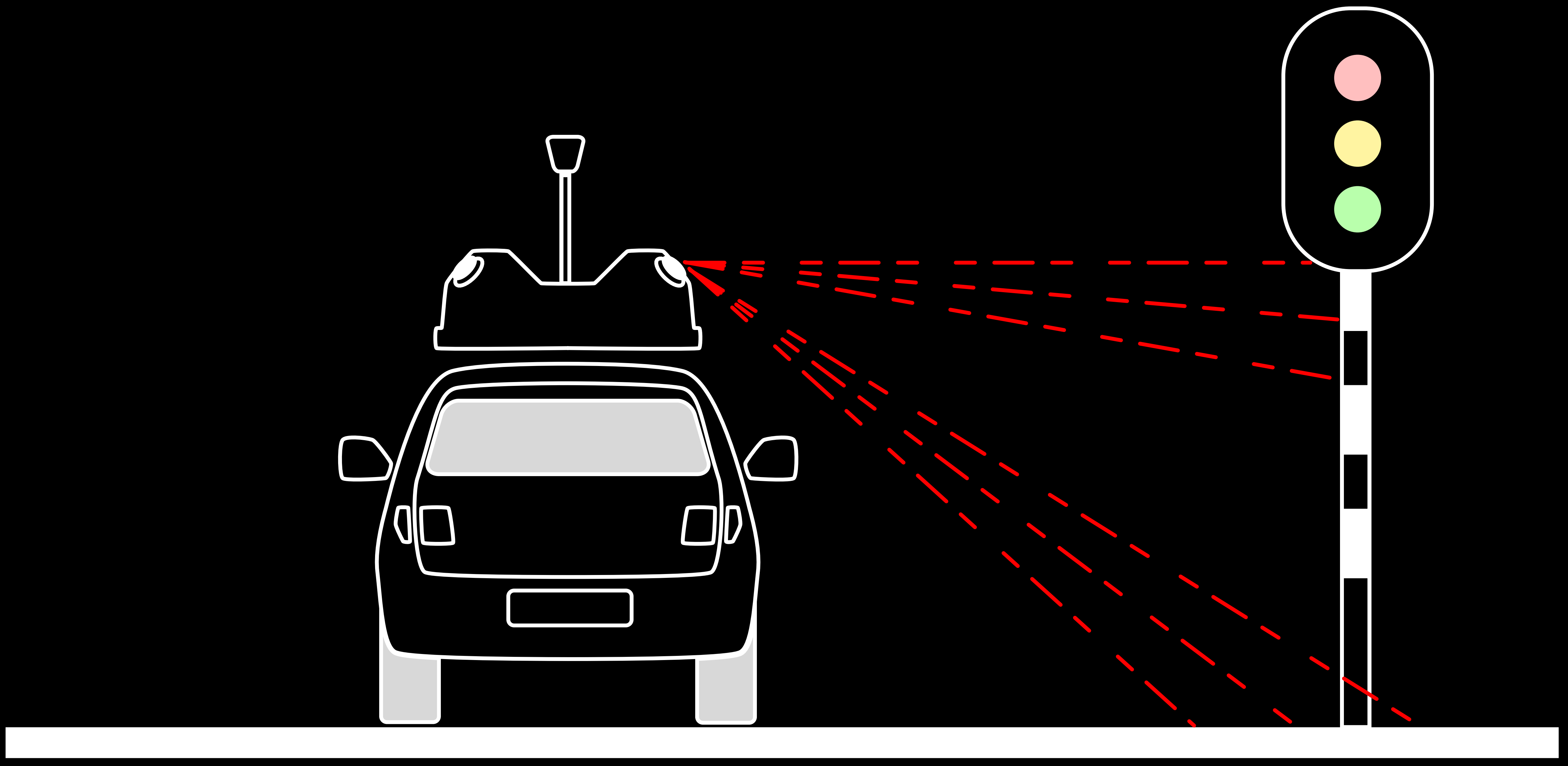
classification of large scale outdoor point clouds using convolutional neural networks

Tom Hemmes

At the TNO office…

Mobile Laser Scanner

Laser scanning



Point cloud

Ring Groningen

Badhoevedorp West


2D Map

2D Map

Research

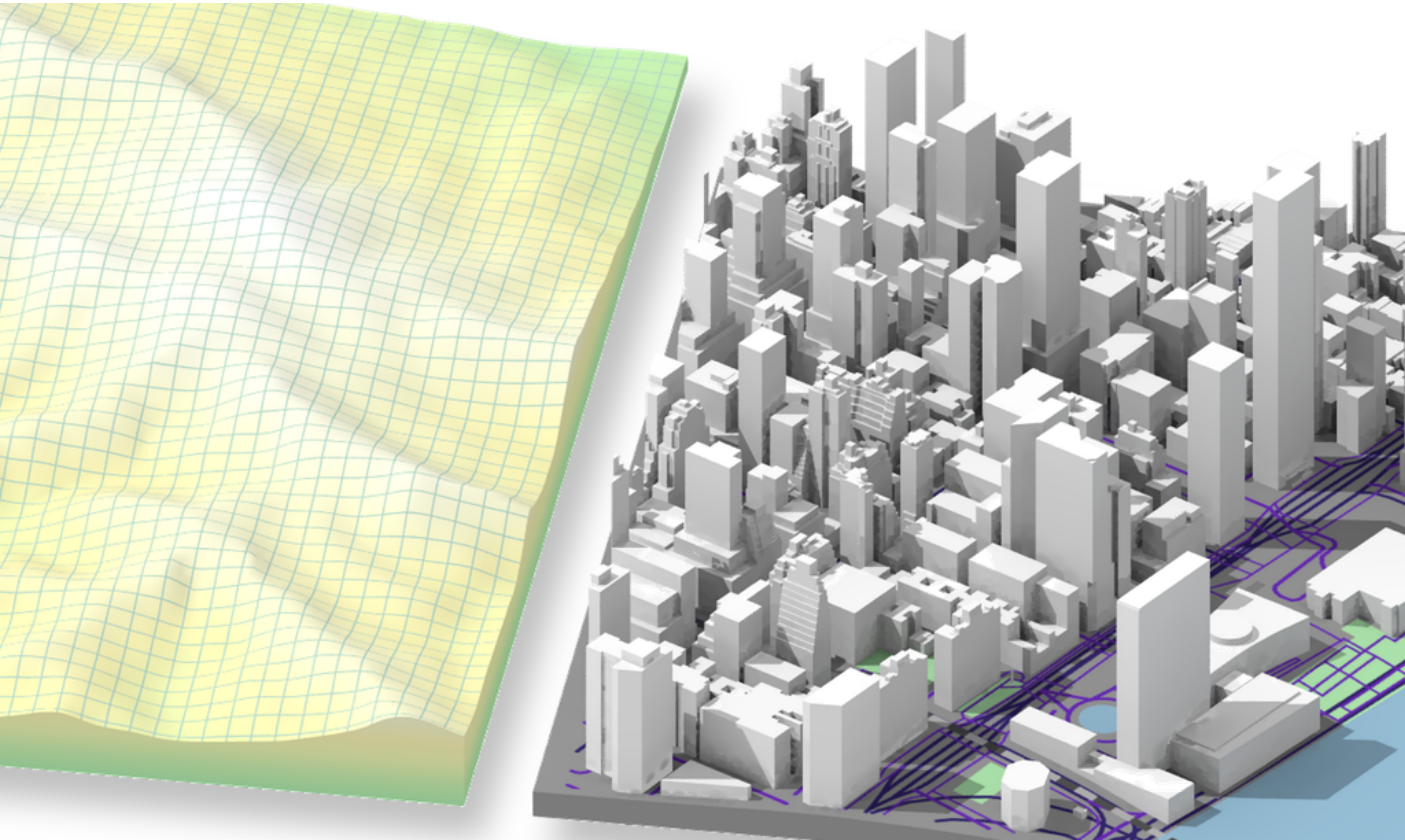
To what extent is deep learning suitable for classification of raw point clouds of a highway scene?

Deep learning on images

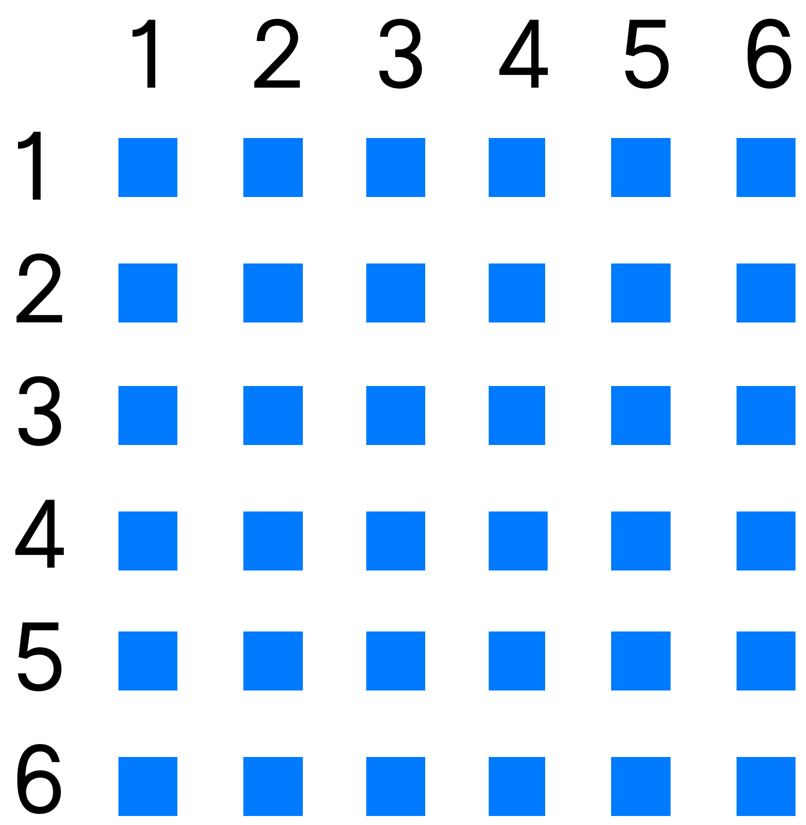
→ A lot of training data available

→ Images are structured

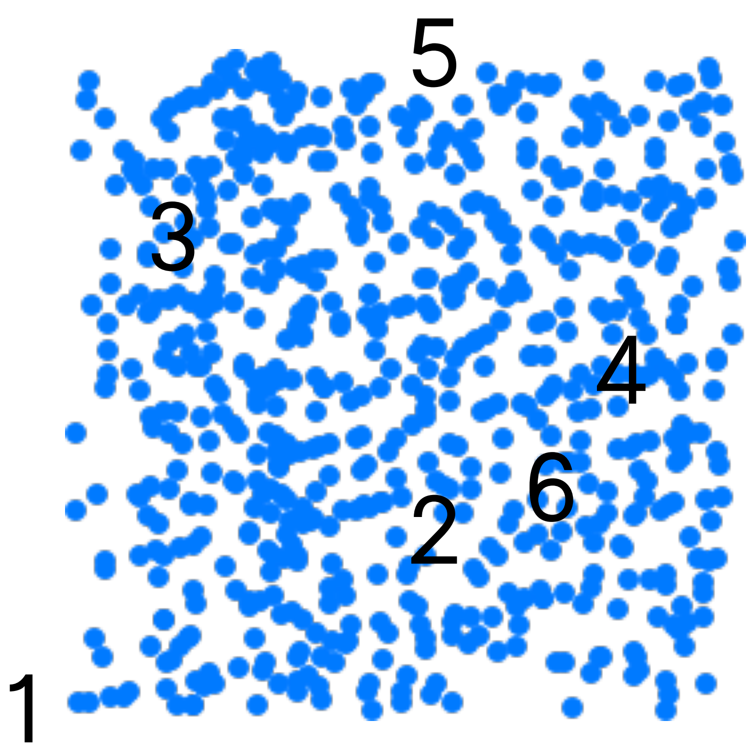
2D → 3D



Structure



Image



Point cloud

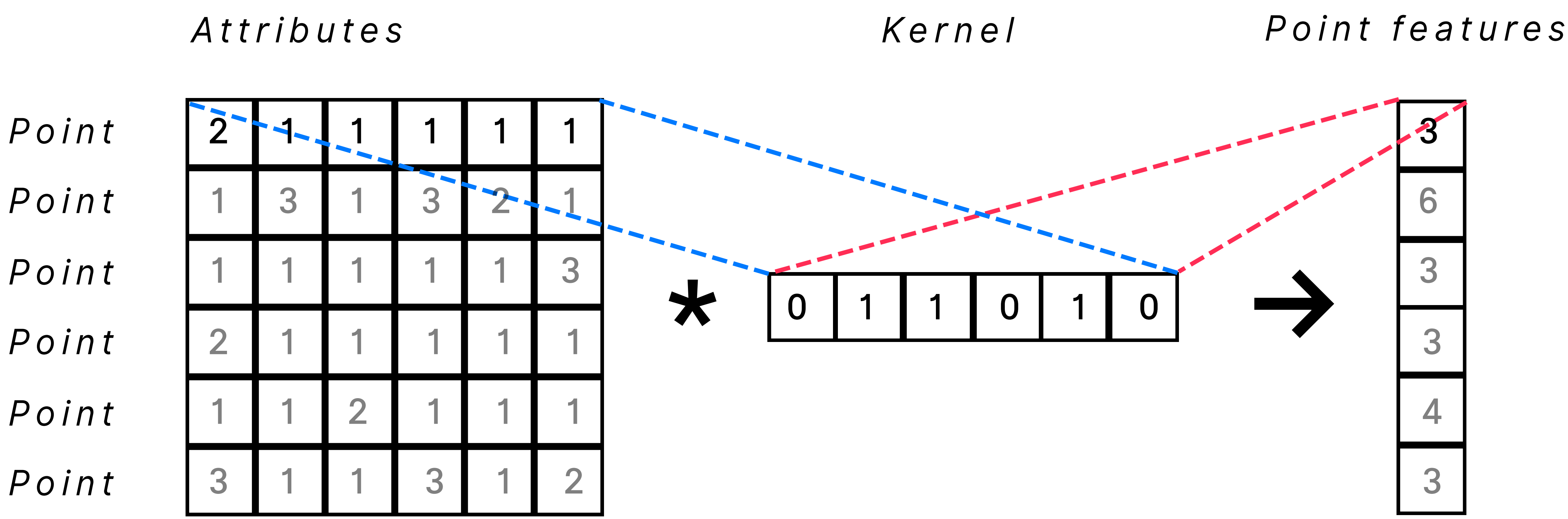
Point set learning

✕ Engineering manual features

✕ Transform representation to use existing deep learning algorithms

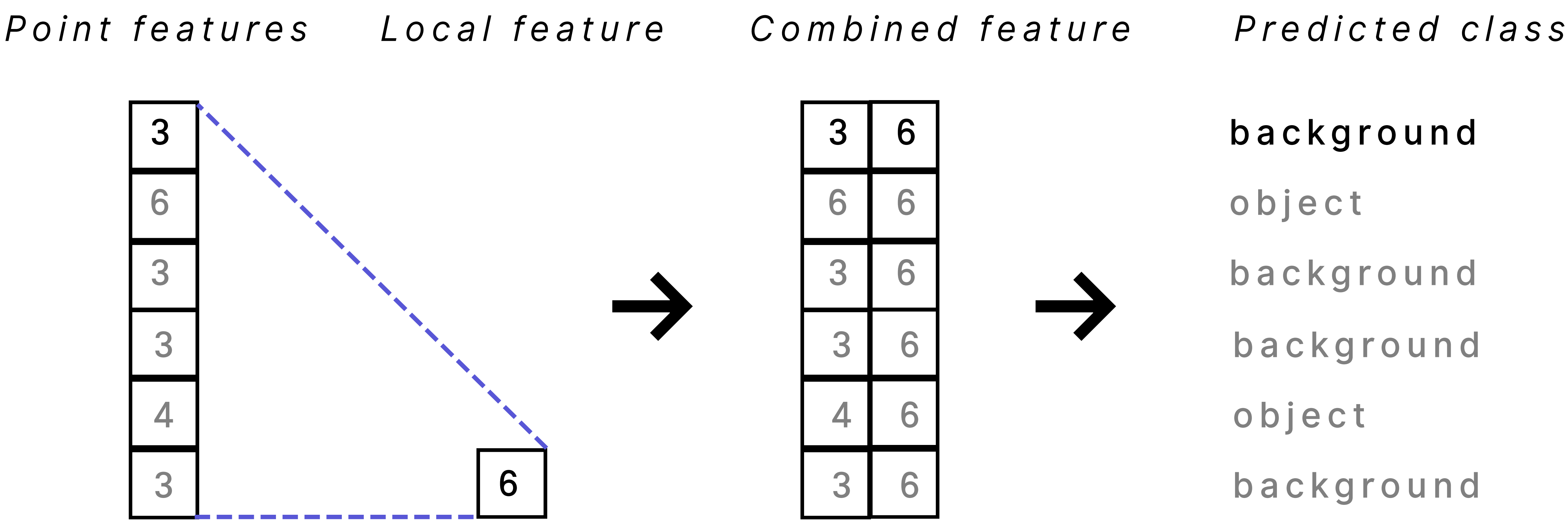
→ Deep learning directly on point clouds

