Automatic Seismic Interpretation Networks

FORCE ML symposium 2019

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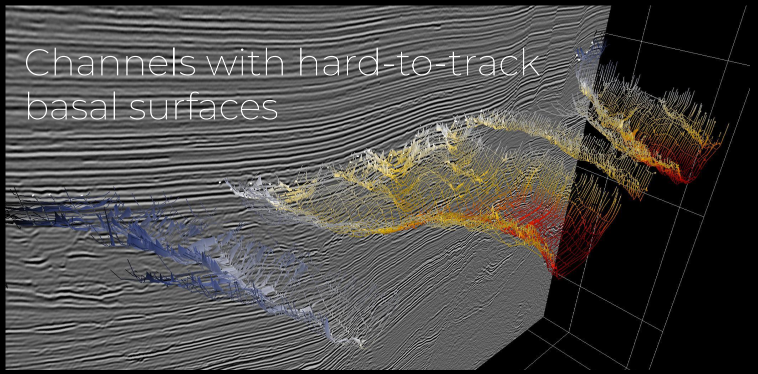
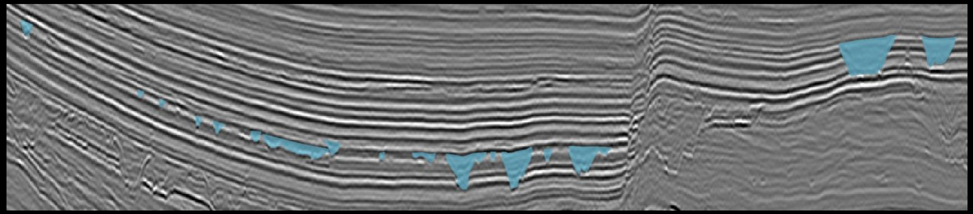
The Geoscience Problem

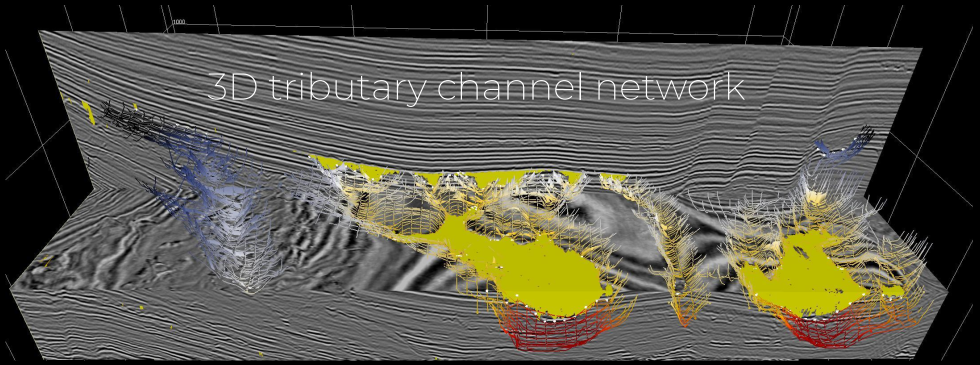
Interpret complex 3D geobodies fast with minimal human input



Manual (point) interpretation:
- time consuming
- prone to errors

Manual 2D interpretation on 18 crosslines





Automatic Seismic Interpretation

Earth Science Analytics acknowledge New Zealand Petroleum and Minerals (NZPM) for providing Parihaka 3D data

Methodology followed

Methods & Parameters controlled:

- Train - Split - Blind
- Training slices: 18 crosslines
- Blind slices: 2 crosslines
- Patch size: 256 x 256
- Random Noise: 1%
- Dropout: 0.2
- Epochs: 100

Architectures tested:

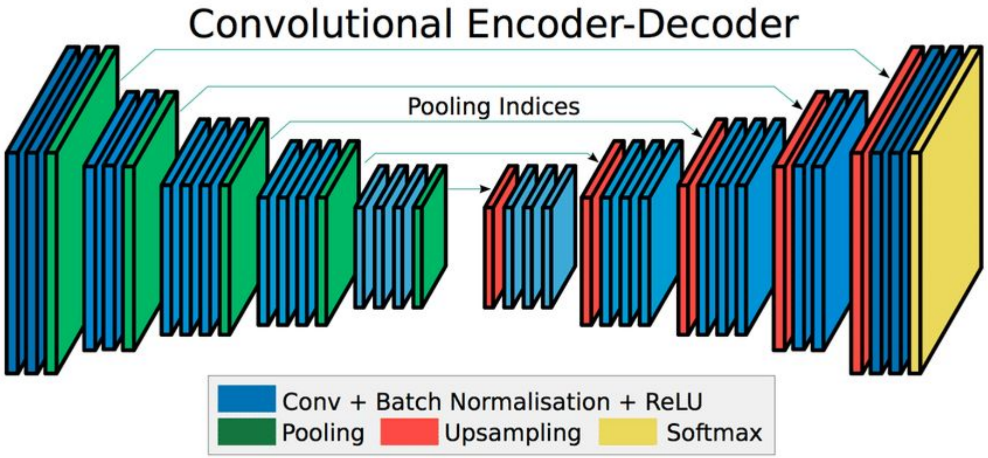
- Unet - Light Unet
- Segnet - Light Segnet
- PSP - Light PSP
- DeepLab3+ - Light DeepLab3+

Loss functions:

- Weighted cross entropy
- Dice
- Jaccard

Segnet

Classic Segnet Architecture [1]



Year released: 2015
Benchmarks (VOC2012)[5] -Mean IOU: 0.599

Light - Segnet

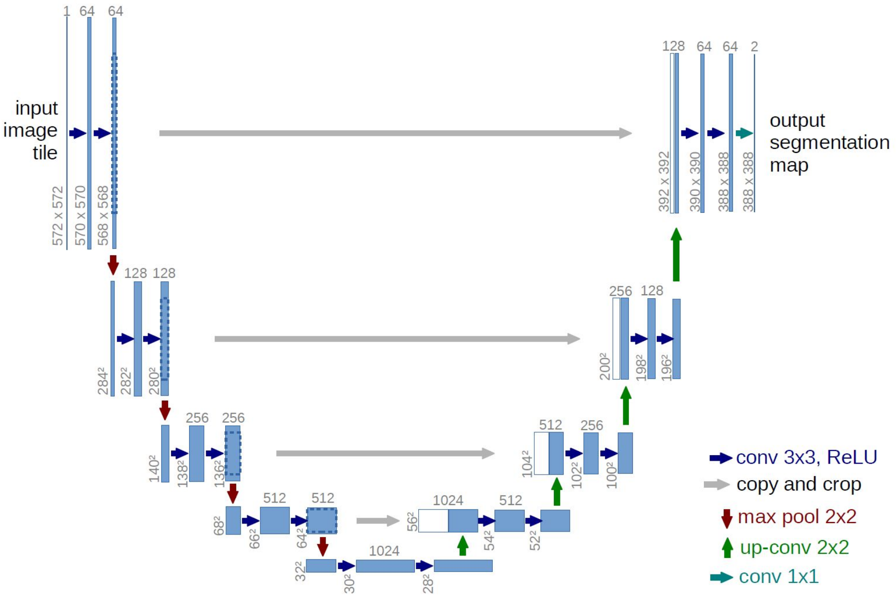
- Add/remove any number of layers
- Respectively customize filters on convolution layers

This results in full control over network depth and number of training parameters.

