Towards Federated Fleet Learning Leveraging Unannotated Data

Master's thesis in Data Science & AI

Alexander Viala Bellander & Yazan Ghafir

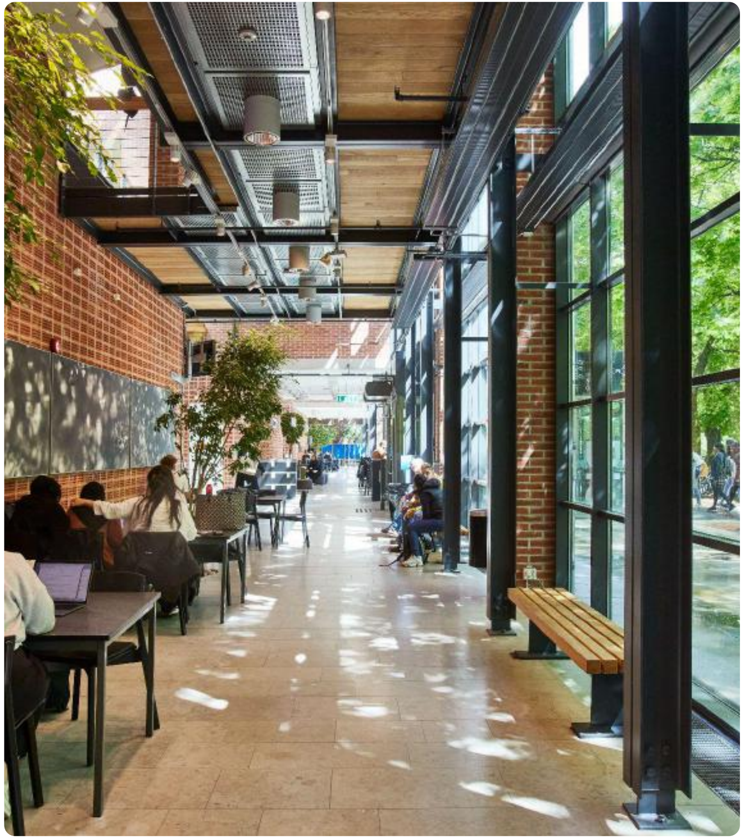
Heeey 👋

This is our research team

Alexander Viala Bellander
Datateknik, MPDSC

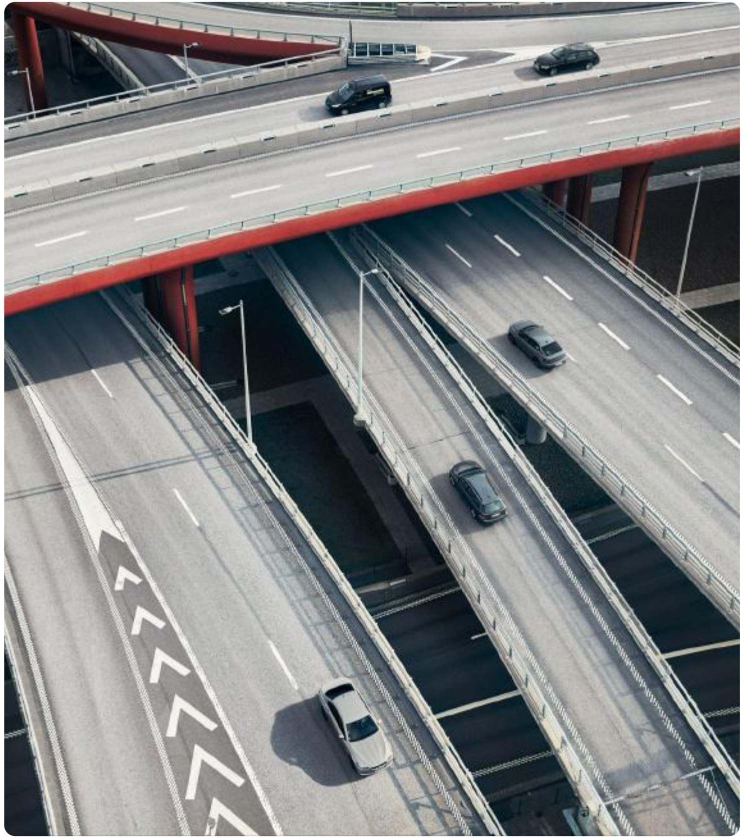
Yazan Ghafir
Informationsteknik, MPDSC

Supporting us are:



Our thesis is about
Federated Learning (FL) in the autonomous driving domain

- Is FL feasible?
- Can we leverage unlabelled data?
- Does semi-, self-, and/or unsupervised methods support the implementation of FL?



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Agenda and Outline

- Introduction
- Background
- Trajectory Prediction

- Road Segmentation
- FL in AD Discussion
- Conclusion

Before we begin with the motivation for our research

Let's begin by clarifying some key definitions.