PointNet



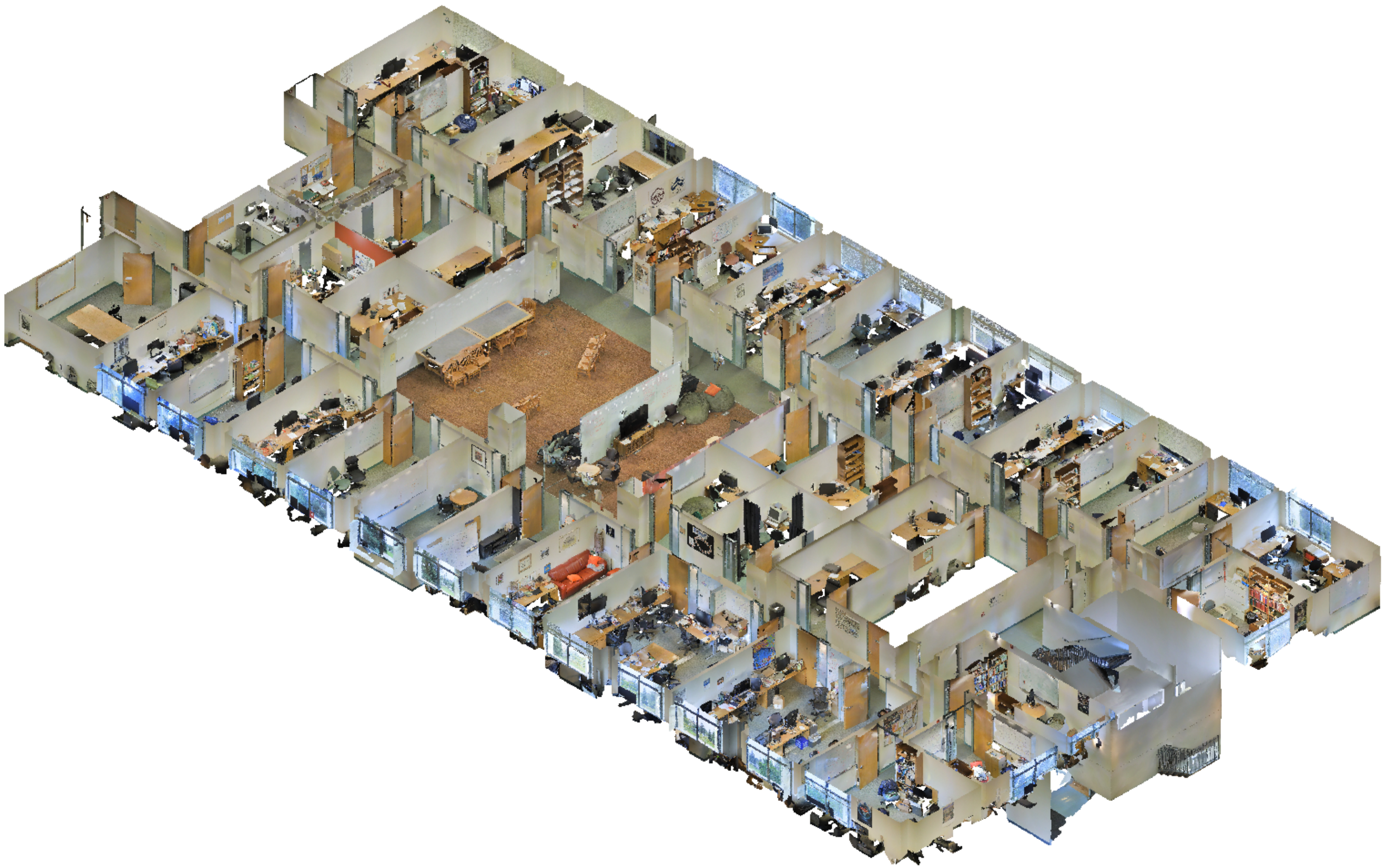
Charles Qi, et al. 2016

PointNet

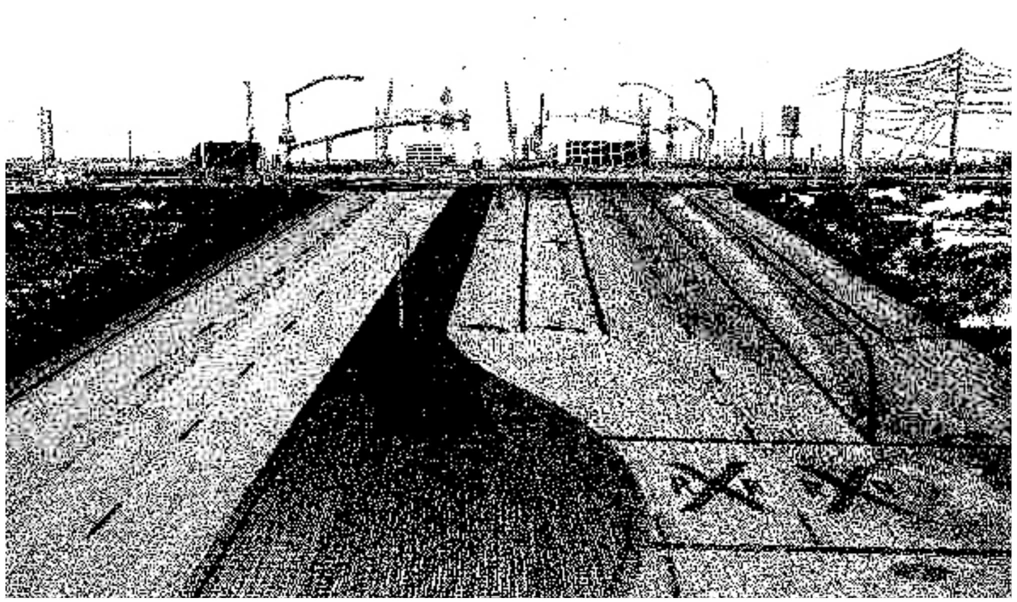


Charles Qi, et al. 2016

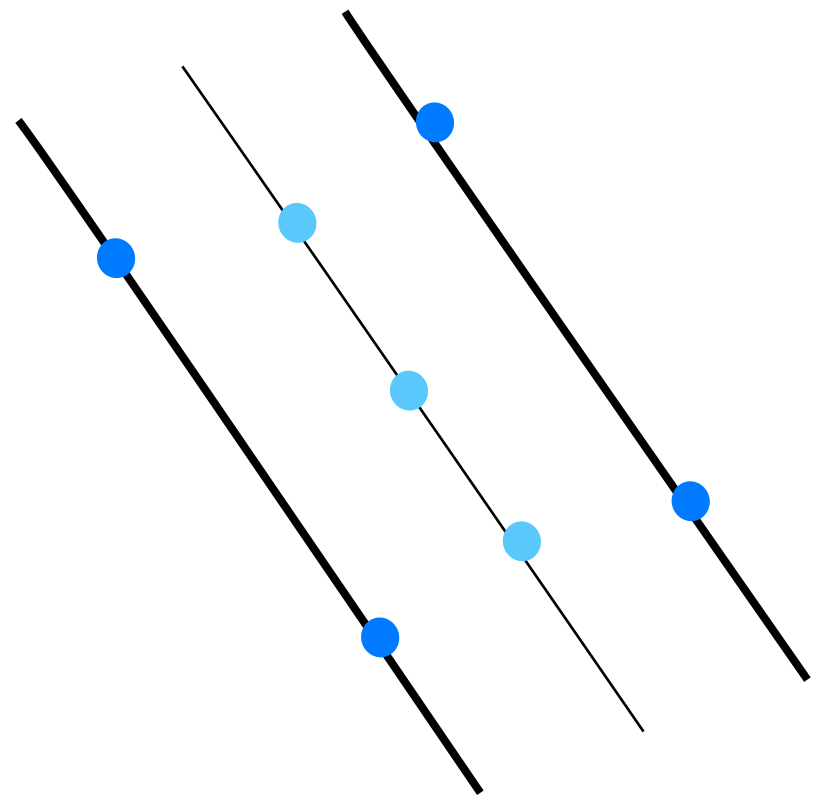
Indoor to outdoor



Research

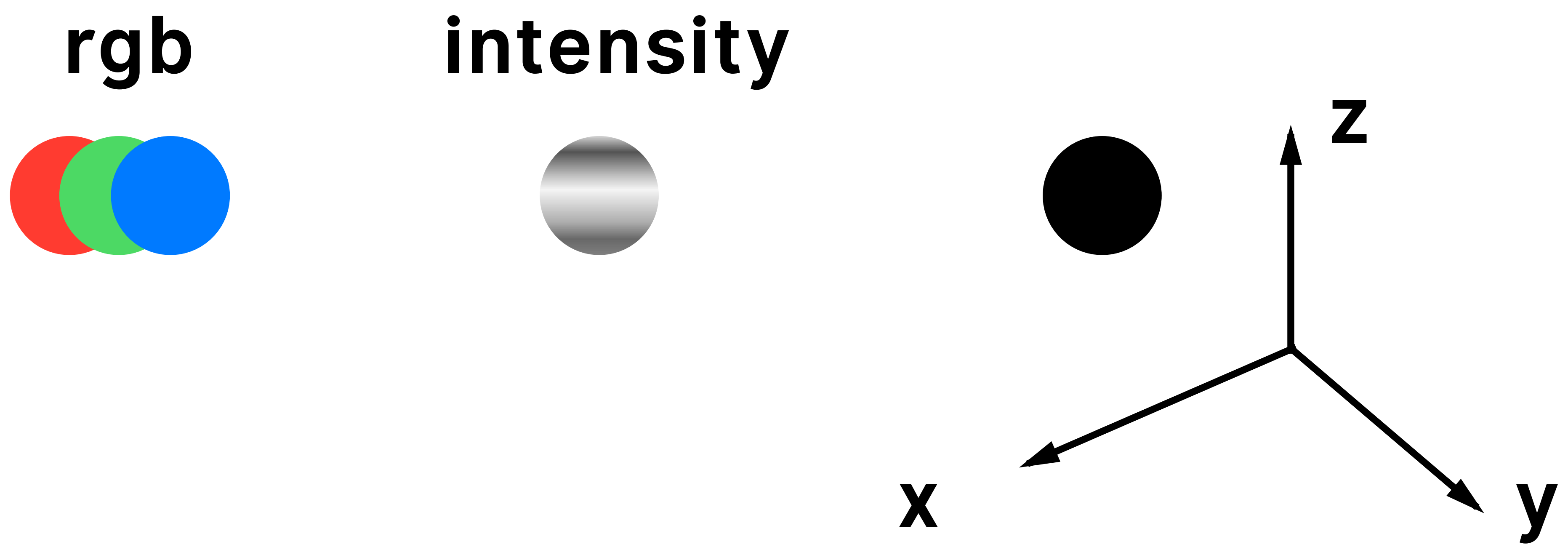


+



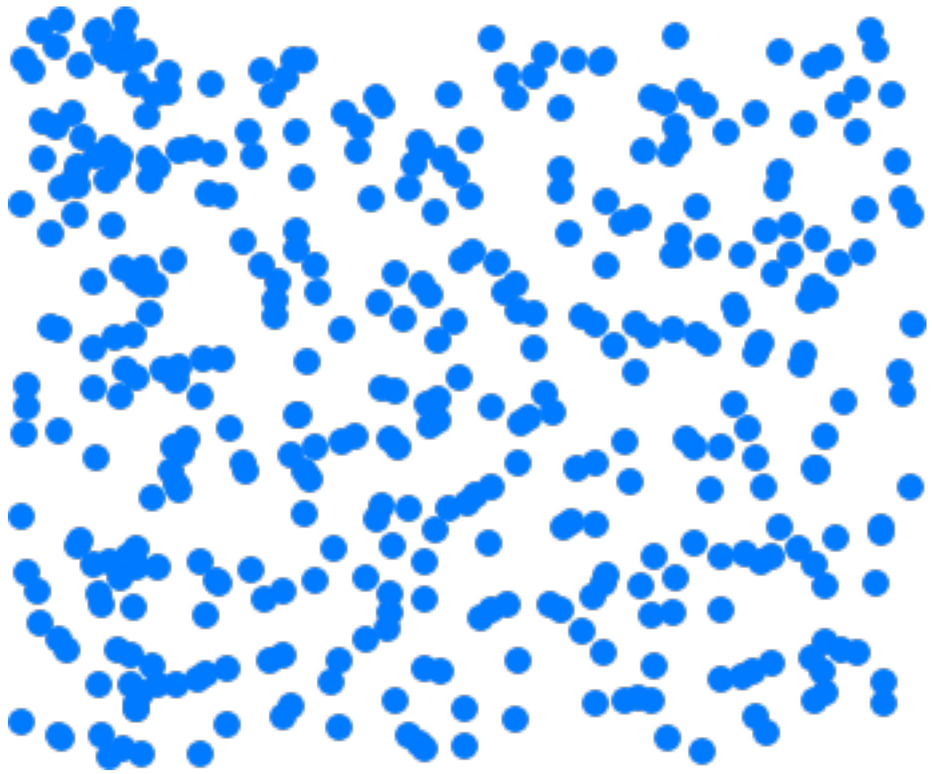
→ To what extent can usable training data be automatically created from point clouds and known object locations?

Research



→ What is the best way to represent 3D points for deep learning?

Research



→ What is the optimal sampling of points for classification of road side objects?

Research

Train

→

Test

→ Does the model generalize so it can be used at other locations?