Earth Science Analytics

Unet

Classic Unet Architecture [2]



Year released: 2015
Benchmarks (ISBI cell tracking challenge) -Mean IOU: 0.775

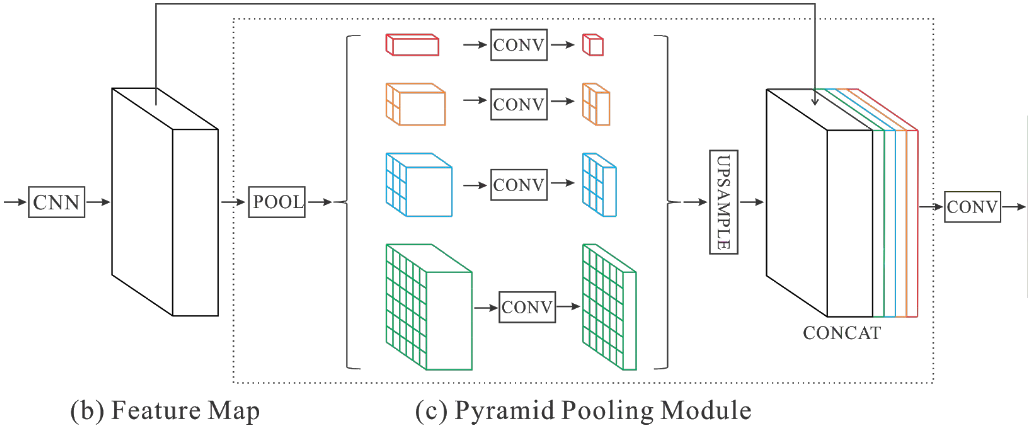
Light Unet

- Add/remove any number of layers
- Respectively customize filters on convolution layers

This results in full control over network depth and number of training parameters.

Pyramid Scene Parsing Network (Psp Net)

Classic Psp architecture [3]



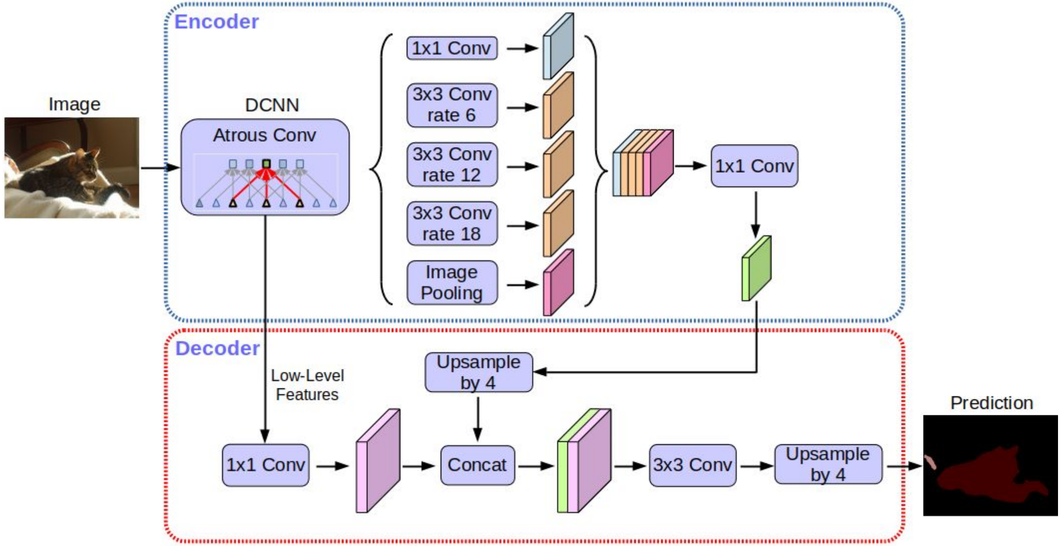
Year released: 2017
Benchmarks (VOC2012) -Mean IOU: 85.4

Light PSP

- During Feature Map phase usually a Resnet (huge) is used so we:
    - Reduce Resnet's overall size
- During Pyramid Pooling Module one can modify the dimensions of the sub-regions

DeepLab v3+

Classic DeepLabV3+ architecture [4]

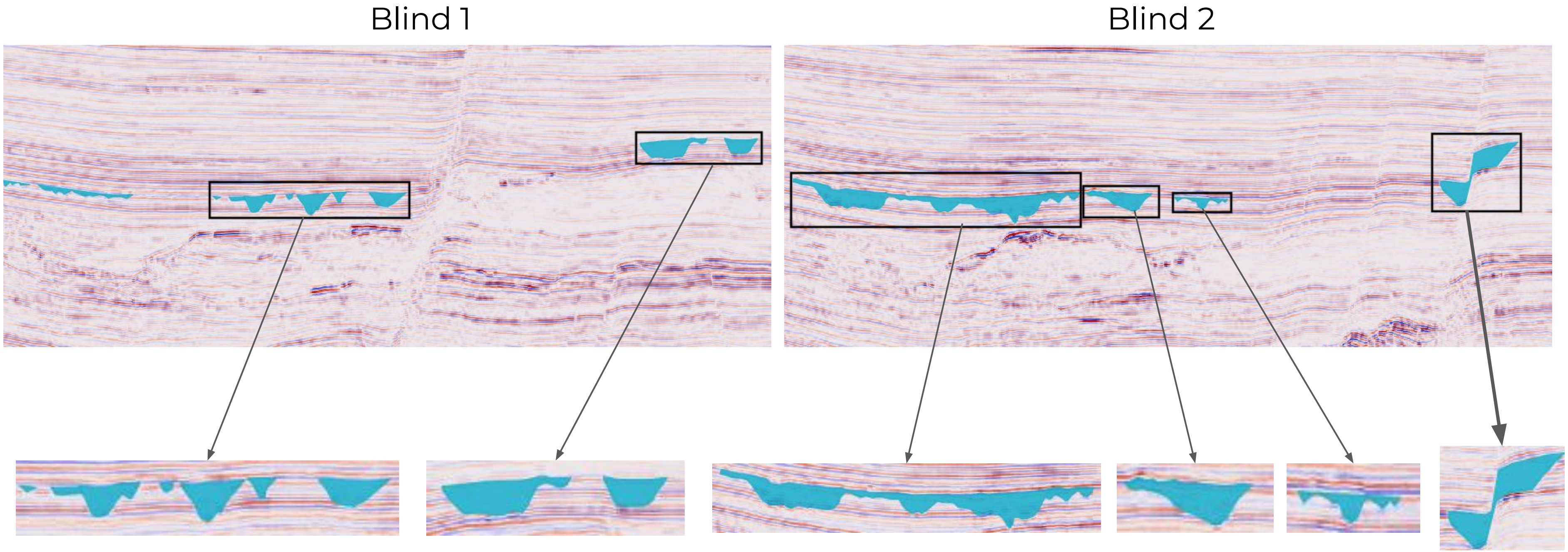


Year released: 2018
Benchmarks (VOC2012) -Mean IOU: 87.8

Light Deeplab

Same as the Psp Net one can use smaller CNN's as feature extractors and different Convolution dilation rates (Atrous Conv)

