



Trustworthy AI for Geodesy: Faulty Training Data Detection

Never Stand Still

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Outline

- **Key milestones in geodesy and mapping:**
Emerging AI versus evolving geodesy
- **Outliers versus faulty labels:**
Case studies
- **Concluding remarks**

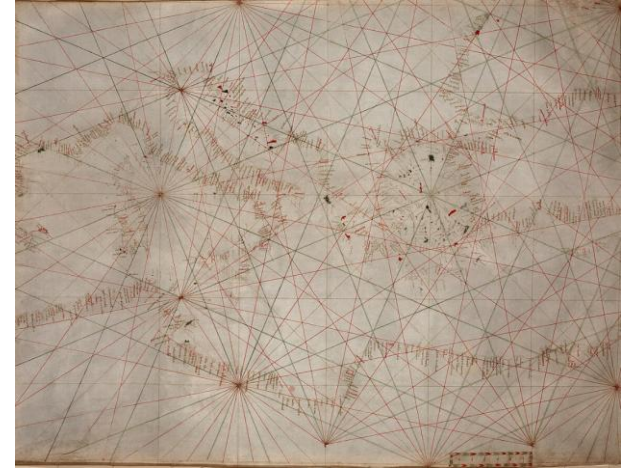
Key milestones in geodesy/mapping

800-year old Portolan (navigation) Chart of the Mediterranean

- regarded as the **first “true” map based on measurements!**

1821-1825, Carl F. Gauss,
triangulated Hannover for mapping.

- **Least Squares method was used**



1980s: Gauss's geodetic methods adopted for Simultaneous Localization and Mapping (SLAM)

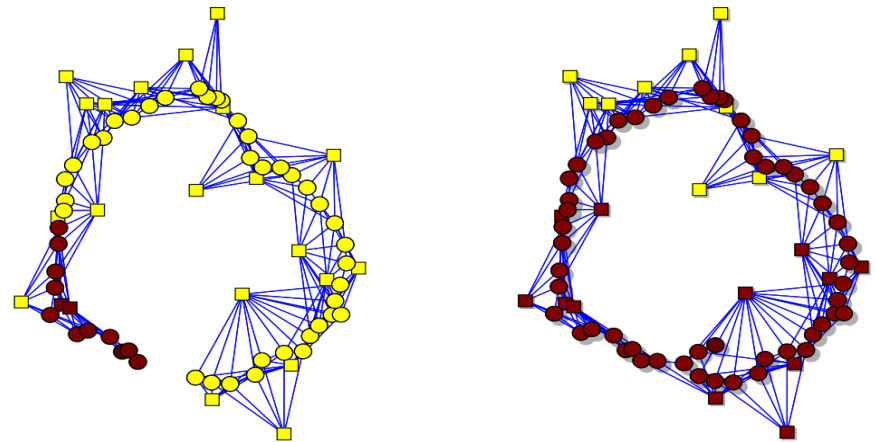
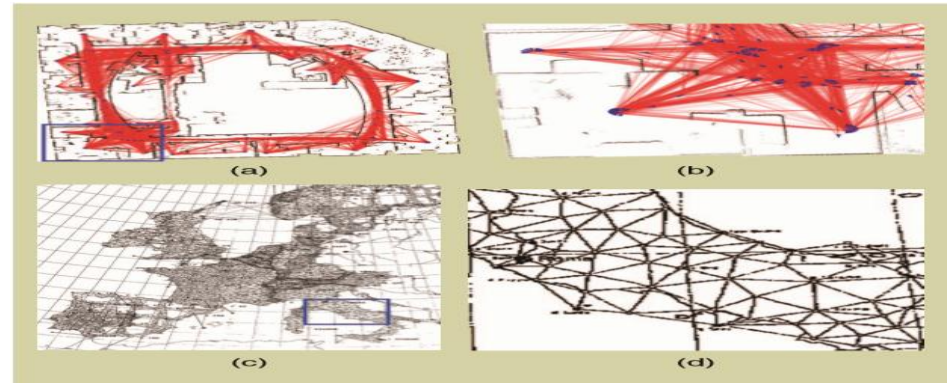
- for robotic autonomous navigation



Survey of Geodetic Mapping Methods

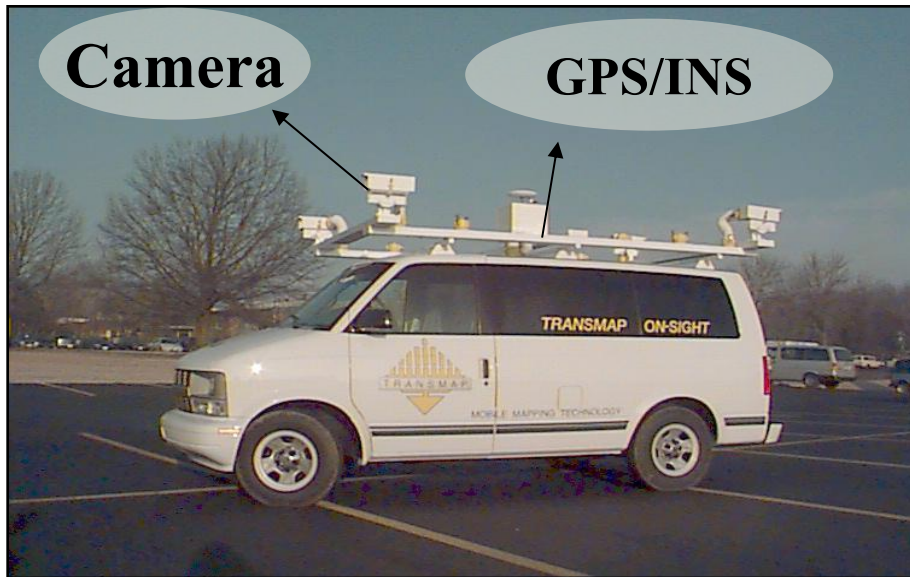
Geodetic Approaches to Mapping and the Relationship to Graph-Based SLAM

By Pratik Agarwal, Wolfram Burgard, and Cyrill Stachniss



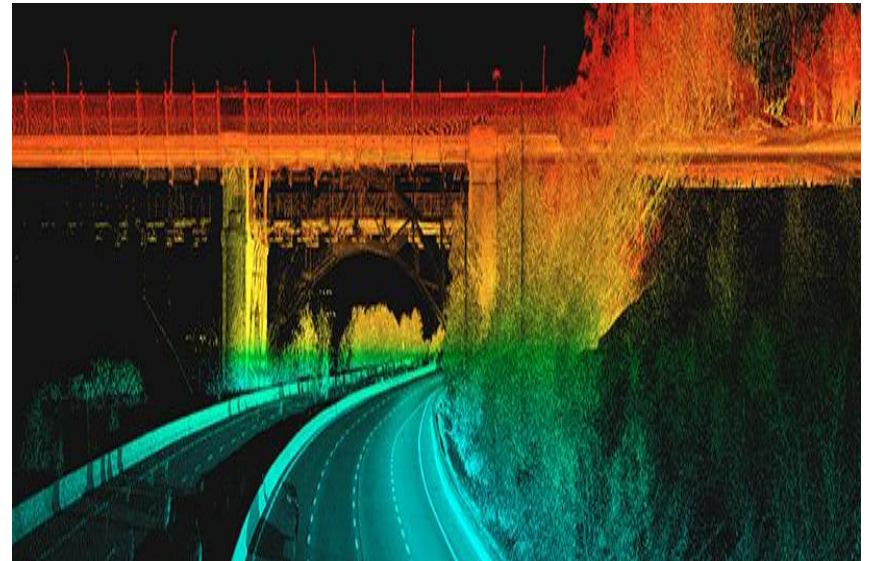
IEEE Robotics & Automation Magazine, Sept 2014

1990s: Mobile Mapping Systems



The pioneering mobile mapping system in 1990s – before the Google Street View mapping systems!

