Automated seismic interpretation using machine learning and field interpretations

Force Hackathon and Advances of Machine Learning on Subsurface Data

Stavanger, September 20 2018

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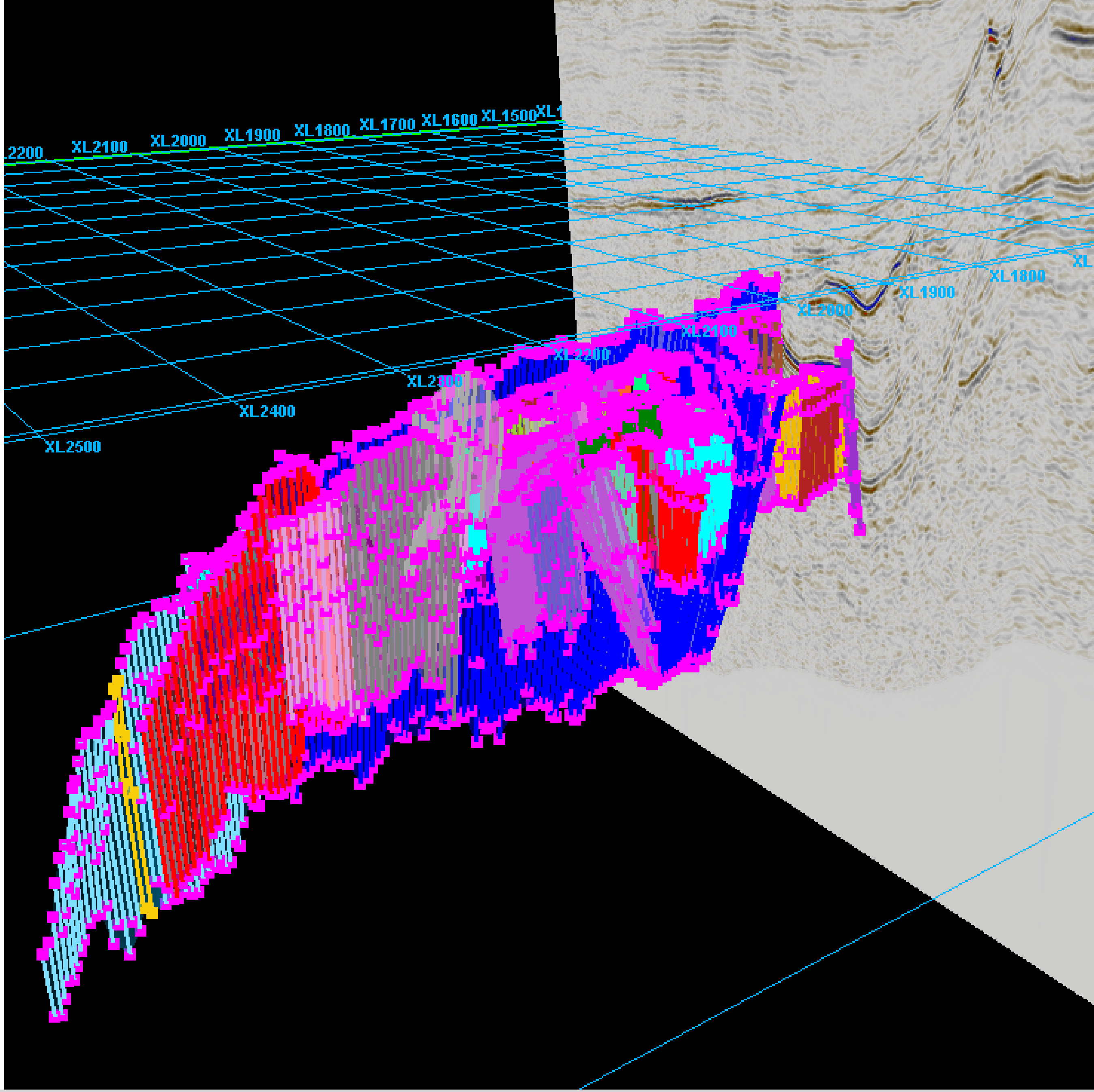
Background

Goals

- Proof-of-concept study for predicting **faults** and **horizons**
- Real data needed to be involved
- Train using **human interpretations** from **multiple fields**
  - Exploration and production areas
- **Binary** sample prediction and **pixel-level** prediction (segmentation)
- **2D** and **3D** training data