Truth Labels on Blind Test Slices



Human expert's seismic interpretation (labels) are regarded as ground truth

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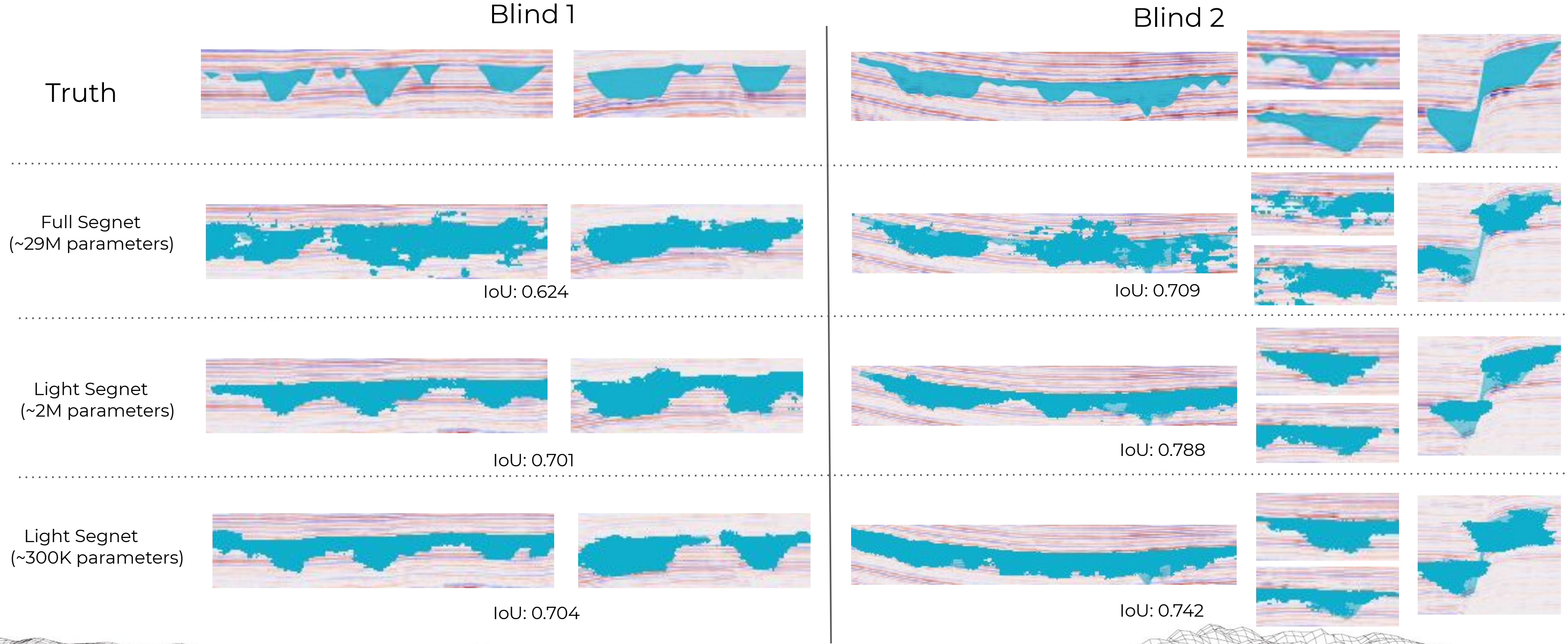
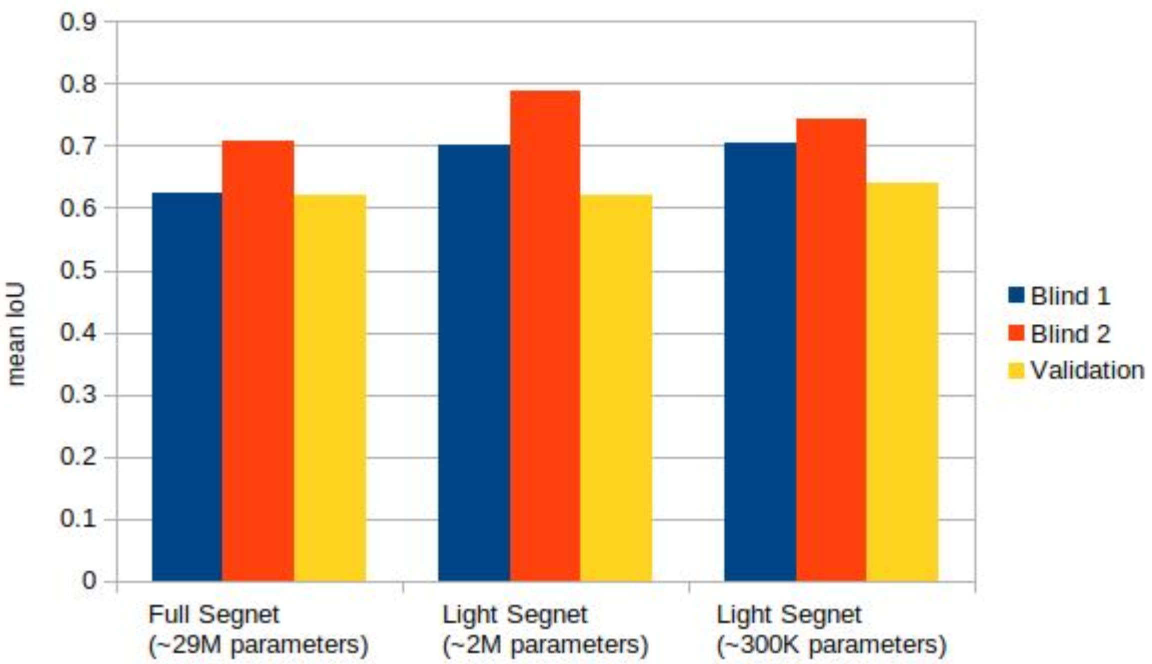
Segnet results