GPS Real-Time-Kinematic (RTK) Positioning- **cm level accuracy!**

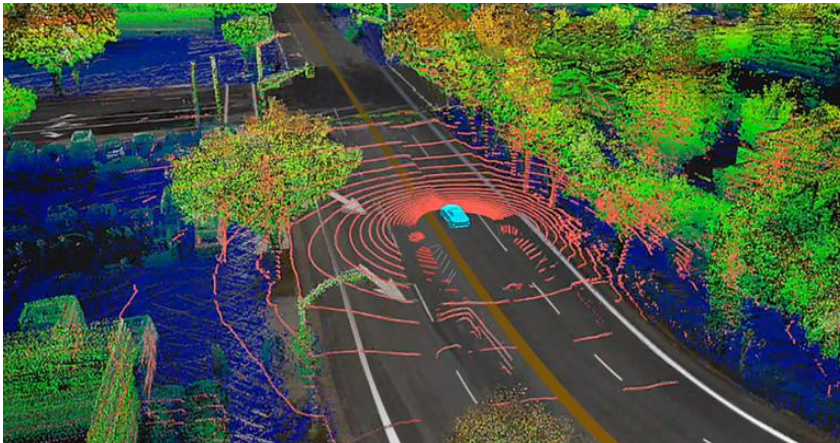
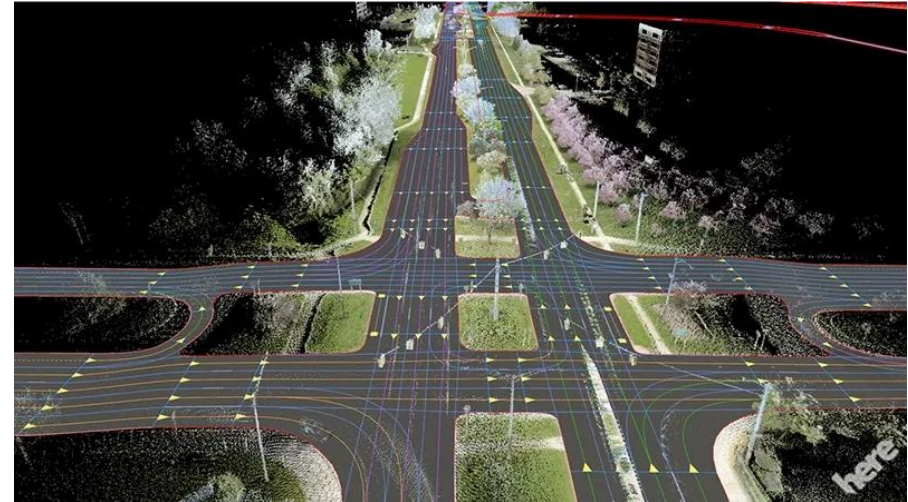


Multi sensors onboard an autonomous vehicle (AV)



2013: High Definition (HD) Map for autonomous driving

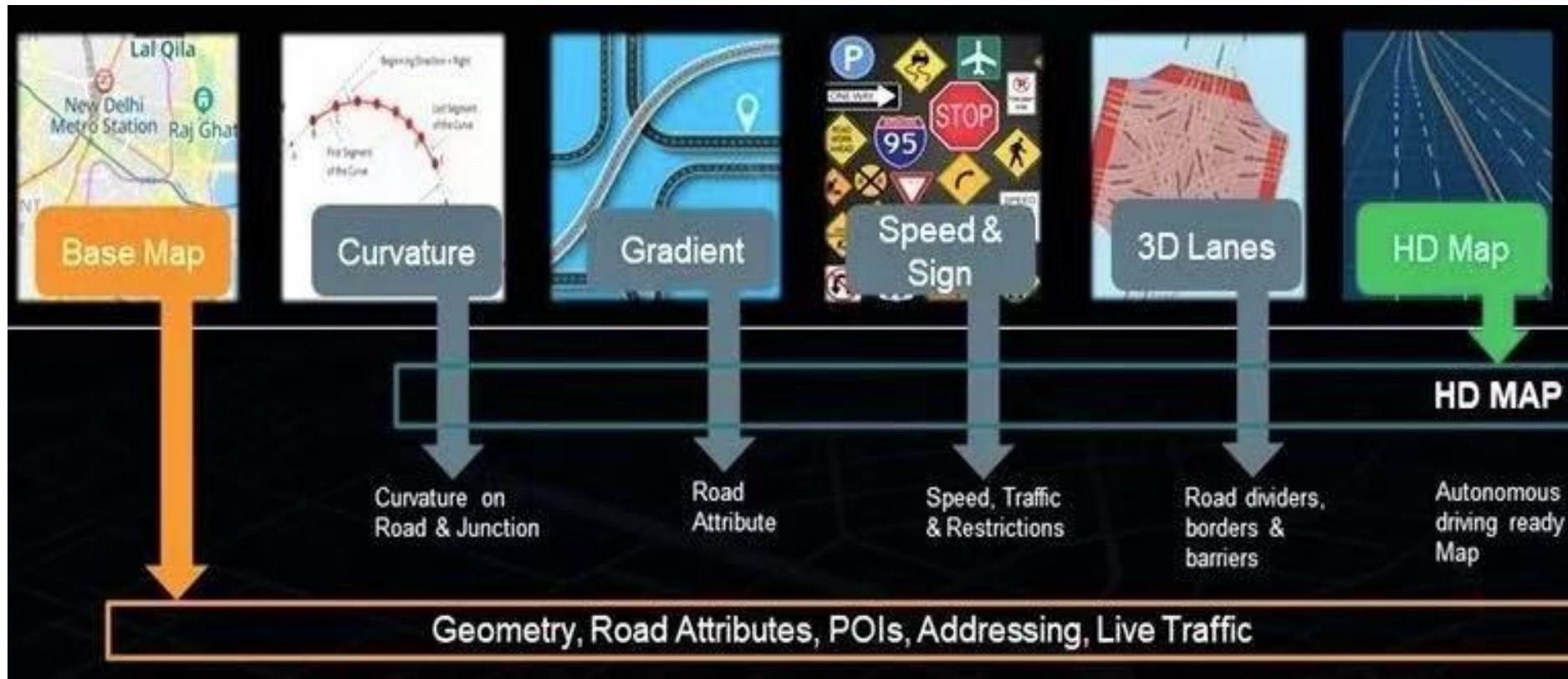
HD Maps are also used as a special localization sensor via map-matching





AMAP – AutoNavi Map

Machine readable HD map for Autonomous vehicles



Kota P (2021) <https://www.linkedin.com/pulse/power-location-intelligence-hd-mapping-autonomous-vehicle-prasad-kota>

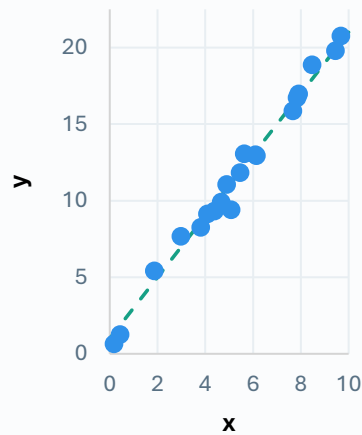
Traffic sign labels with various quality!

Representative GTSRB Training Samples

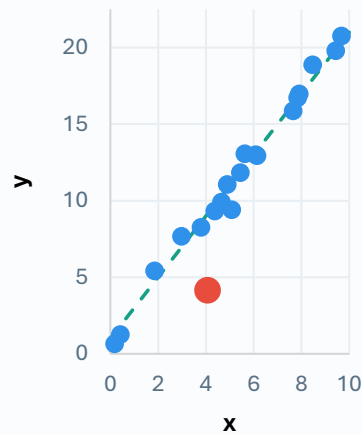


Case Study: Line Fitting with Neural Networks

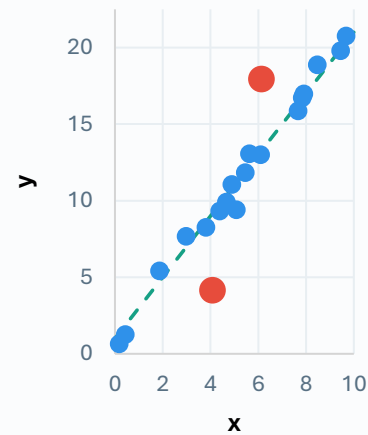
$$y_i = 2x_i + 1 + \varepsilon_i, \quad \varepsilon_i \sim N(0, 0.5^2), \quad i = 1, \dots, N$$
$$y_i^{\text{outlier}} = y_i + \Delta_i$$



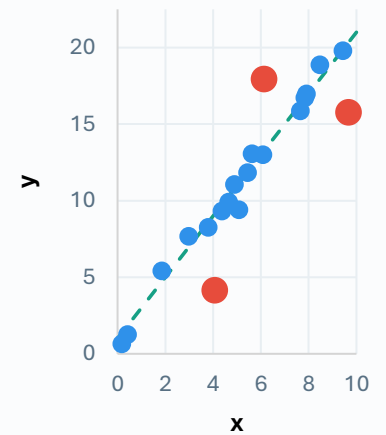
Clean Data



1 Outlier



2 Outliers



3 Outliers

Neural Network Model and Loss Functions

General Neural Network Model

$$\begin{aligned}a_i^0 &= x_i \\z_i^l &= W^{(l)}a_i^{l-1} + b^l \\a_i^l &= \phi(z_i^l), \quad l = 1, \dots, L-1 \\\hat{y}_i &= W^{(L)}a_i^{L-1} + b^L\end{aligned}$$

where the activation function is:

$$\phi(z) = \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

Loss Functions

$$\mathcal{L} = \left(\frac{1}{N}\right) \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