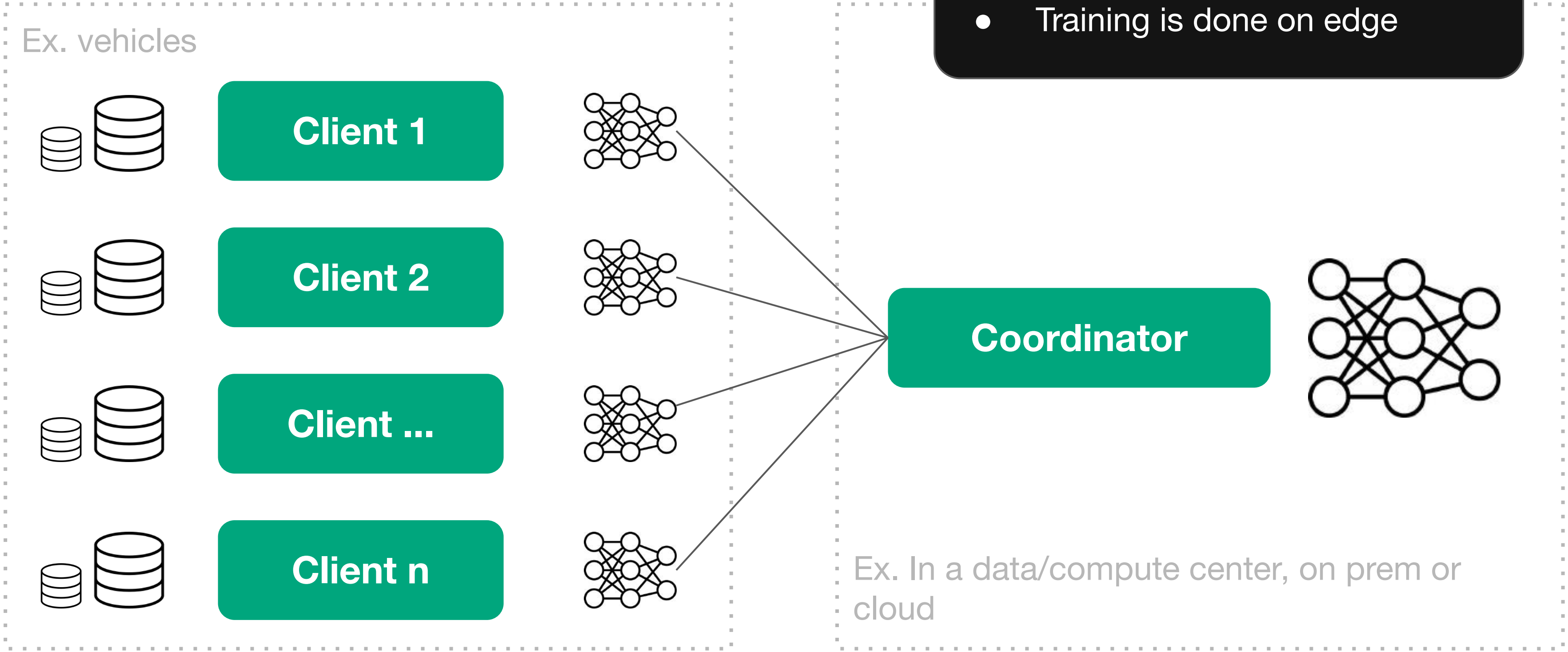
Centralised Learning

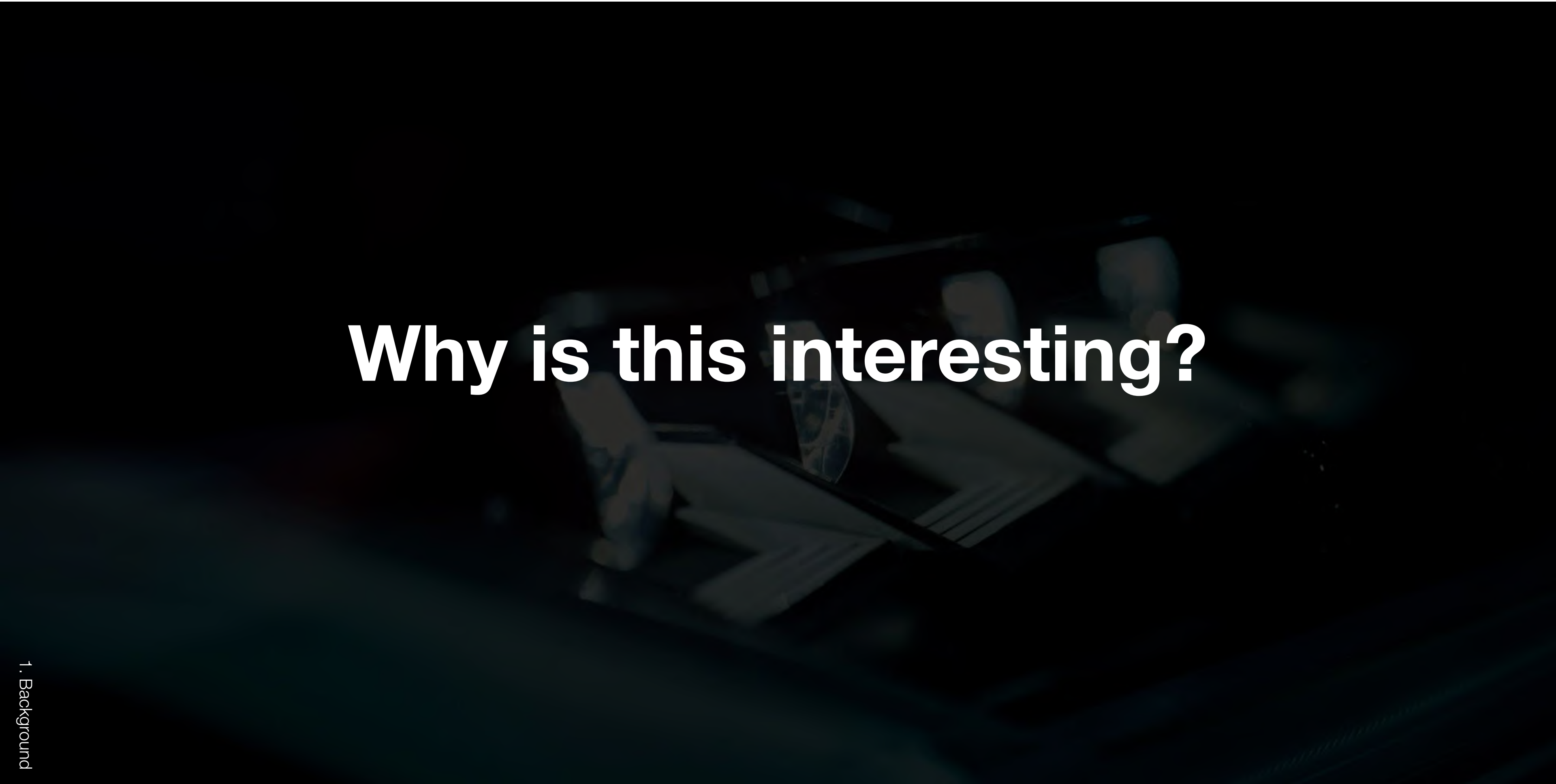
- Data must be transferred to centralised storage
- Training is done centrally