Overview

- Topic
- Relevance
- Method
- Results
- Conclusion
- Recommendations

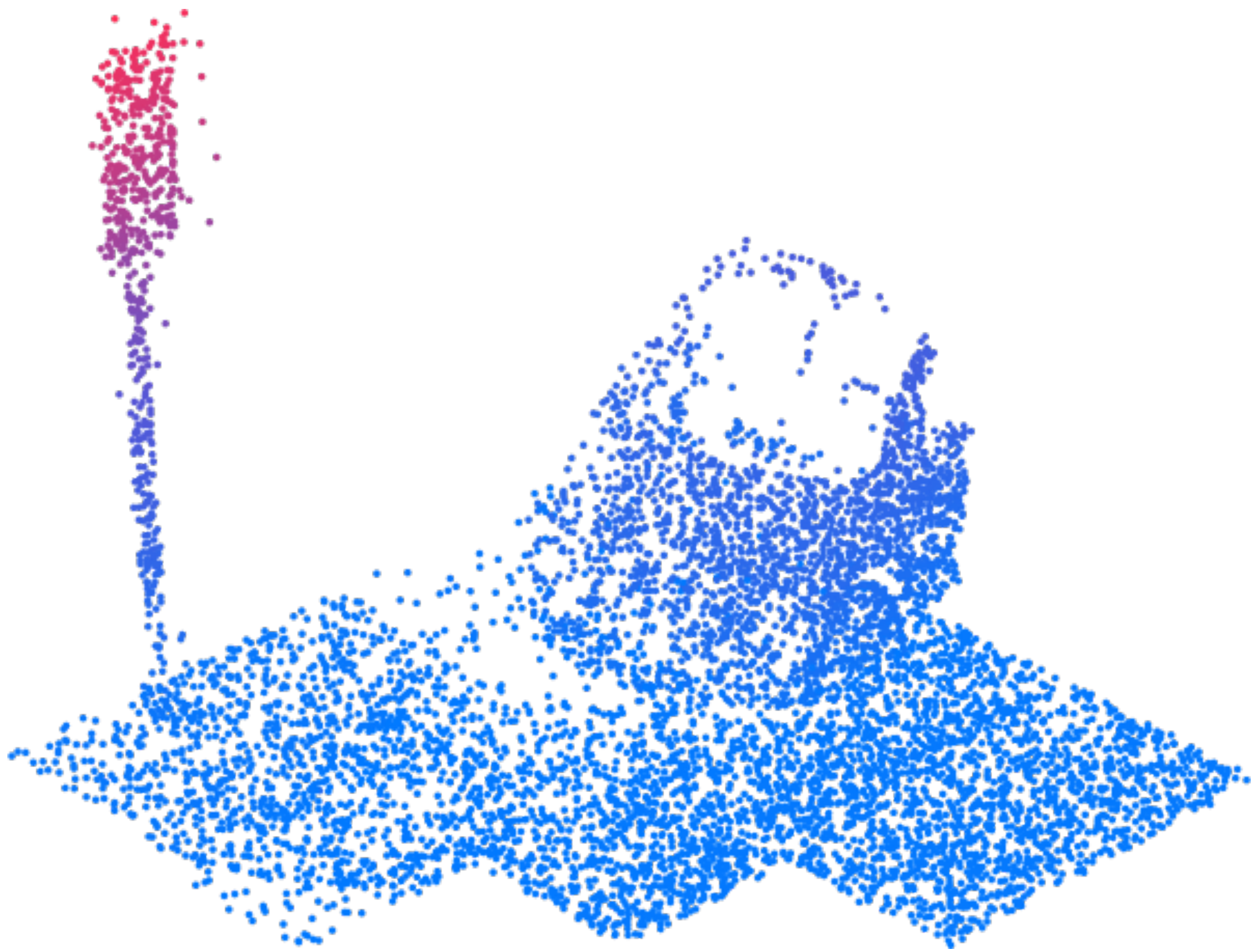
Method

- Create training data

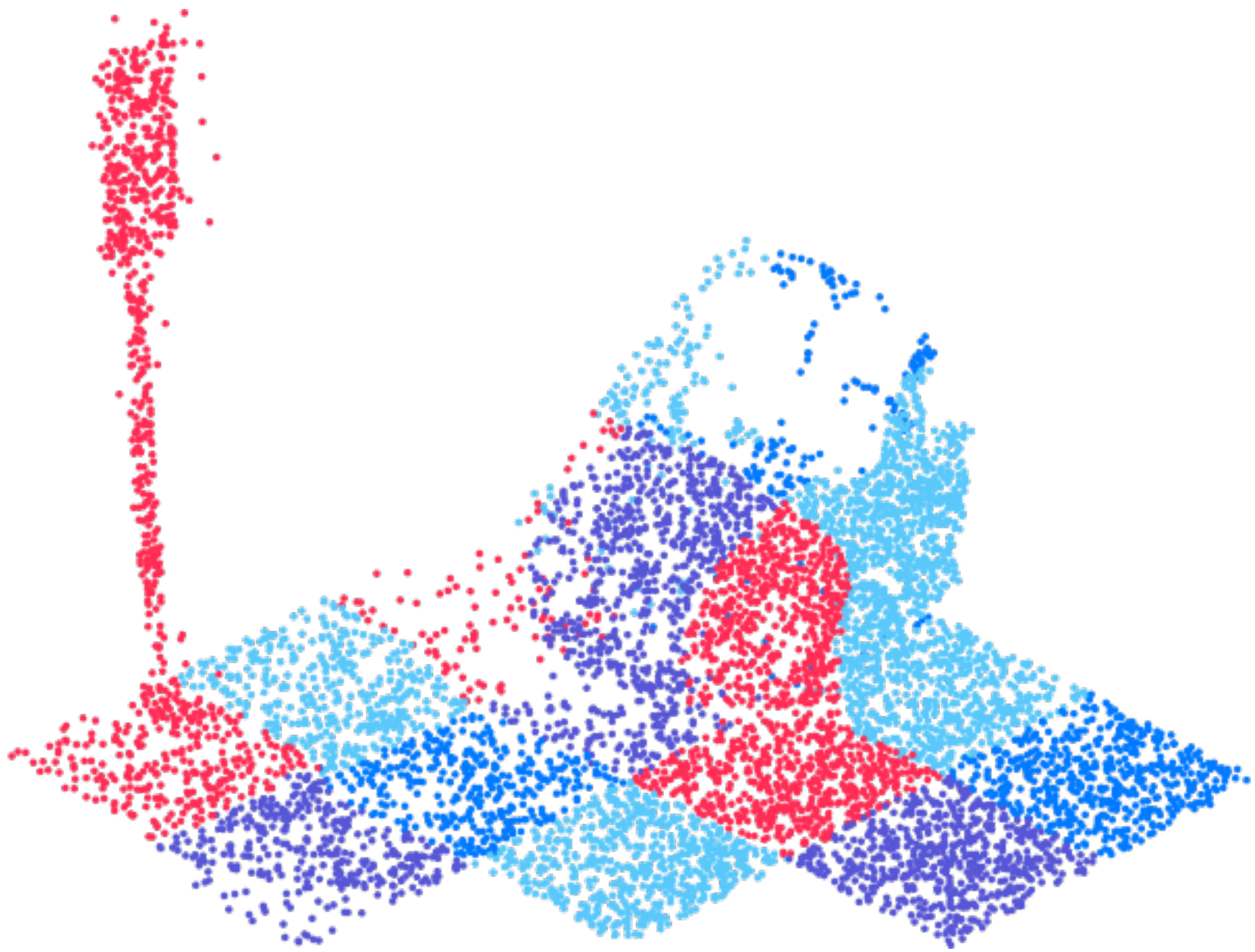
Prepare, train and apply model

Cluster and map predictions

Grid partitioning

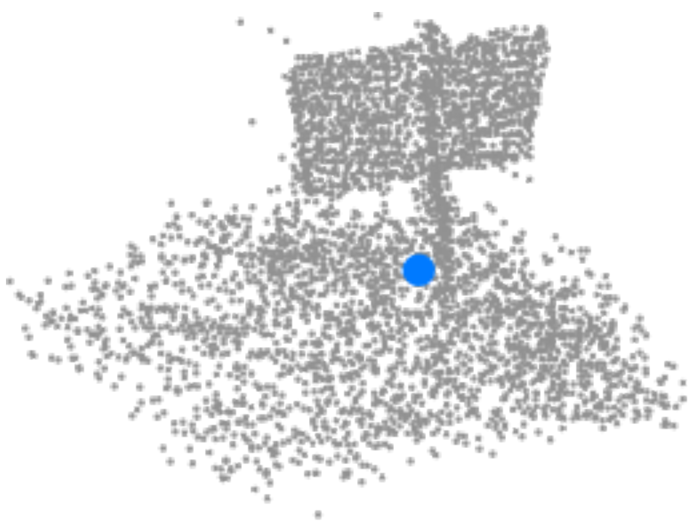


Grid partitioning

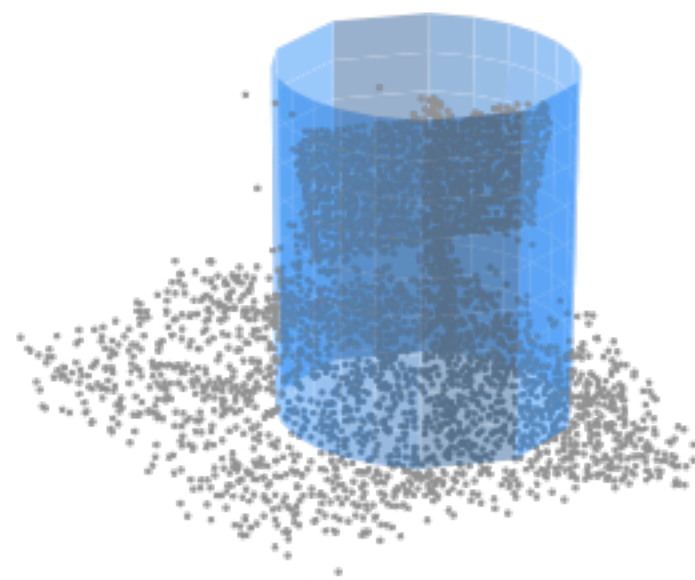


Spatial join

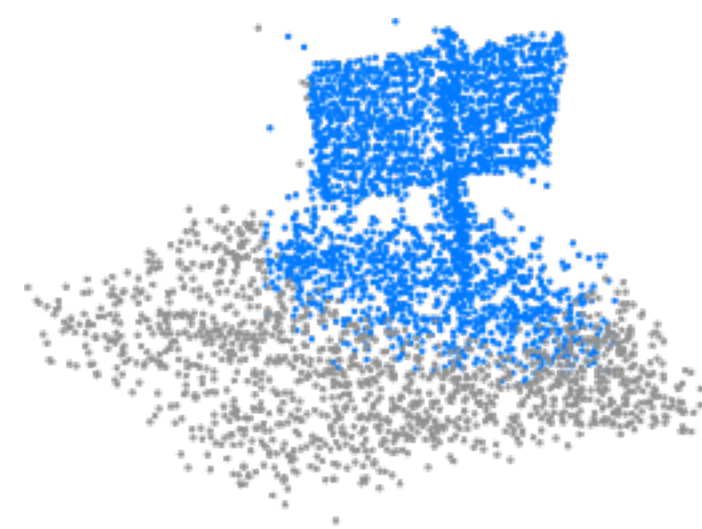
Overlay



Buffer

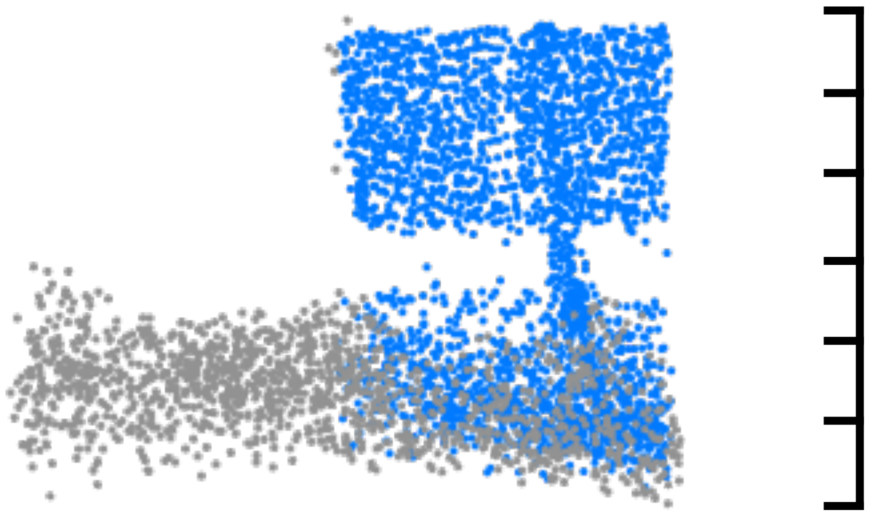


Intersect

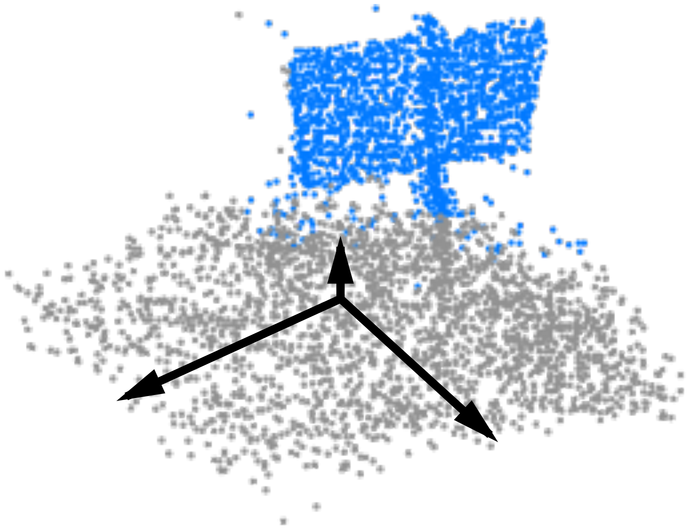


Ground filter

Flatness

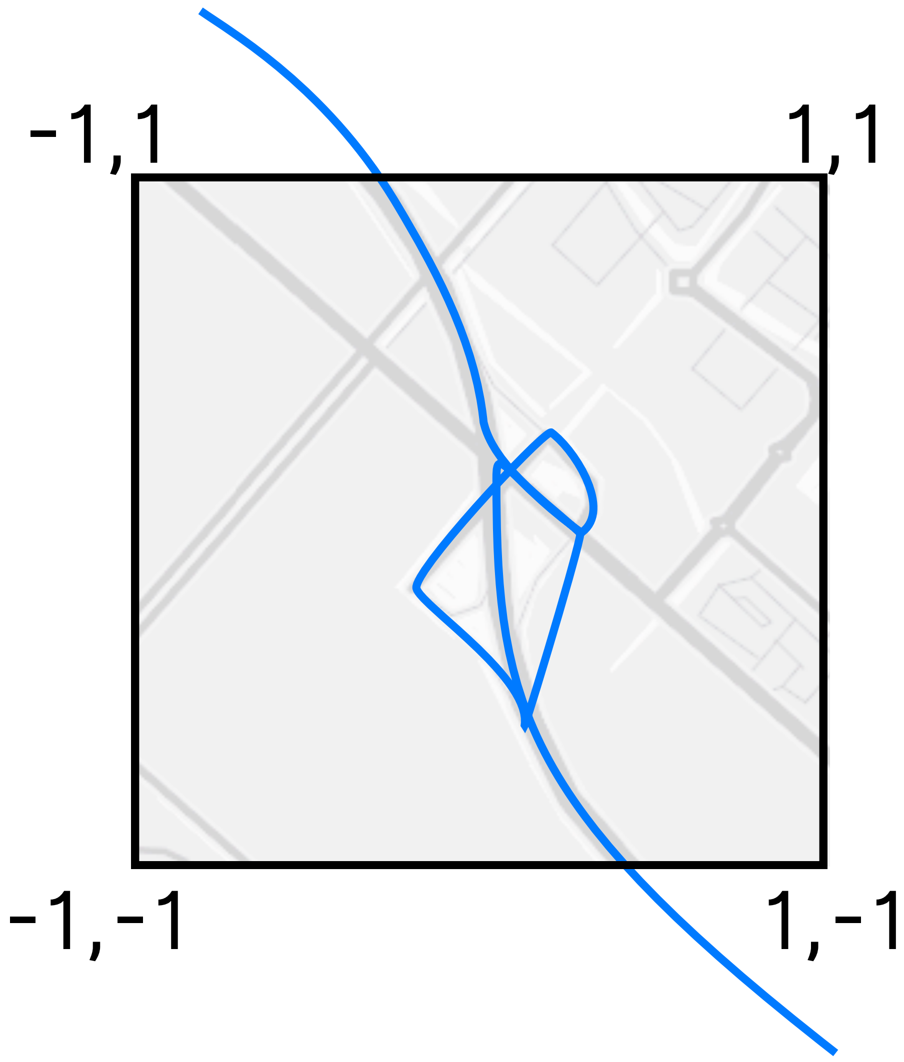


Filter

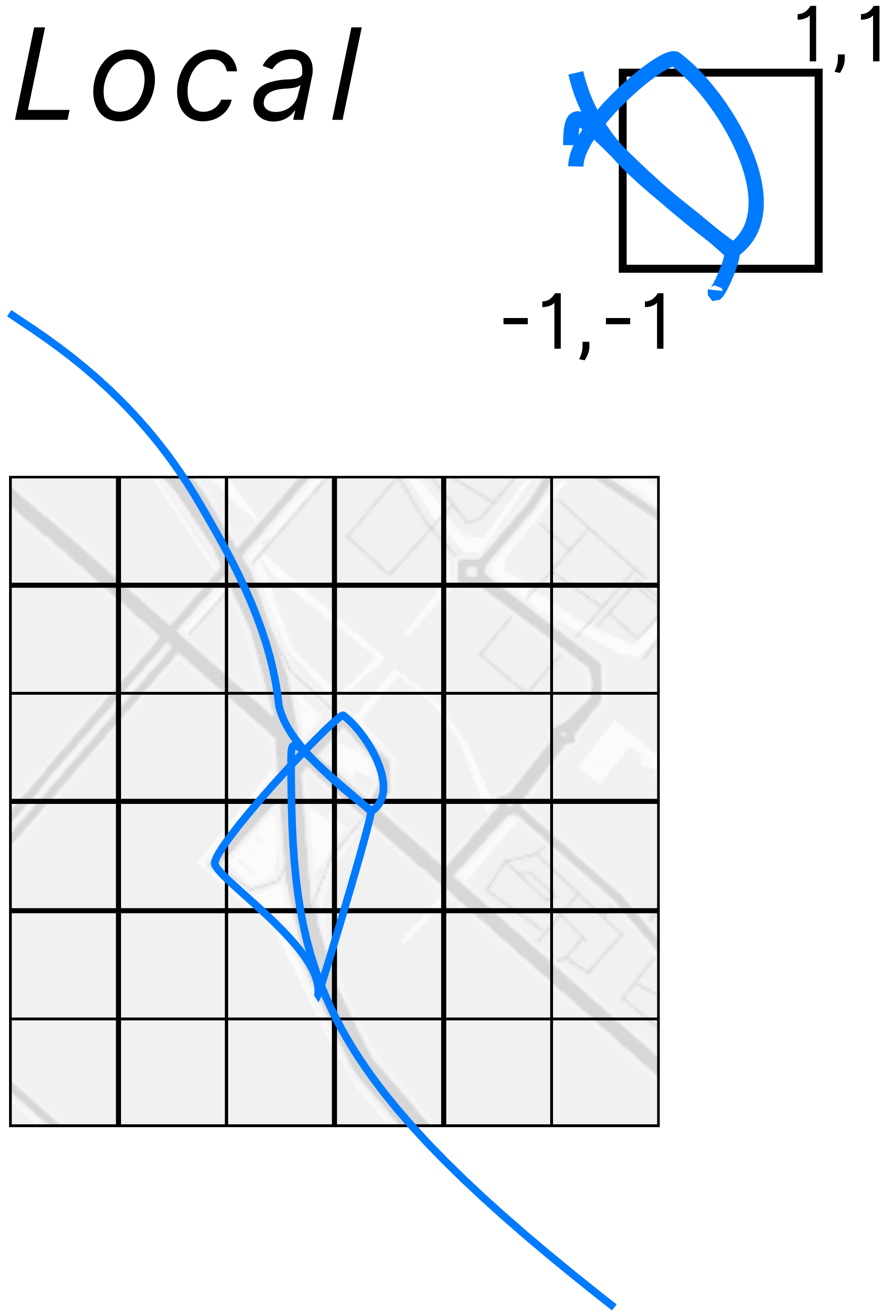


Spatial reference

Global



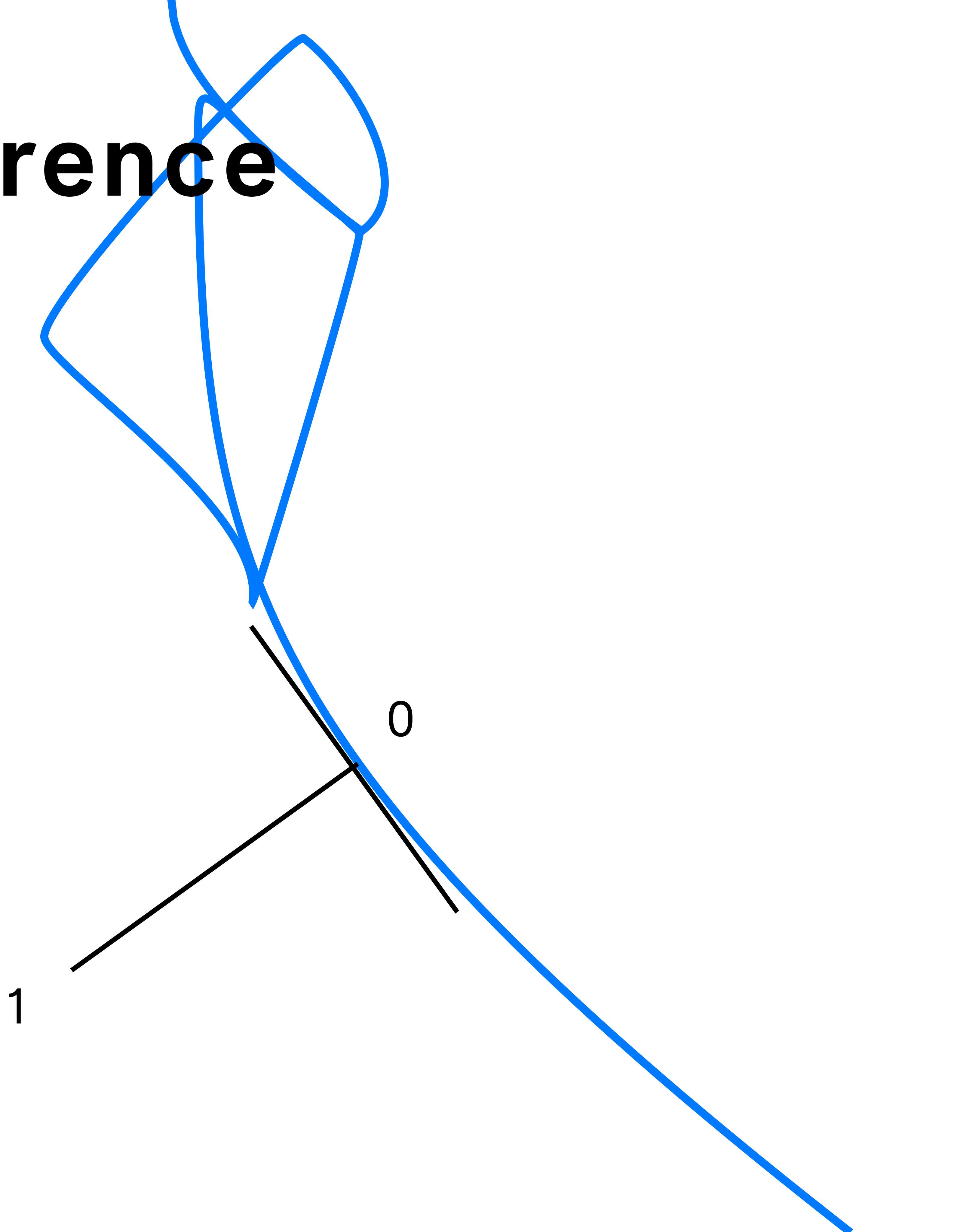
Local



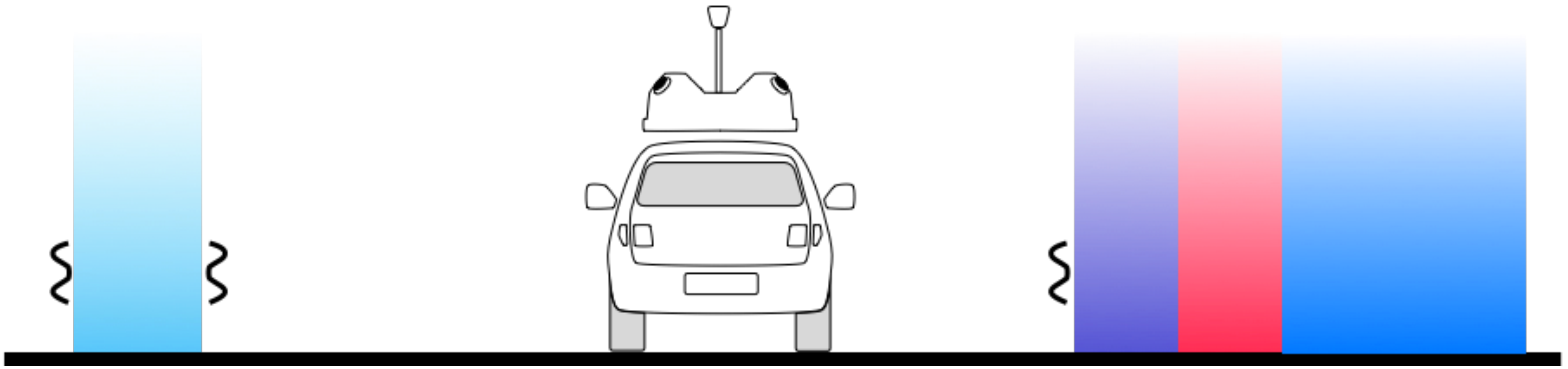
Trajectory

Spatial reference

Trajectory



Zonal arrangement

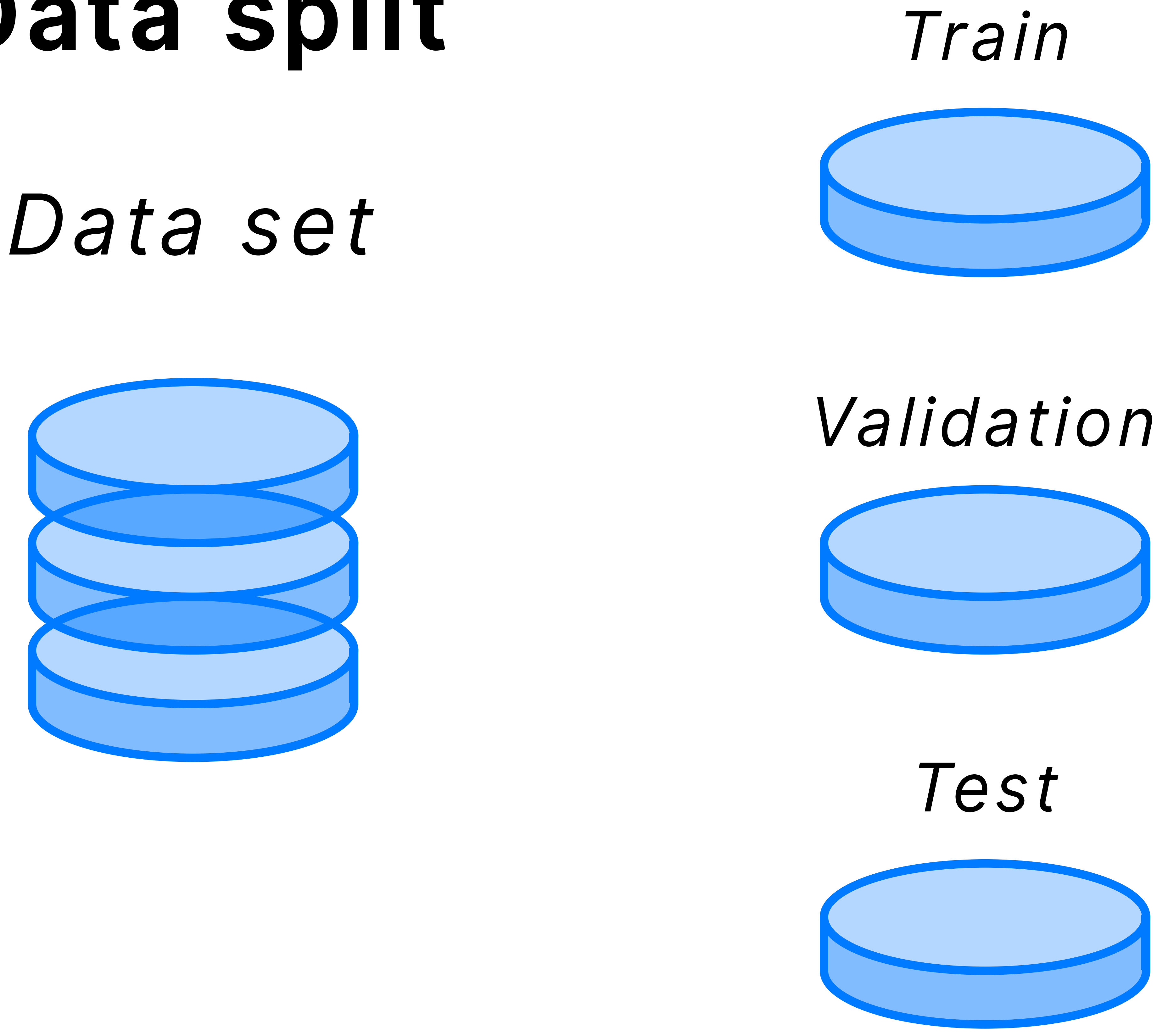


- *Lamppost*
- *Hectometer sign*
- *Road sign*
- *Traffic light*

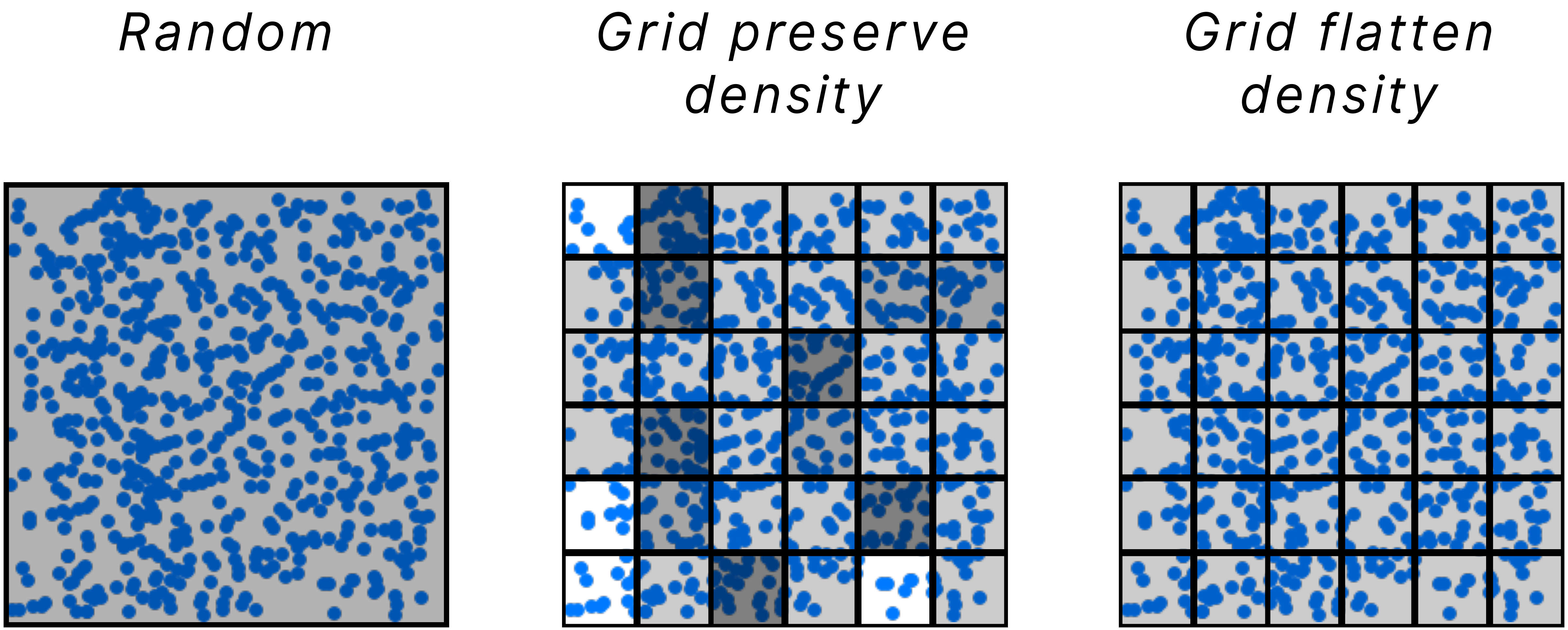
Method

- Create training data
- Prepare, train and apply model
- Cluster and map predictions

