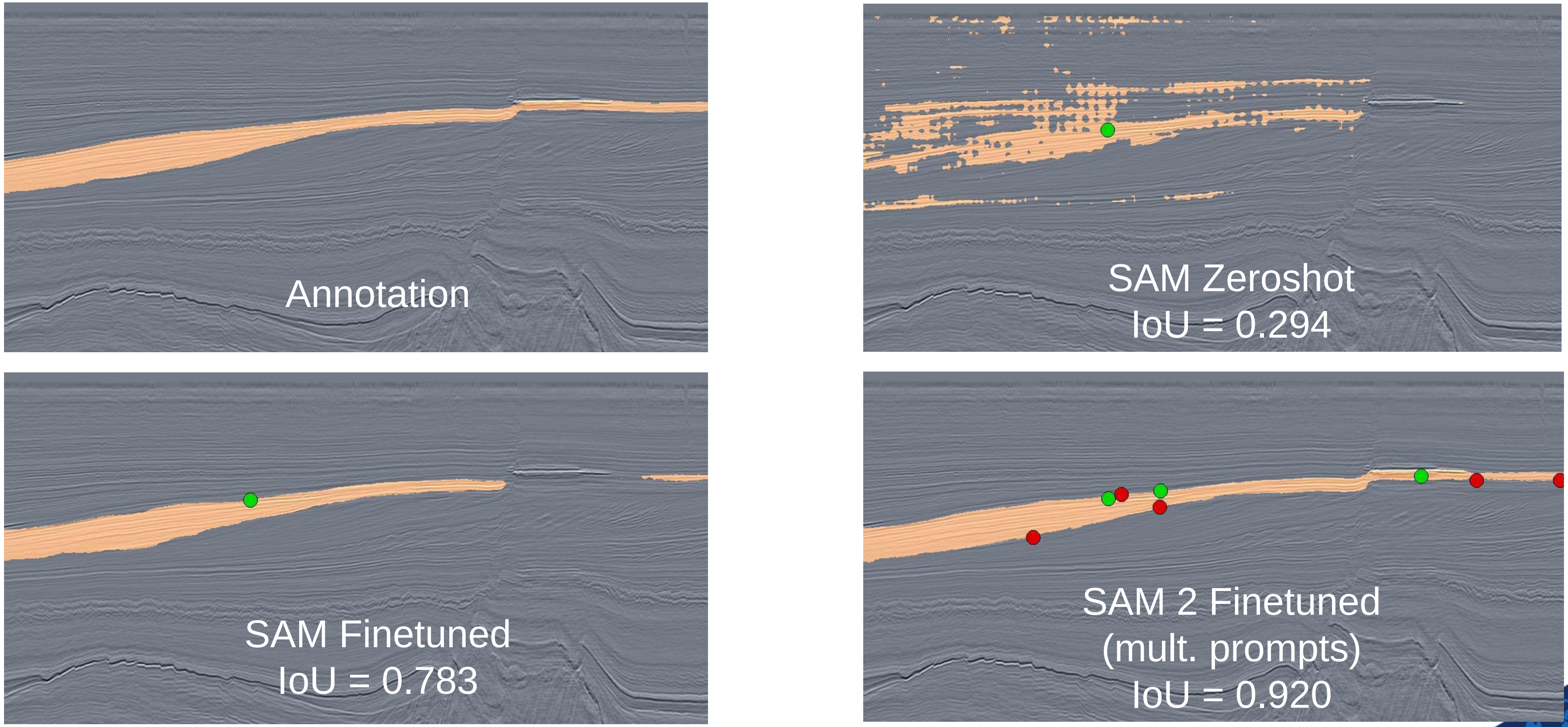
Results

- Segmentation sample results: Parihaka iline 78



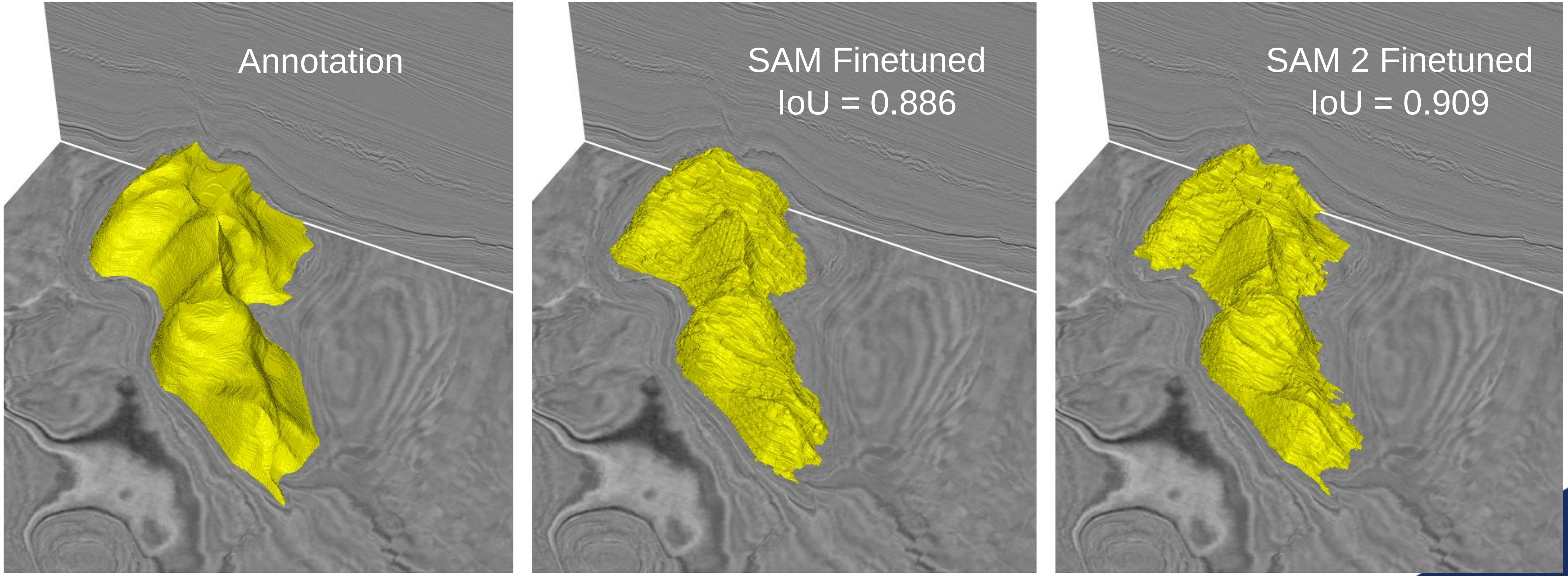
Results

- Segmentation sample results: F3 iline 129



Results

- 3D Segmentation: propagating predictions inline by inline



Conclusion

- Finetuning considerably improved segmentation performance of SAM/SAM2 on seismic data

- Flexible model
  - not task-specific
  - Interactive inputs allow fine adjustments without retraining

- Good 3D segmentation performance by slice by slice propagation

thiagoaoyagi@ipt.br

Find out more about IPT

linkedin.com/school/iptsp/

instagram.com/ipt_oficial/

youtube.com/@IPTbr/

ipt INSTITUTO DE PESQUISAS TECNOLÓGICAS

BR PETROBRAS

SEG | AAPG image International Meeting for Applied Geoscience & Energy