Ex. In a data/compute center, on prem or cloud

Federated Learning

- Data never leaves the clients
- Training is done on edge



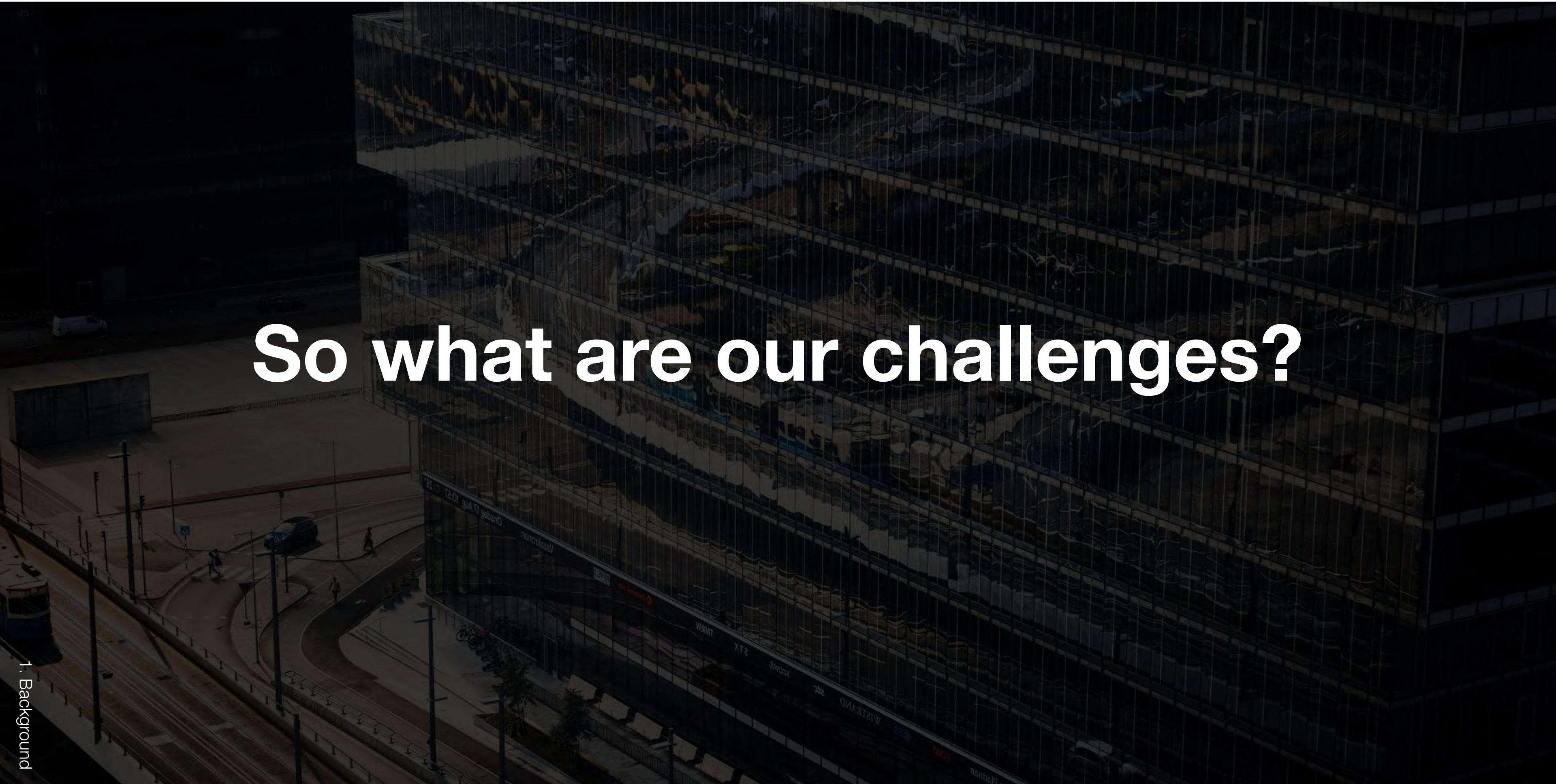


Why is this interesting?

The benefits of FL

Federated learning allows collaborative machine learning without sharing raw data.

- Promising for driver monitoring systems.
- Collaborative learning across different devices or entities.
- Beneficial in regulatory constrained environments.

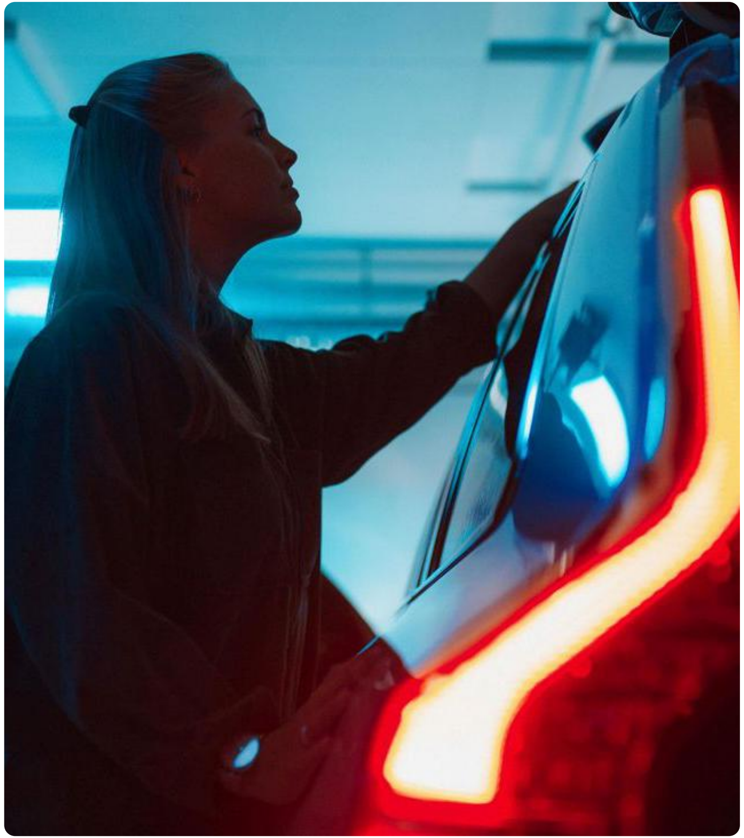


So what are our challenges?

The data must not leave the vehicle, yet is should learn

How do we train ML models with data generated by the car, on the car?

- Label generation on the car is non-trivial
- Limited resources on the vehicle
- Unlabelled data in varying distributions

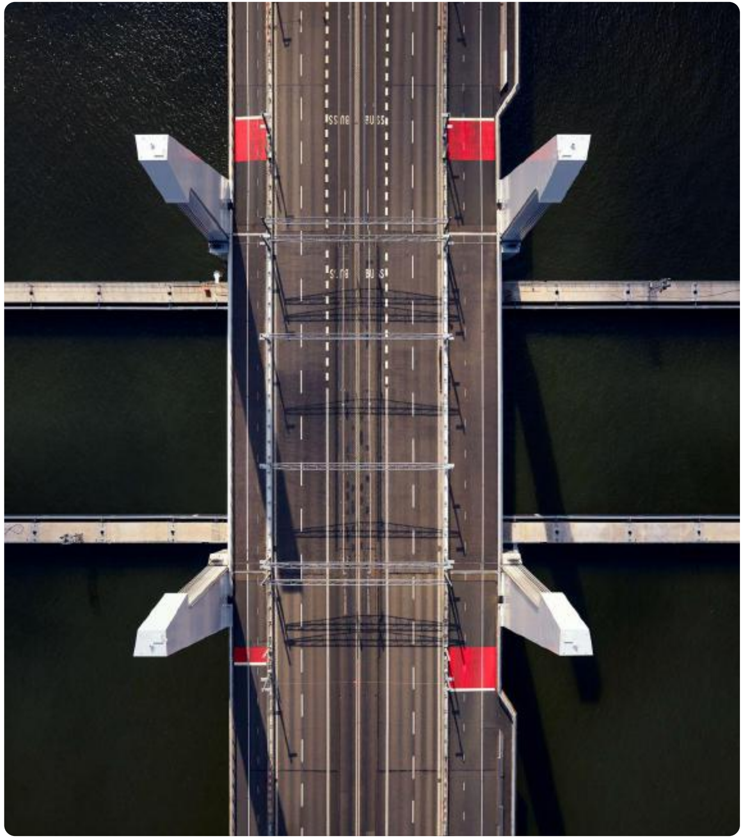


Our methods

- Twofold experiment where an AD ML model is trained on edge on vehicle generated data.

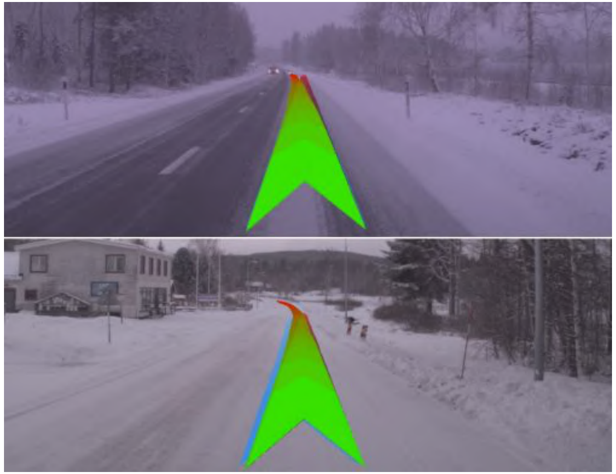
- Different benchmarks
  - Central
  - Federated
  - Isolated

- Compare to understand feasibility.