Data split

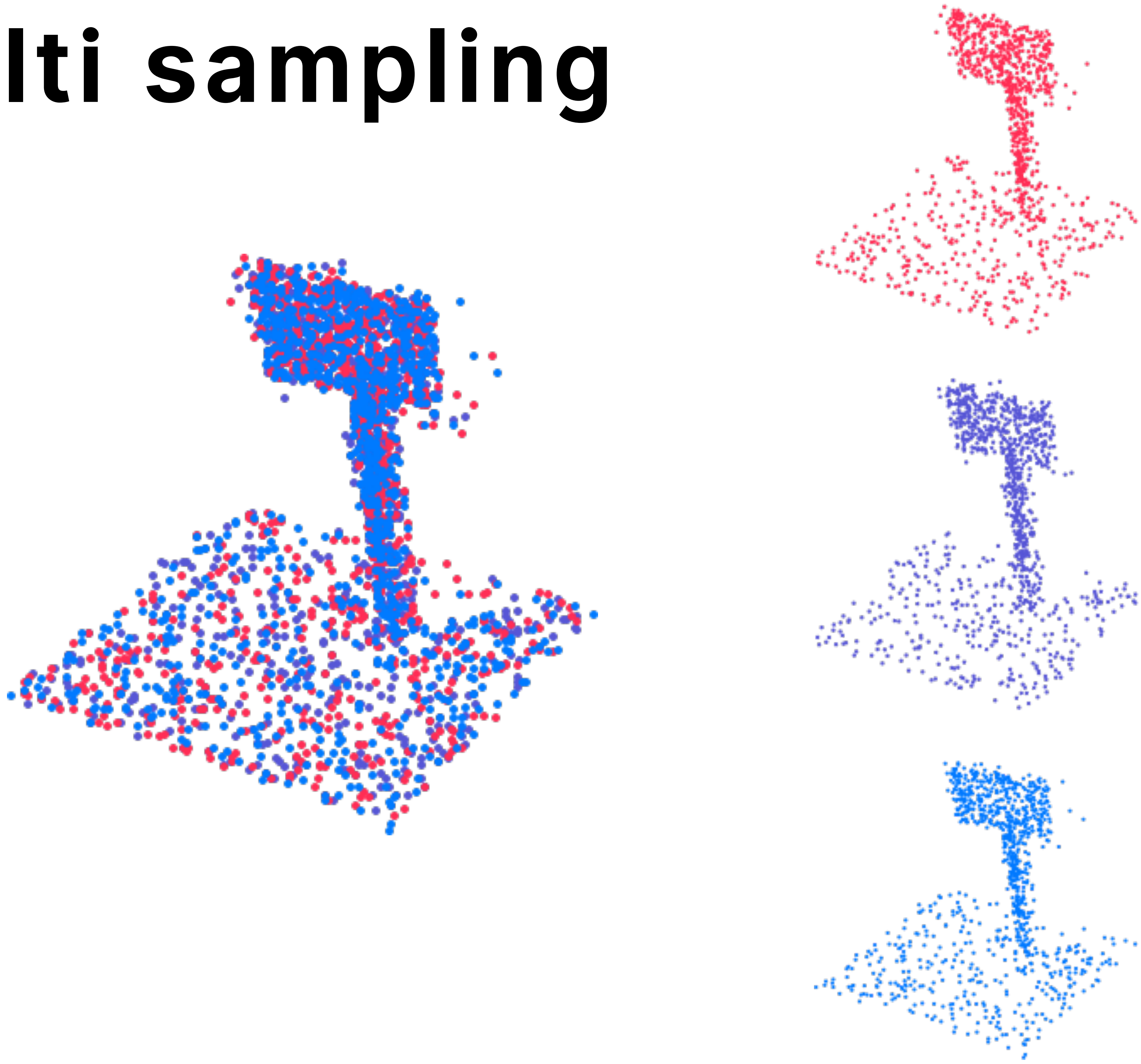


Sampling method

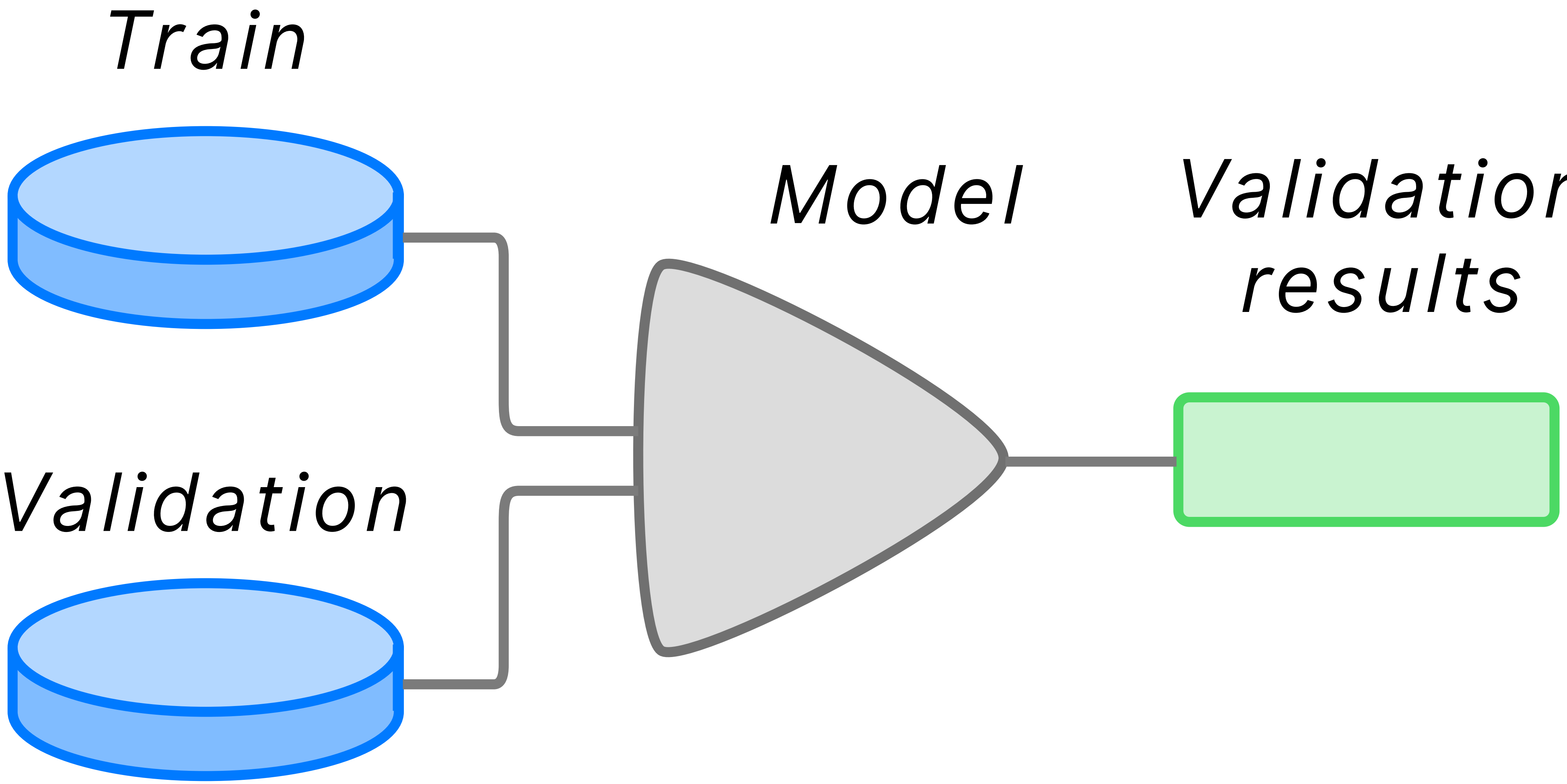


**** actually in 3D***

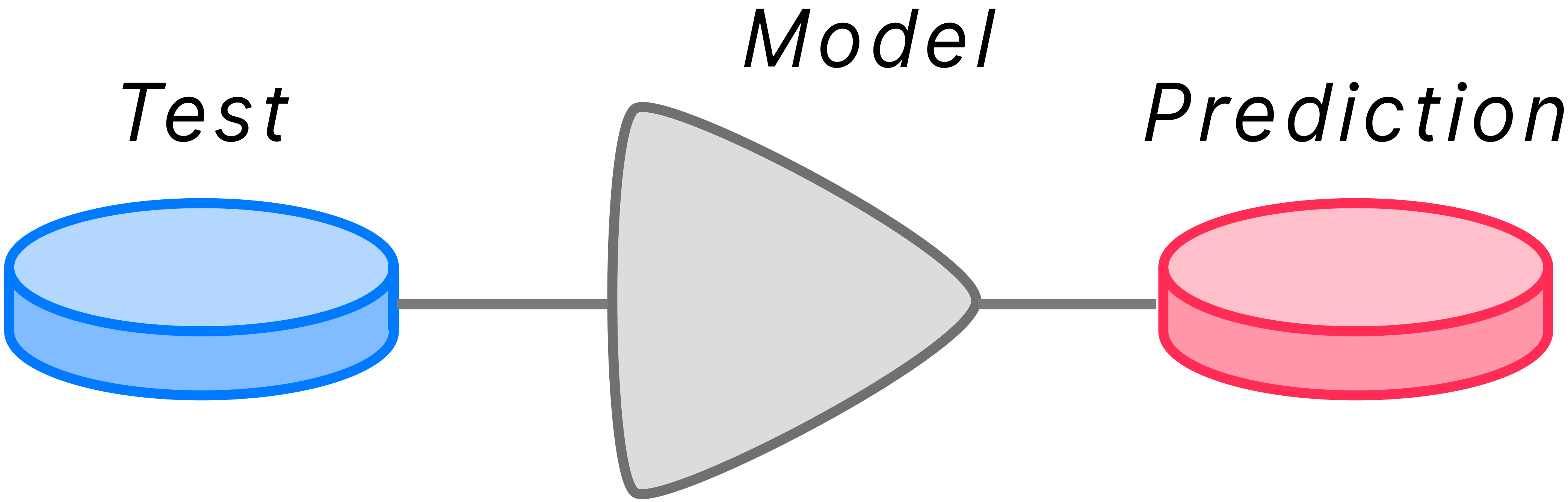
Multi sampling



Train and apply



Train and apply



Method

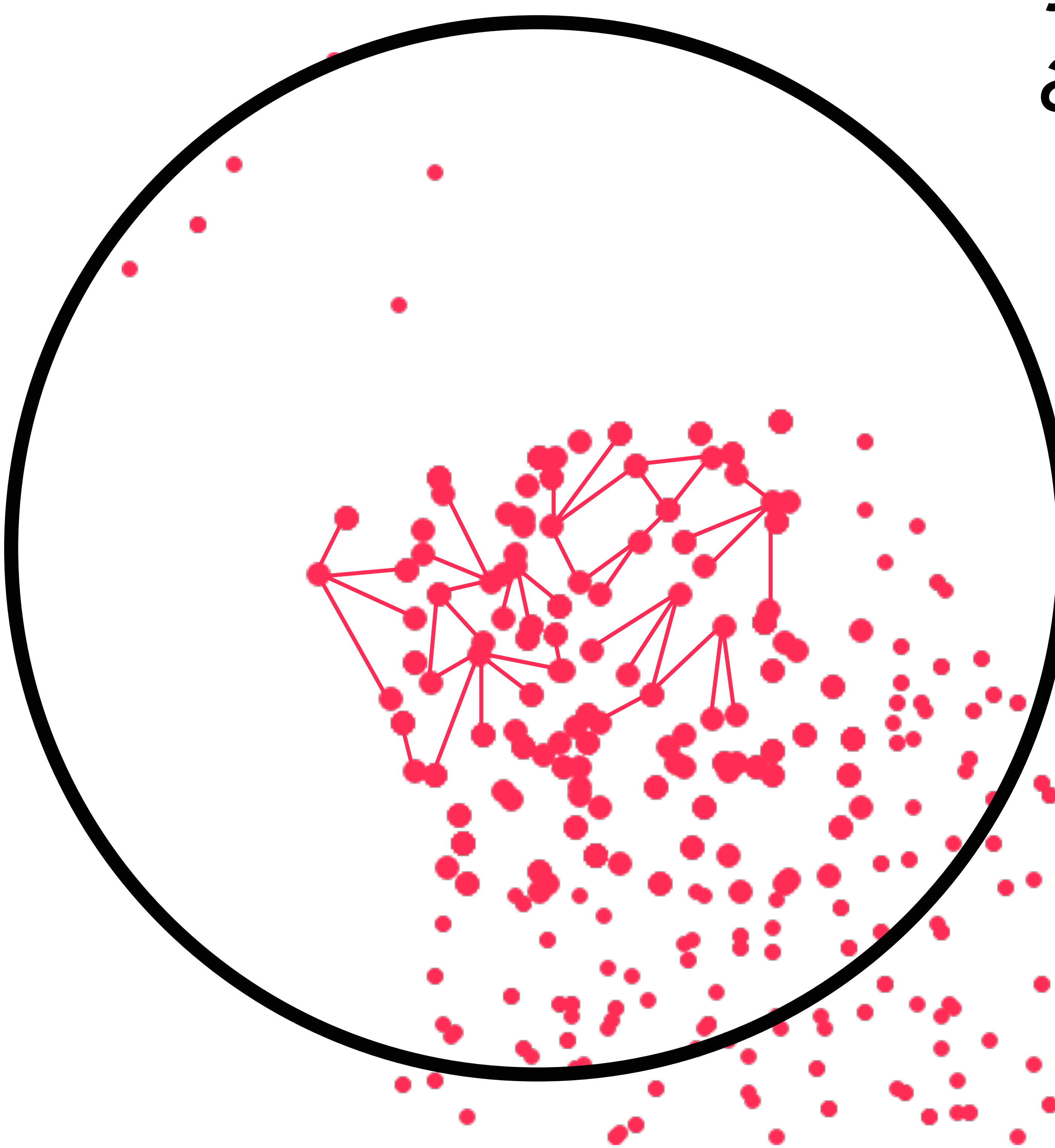
Create training data

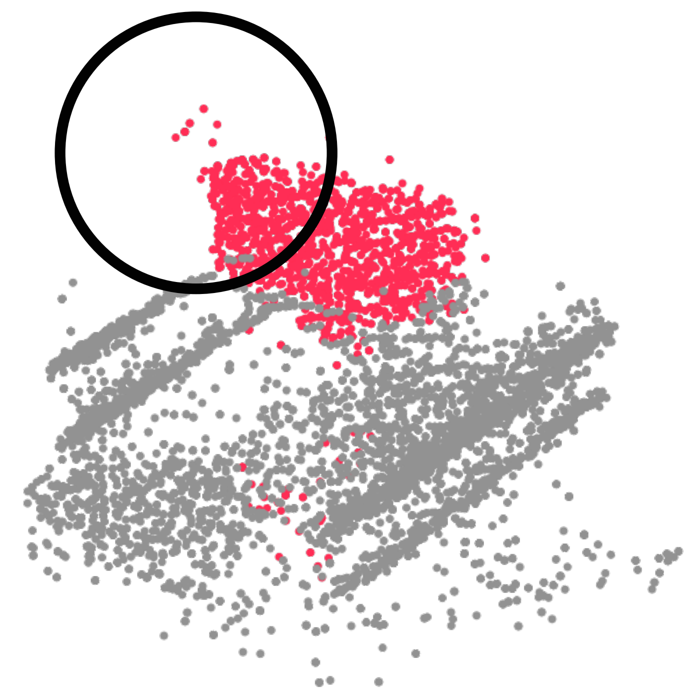
Prepare, train and apply model

- Cluster and map predictions

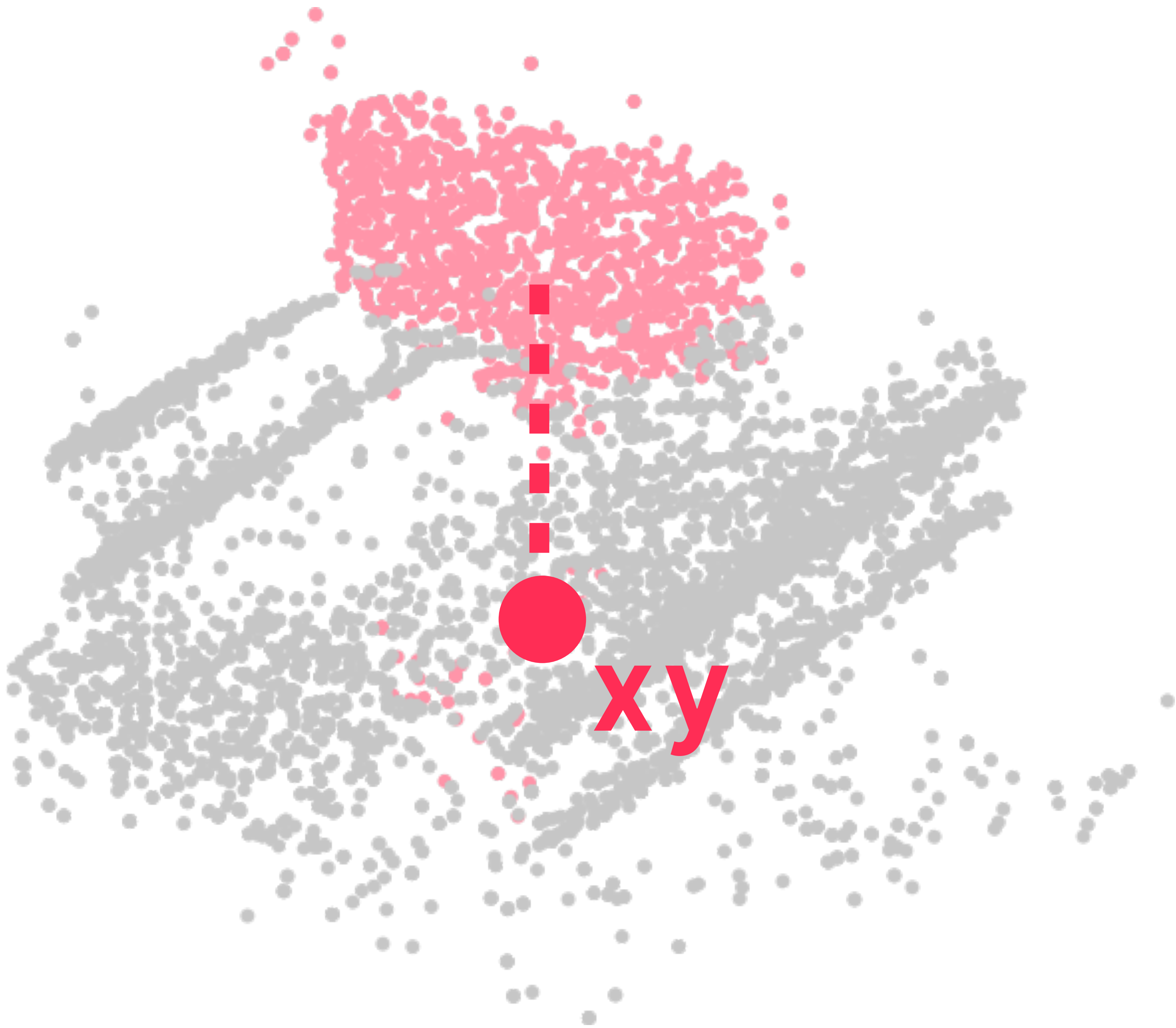
Cluster

By distance and class





Map



Overview

- Topic
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Results

- Training data

  Represent a point

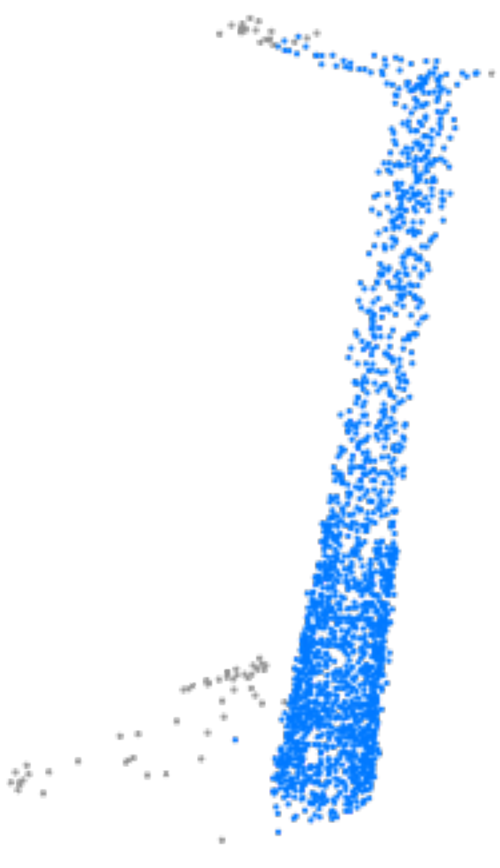
  Select points

  Generalization

  Overall suitability

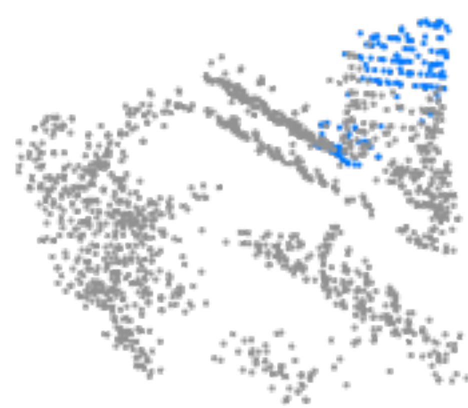