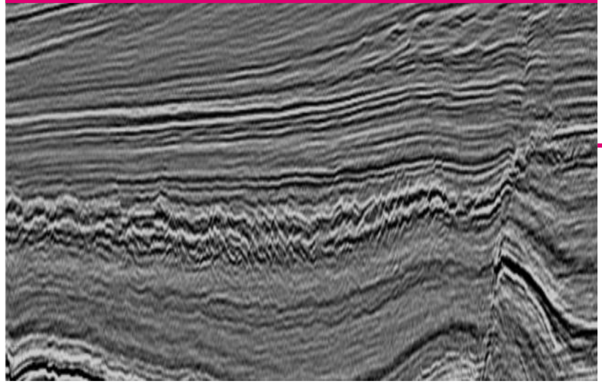


Approach

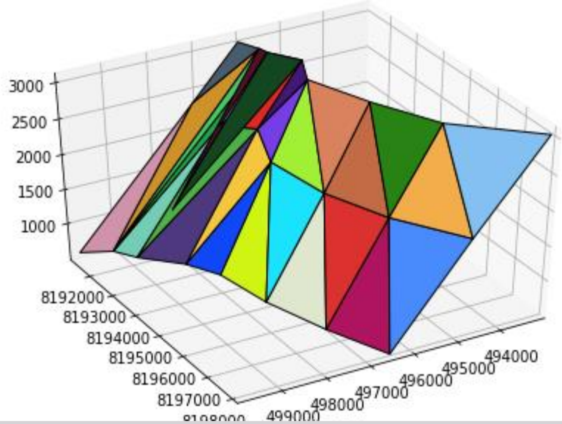
APPROACH

Training data work flow overview

Seismic data sample



Interpretations

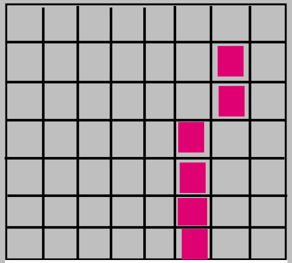


Projection

Target

0	1

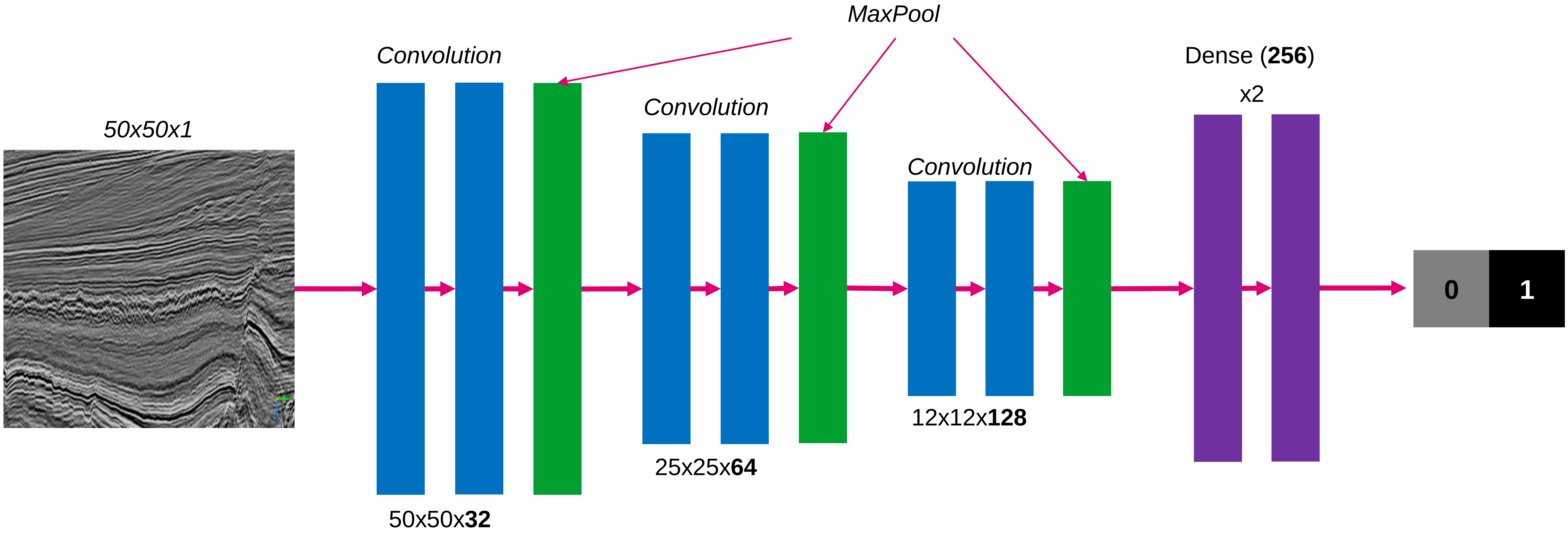
Binary



Pixel

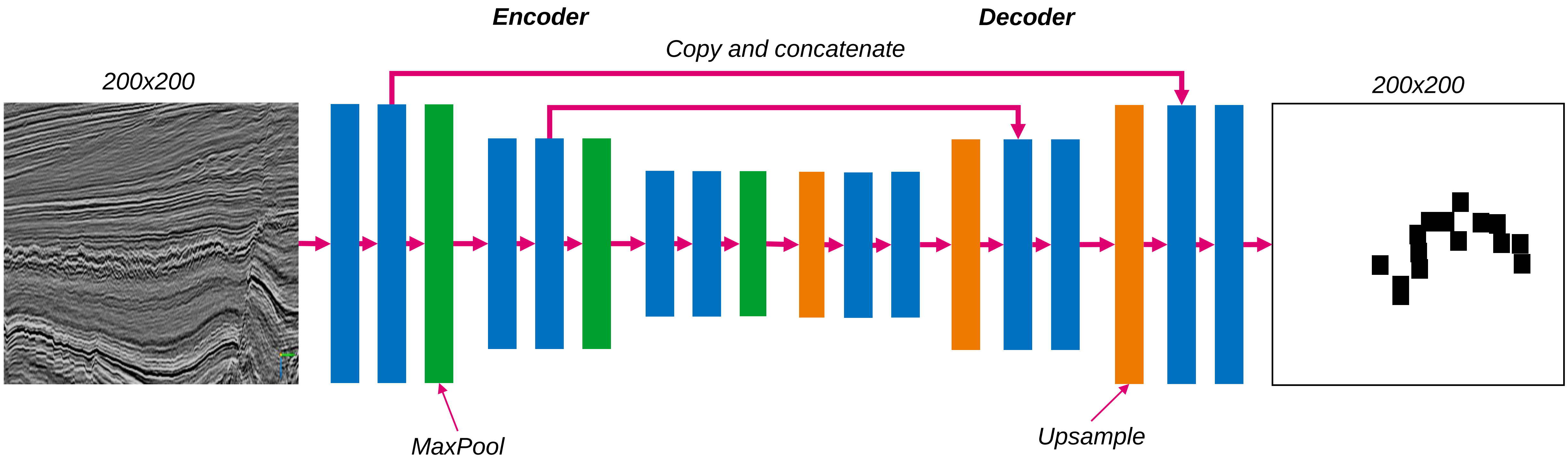
APPROACH

Neural network: Binary sample prediction



Note: Small version of the VGG architecture (*Simonyan and Zisserman, 2014*)

Neural network: Pixel prediction (image segmentation)

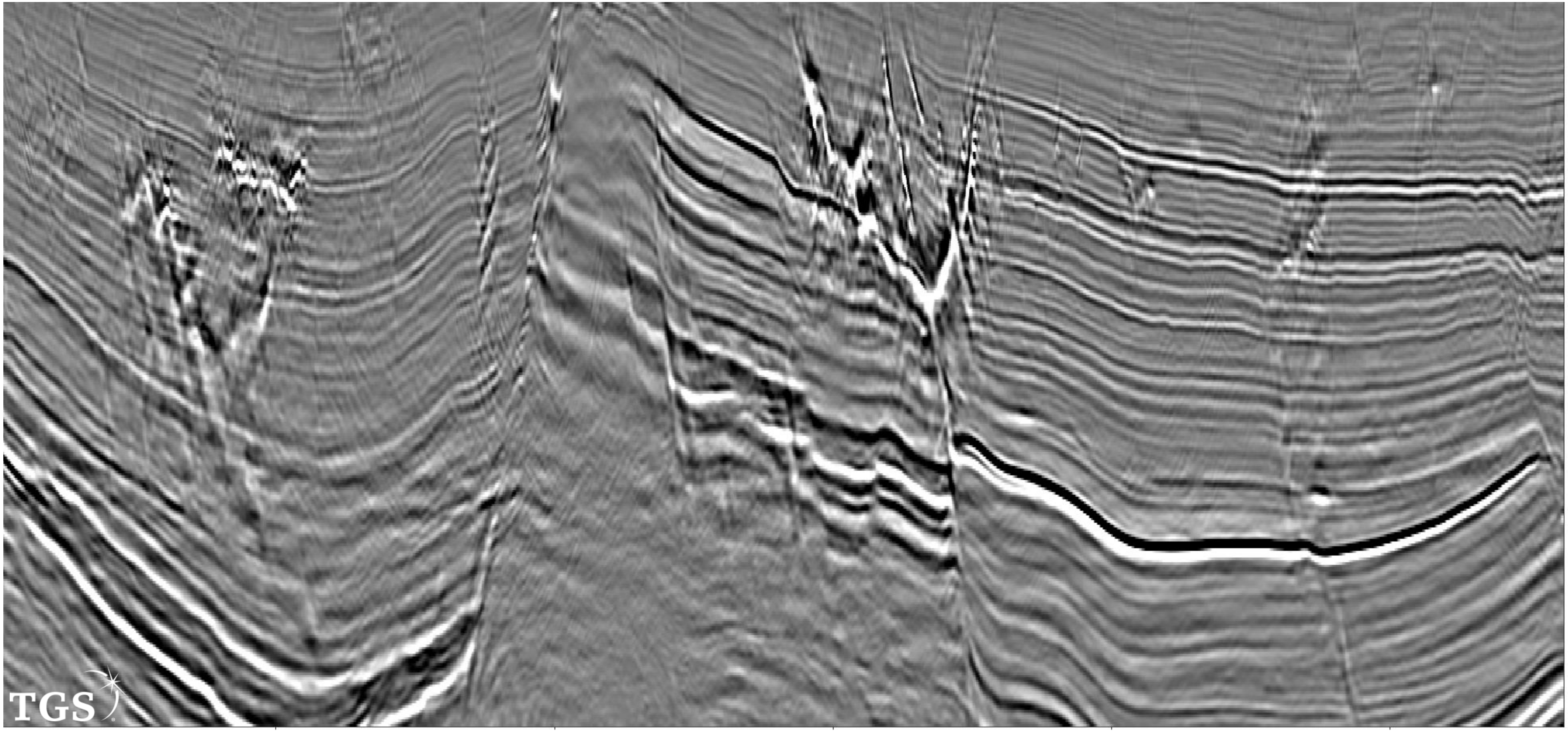


Note: Small version of the SegNet architecture (Badrinarayanan et al., 2015)