Our experiments and AD ML tasks

Trajectory Prediction
Approach: Imitation learning



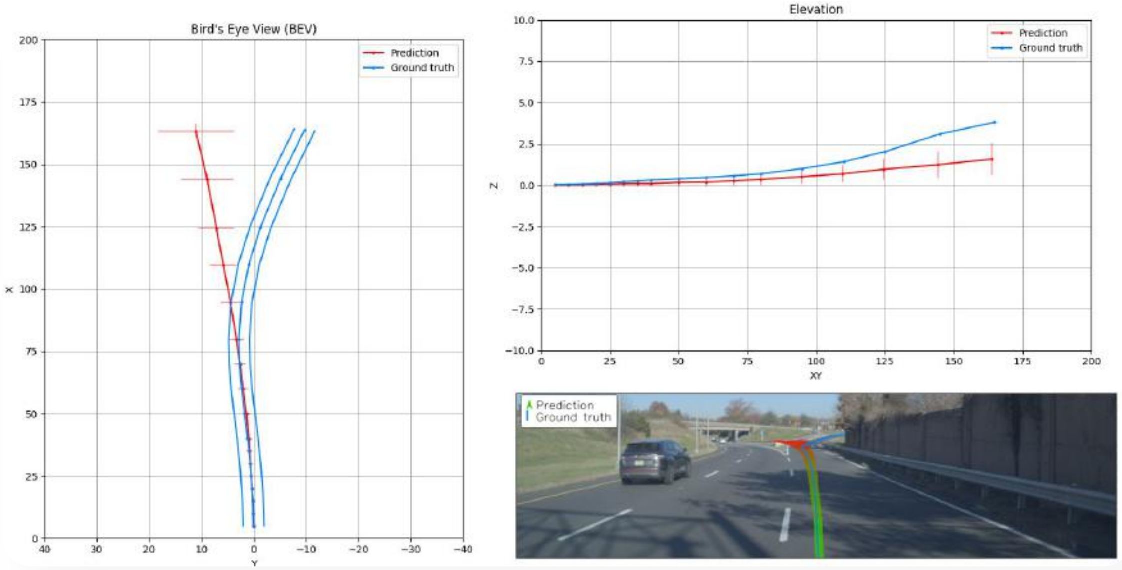
Road segmentation
Approach: Semi-supervision

Trajectory Prediction

Label auto-extraction, supervision, federated learning, centralised learning, isolation

Trajectory Prediction

Goal: Predict the future path of the vehicle from an image.



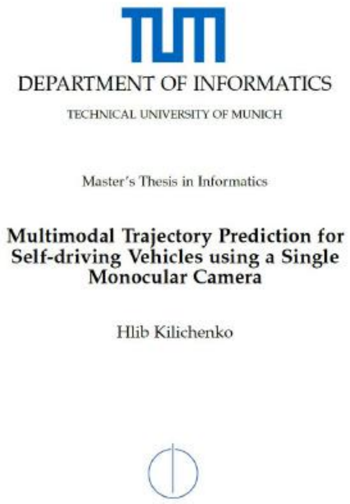
Uses high precision GNSS/Inertial (OXTS)

Train: 1635 images
Val: 3453 images

Scaled imgsize: 182x68

We based our method heavily on previous MSc work

Kilichenko & Khakhlyuk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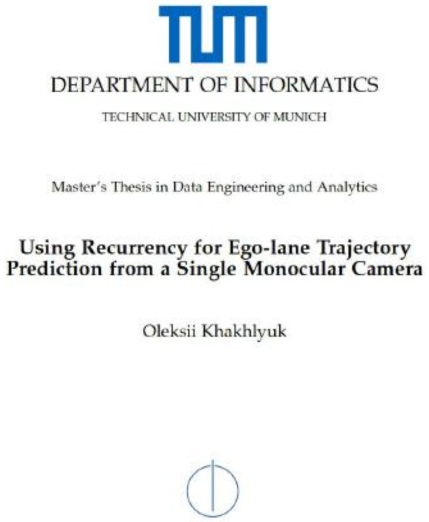
Master's Thesis in Informatics

Multimodal Trajectory Prediction for Self-driving Vehicles using a Single Monocular Camera

Hlib Kilichenko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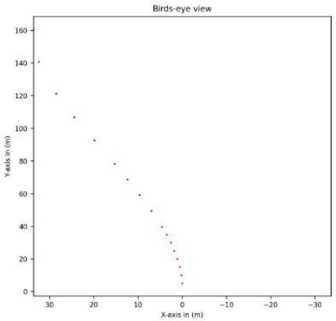
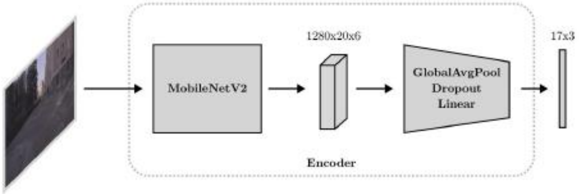
Master's Thesis in Data Engineering and Analytics

Using Recurrency for Ego-lane Trajectory Prediction from a Single Monocular Camera