Segnet results



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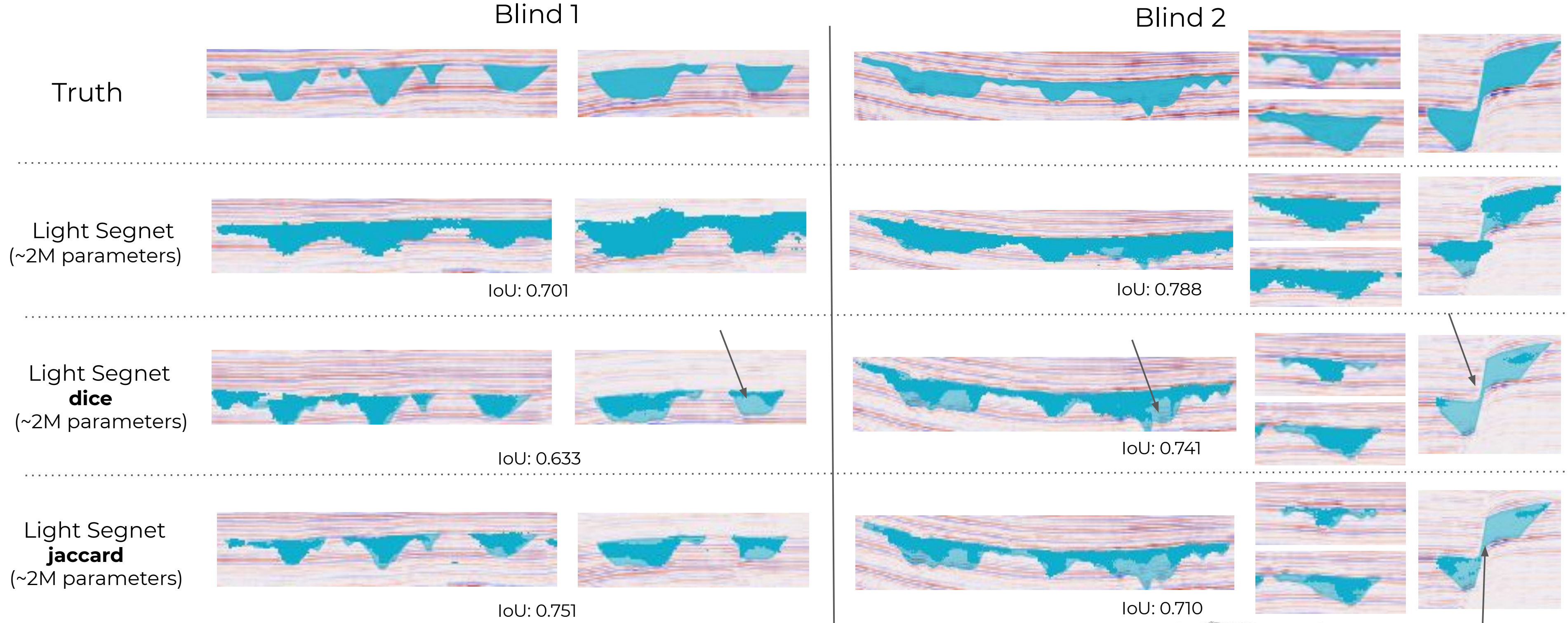
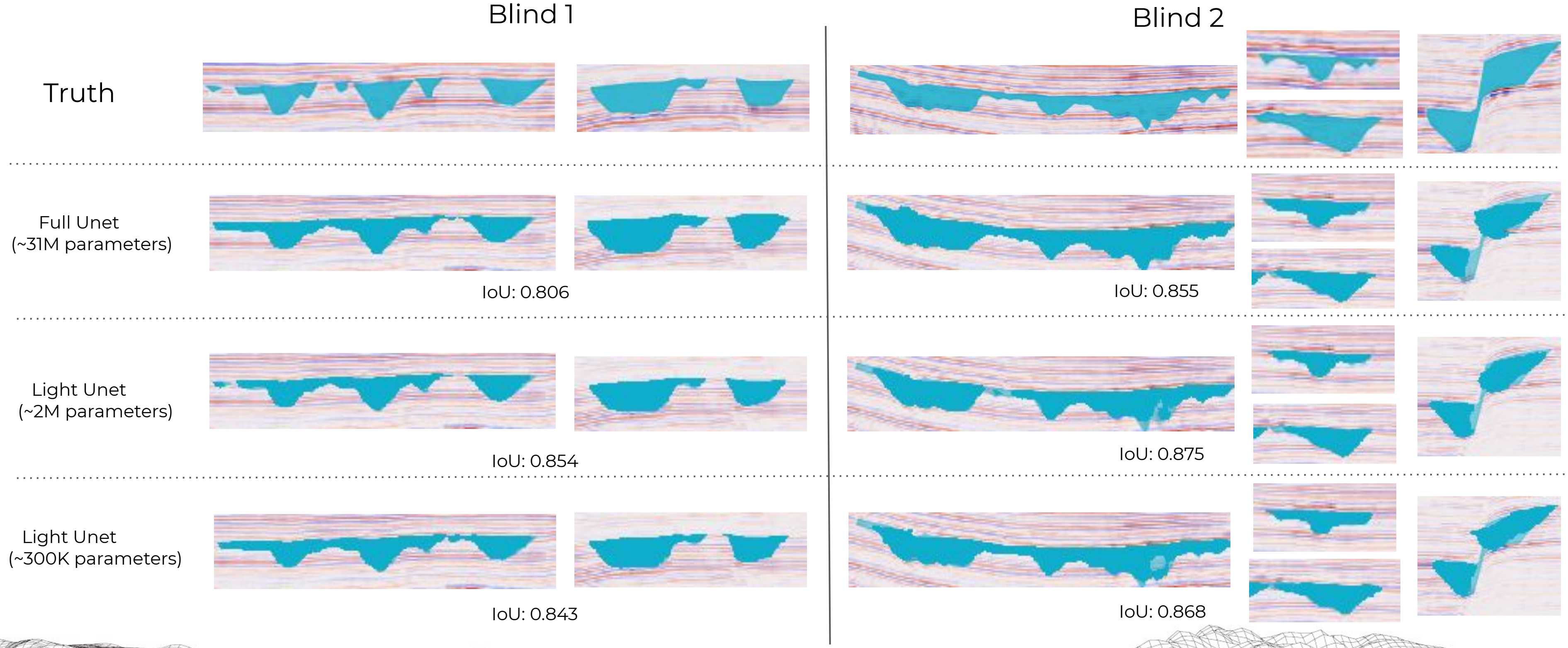
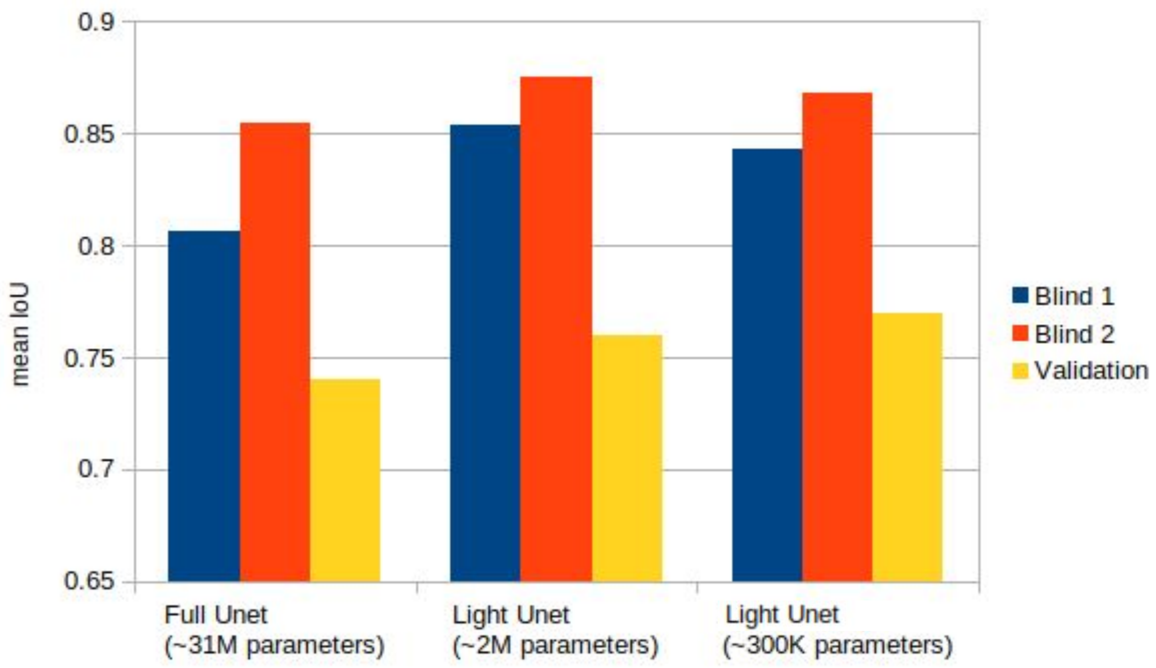
Light Segnet results against loss functions