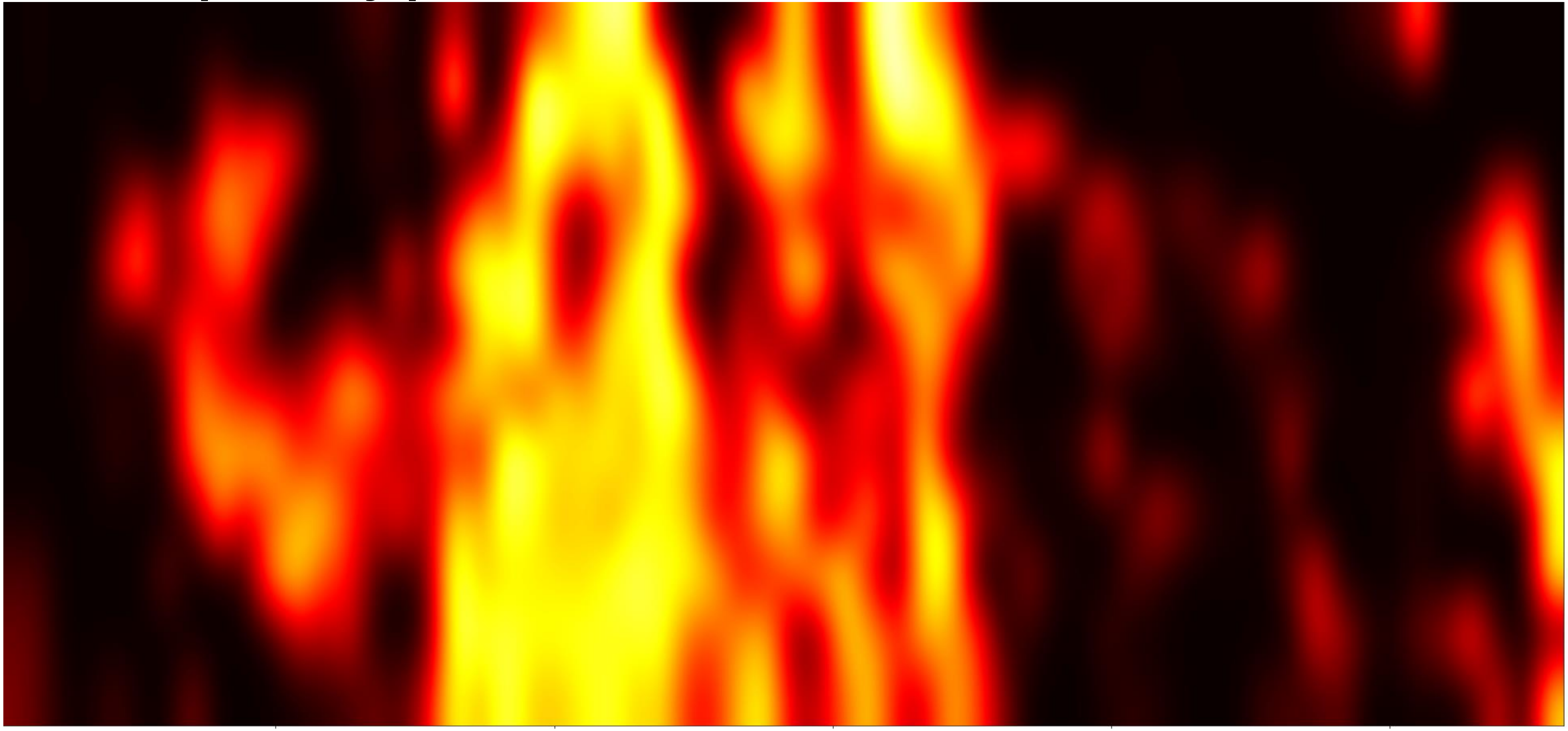
Results

RESULTS: FAULT PREDICTION

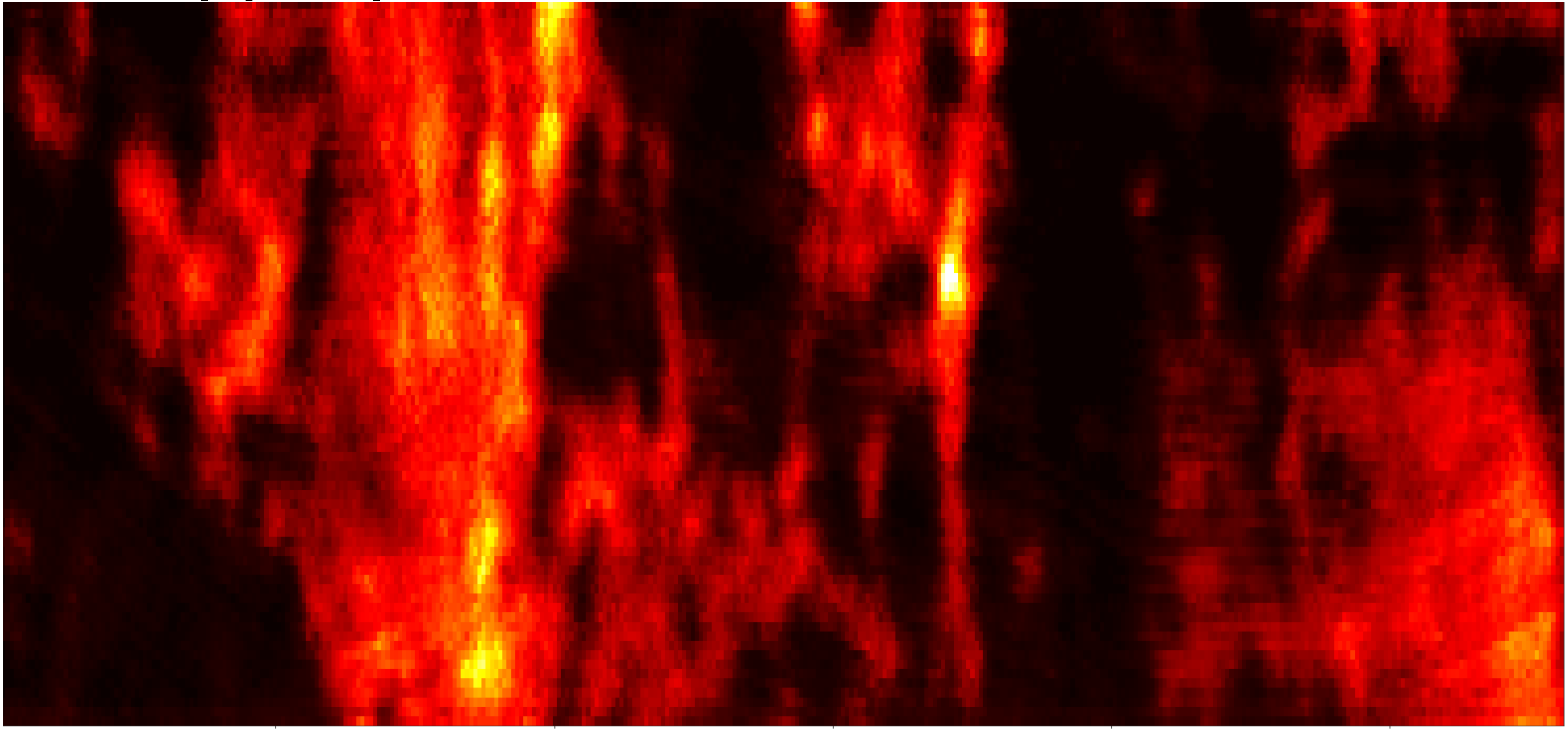
Seismic slice



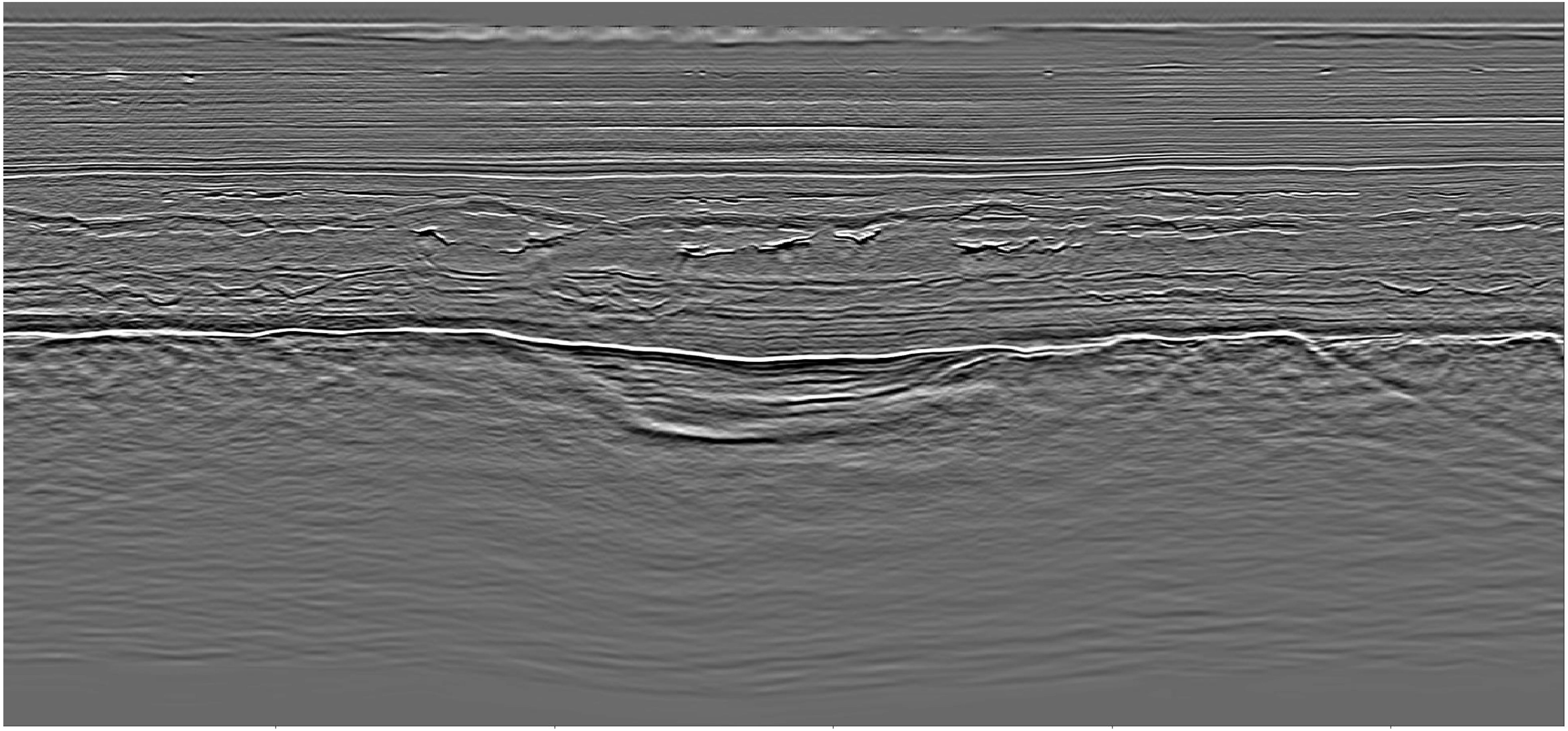
Heat map binary prediction