Types of objects

Lamppost

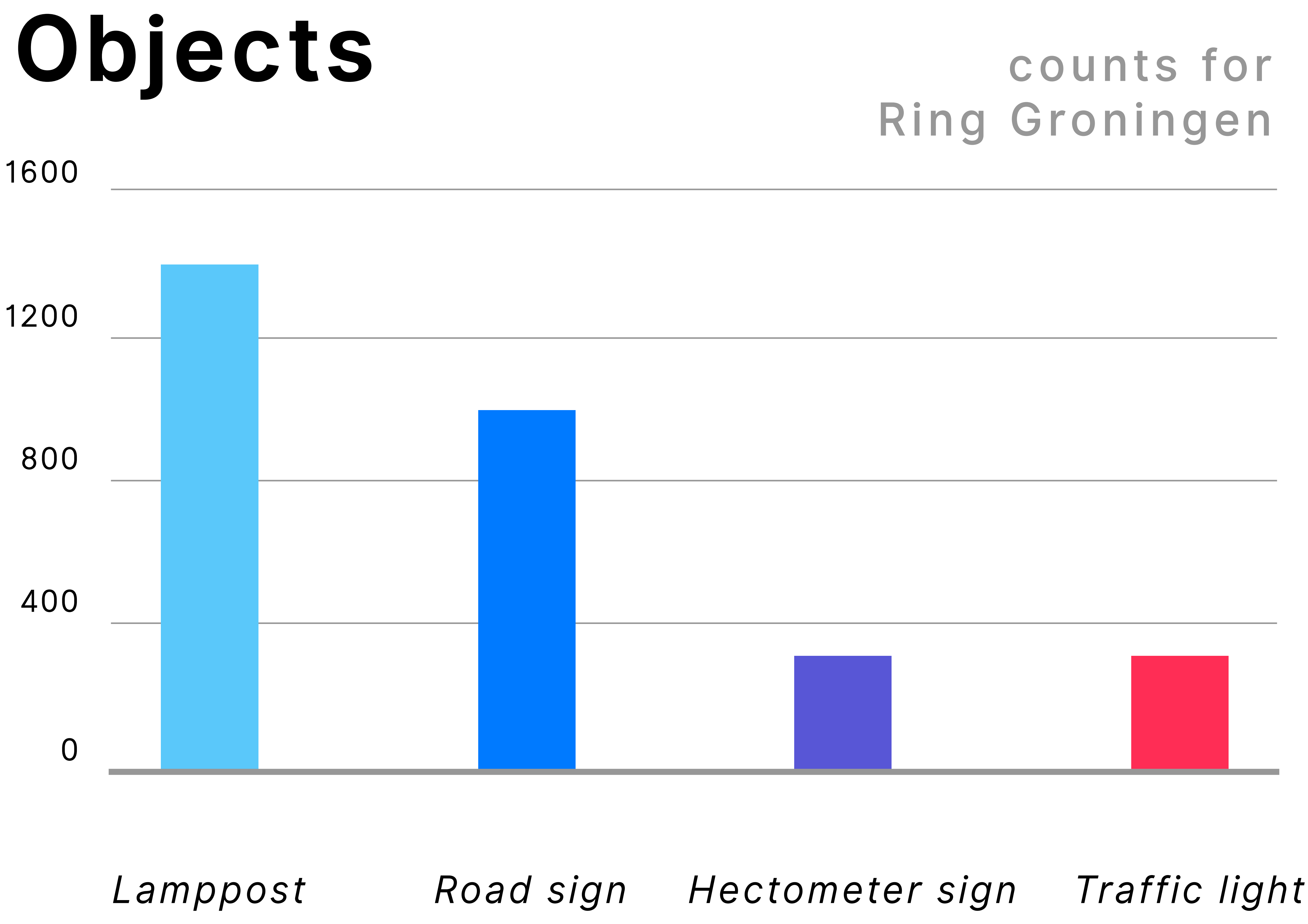


Road sign

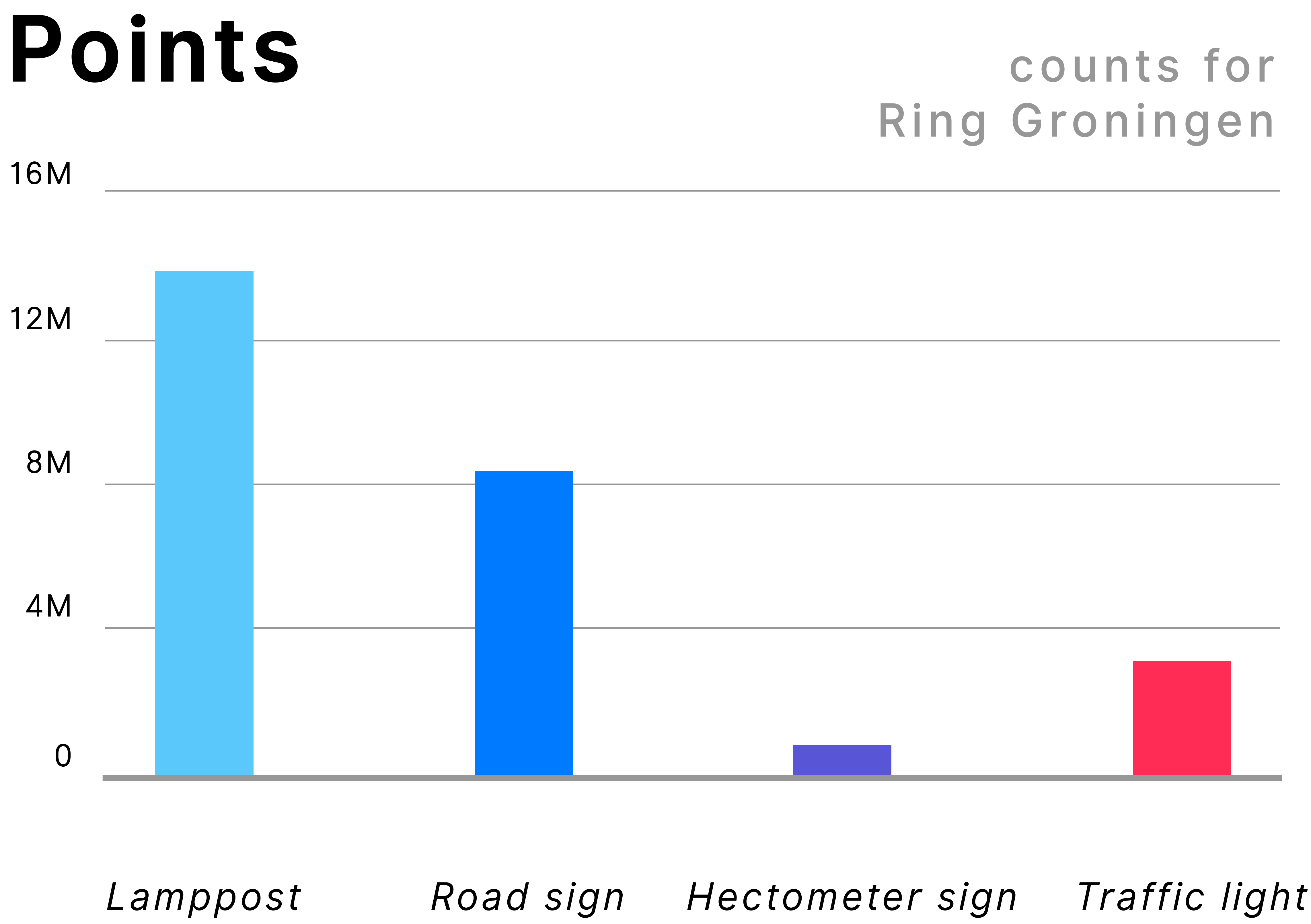
Hectometer sign



Traffic light

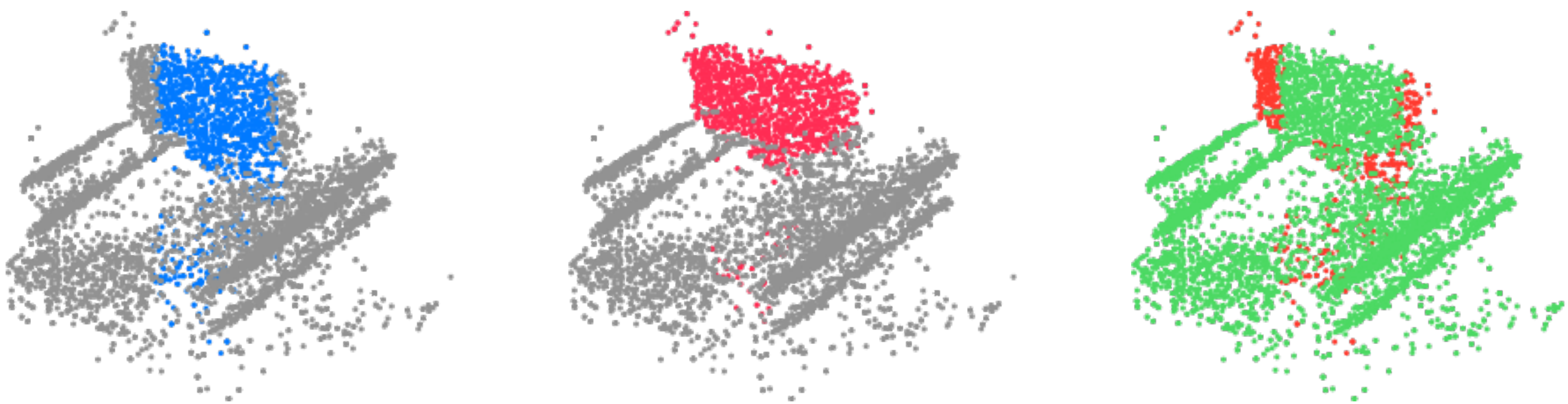


Objects
counts for
Ring Groningen
1600
1200
800
400
0
Lamppost
Road sign
Hectometer sign
Traffic light


Points
counts for
Ring Groningen
16M
12M
8M
4M
0
Lamppost
Road sign
Hectometer sign
Traffic light

Training data quality

Ground truth *Prediction* *Difference*



Training data

spatial intersection
Inaccuracy of CAD map
Non-identical objects in one class
Combined objects

ground filter
Grass or low vegetation
Sloped surface

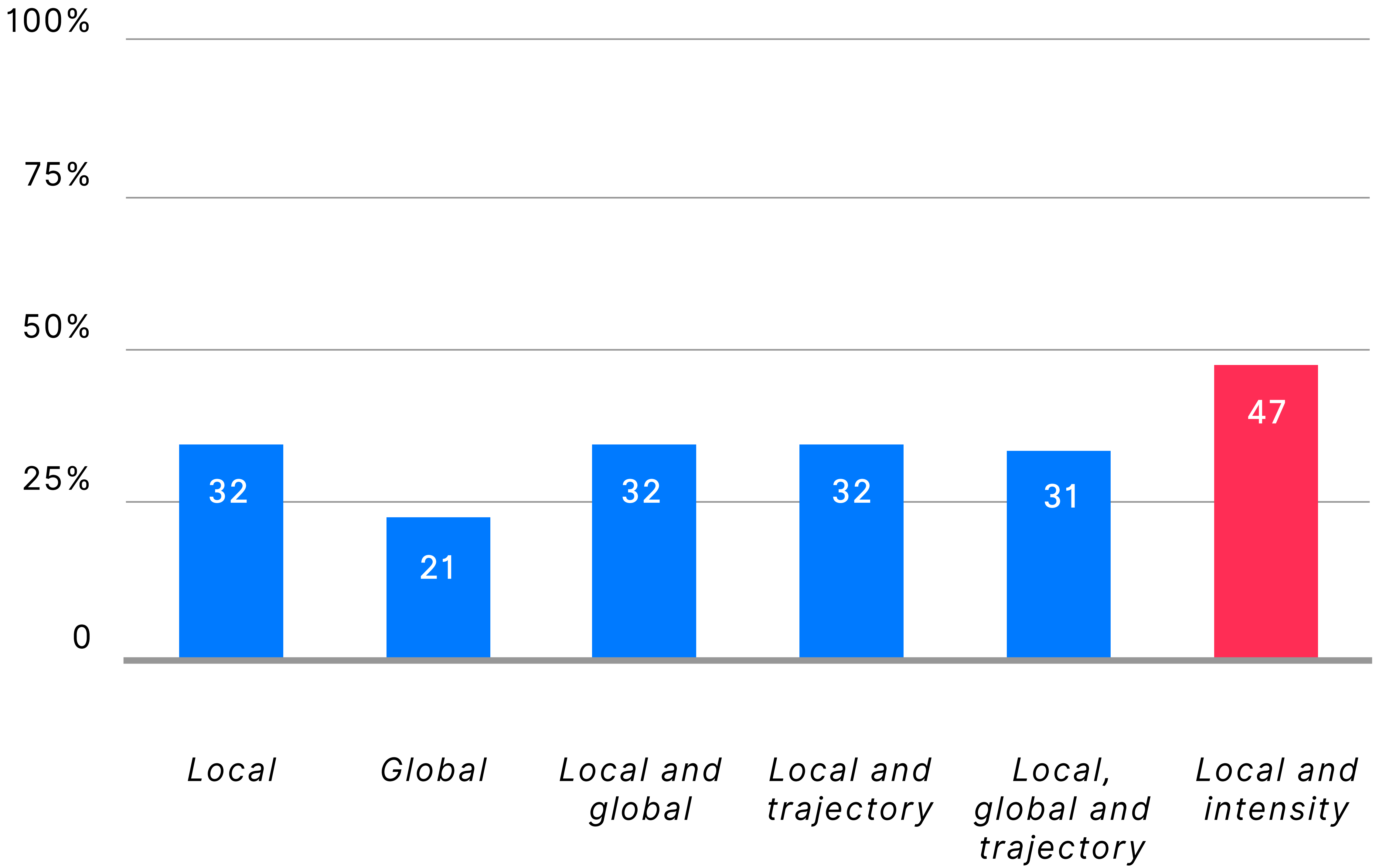
→ Usable training samples with ~15% inaccuracy can be created