Oleksii Khakhlyuk





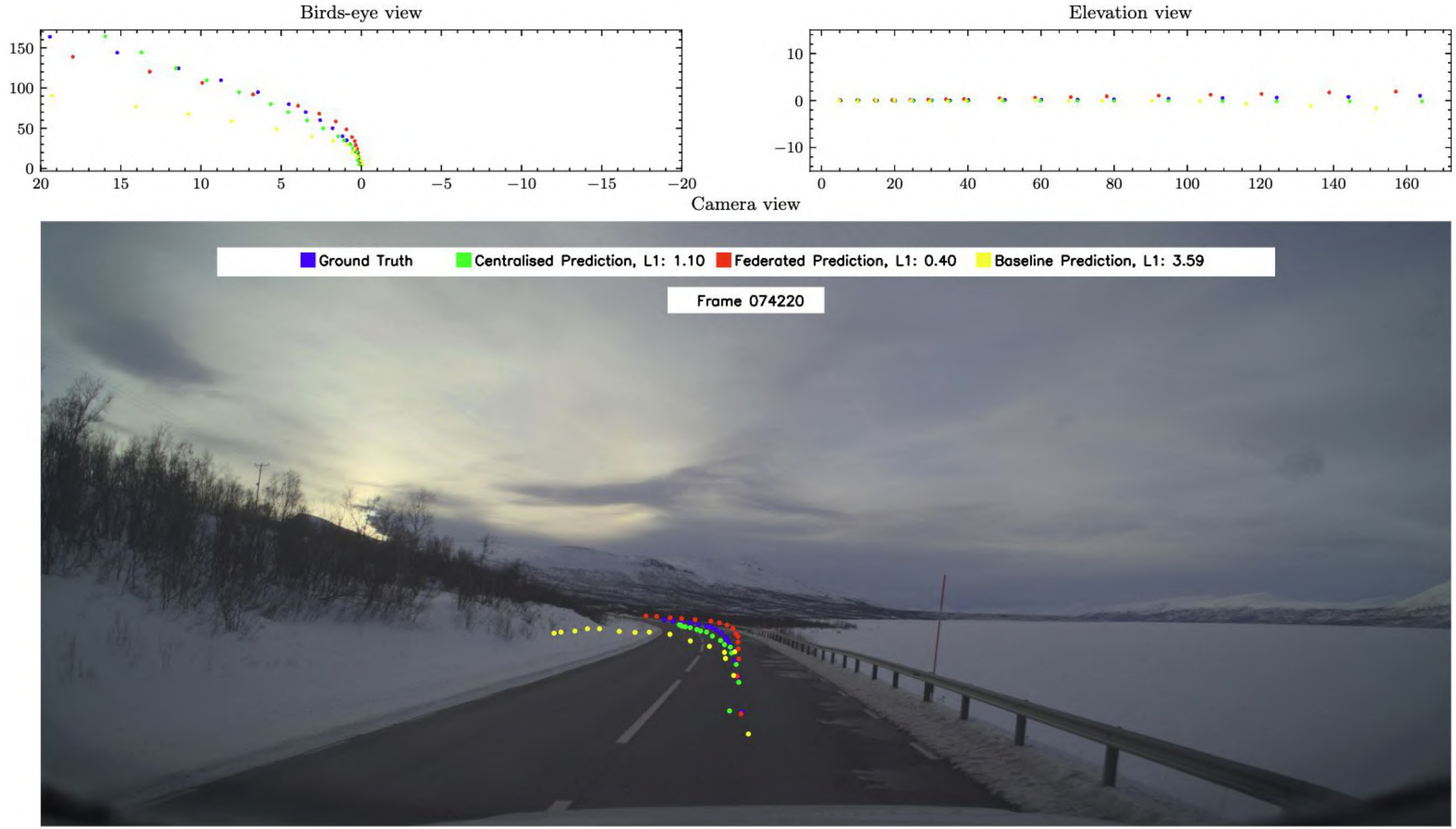
The trajectory prediction task

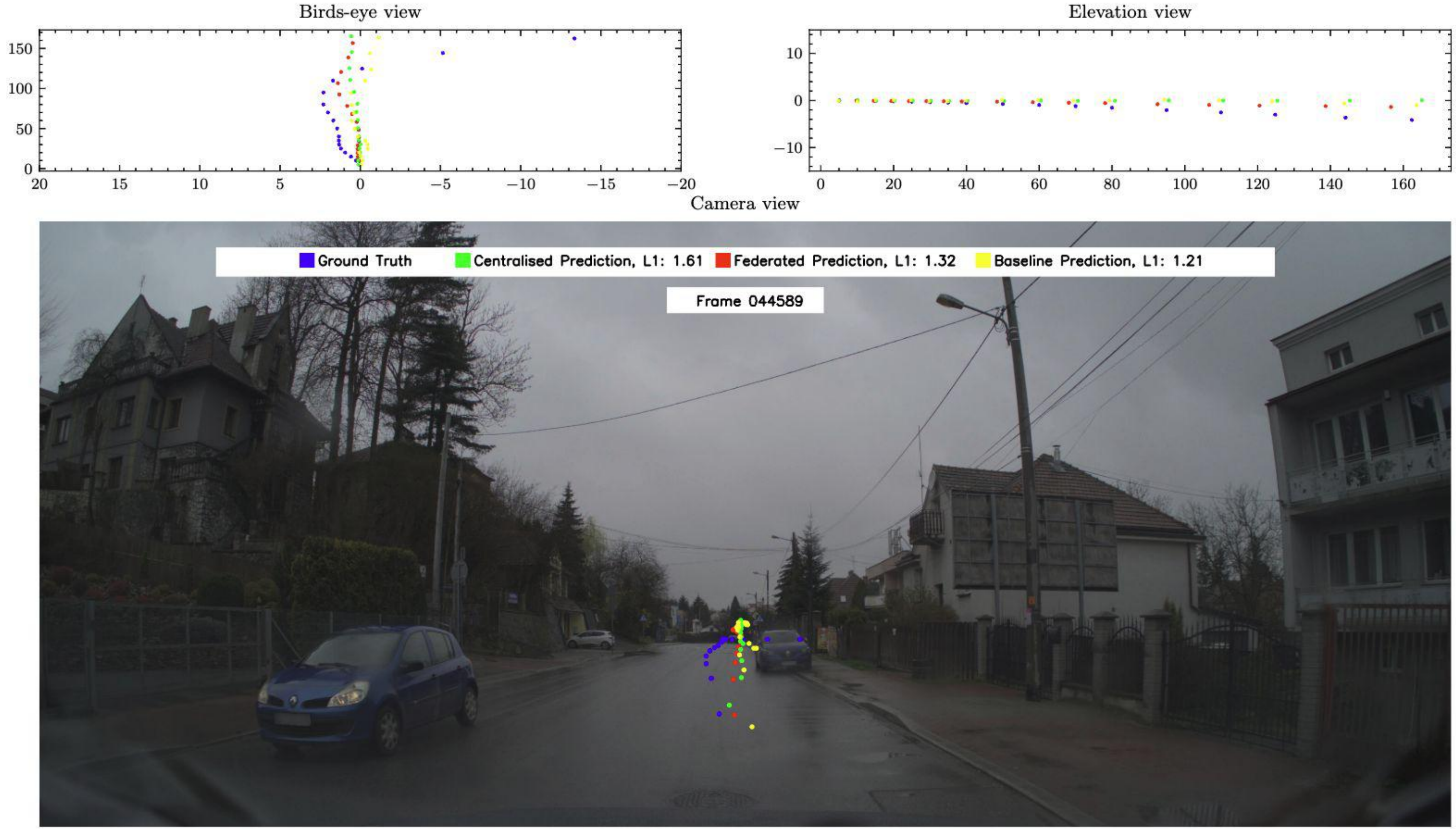
A regression problem.
- Image as input
- 17x3 vector as output (17 xyz points)

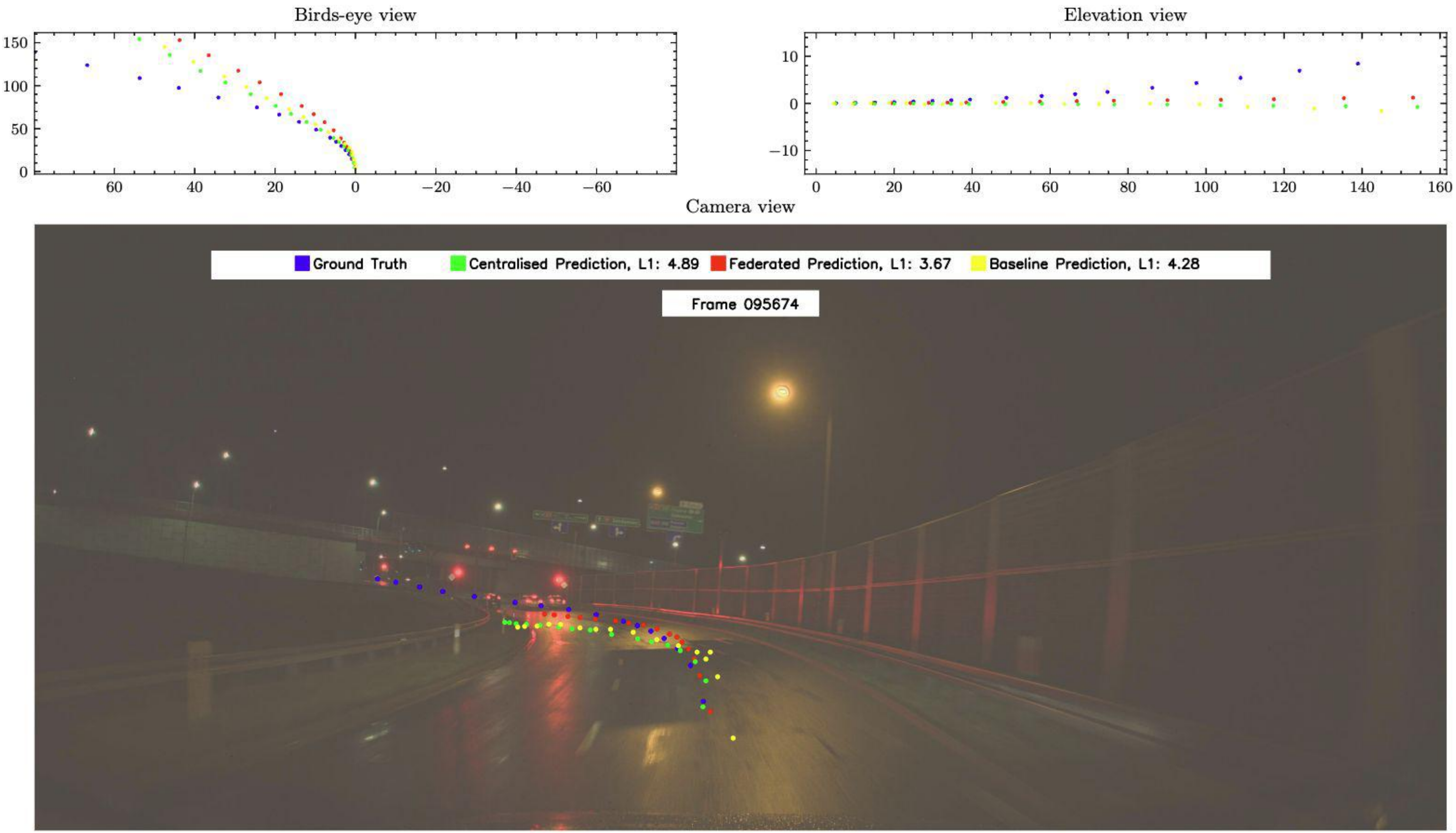
L1 loss for training and evaluation
- Validation set is also our test set