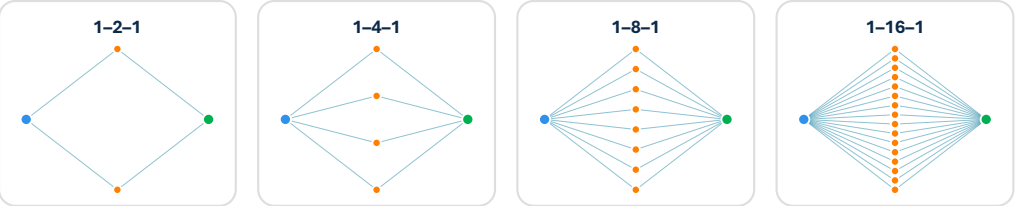
y_i observed value of sample i

$\hat{y}_i$ model prediction for sample i

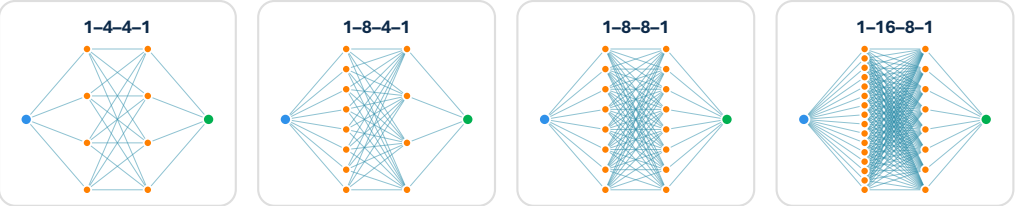
Neural Network Architectures and Model Capacity

Architecture overview

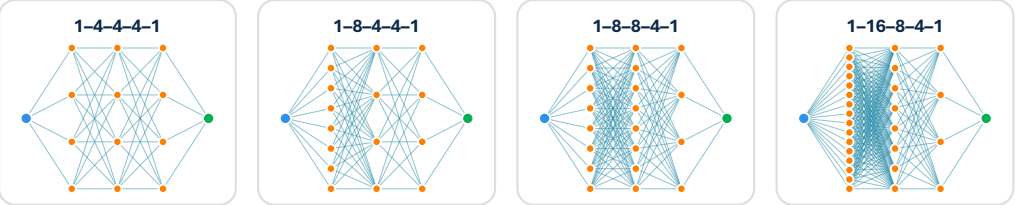
One hidden layer



Two hidden layers



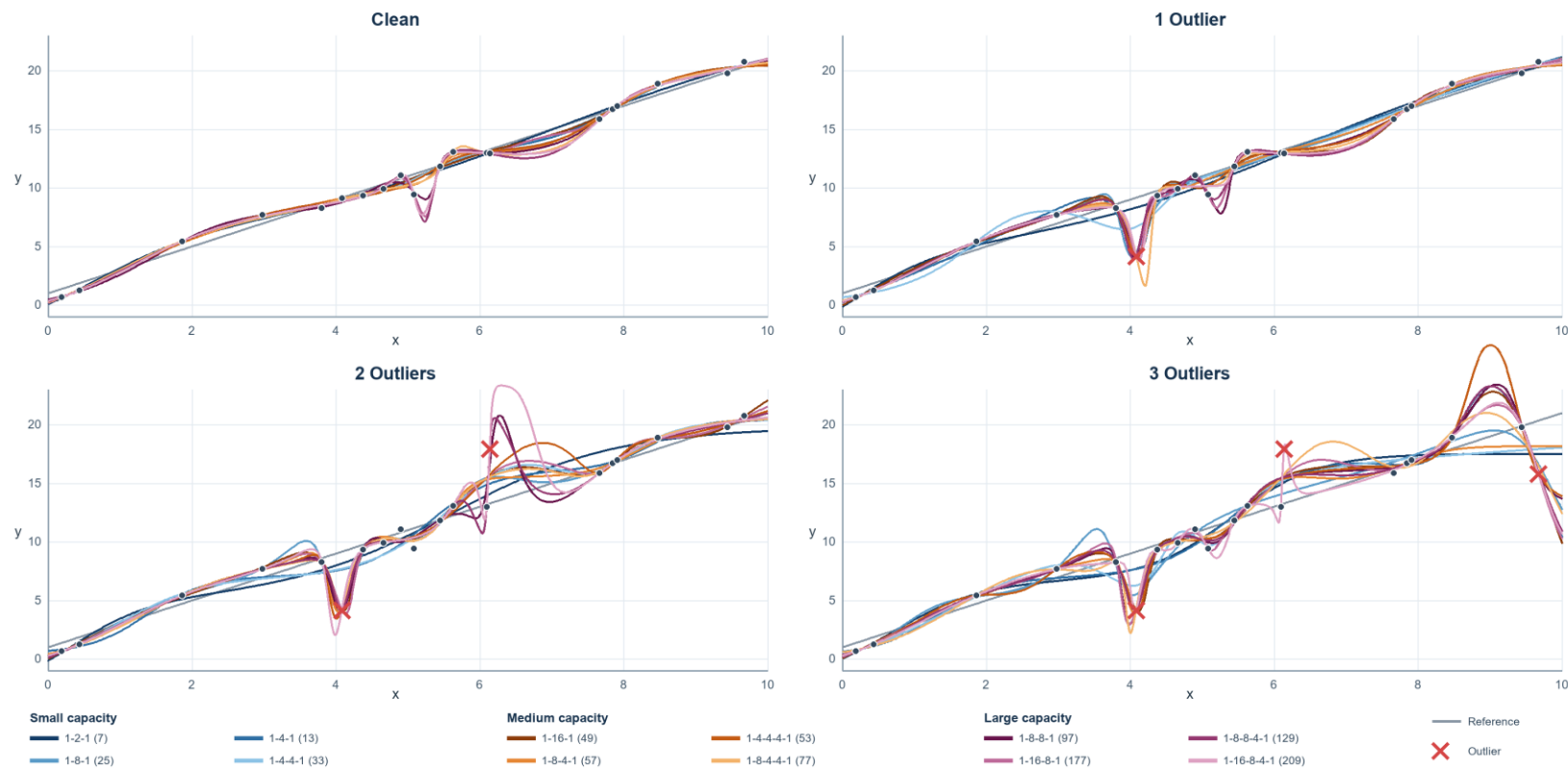
Three hidden layers



Model parameters

Hidden layers	Architecture	Parameters
1 1 1 1	1-2-1	7
	1-4-1	13
	1-8-1	25
	1-16-1	49
2 2 2 2	1-4-4-1	33
	1-8-4-1	57
	1-8-8-1	97
	1-16-8-1	177
3 3 3 3	1-4-4-4-1	53
	1-8-4-4-1	77
	1-8-8-4-1	129
	1-16-8-4-1	209

Final Fitting Results: N = 20



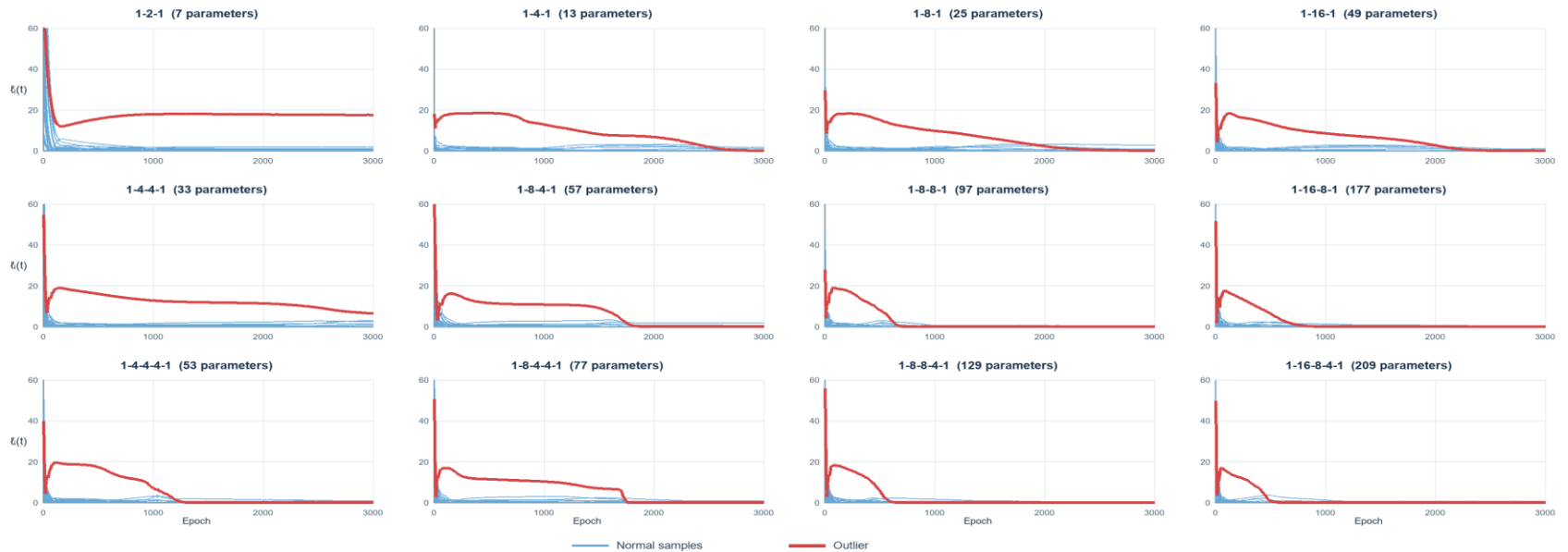
As the number of model parameters increases, overfitting to outliers becomes more pronounced, making the outliers increasingly difficult to detect.