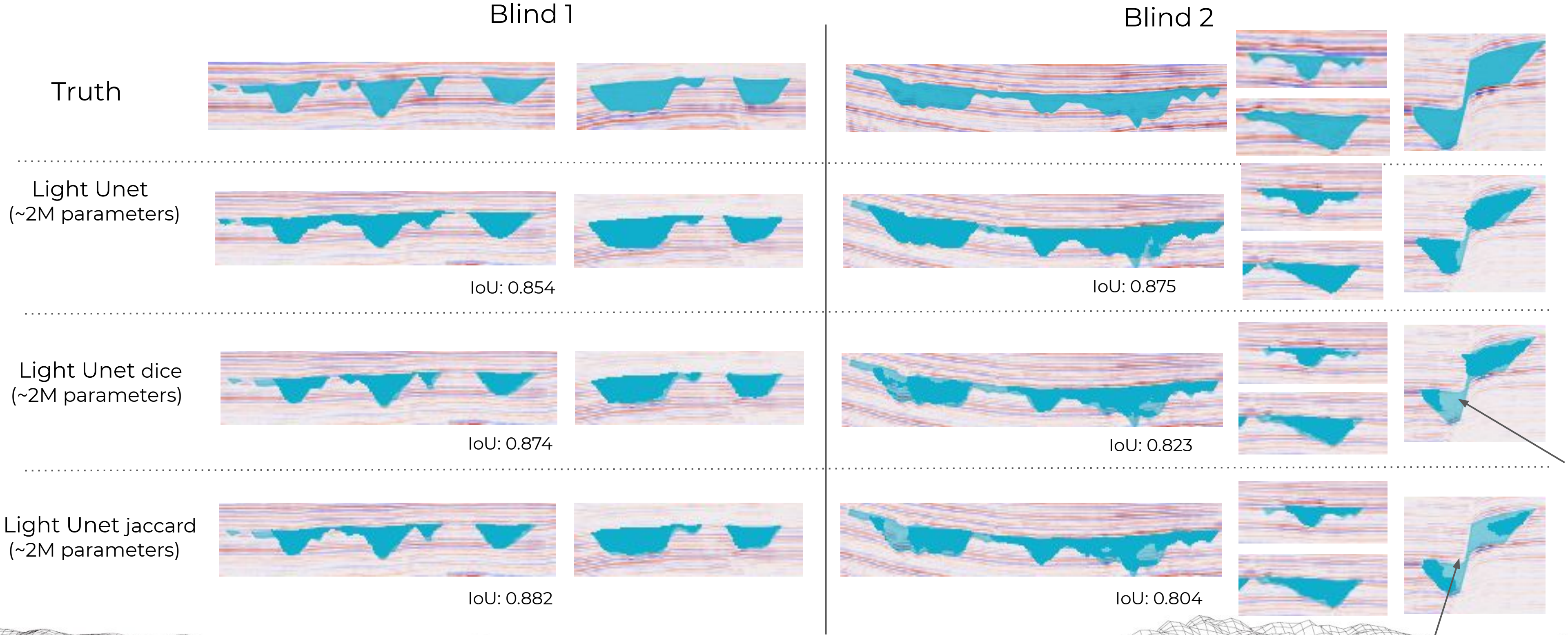
Unet results



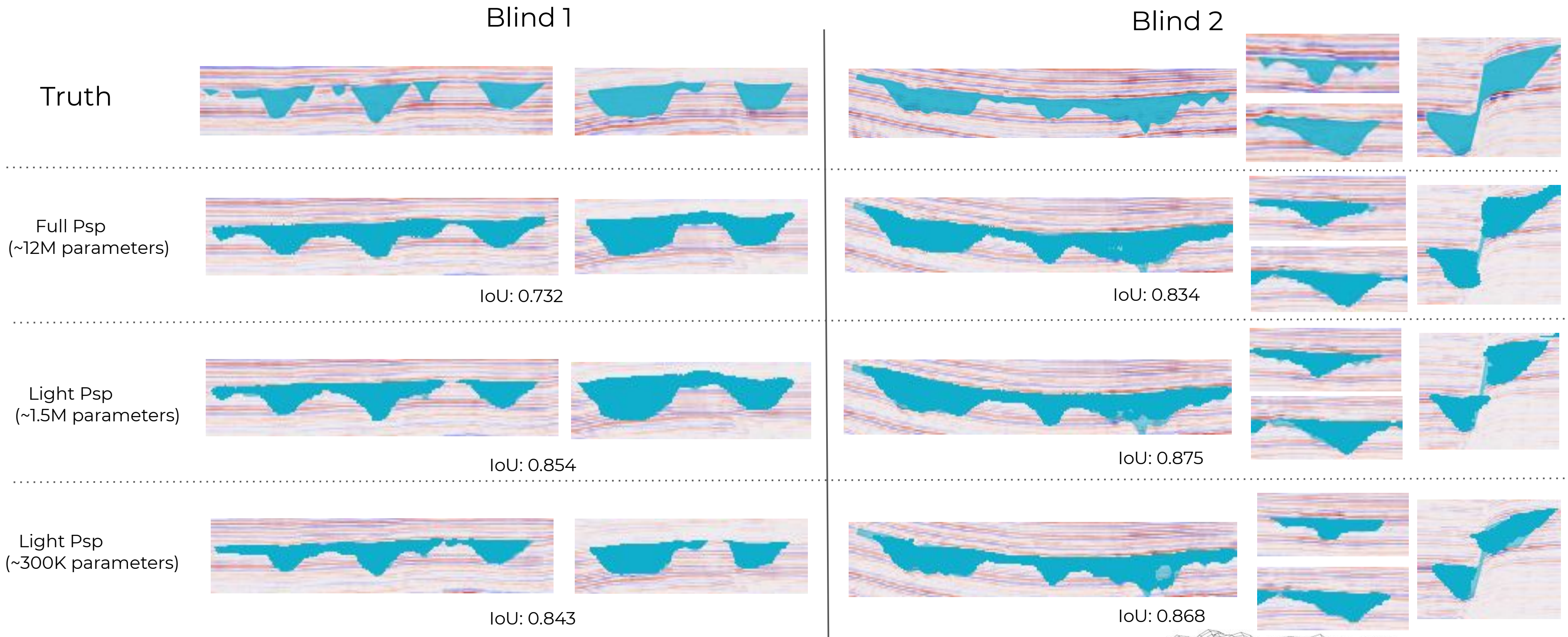
Unet results



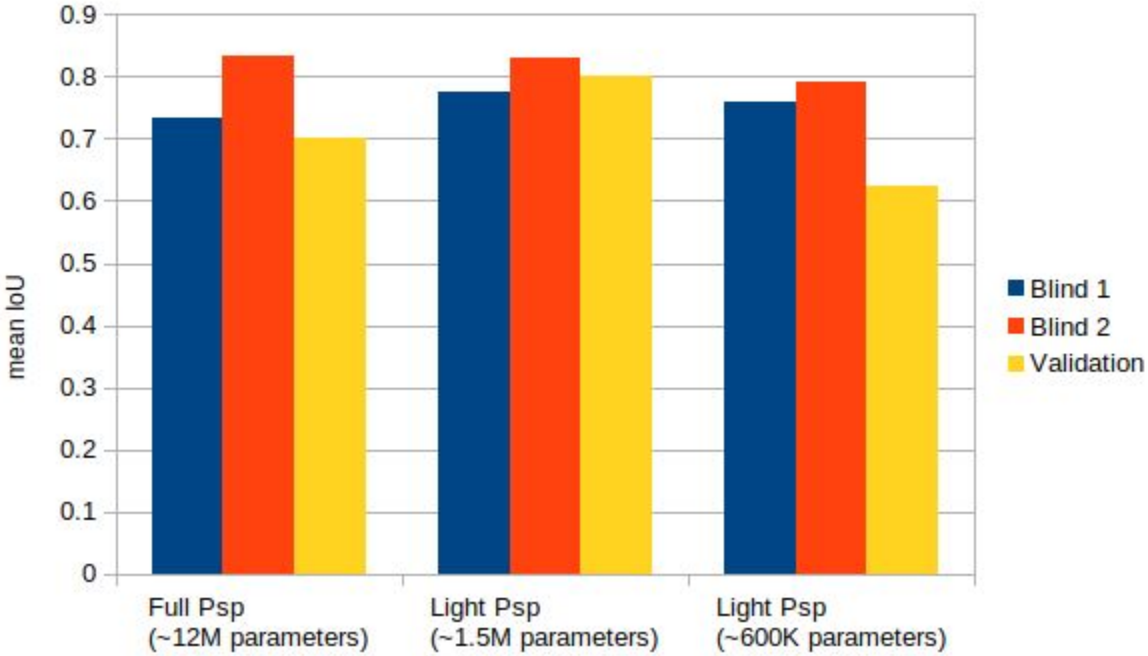
Light Unet results against loss functions



Psp results


Blind 1
Blind 2
Truth
Full Psp
(~12M parameters)
IoU: 0.732
IoU: 0.834
Light Psp
(~1.5M parameters)
IoU: 0.854
IoU: 0.875
Light Psp
(~300K parameters)
IoU: 0.843
IoU: 0.868