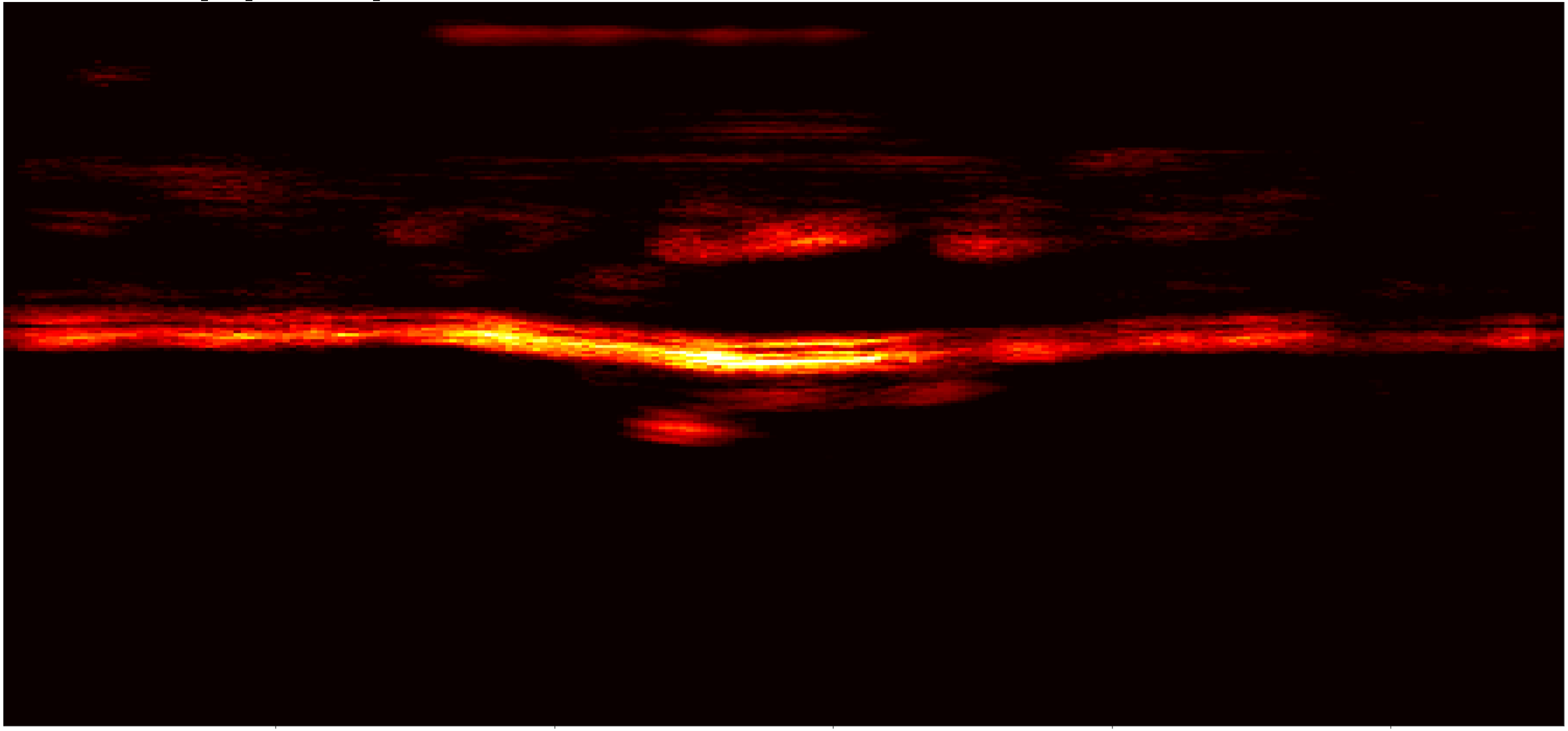
Heat map pixel prediction



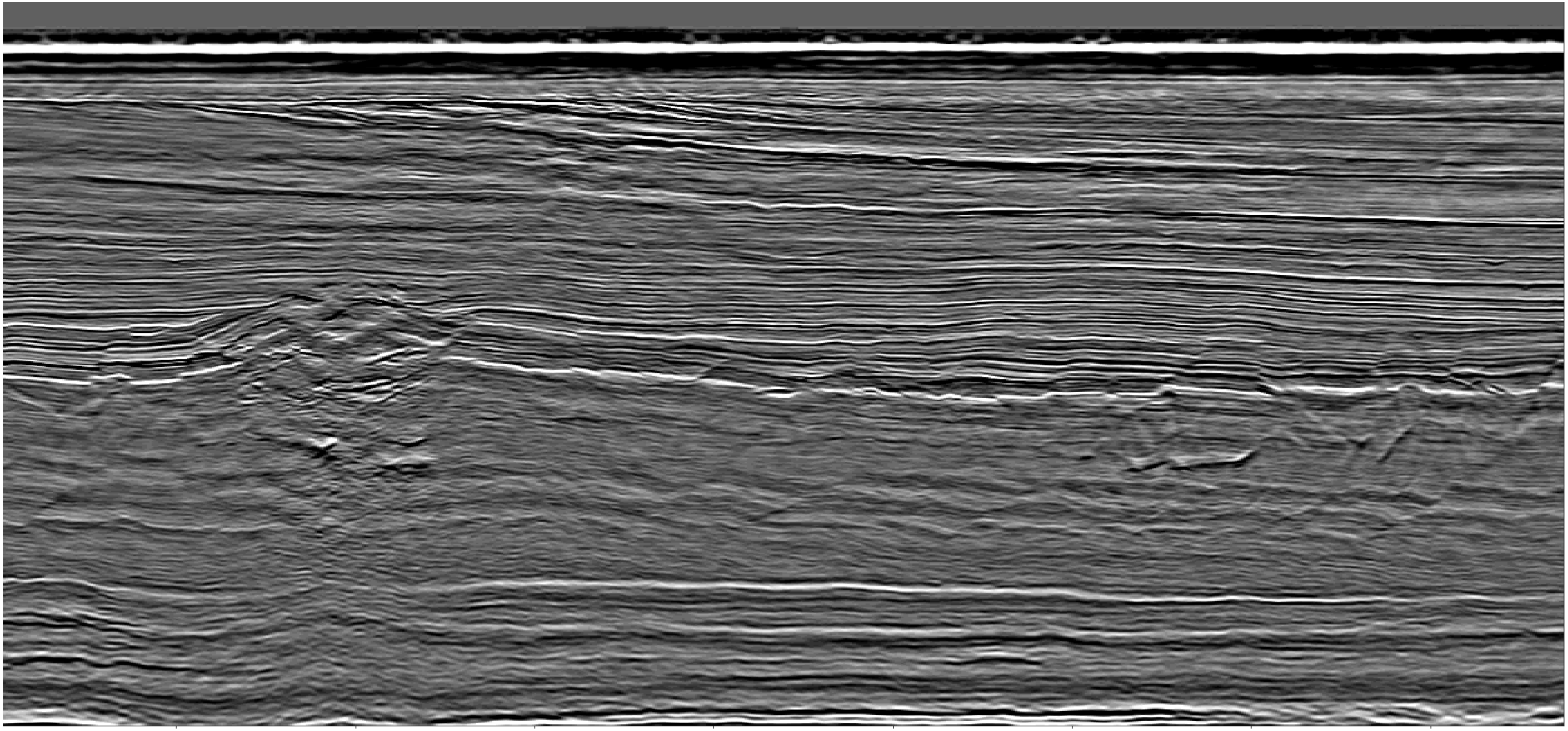
Seismic slice



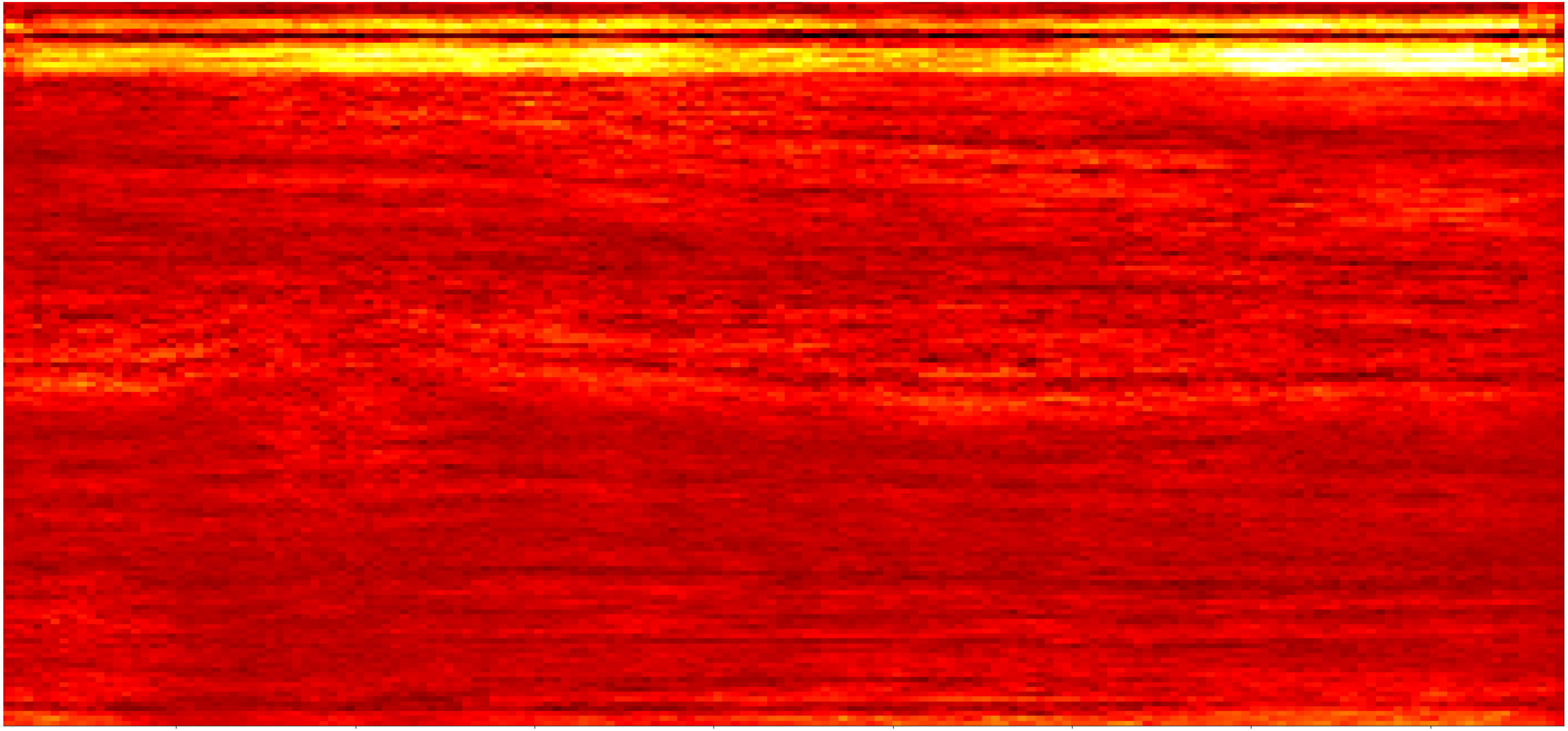
Heat map pixel prediction