Pointwise Loss during Training: N = 20, 1 Outlier

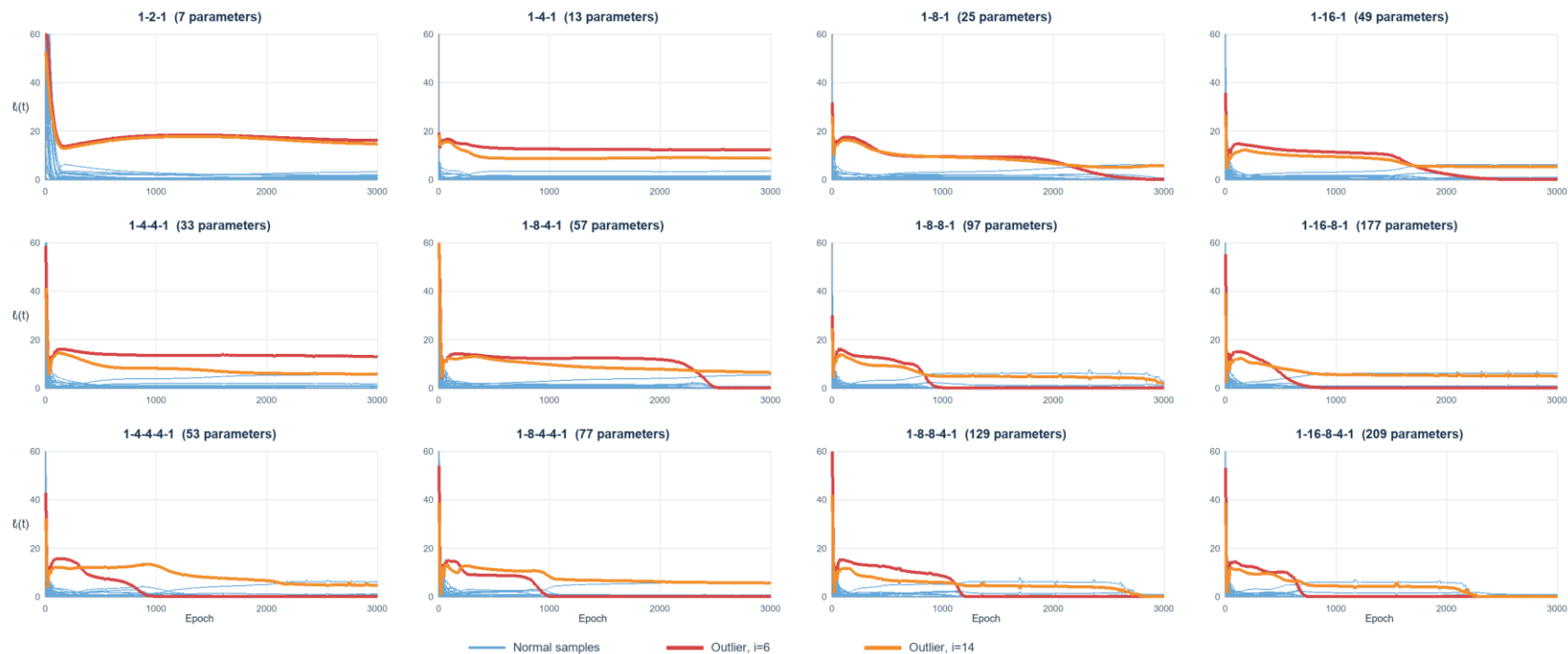
The pointwise loss is the squared prediction error assigned to sample i at epoch t :

$$\ell_{i(t)} = [y_i - \hat{y}_{i(t)}]^2$$

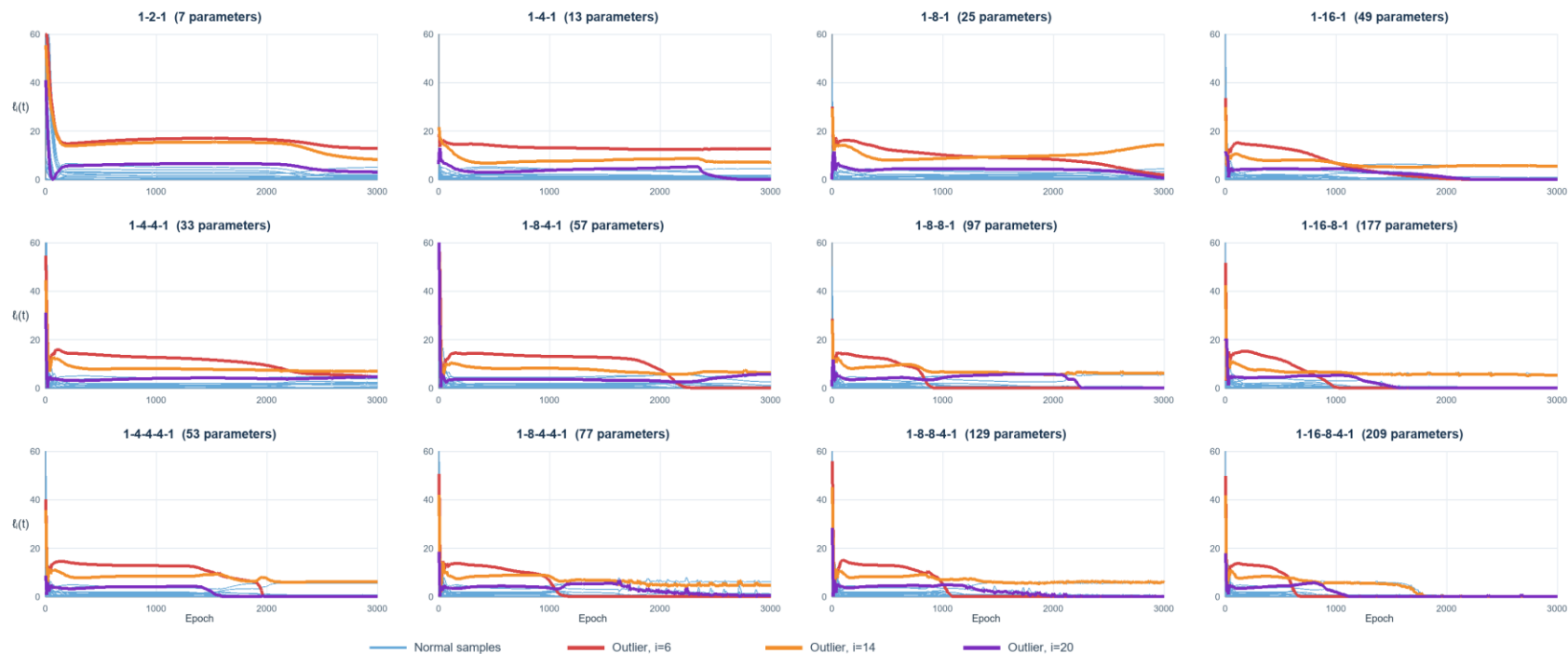
Pointwise loss is used as the indicator for outlier detection.