Psp net results



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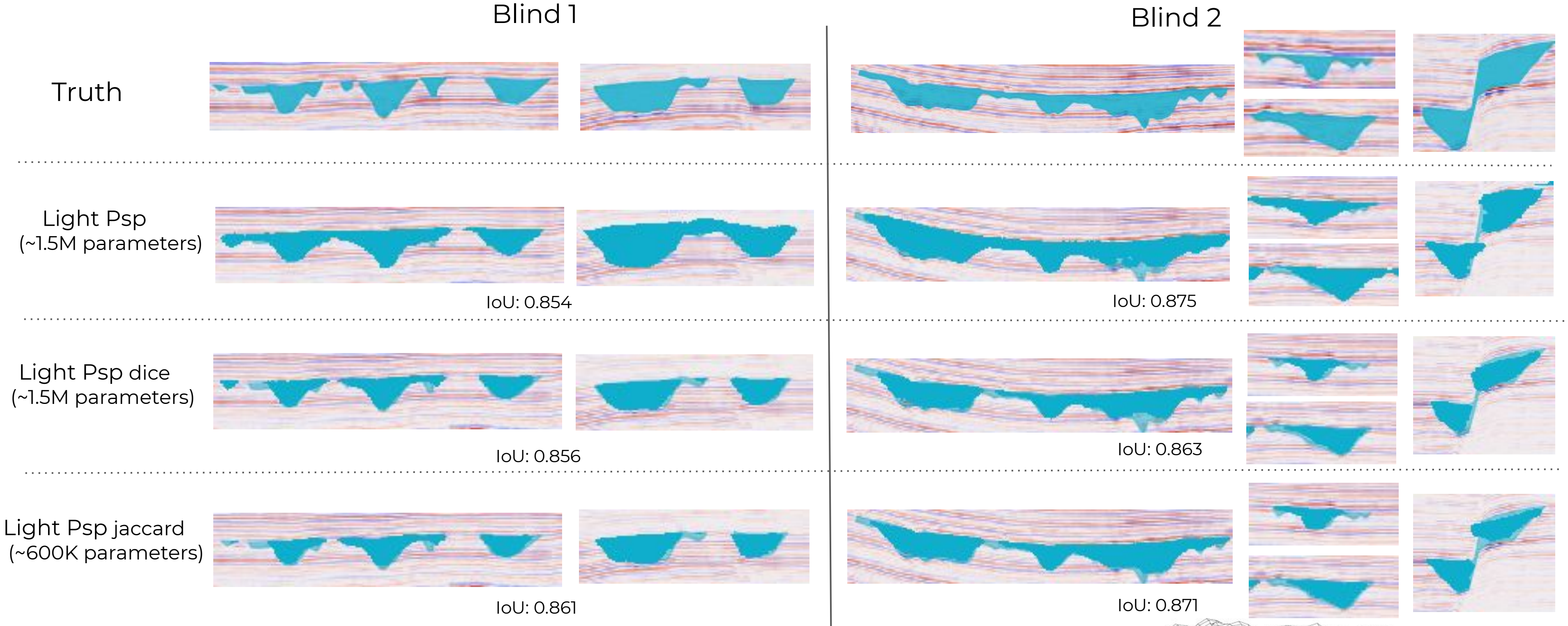
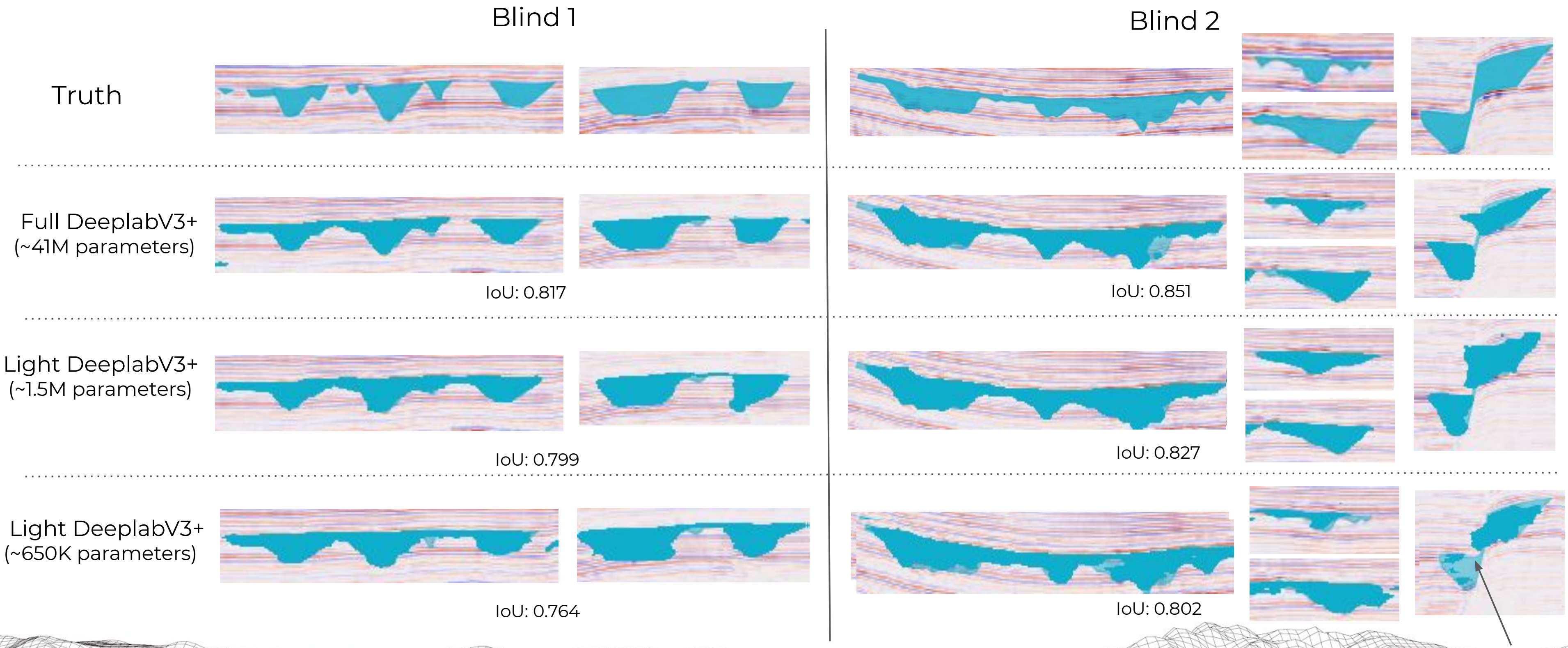
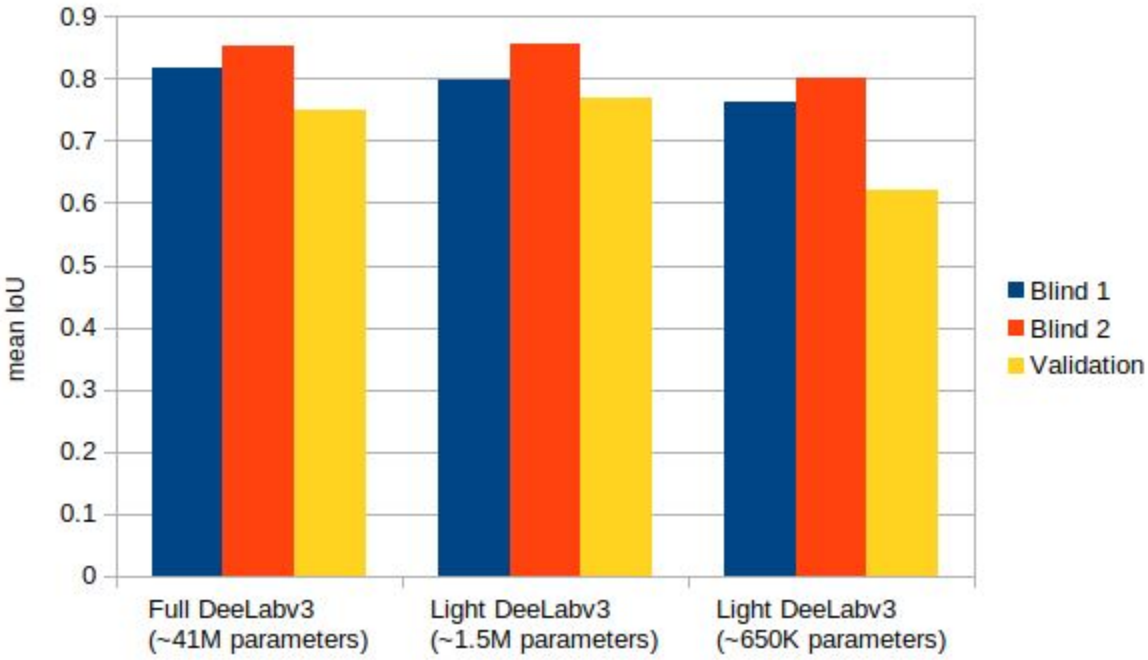
Light PSP results against loss functions