Results

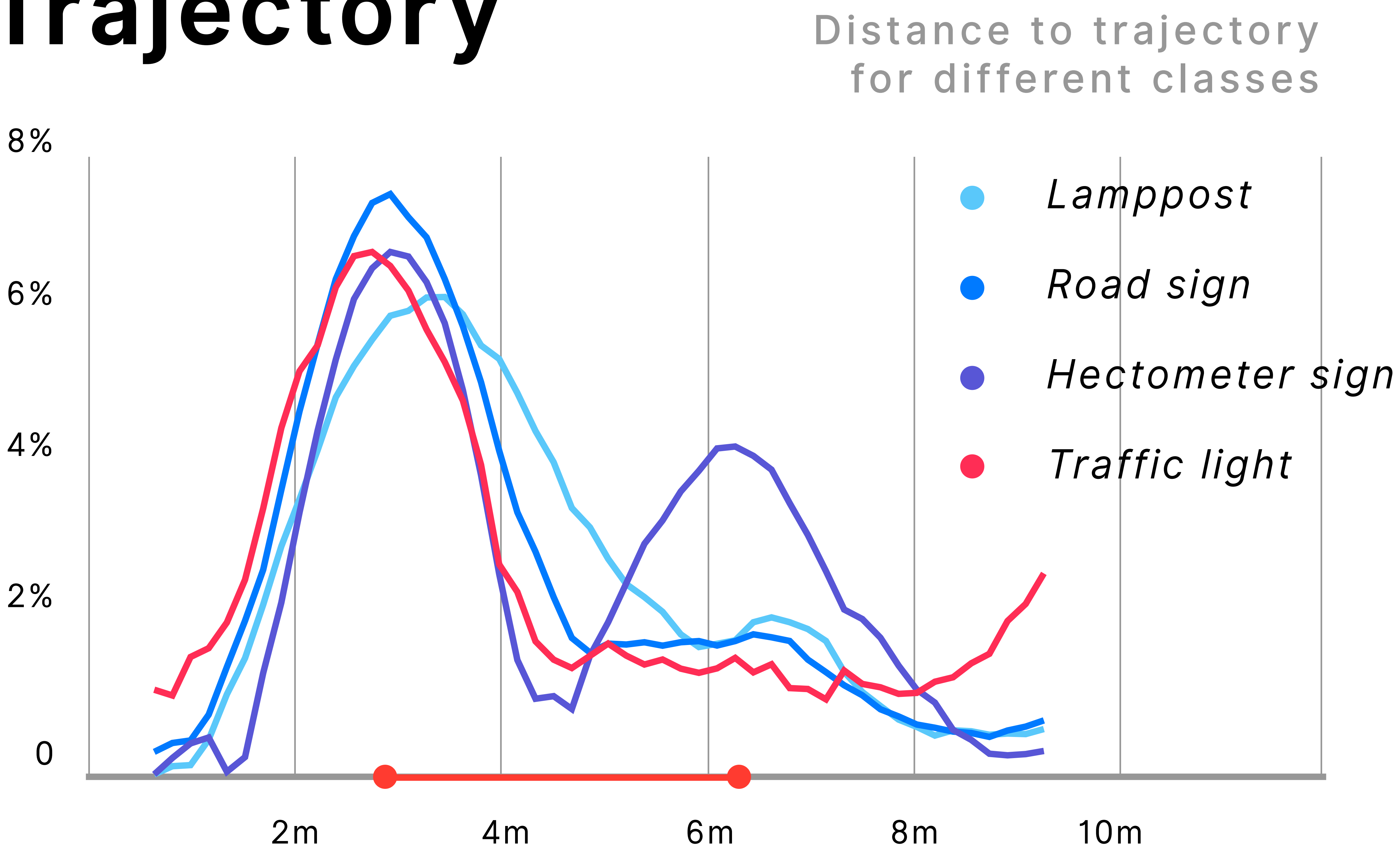
- Training data
- Represent a point
- Select points
- Generalization
- Overall suitability

Attributes

MIOU for different attribute combinations



Trajectory



Distance to trajectory
for different classes
8%
6%
4%
2%
0
Lamppost
Road sign
Hectometer sign
Traffic light
2m
4m
6m
8m
10m

Represent 3D point

spatial reference
Global spatial reference is unique
Trajectory reference is too similar

other attributes
Intensity value contributes to classification accuracy

→ Best representation is local spatial reference with intensity

Results

Training data

Represent a point

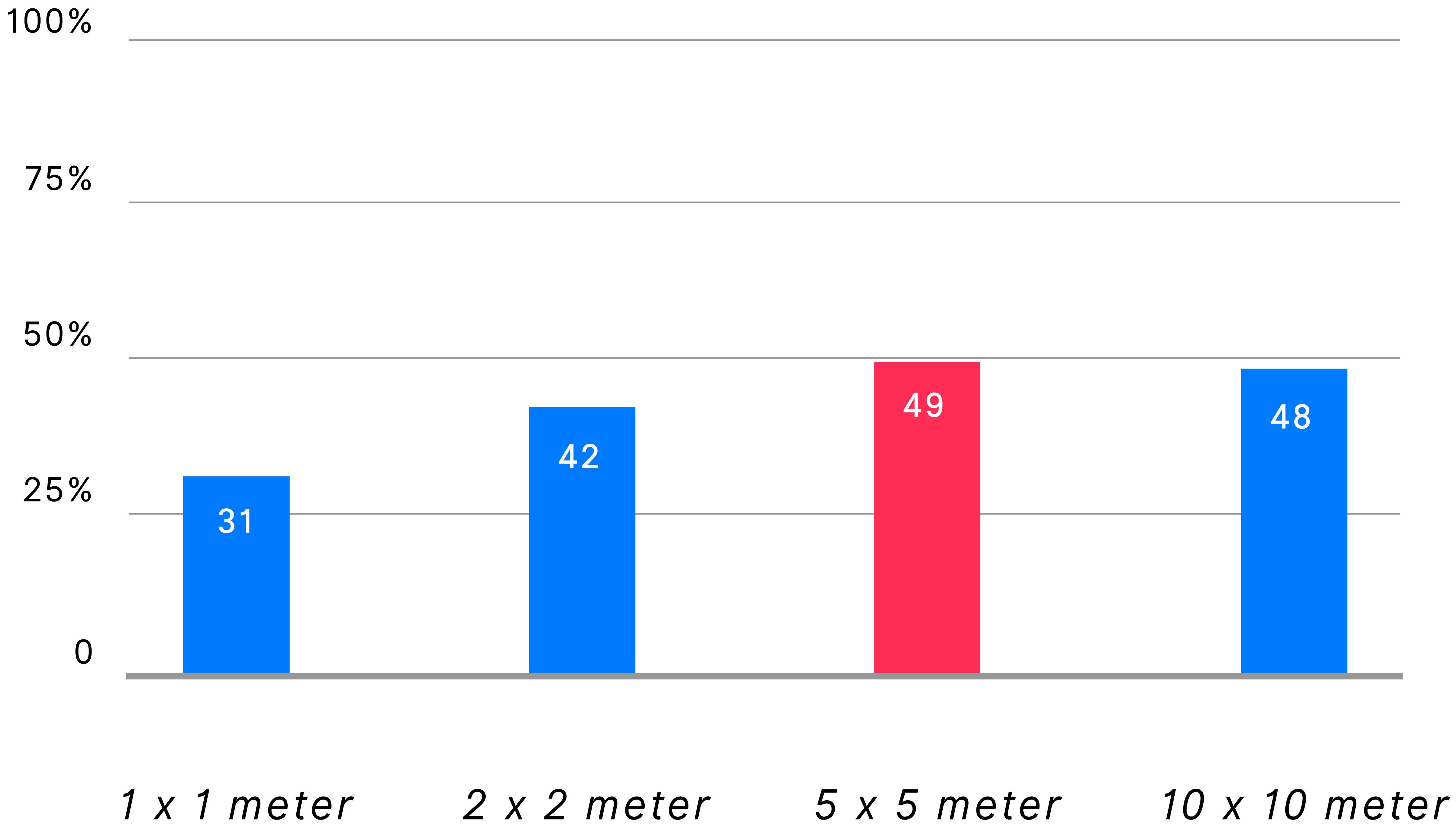
- Select points

Generalization

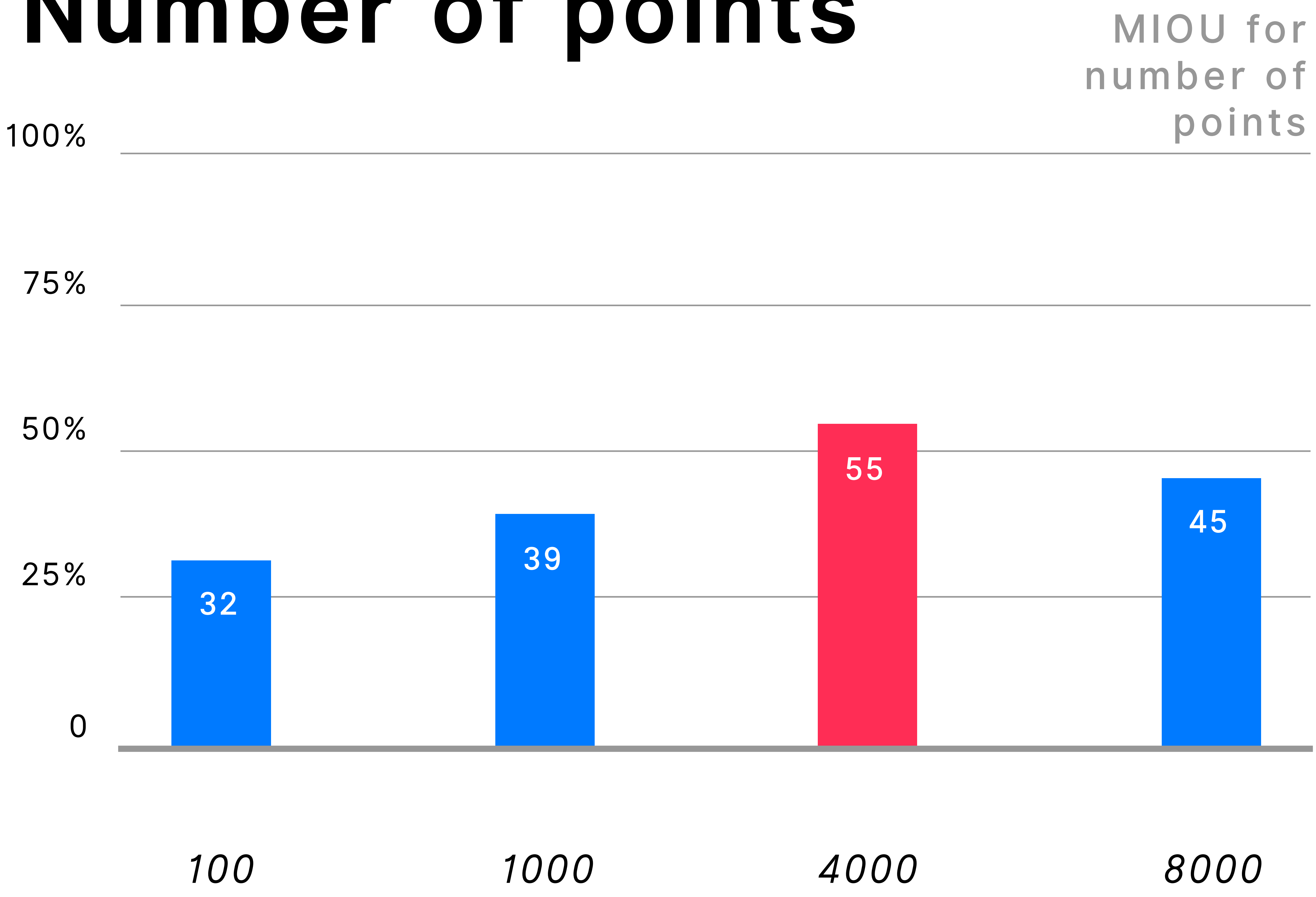
Overall suitability

Grid size

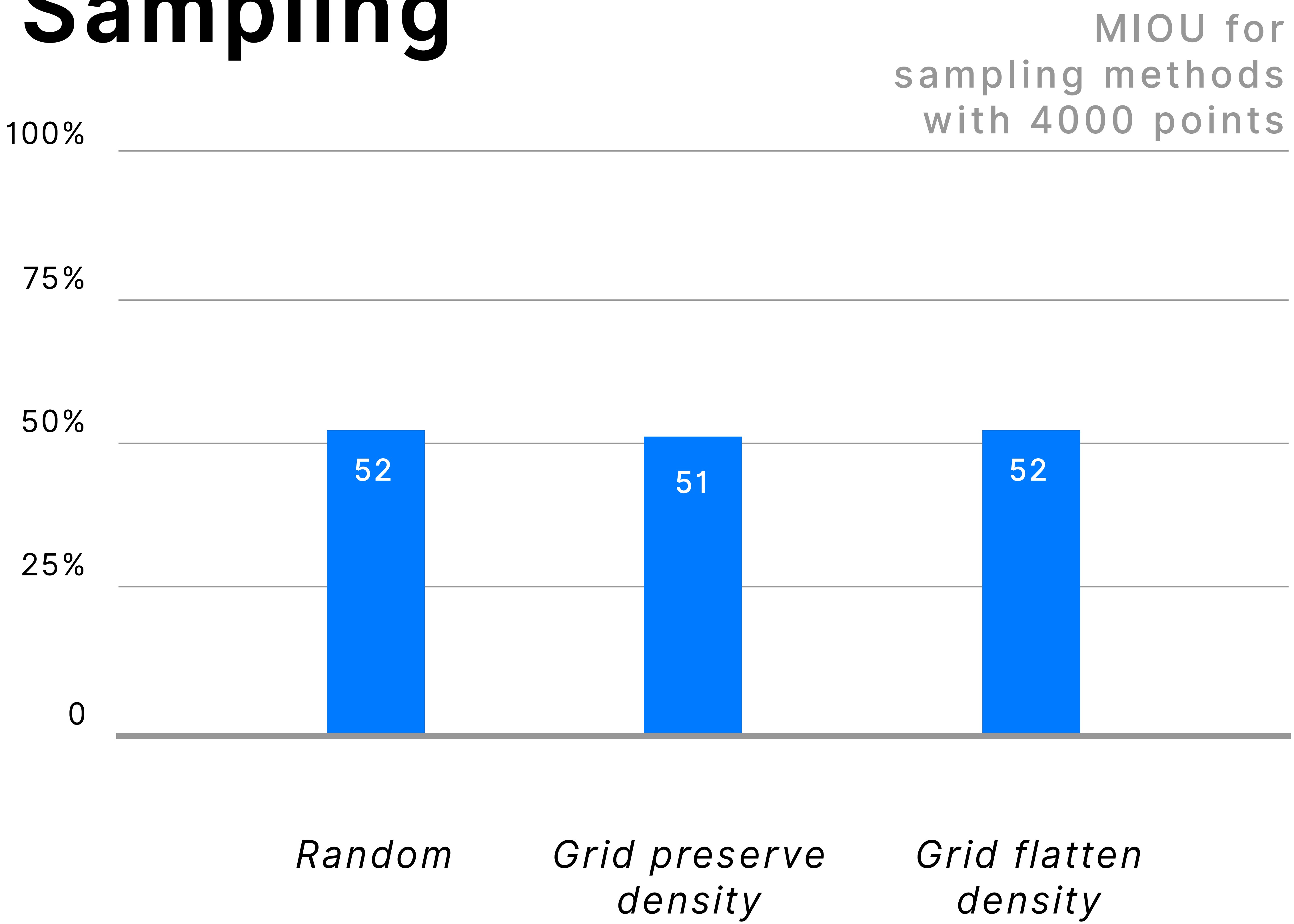
MIOU for multiple grid sizes



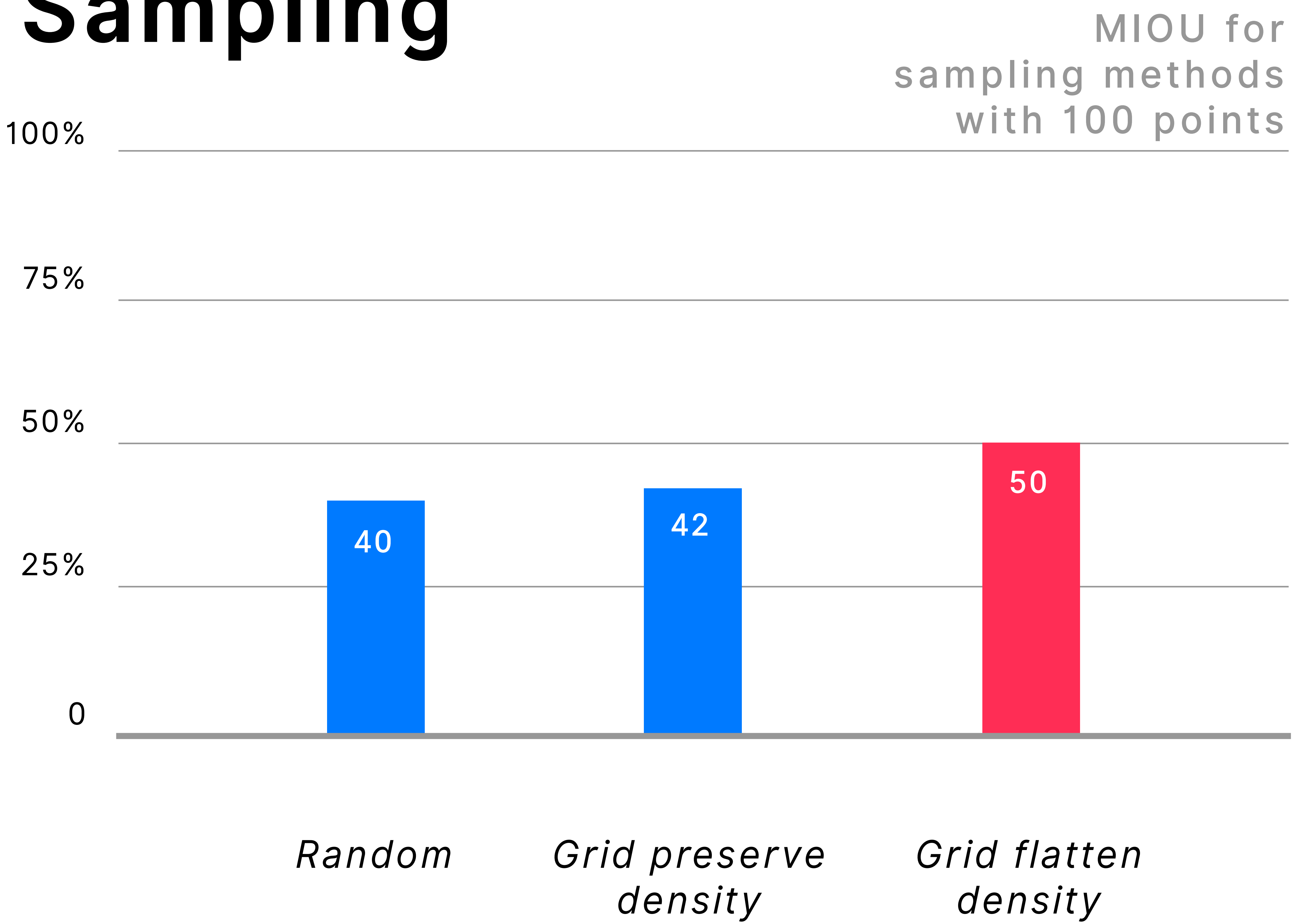
Number of points



Sampling


MIOU for sampling methods with 4000 points
100%
75%
50%
25%
0
52
51
52
Random
Grid preserve density
Grid flatten density

Sampling


MIOU for
sampling methods
with 100 points
100%
75%
50%
25%
0
40
42
50
Random
Grid preserve
density
Grid flatten
density