We balance the dataset from categories {left, straight, right}

Clients sample from the same distribution, IID assumption


Birds-eye view
Elevation view
Camera view
Ground Truth
Centralised Prediction, L1: 1.10
Federated Prediction, L1: 0.40
Baseline Prediction, L1: 3.59
Frame 074220


Birds-eye view
150
100
50
0
20 15 10 5 0 −5 −10 −15 −20
Elevation view
10
0
−10
0 20 40 60 80 100 120 140 160
Camera view
Ground Truth
Centralised Prediction, L1: 1.61
Federated Prediction, L1: 1.32
Baseline Prediction, L1: 1.21
Frame 044589


Birds-eye view
Elevation view
Camera view
Ground Truth
Centralised Prediction, L1: 4.89
Federated Prediction, L1: 3.67
Baseline Prediction, L1: 4.28
Frame 095674

Results

Benchmark comparison

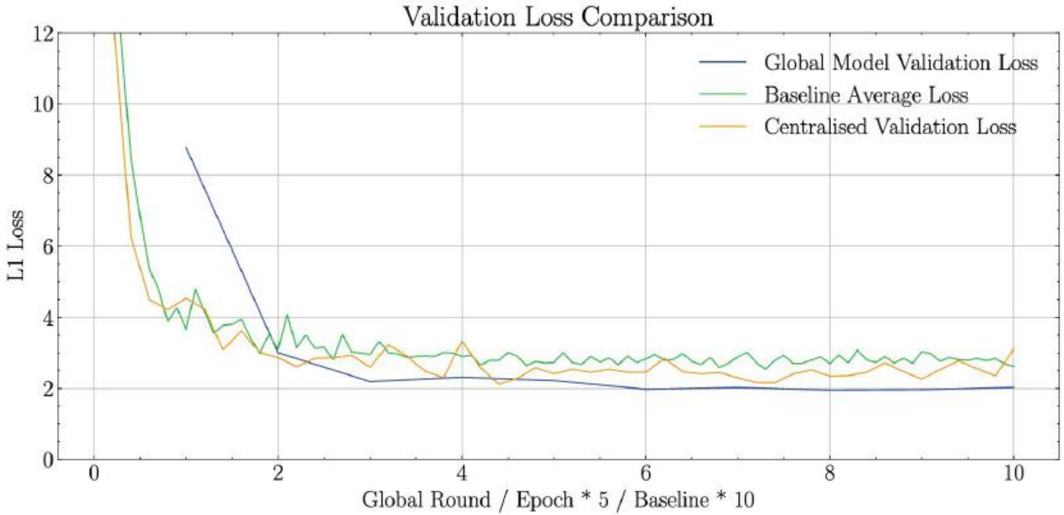


Table 3.1: Model Evaluation Metrics

Model	min L1
Centralised Traditional Machine Learning (ML)	2.12
Federated Learning (Global Model)	**1.95**
Local Centralised Machine Learning (Baseline)*	2.54

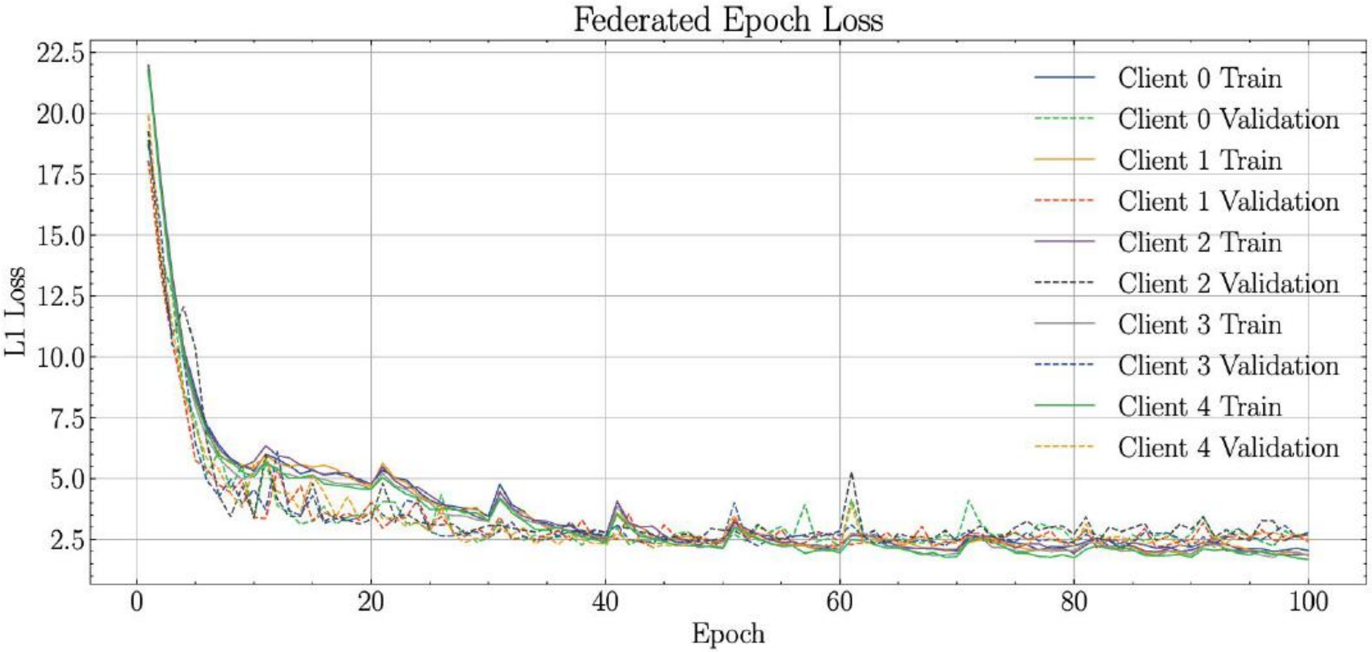
*This refers to the mean value of the lowest validation losses recorded for each individual client.