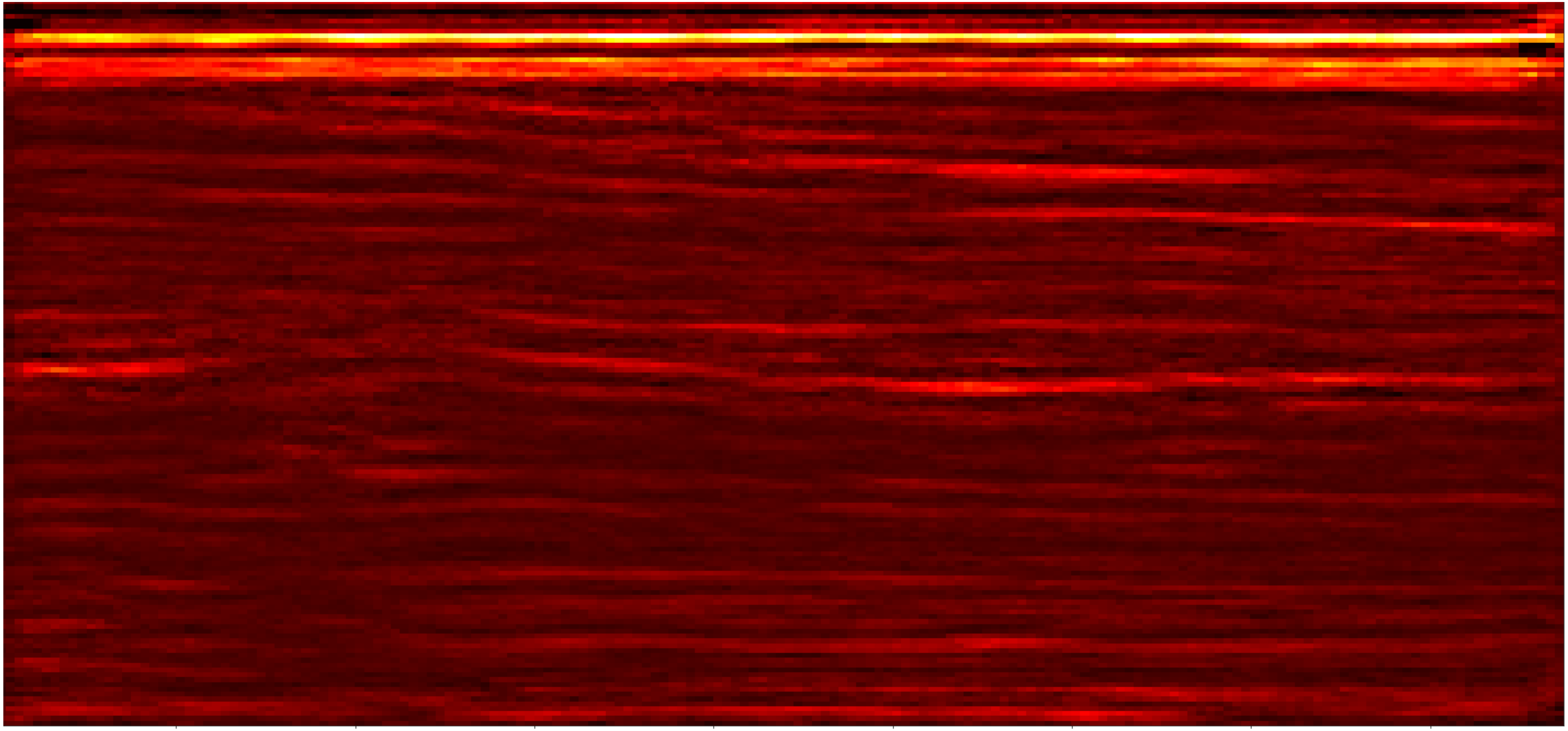
Seismic



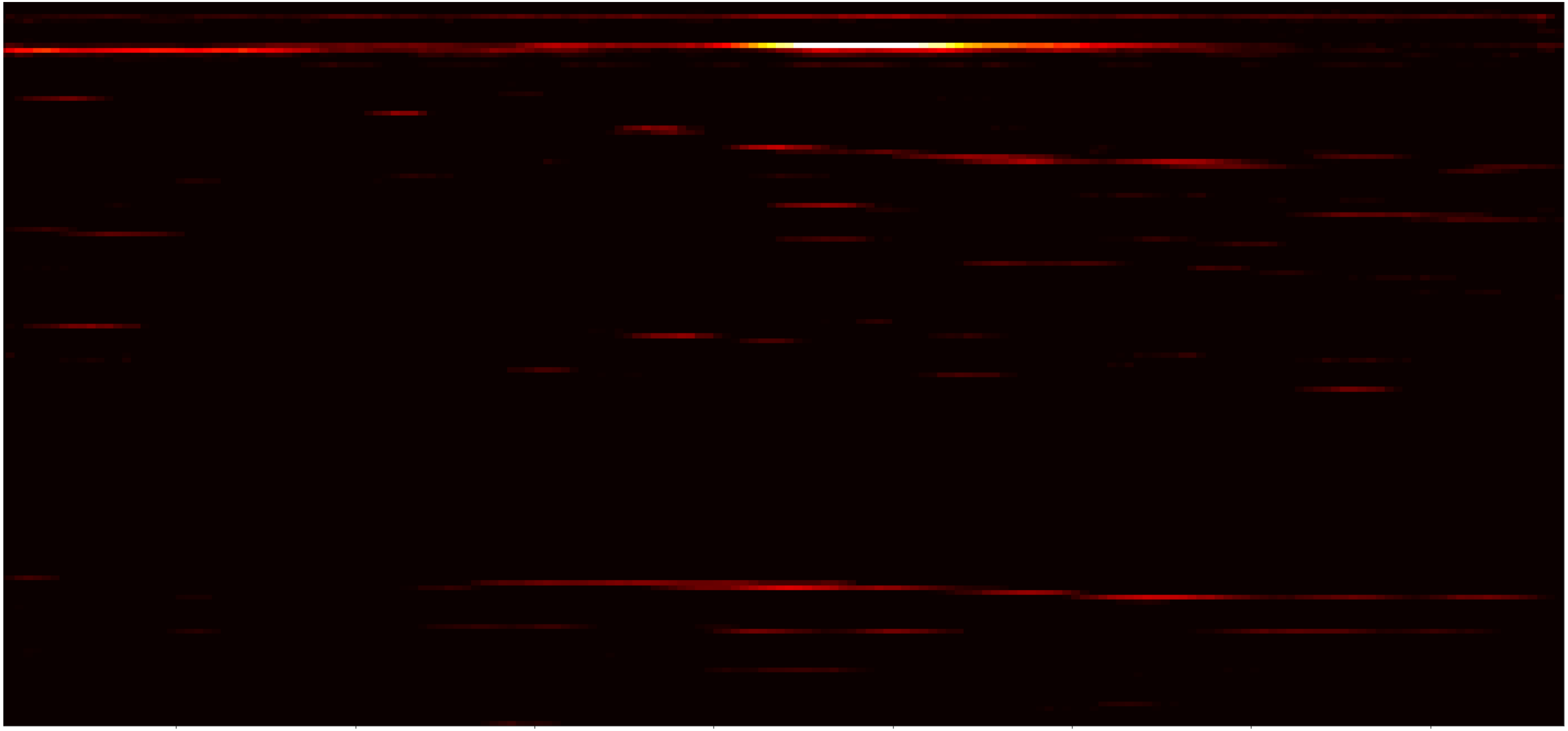
Heat map: Trained on one dataset



Heat map: Trained on another dataset



Heat map: Trained on two datasets