Sampling of points

grid size
edge cases versus classes per sample

number of points
unique points versus class balance

sampling method
only for small number of points

→ Best are samples of 5 by 5 meter,
4000 points and random sampling

Results

Training data

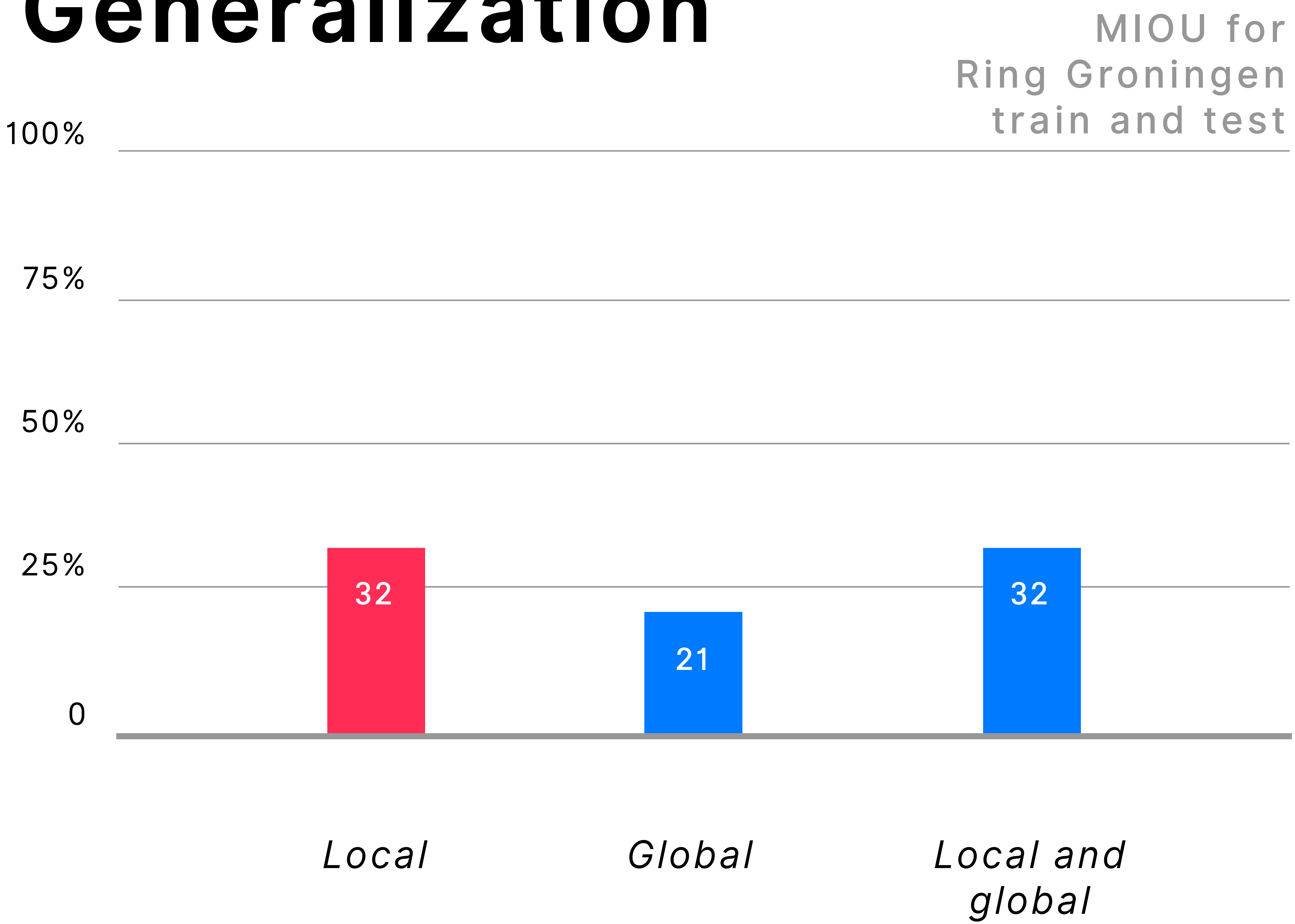
Represent a point

Select points

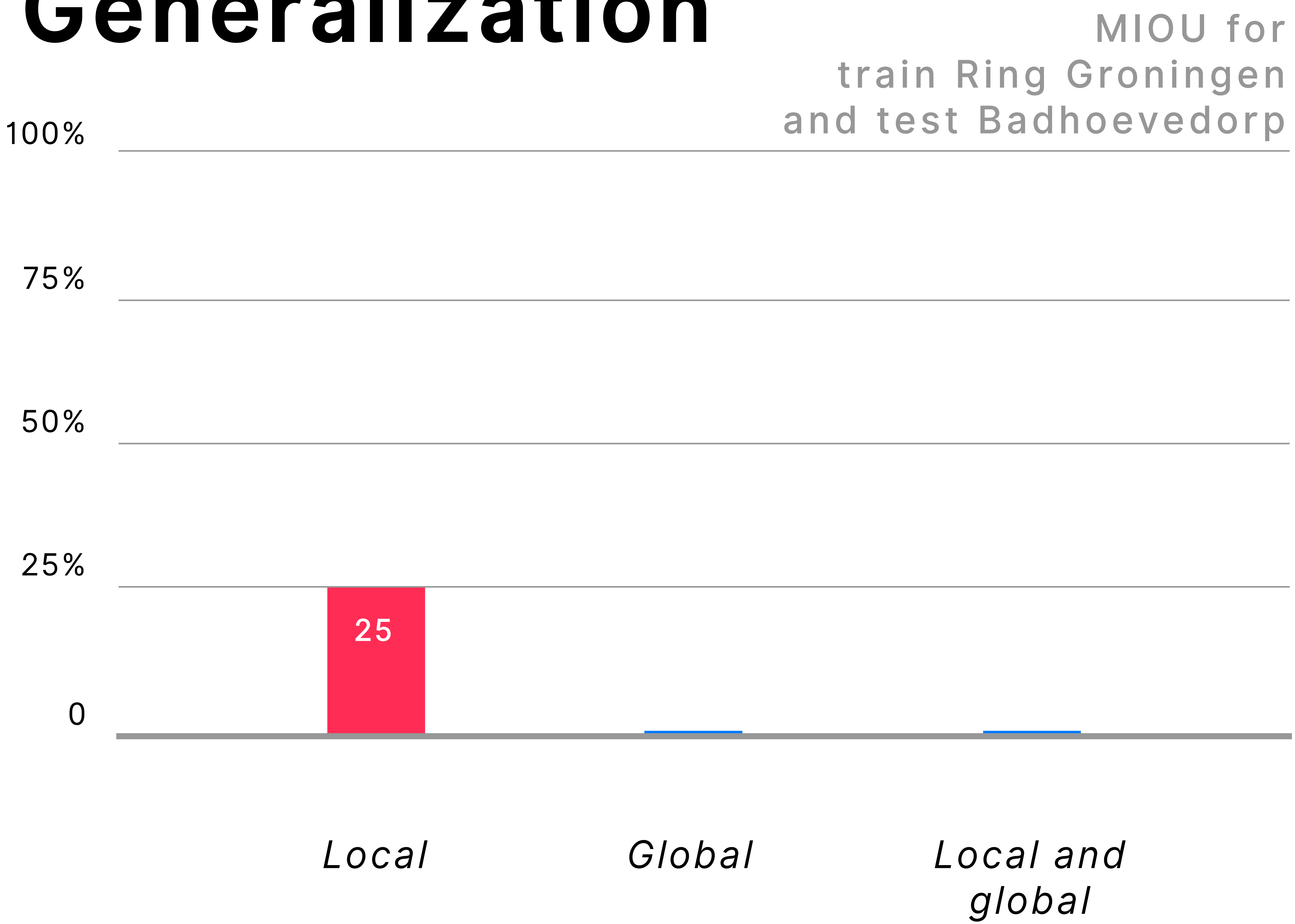
- Generalization

Overall suitability

Generalization



Generalization



Generalization

global reference
does not generalize, is unique

local reference
does generalize, decrease in performance
due to moment of acquisition

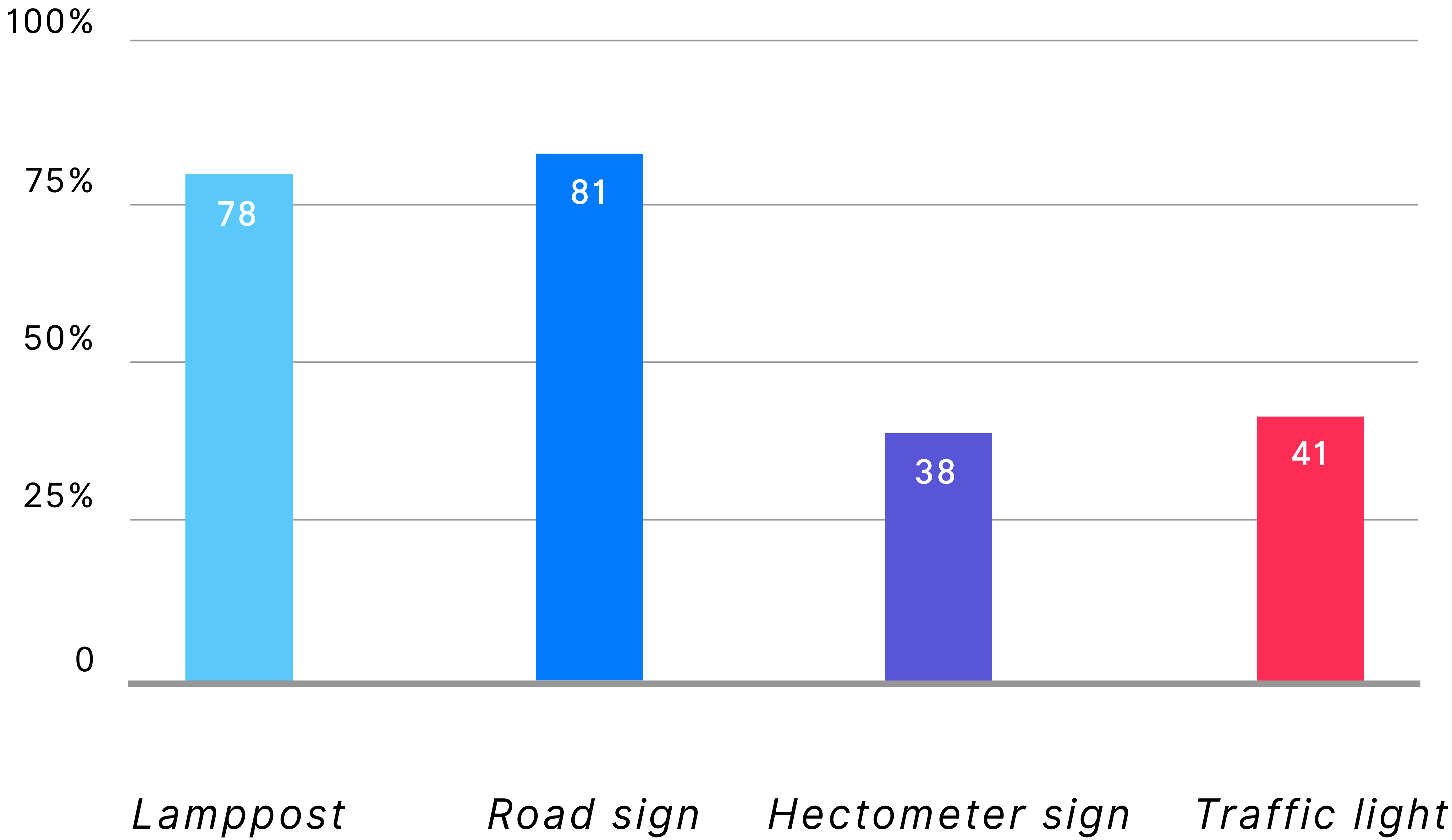
→ Model based on location reference
generalizes to other locations

Results

- Training data
- Represent a point
- Select points
- Generalization
- Overall suitability

Suitability

IOU per class



Suitability

Confusion matrix
point classification percentage

		Lamppost	Road sign	Hectometer sign	Traffic light	Background
Lamppost	.5M	78	9	0	0	11
Road sign	.2M	3	81	1	4	9
Hectometersign	63K	0	22	38	1	37
Traffic light	28K	13	8	0	41	37
Background	1.6M	5	2	0	1	90

Suitability

Confusion matrix
final mapping counts

		Lamppost	Road sign	Hectometer sign	Traffic light	Missing
Lamppost	151	78	16	1	2	2
Road sign	87	19	63	6	9	1
Hectometersign	62	3	30	58	5	2
Traffic light	13	11	22	0	44	22

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Summary

→ Usable training samples can be created

→ Best representation is local spatial reference with intensity

→ Best take samples of 5 by 5 meters, 4000 points and random sampling

→ Local reference generalizes to other locations

Conclusion

To what extent is PointNet suitable for classification of raw point clouds of a highway scene?

→ With the presented methodology PointNet is able to predict **50% MIOU point-wise** and **60% of object locations**.

A succesful exploration of PointNet directly on outdoor point clouds with many opportunities for improvement.

Overview

Topic

Relevance

Method

Results

Conclusion

- Recommendations

Recommendations

1. Refine the current methodology
2. Broaden research and results
3. Upgrade the model

Refine

- → Divide classes into hierarchy of more specific classes
- → Ground filtering
- → Additional “augmentation”, like multi-sampling
- → Clustering

Broaden

- → Tune the model architecture and learning hyper-parameters
- → Use of additional attributes (e.g. RGB)
- → Apply methodology to open data sets

Upgrade

- → new deep learning models implement multiple scales of local neighbourhoods
- → Semi-supervised learning

Thanks!