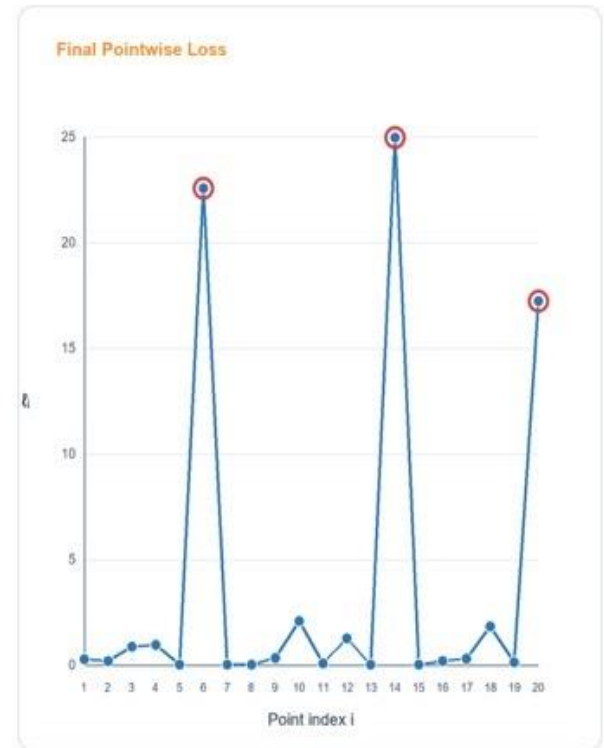
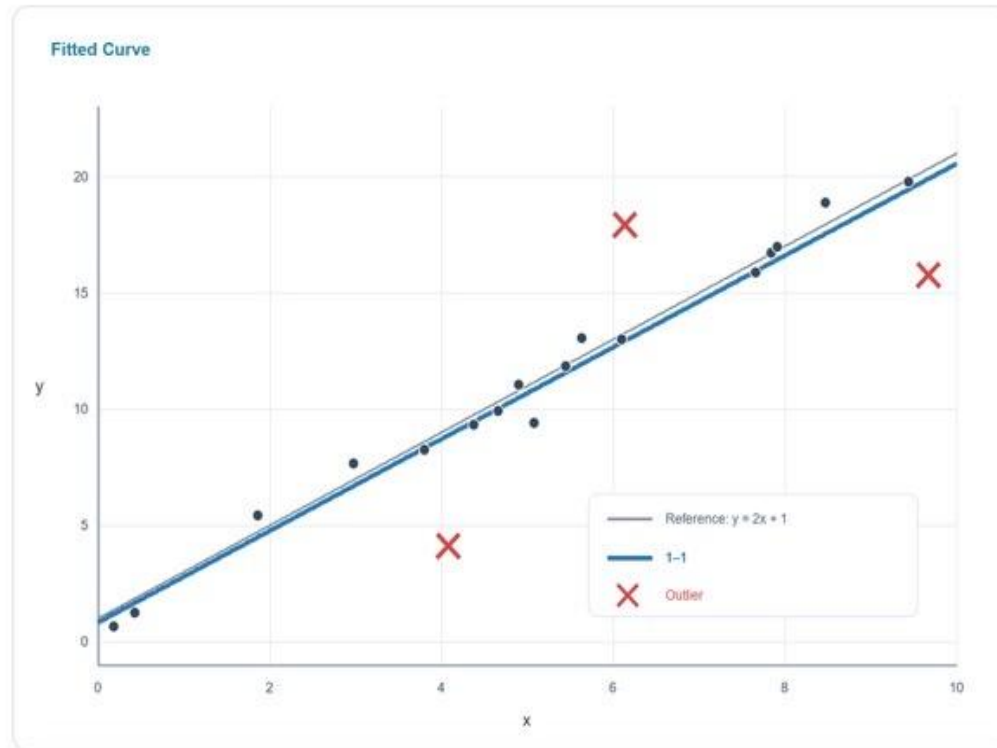
Pointwise Loss during Training: N = 20, 2 Outliers



Pointwise Loss during Training: N = 20, 3 Outliers

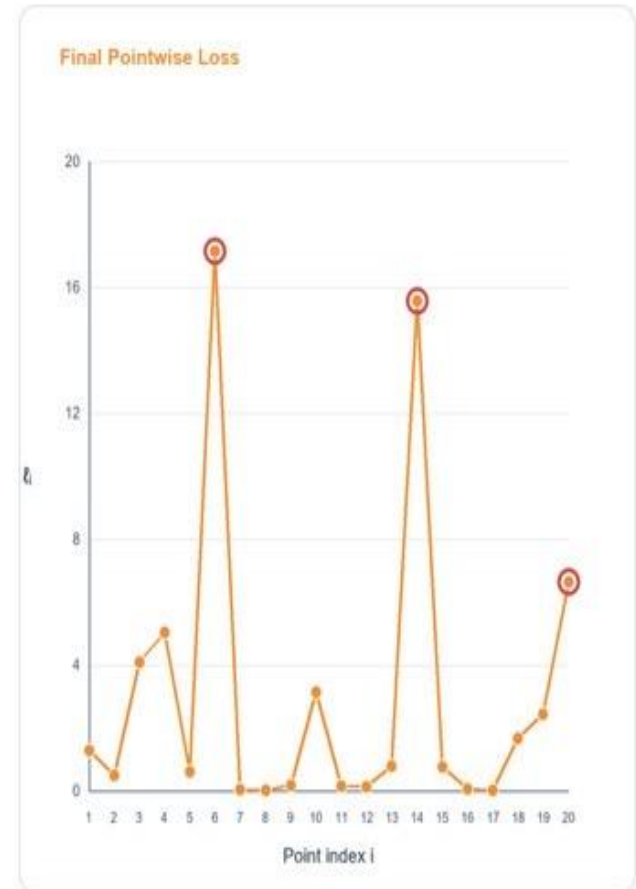
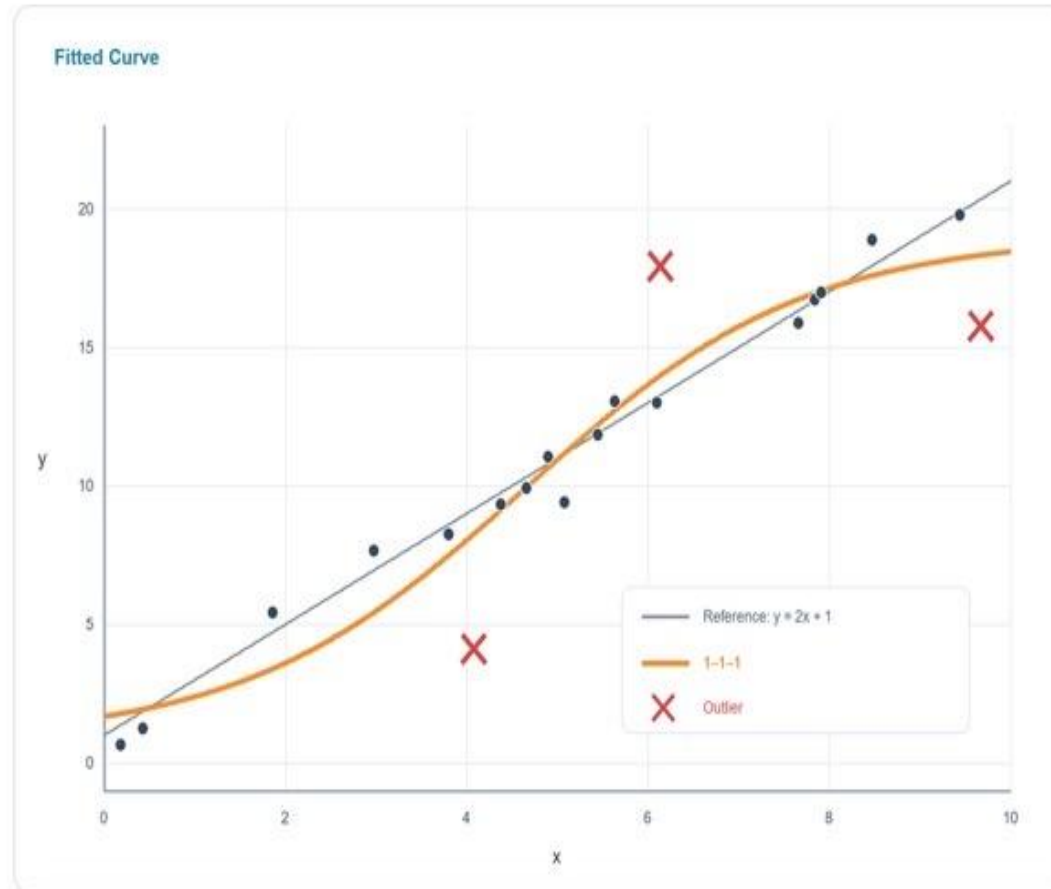


Fitting and Pointwise Loss: 1-1



Low model capacity prevents local absorption of the three outliers; their final pointwise losses occupy ranks 1-3.