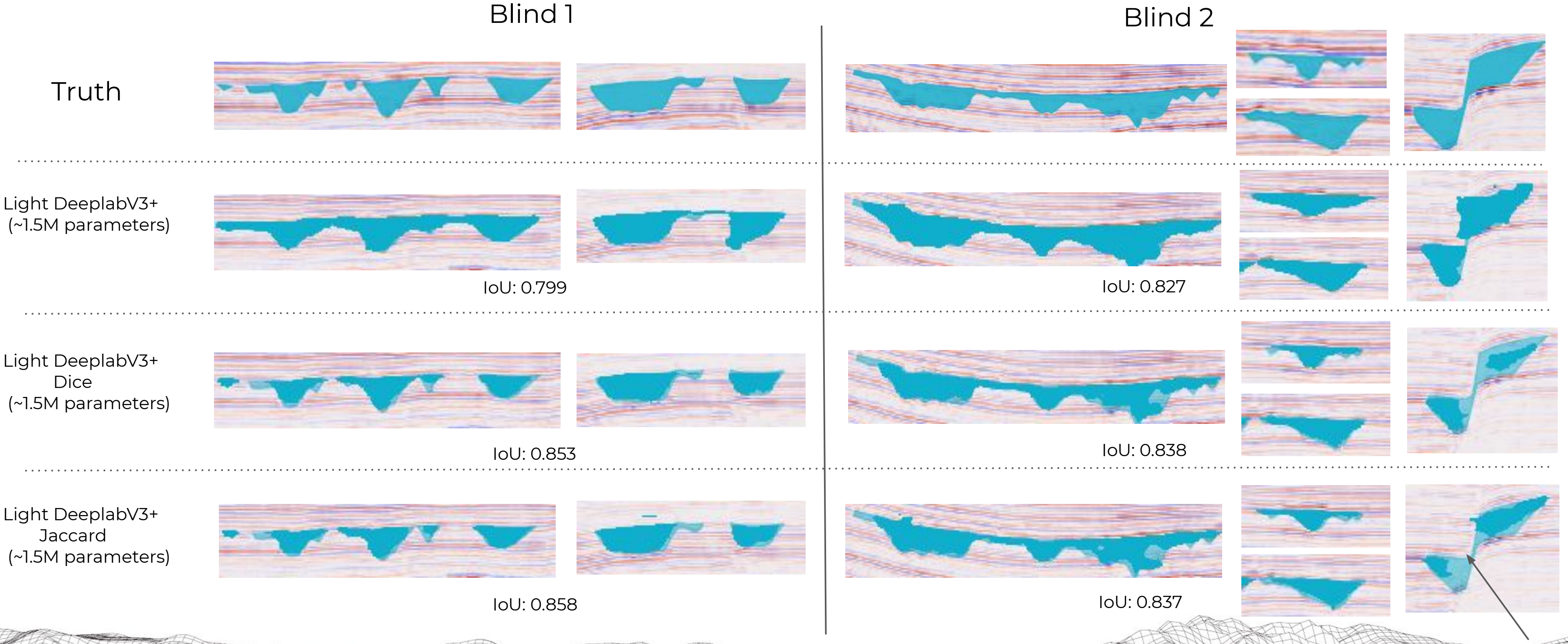
DeepLabv3+ results (Xception feature extractor)



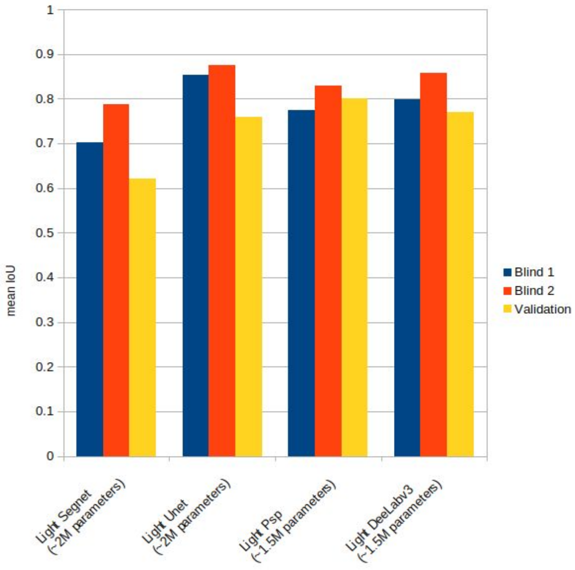
DeepLabv3+ results



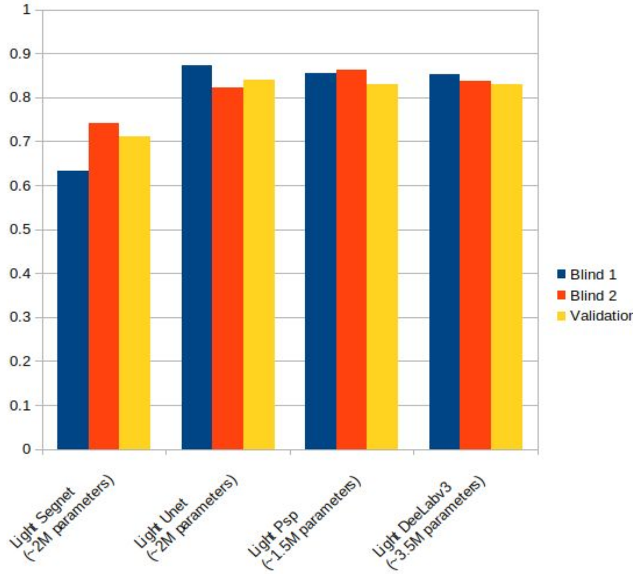
Light DeepLabv3+ results against loss functions