Similar curves

Uses the same validation set

Results

Federated learning results



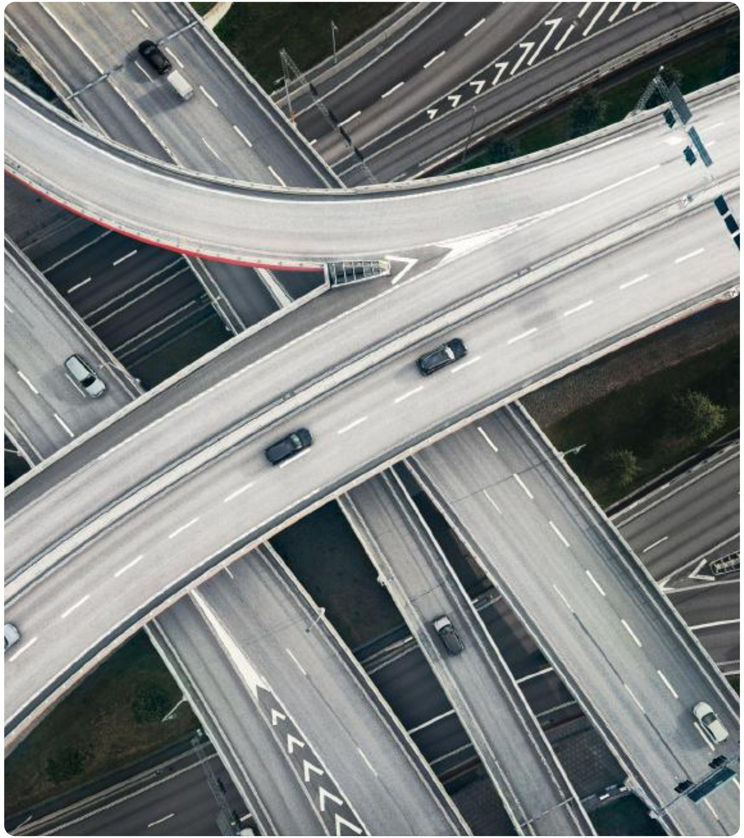
Concluding Trajectory Prediction

This is what we've learned.

- FL is applicable for trajectory prediction
- FL provides comparable accuracy
- Uses only on-car generated data

We recognise

- Simplification of the problem
- Non-IID



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Coming up

- Introduction
- Theory
- Trajectory Prediction

- Road Segmentation
- FL in AD Discussion
- Conclusion

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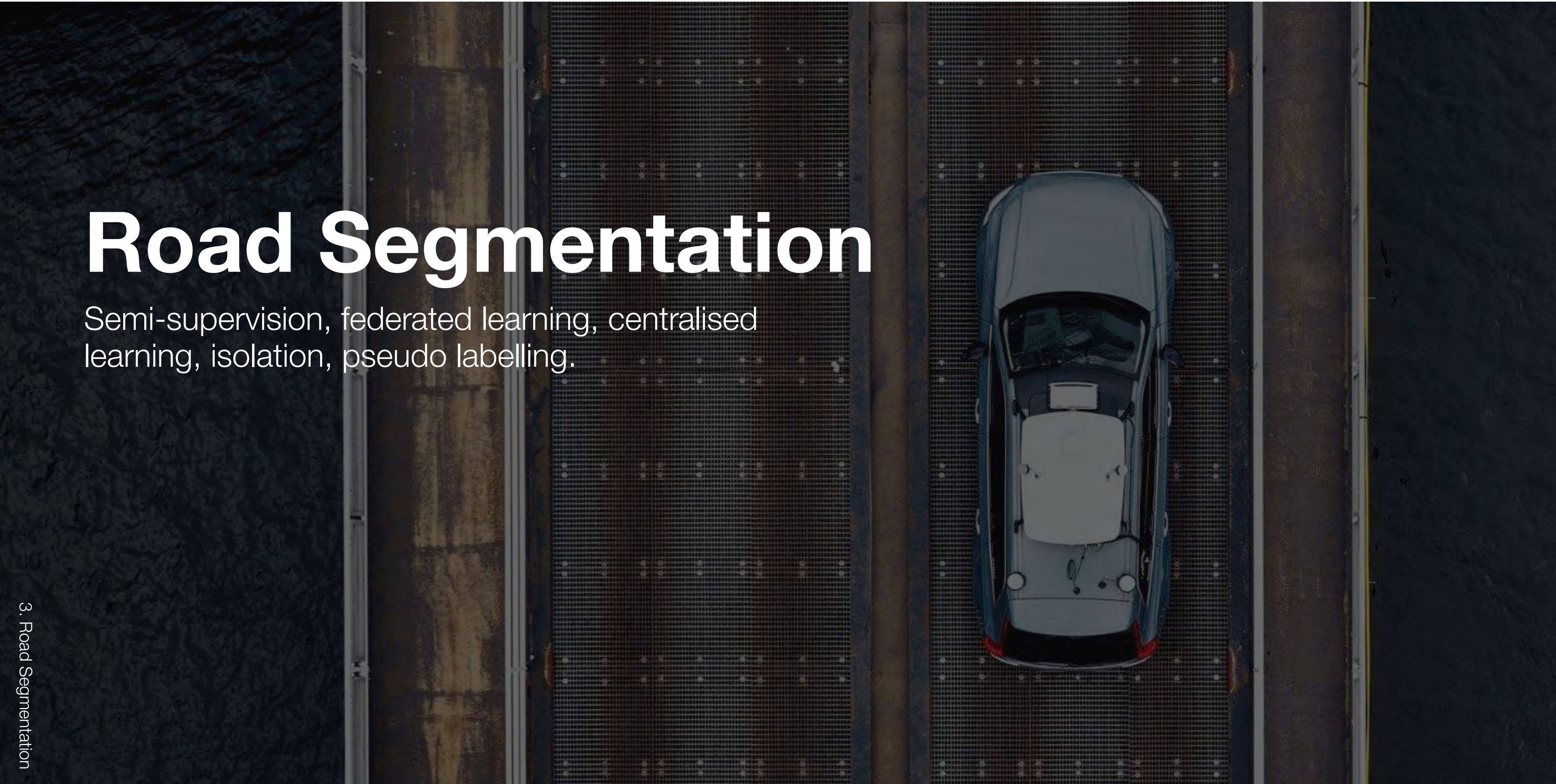


Road Segmentation

Semi-supervision, federated learning, centralised learning, isolation, pseudo labelling.

Road Segmentation

Road Segmentation

Road Segmentation

Road Segmentation

Road Segmentation

Road Segmentation

How did we approach this problem?

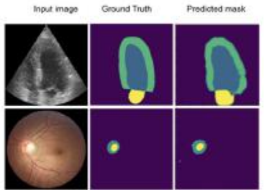
Recall: the data must stay on the car.