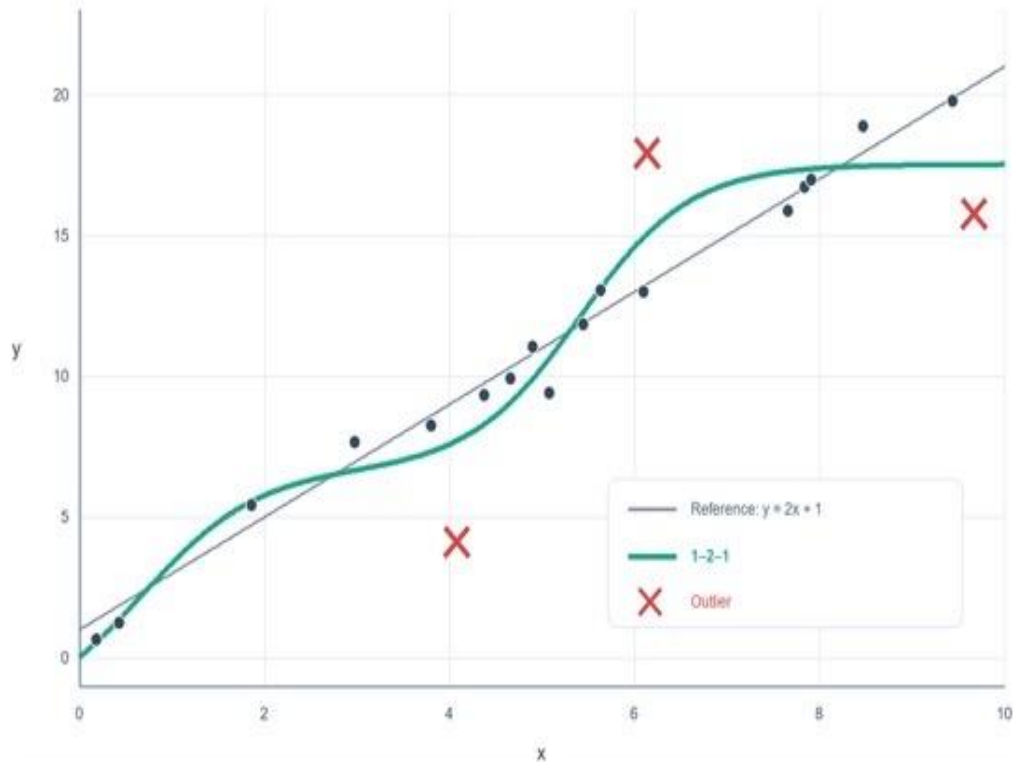
Fitting and Pointwise Loss: 1-1-1



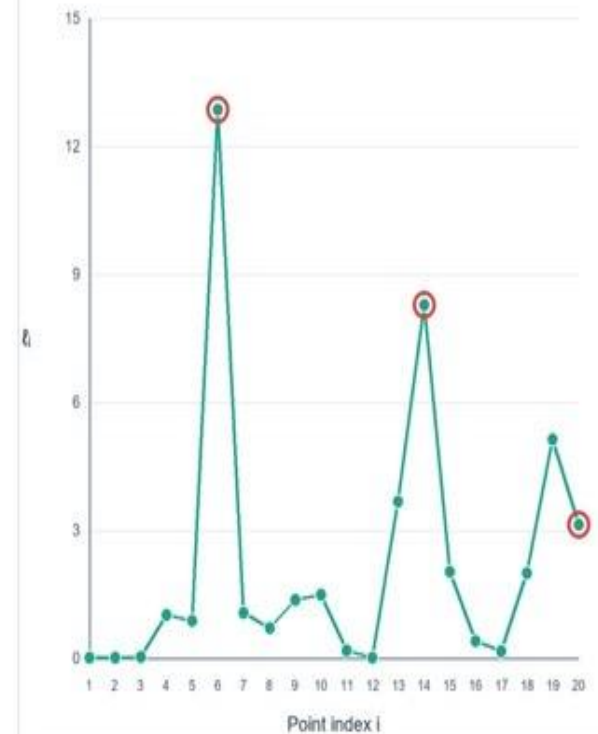
Low model capacity prevents local absorption of the three outliers; their final pointwise losses occupy ranks 1-3.

Fitting and Pointwise Loss: 1-2-1

Fitted Curve

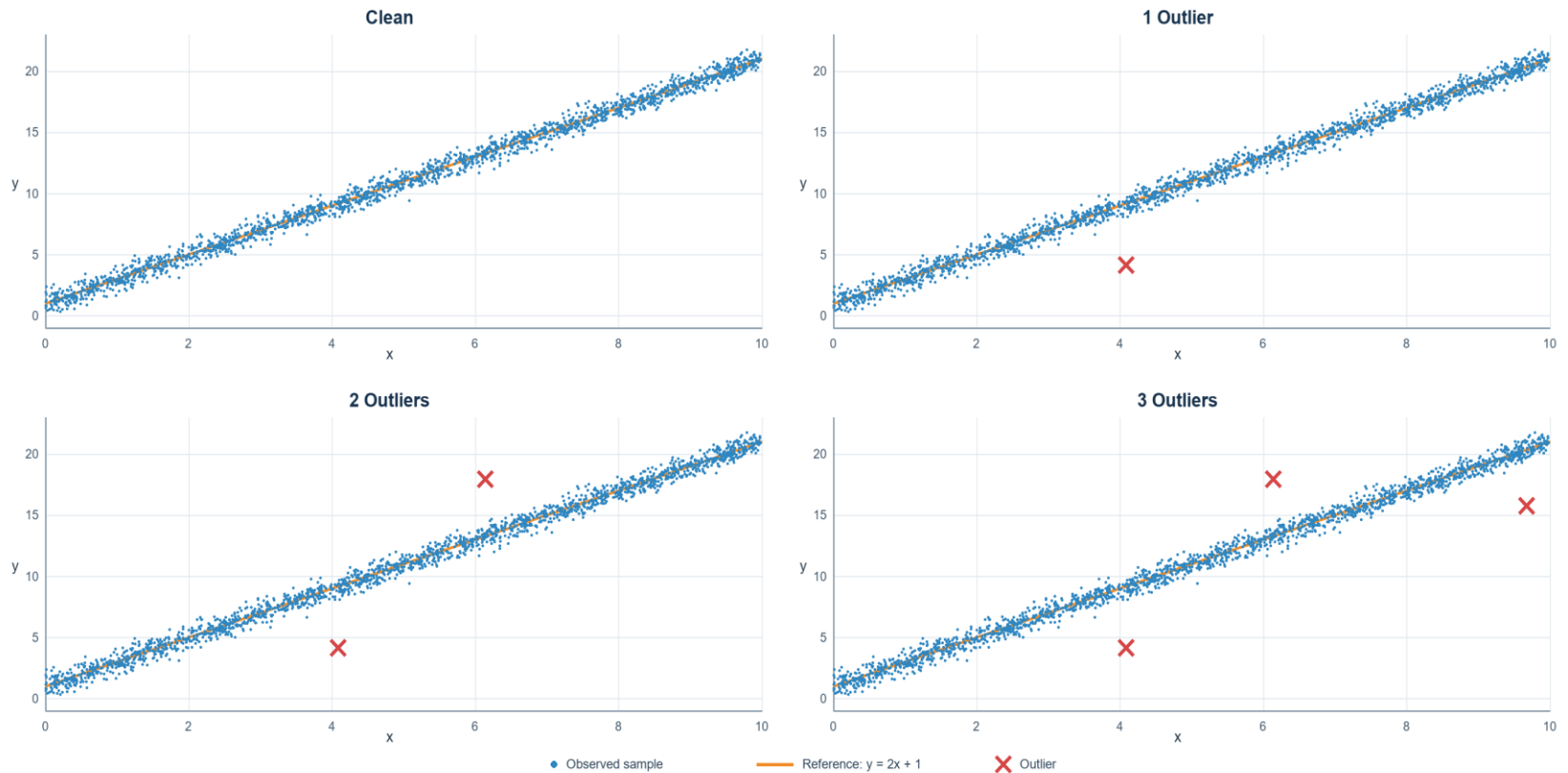


Final Pointwise Loss

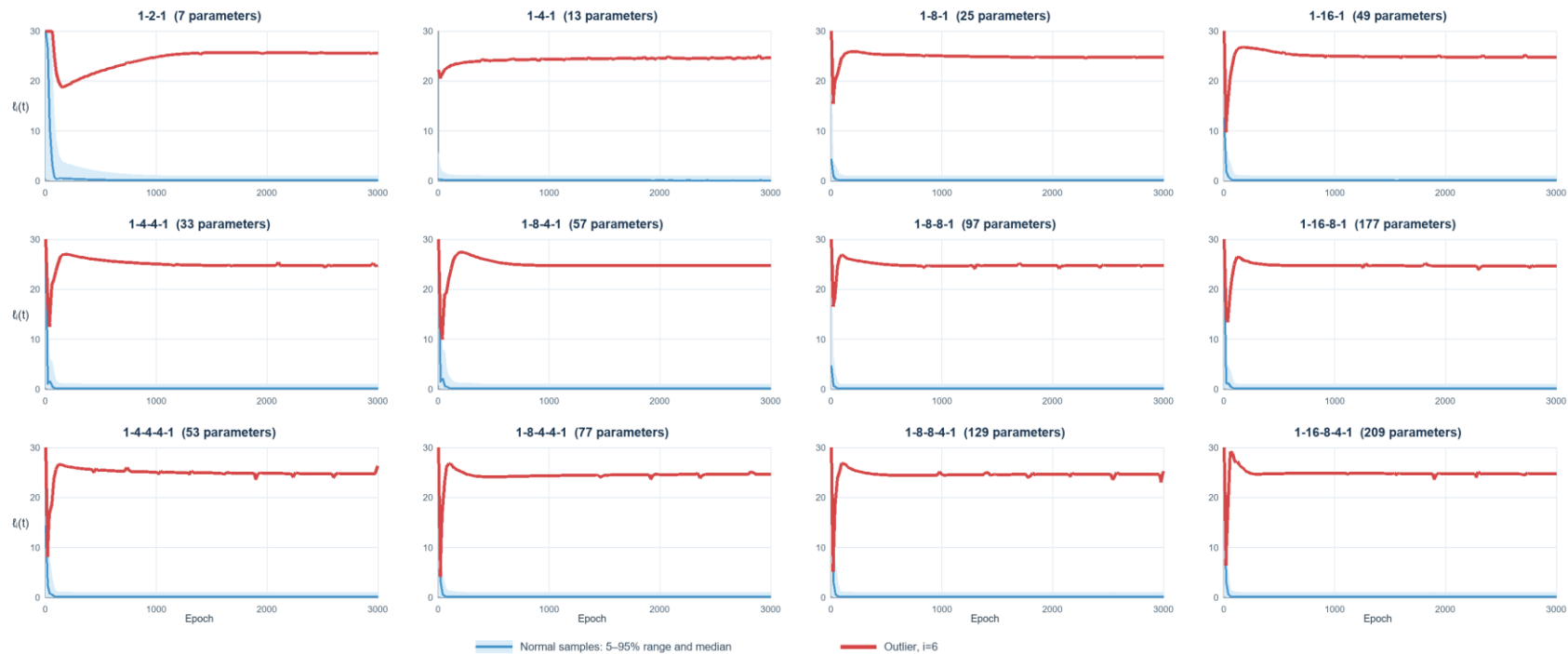


The 1-2-1 model begins to absorb local deviations; the three outlier loss ranks are 1, 2, and 5.