Tom Hemmes

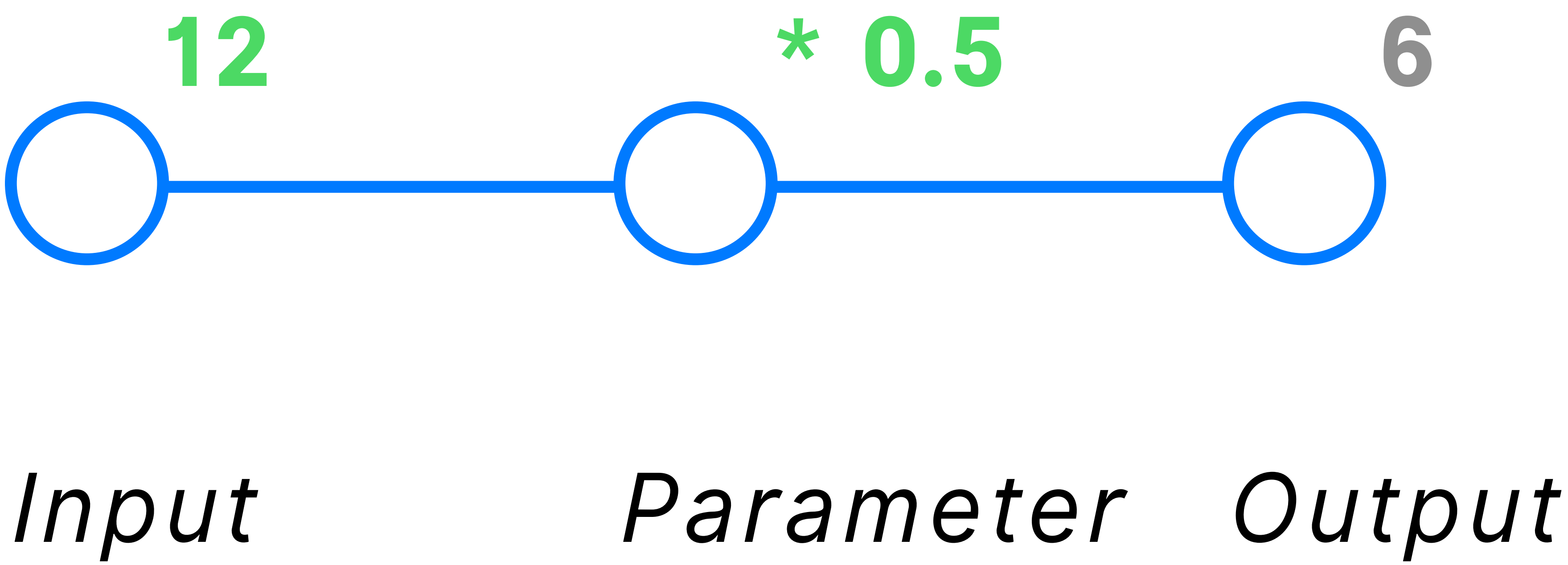
Mathias Lemmens
TU Delft, Geomatics

Maarten Kruithof
TNO, Intelligent Imaging

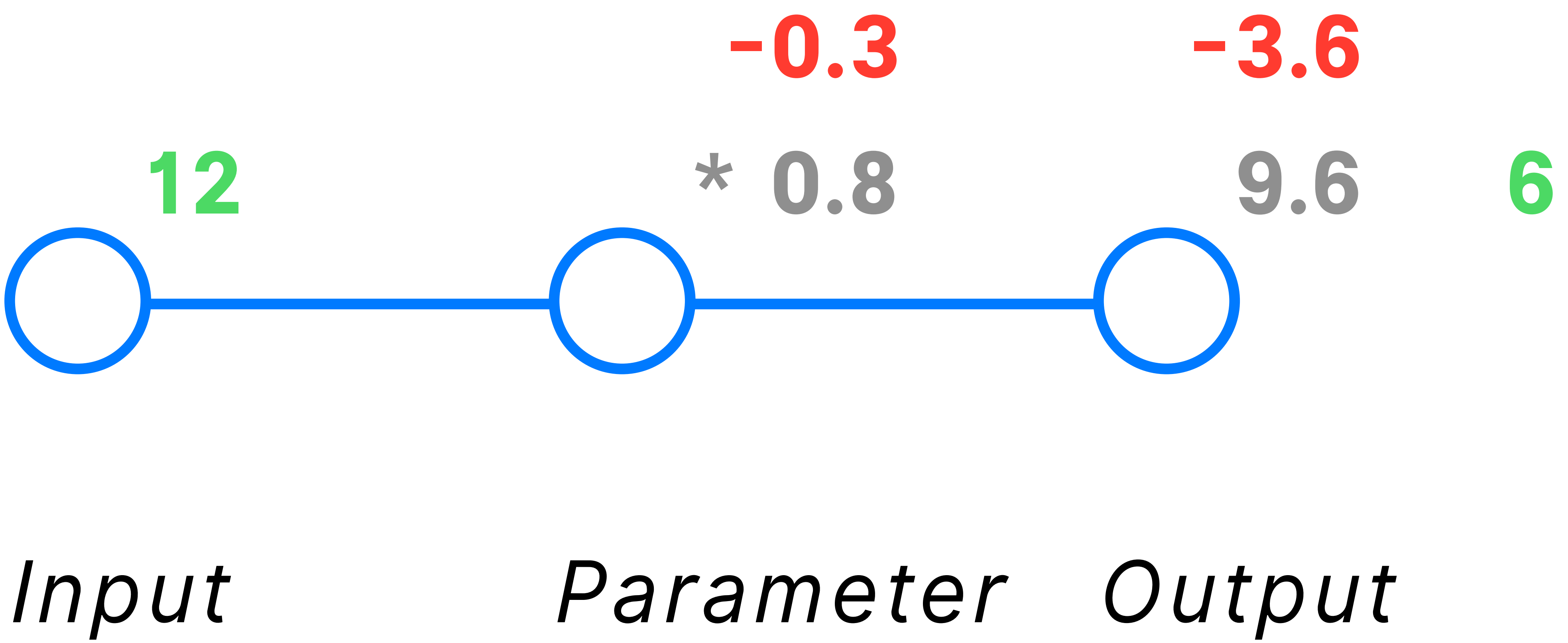
Peter van Oosterom
TU Delft, Geomatics

Kaixuan Zhou
TU Delft, Remote sensing

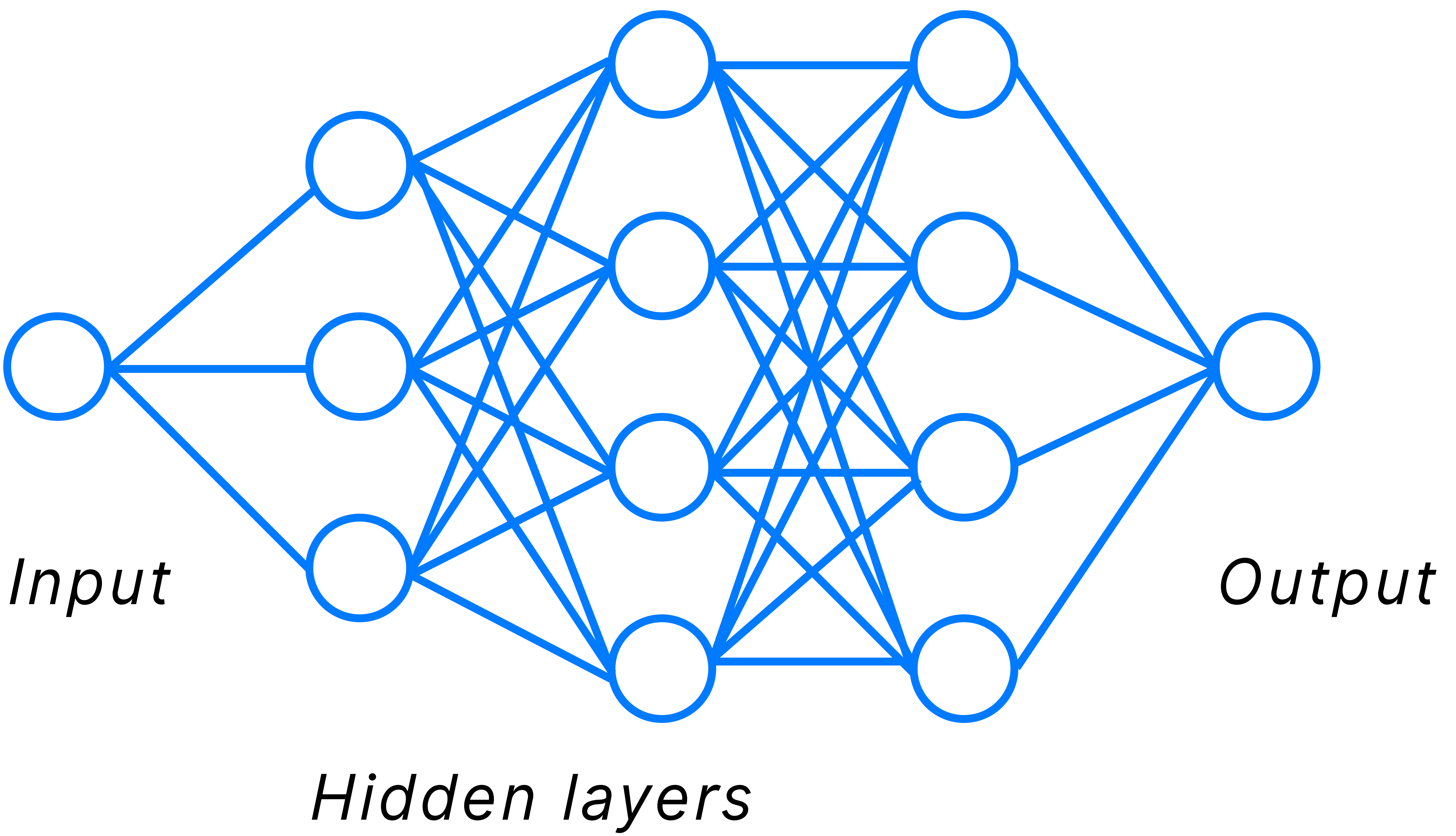
Algorithm



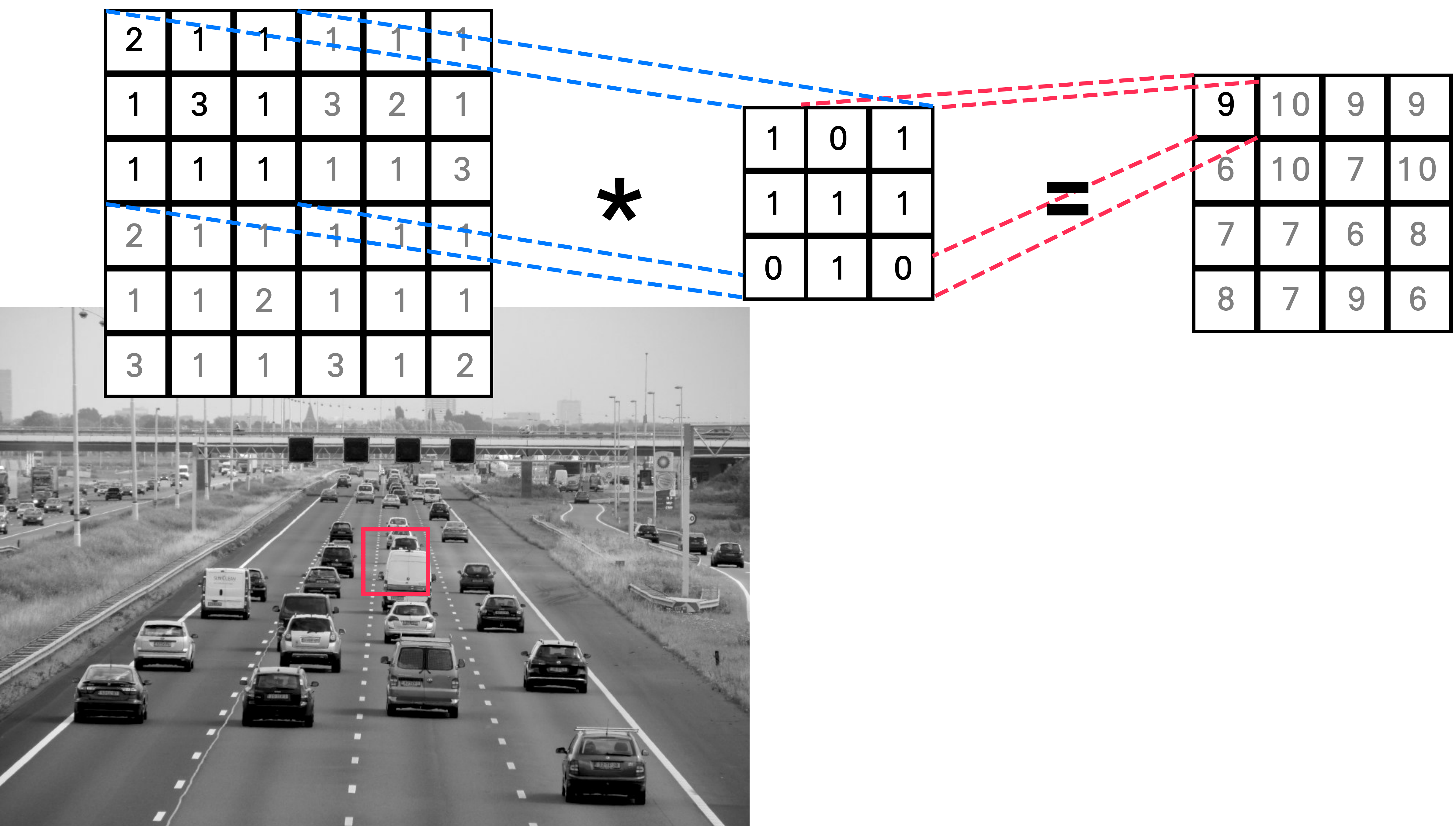
Learning algorithm



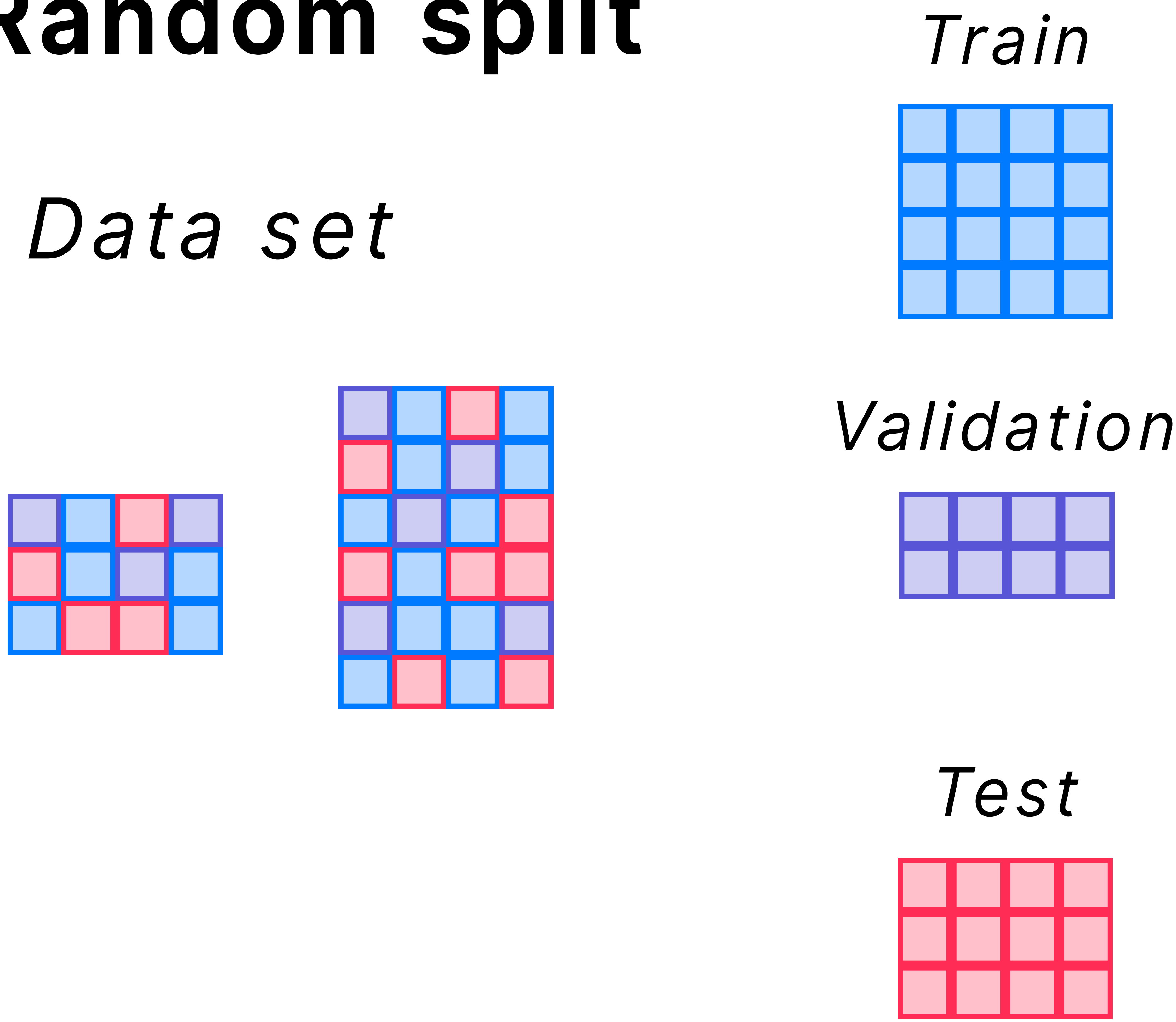
Deep learning



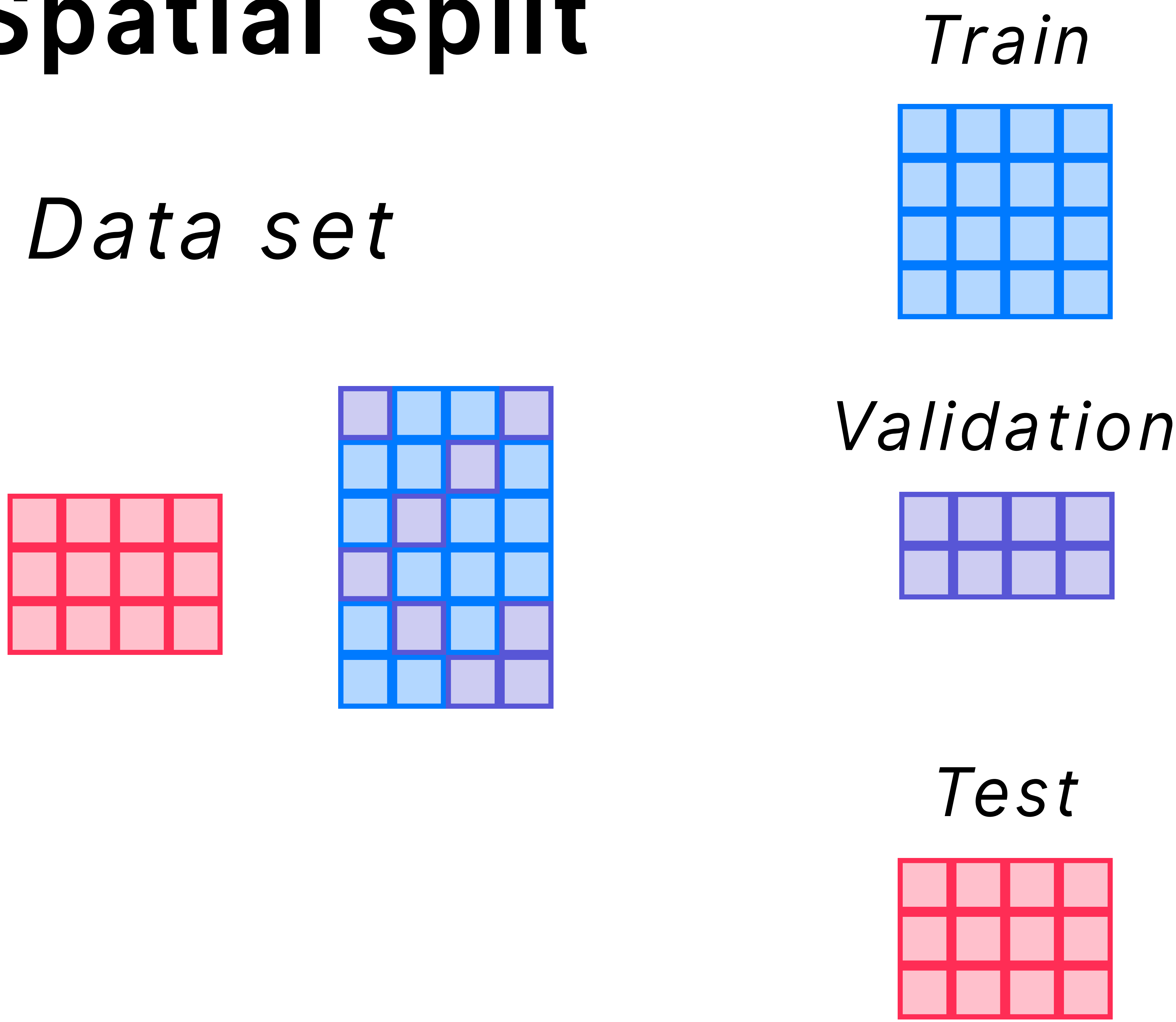
Convolutional Neural Network



Random split



Spatial split



Accuracy measure

IOU

for a specific class

$$\frac{\text{correct labels}}{\text{all points}} * 100$$

MIOU

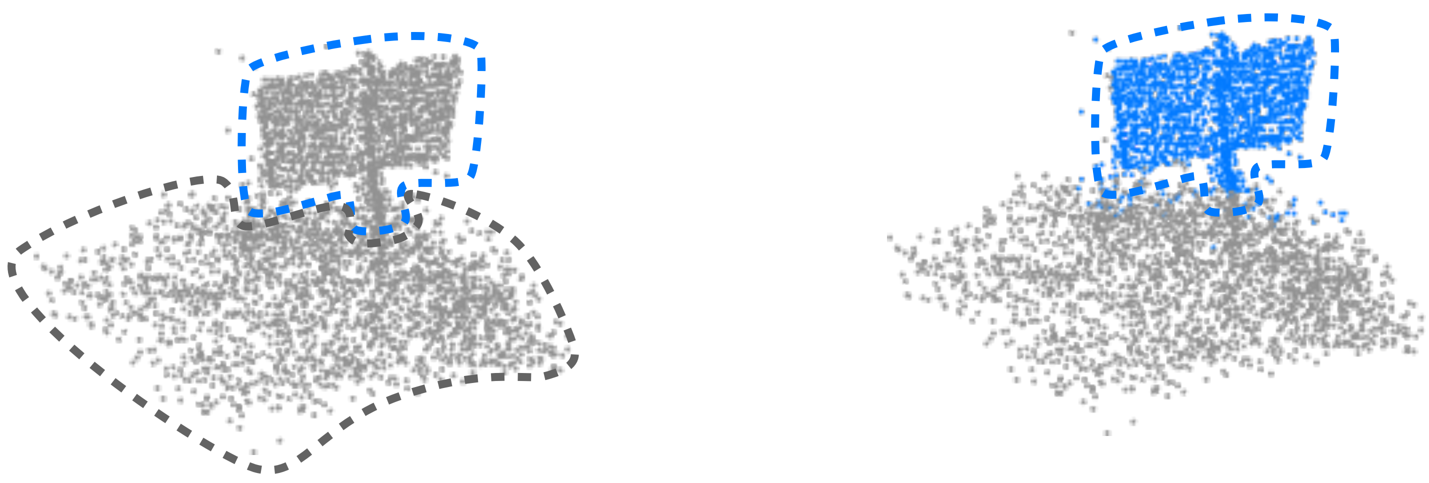
average of all classes

$$\frac{\text{IOU1 + IOU2 ...}}{\text{number of classes}}$$

Classification

Point-wise

Object



Classification

Point-wise

\+ directly on point cloud *

\- poor neighbourhood definition

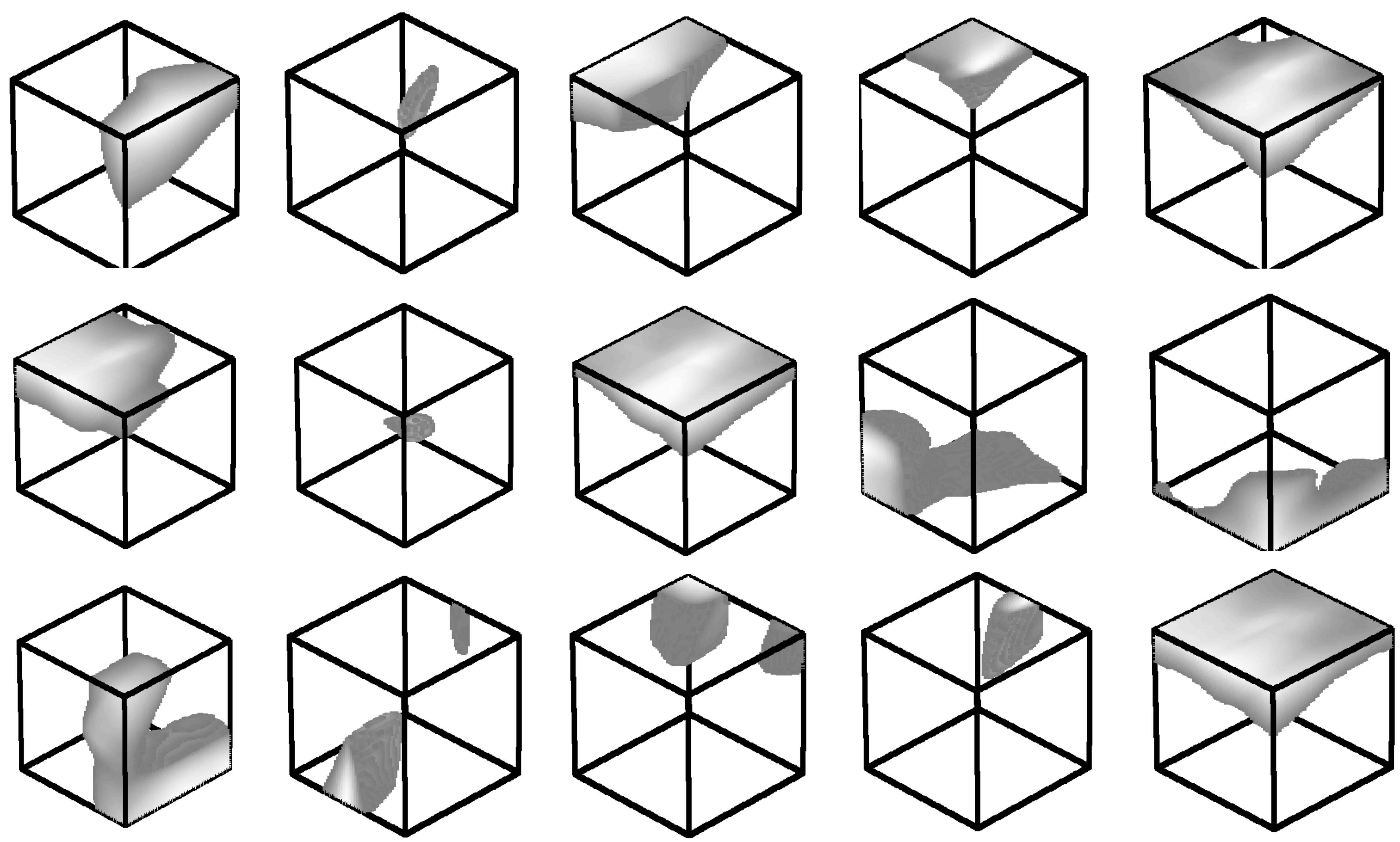
Object

\- requires segmentation *

\+ use of all points for classification

PointNet kernels

Kernel with activation region



Charles Qi, et al. 2016

Time of acquisition

Season

lower density of vegetation during winter

Weather

backscatter from snowflakes or water droplets

Rasshofer, et al. 2011

Artificial Intelligence

Machine Learning

Deep Learning