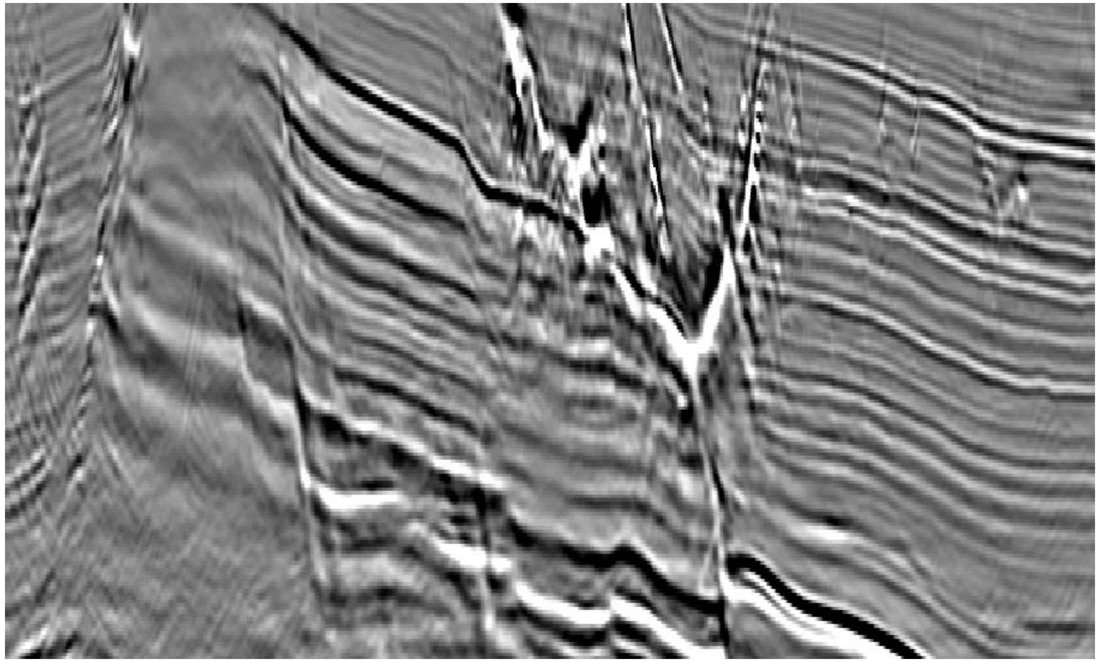
Discussion and conclusion

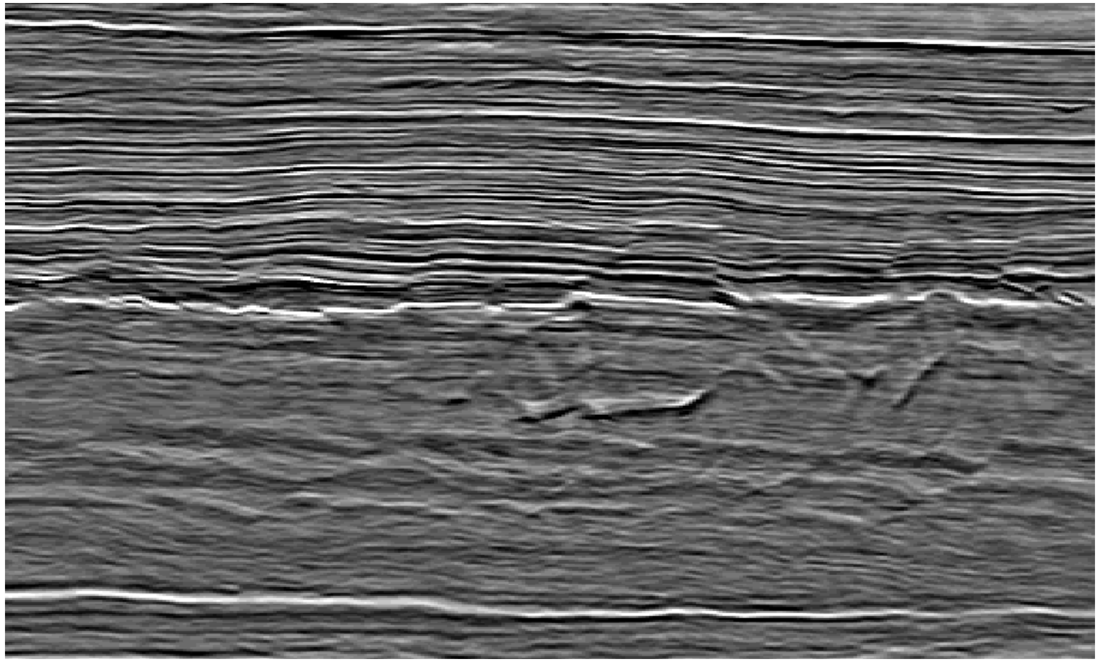
Areas are different

- Differences in
  - Geology
  - Data quality
- Number of interpretations varies dependent on where the area is in the development phase

Suggestions

- More data to train on
- Representative data of the geology
- Model adaption to the area to be used on
- Apply techniques for preventing over-fitting