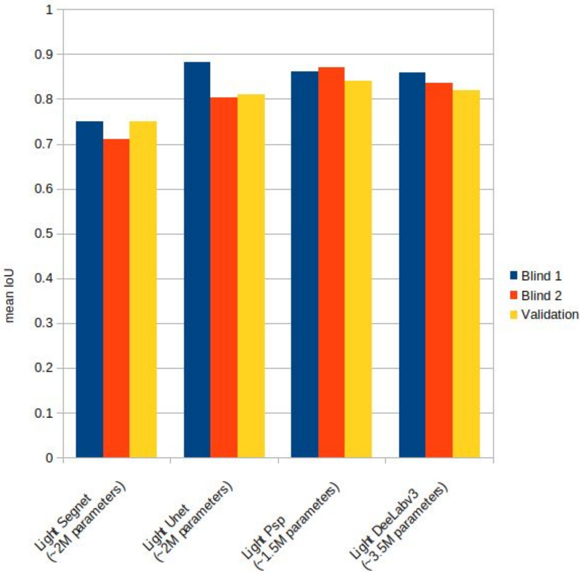
Comparison of light networks vs Loss



Weighted
Categorical Crossentropy



Dice



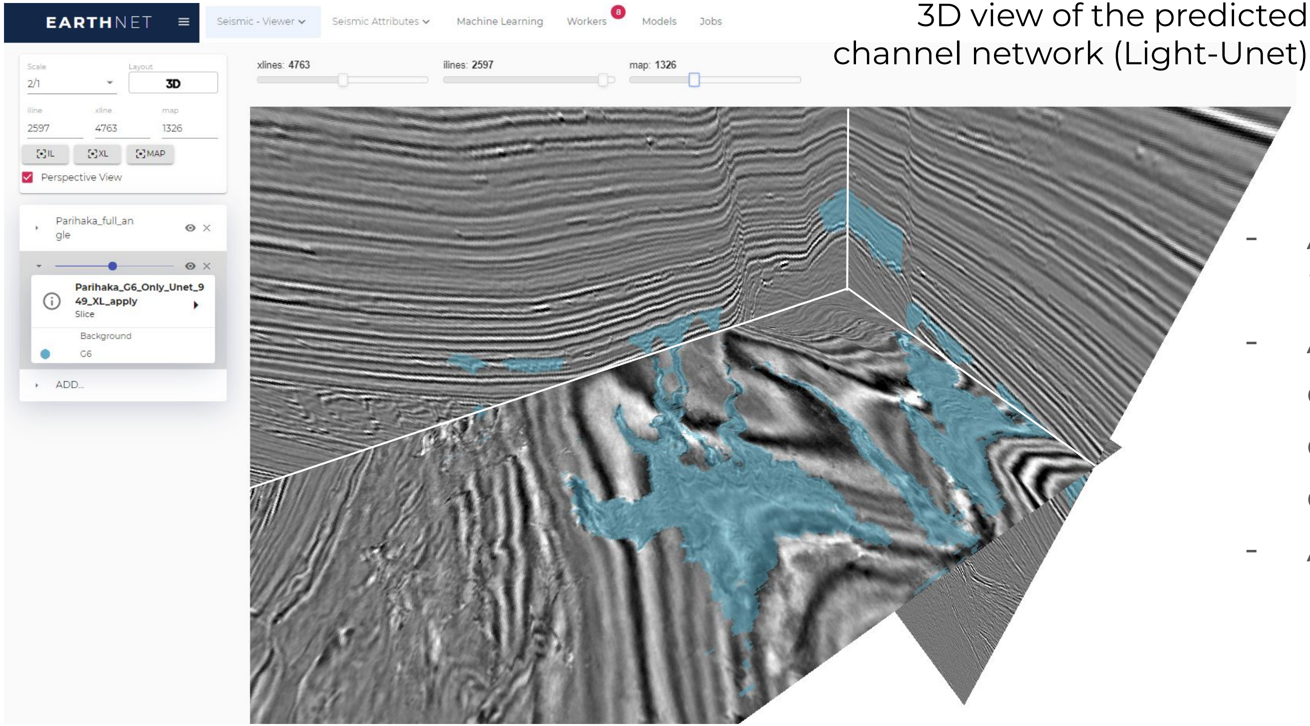
Jaccard

Conclusions Architectures, Data driven

- On limited dataset large (public) networks tend to overfit
- Large networks do not guarantee better performance
- Revisit results obtained by Segnet architectures
- Smaller networks easier (and cheaper) to train
- Weighted Cross Entropy Loss slightly tends to overestimate volumes of unbalanced class (channels in the specific problem)
- Dice and Jaccard Loss slightly tends to underestimate volumes of unbalanced class

It is important to check network size with respect of the available labels

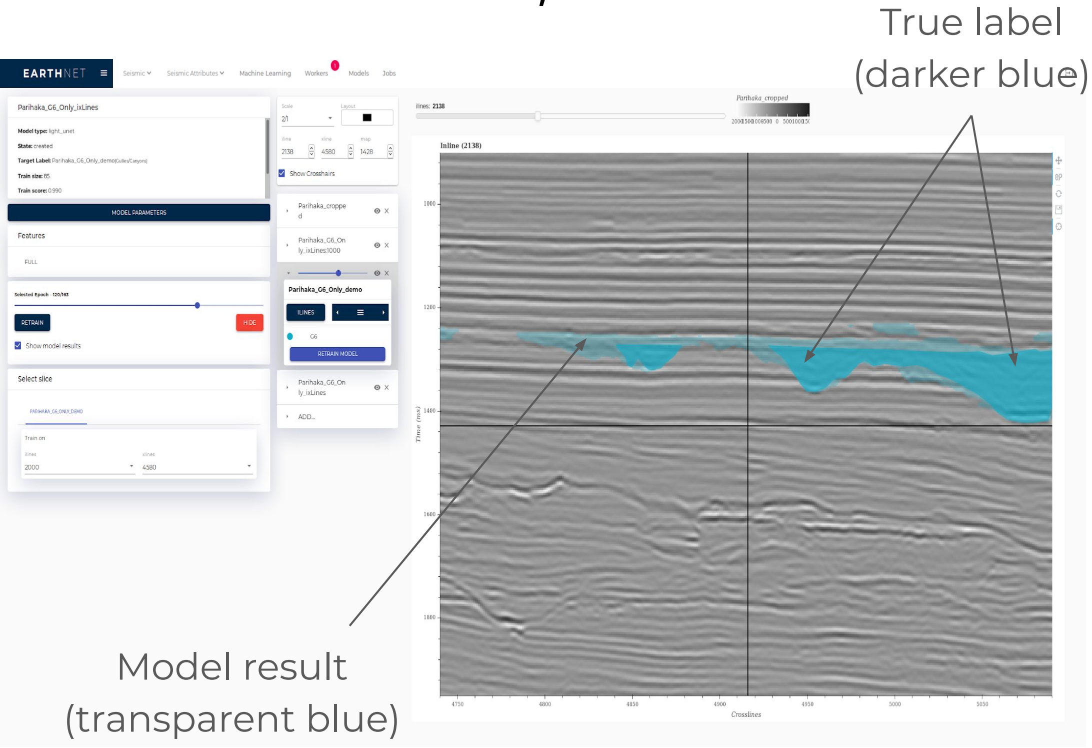
Conclusions, G&G



3D view of the predicted channel network (Light-Unet)

- ASI reduces interpretation cycle time
- ASI can improve quality of interpretation of very complex geological objects
- ASI 3D output can be used in for 3D geological models

Conclusions, G&G



Interactive labeling

- Model seems to predict 'better' than the labeler in some slices
- Obtaining True labels is a challenge, but key in order to train properly
- Interactive approach gives an effective suggestion for the labeller to make a decision.
- With the real time helping from DNN, the labeller can resolve challenges in complex areas
- DNN architectures smooth out possible inconsistency in labels by minimizing a global loss

References

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2. Olaf Ronneberger, Philipp Fischer, Thomas Brox. U-Net: Convolutional Networks for Biomedical Image Segmentation. arXiv:1505.04597, 2015
3. Hengshuang Zhao, Jianping Shi, Xiaojuan Qi, Xiaogang Wang, Jiaya Jia. Pyramid Scene Parsing Network. arXiv:1612.01105, 2017
4. Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, Hartwig Adam. Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation. arXiv:1802.02611, 2018
5. PASCAL VOC Challenge performance evaluation, Leaderboard link

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