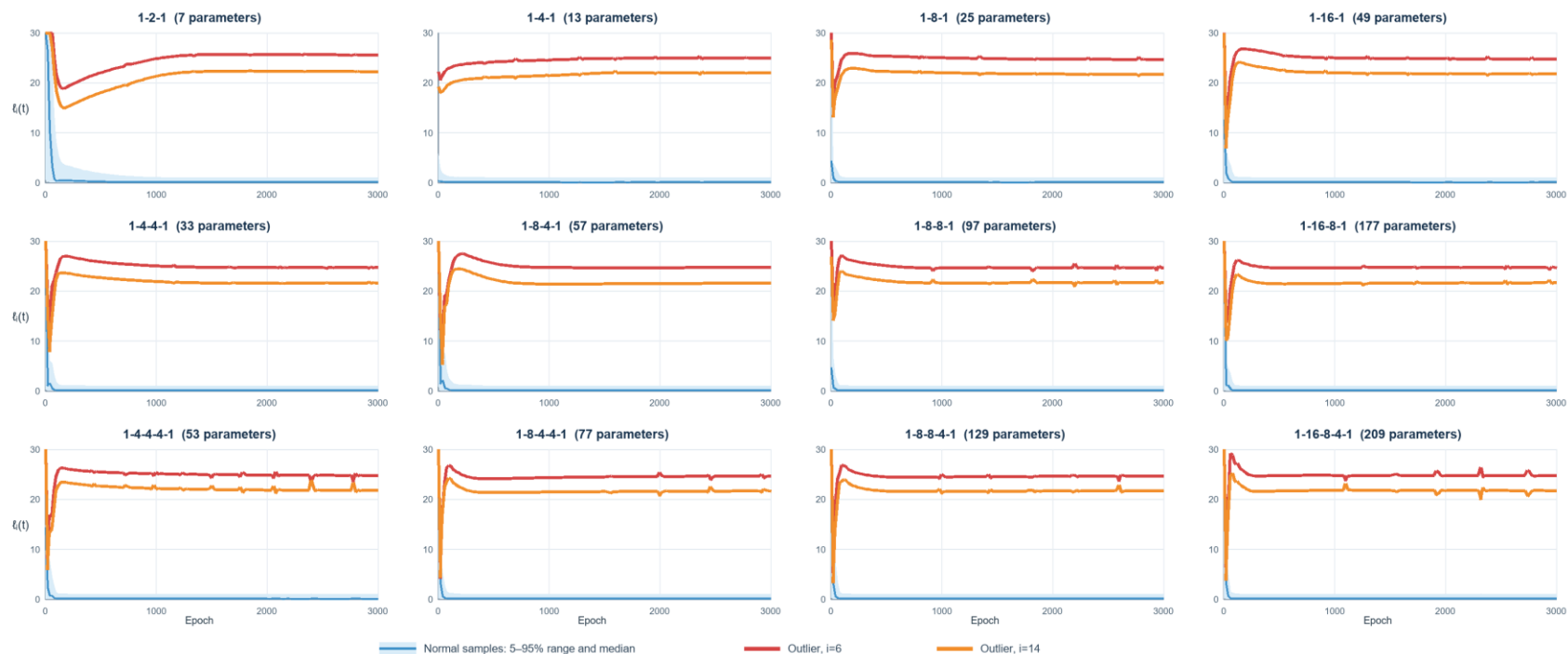
Large-Sample Case Study: N = 2,000



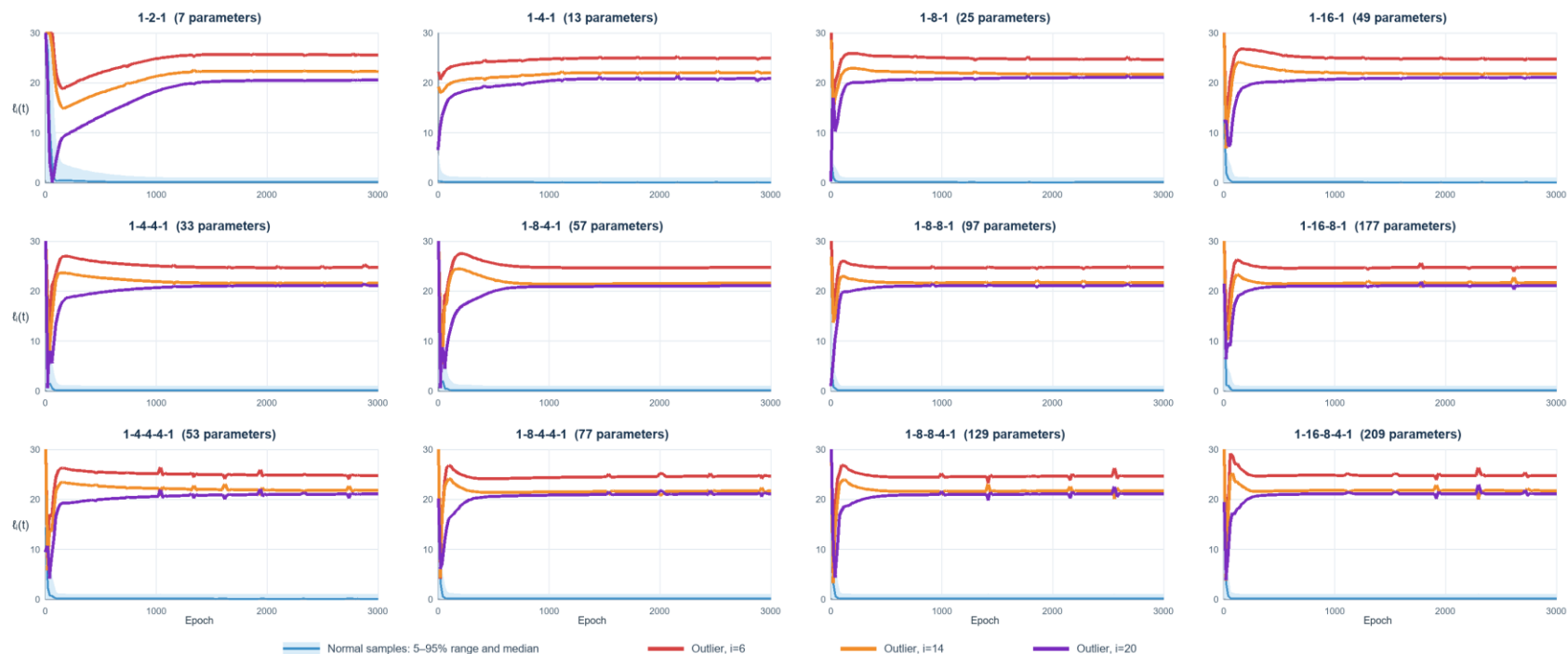
Pointwise Loss during Training: N = 2,000, 1 Outlier



Pointwise Loss during Training: N = 2,000, 2 Outliers



Pointwise Loss during Training: N = 2,000, 3 Outliers



Traffic sign labels with various quality!

Representative GTSRB Training Samples



Traffic sign data set (images)