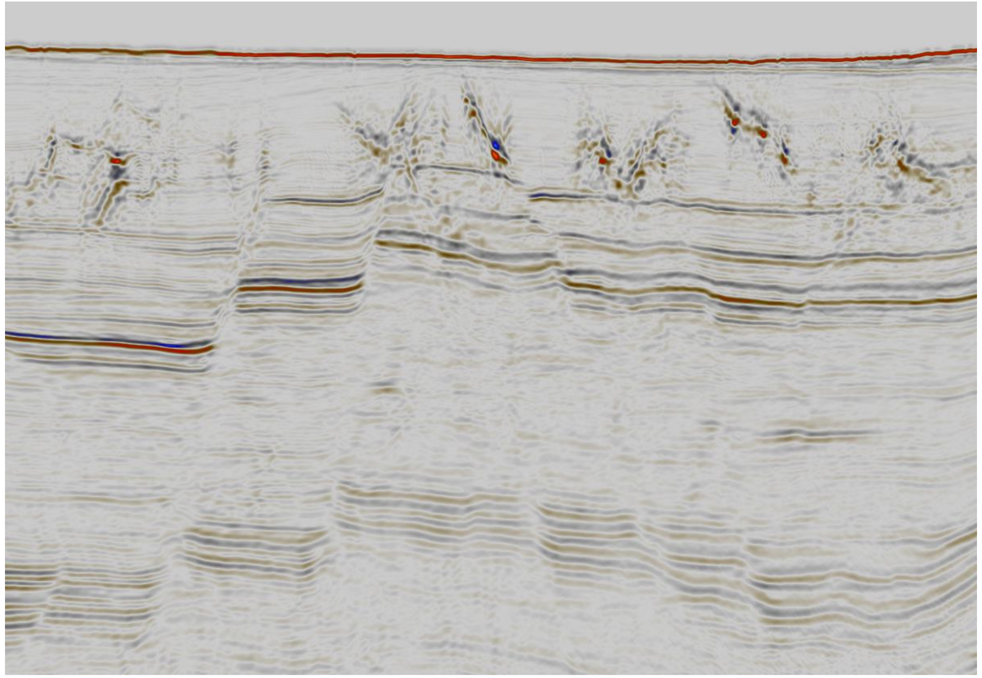
DISCUSSION

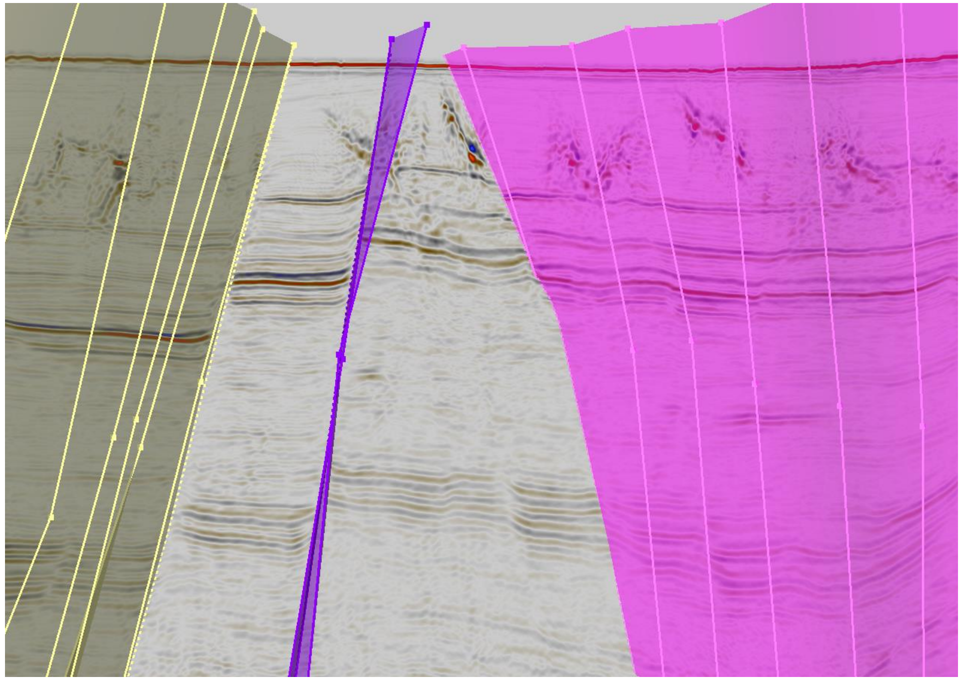
Using human interpretations

- Using human interpretations are not straight forward
- **Many** false negatives
- **Very few** false positives
- Non-symmetric label noise

Suggestions

- Use synthetic data
- Mix of synthetic and human-made data
- Manually QC-ed human-made data
- Use data from areas with enough interpretations

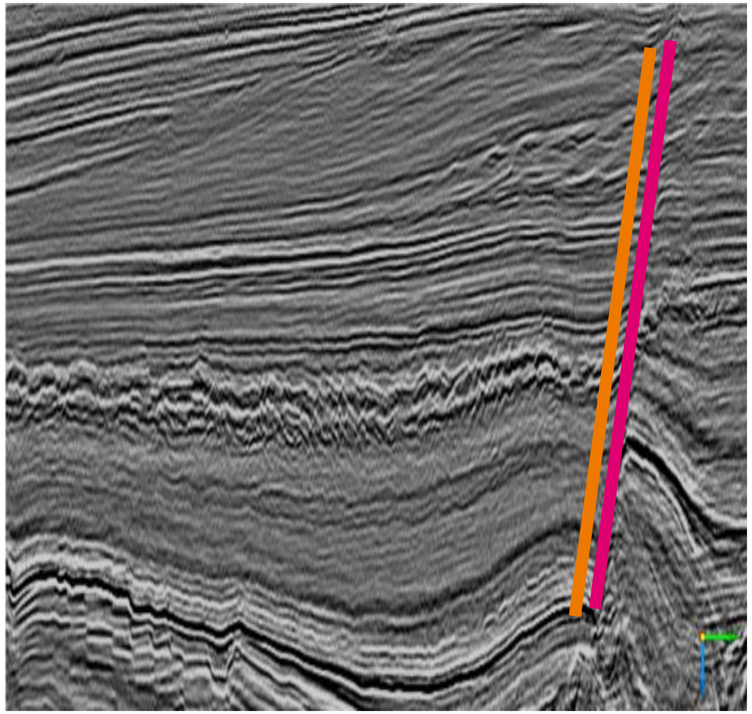


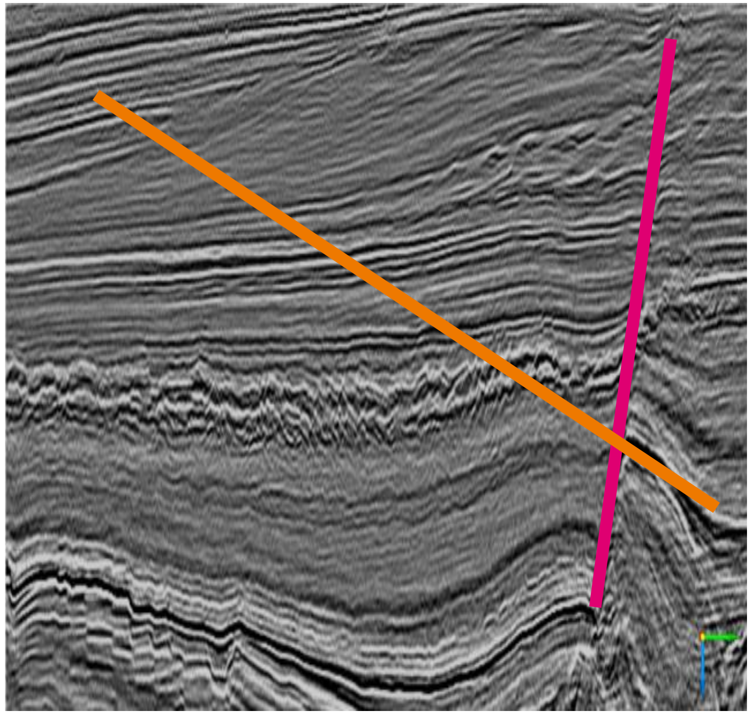


Straight lines are difficult

- Out-of-the box neural networks with standard loss functions struggle with finding straight lines
  - Learning best on objects with some «extent»
- Standard metrics not ideal

- New and better loss functions
- Take topology into account
- Post processing steps on the heat maps





Prediction

True value

Conclusion

- **Summary**
  - Image recognition by training models on human interpretations projected onto seismic samples
  - Features predicted
    - Faults
    - Horizons

- **Challenges**
  - Non-symmetric label noise (false negatives) due to incomplete interpretations (manual data quality check is time-consuming)
  - Prediction accuracy suffers when applying a model to a different field
  - Standard image recognition is not well suited for detecting lines and planes
  - **A reference data set for benchmarking** these kinds of models is badly needed

- **Future work**
  - Transfer learning using pre-trained weights
  - 3D data augmentation (transformations on real data or artificial data)
  - Better metrics for FCNN
  - Train on large combined datasets from multiple fields
  - Pre-stack seismic data

Acknowledgements

We thank CGG, PGS and TGS for permission to present the seismic data.

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