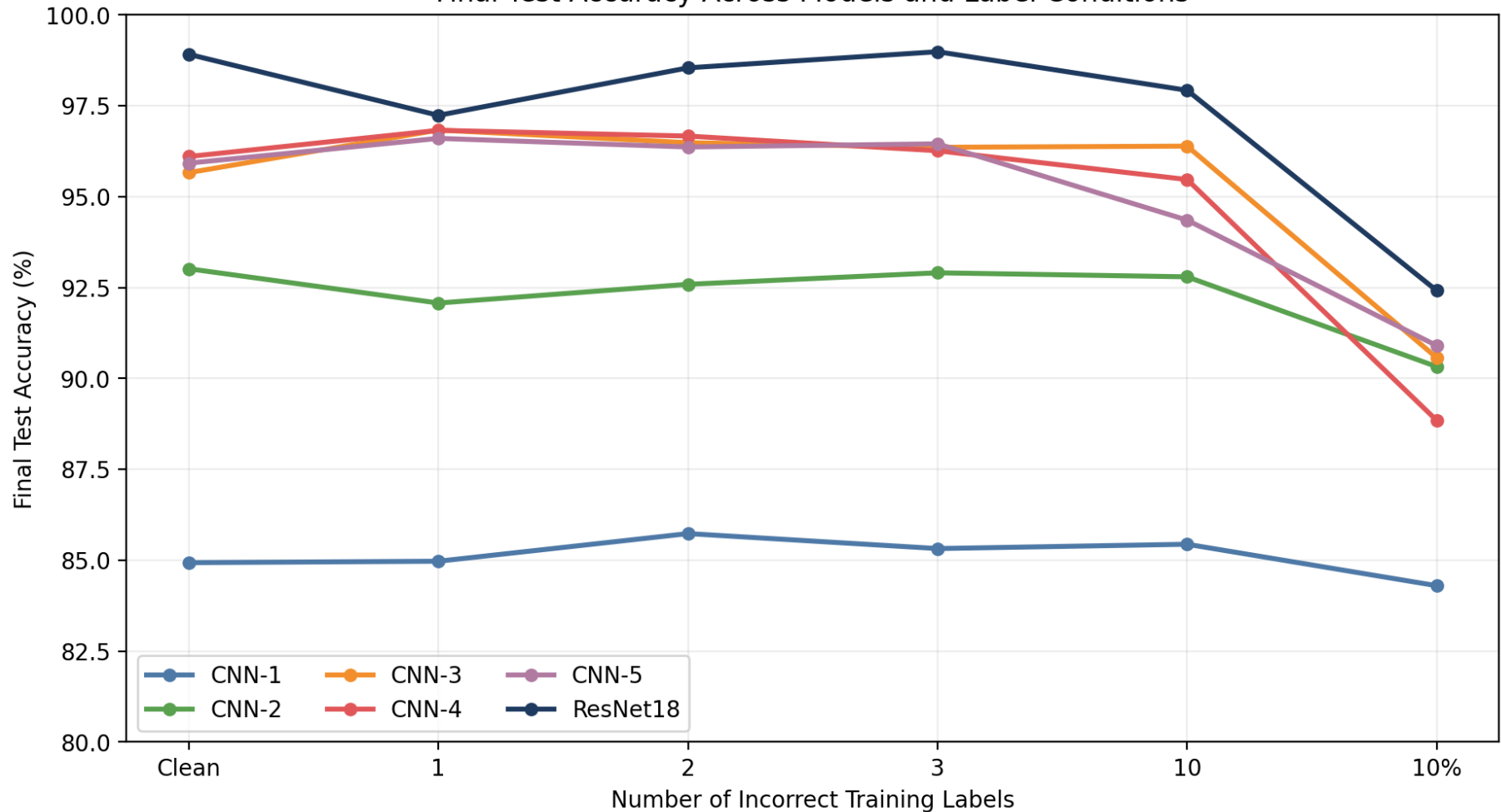
Split	Images	Use
Training	39,209	Optimization and pointwise-loss analysis
Test	12,630	Evaluation at the end of every epoch
Classes	43	Traffic sign categories

CNN models to identify traffic signs

Model	Conv Layers	Channels	Parameters
CNN-1	1	32	307,115
CNN-2	2	32 to 64	620,523
CNN-3	3	32 to 64 to 128	1,284,203
CNN-4	4	32 to 64 to 128 to 256	2,759,019
CNN-5	5	32 to 64 to 128 to 256 to 512	6,298,475
ResNet18	17	Residual convolutional network	11,198,571

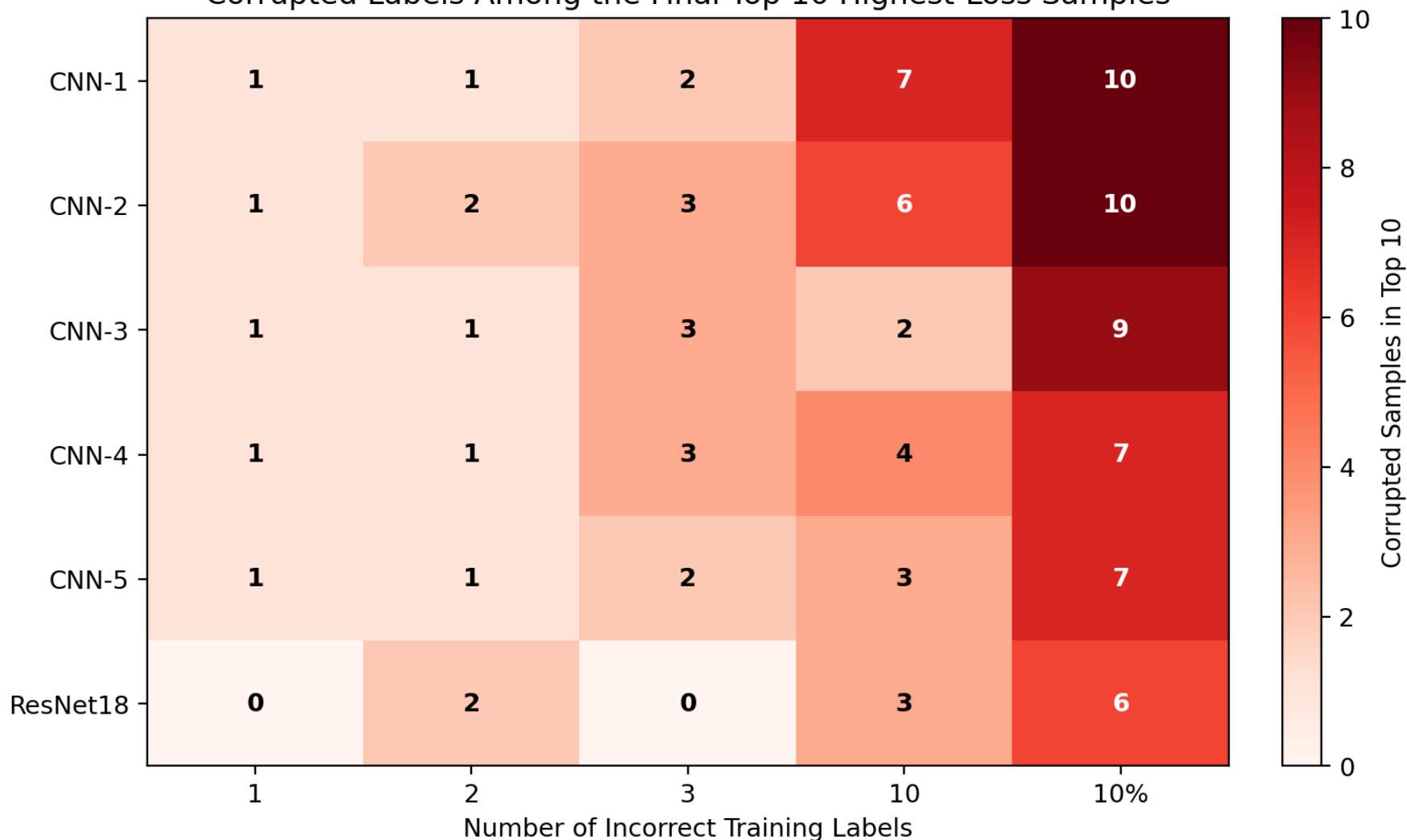
Impacts of Faulty Labels on Model Accuracy

Final Test Accuracy Across Models and Label Conditions



Can we detect the faulty labels?

Corrupted Labels Among the Final Top 10 Highest-Loss Samples



CNN-3 | Clean | Top 5 Highest-Loss Samples

Rank 1 | ID 28829
Loss: 10.7935
Original: Road work (25)
Training: Road work (25)
Predicted: Bicycles crossing (29)



Rank 2 | ID 27270
Loss: 5.3730
Original: Double curve (21)
Training: Double curve (21)
Predicted: Slippery road (23)



Rank 3 | ID 27272
Loss: 4.0915
Original: Double curve (21)
Training: Double curve (21)
Predicted: Slippery road (23)



Rank 4 | ID 17712
Loss: 3.8176
Original: Priority at intersection (11)
Training: Priority at intersection (11)
Predicted: Children crossing (28)



Rank 5 | ID 28827
Loss: 3.4700
Original: Road work (25)
Training: Road work (25)
Predicted: Bicycles crossing (29)



CNN-3 | Clean | Top 5 Lowest-Loss Samples

Rank 1 | ID 20248
Loss: $10^{(-46.51)}$
Original: Yield (13)
Training: Yield (13)
Predicted: Yield (13)



Rank 2 | ID 20249
Loss: $10^{(-45.87)}$
Original: Yield (13)
Training: Yield (13)
Predicted: Yield (13)



Rank 3 | ID 20245
Loss: $10^{(-42.33)}$
Original: Yield (13)
Training: Yield (13)
Predicted: Yield (13)



Rank 4 | ID 20244
Loss: $10^{(-40.96)}$
Original: Yield (13)
Training: Yield (13)
Predicted: Yield (13)



Rank 5 | ID 21024
Loss: $10^{(-40.88)}$
Original: Yield (13)
Training: Yield (13)
Predicted: Yield (13)



Concluding remarks

- AI/ML have demonstrated great potential for applications in geodesy/mapping.
- Similar to the quality control measures for LS/KF estimation, **AI model training data quality should be monitored.**
- Initial studies have demonstrated that loss-function may be useful in detecting faculty labels.
- **A comprehensive study for trustworthy AI for geodesy is an urgent task!**