Semi-Supervised Semantic Road Segmentation

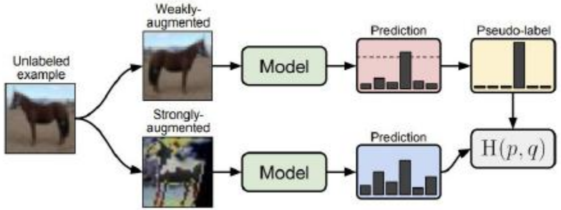
Scarce ground truth scenario with abundance of unlabelled data

- Leverage unlabelled data
- Make FL more applicable for AD

FixMatchSeg: Fixing FixMatch for Semi-Supervised Semantic Segmentation

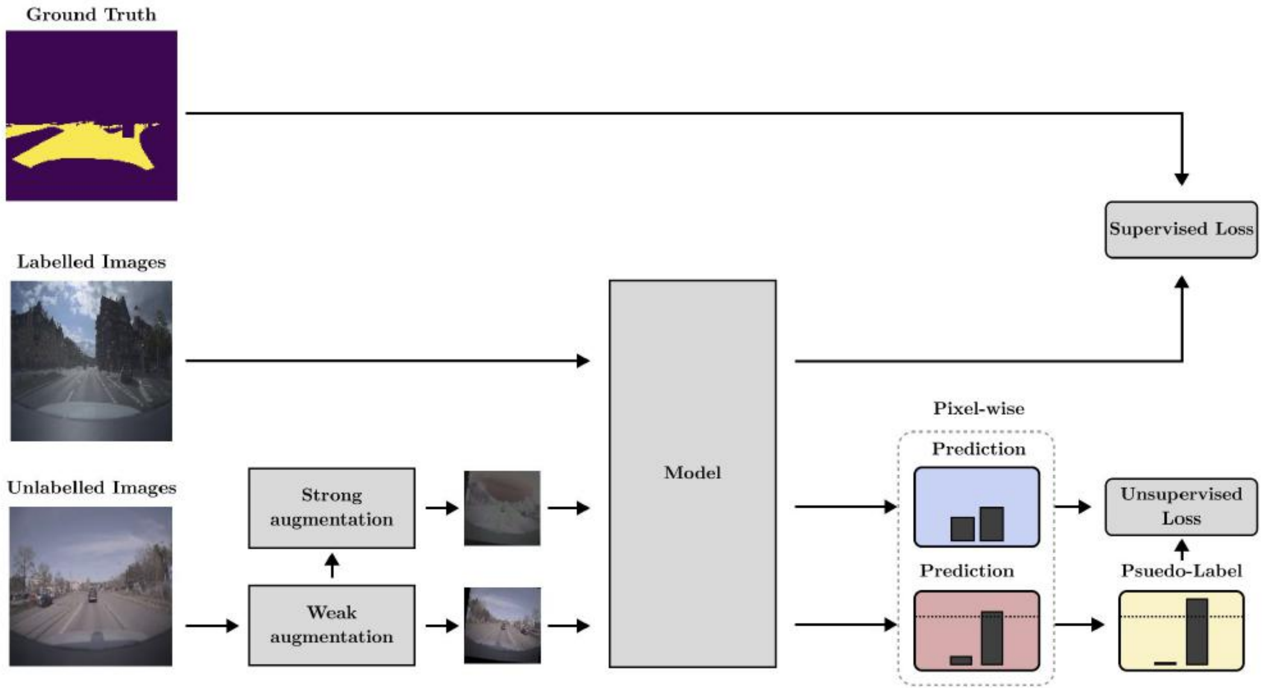


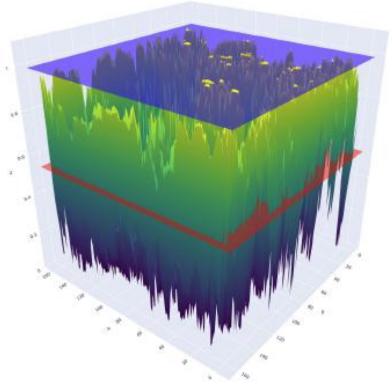
FixMatch: Simplifying Semi-Supervised Learning with Consistency and Confidence



FixMatchSeg for road segmentation

Model setup and pseudo-labelling generation





Our experiment setup and design

Benchmarks and methods

Centralised Supervised Learning

Labelled Images	**5100**
Unlabelled Images	**0**

Normal Supervised Learning

Federated FixMatchSeg

Labelled Images	**100**
Unlabelled Images	**5000**
Clients	**5**

1000 Unlabelled images per client

Labelled Images
[100,100,100,100,100]

Unlabelled Images
[1000,1000,1000,1000,1000]

Centralised FixMatchSeg

Labelled Images	**100**
Unlabelled Images	**5000**
Clients	**5**

FixMatchSeg with 50x unlabelled data

Centralised Local Learning

Labelled Images	**100**
Unlabelled Images	**0**

Supervised learning with limited data

Our experiment setup and design

Centralised Supervised Learning	
5100 Labelled Images	0 Unlabelled Images

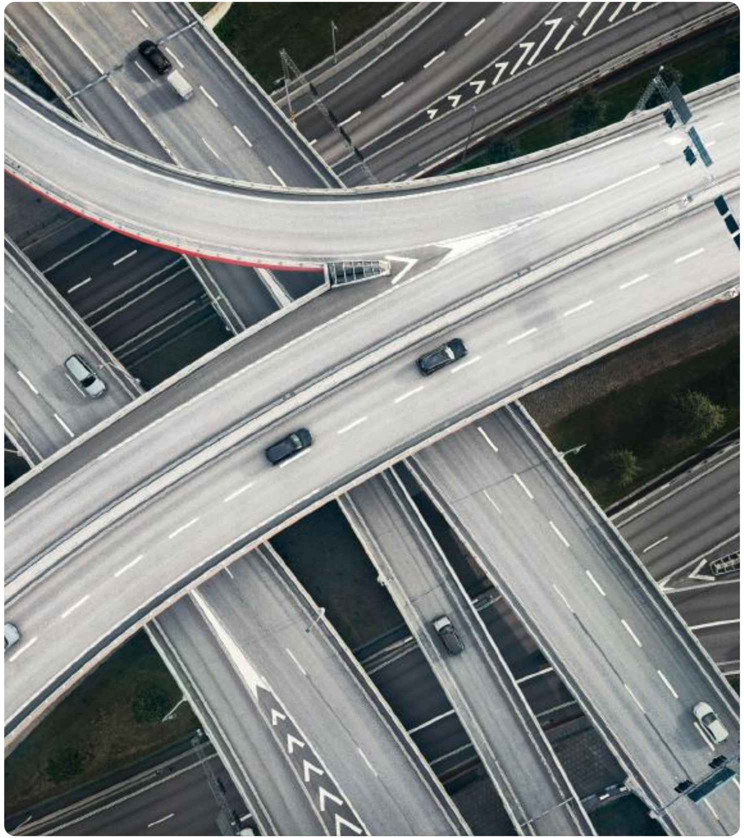
Federated FixMatchSeg Learning	
100 Labelled Images	5000 Unlabelled Images
[100, 100, 100, 100, 100]	[1000, 1000, 1000, 1000, 1000]

Centralised FixMatchSeg Learning	
100 Labelled Images	5000 Unlabelled Images

Centralised Local Learning	
100 Labelled Images	0 Unlabelled Images

Federated Learning
5 Clients
Same Labelled images

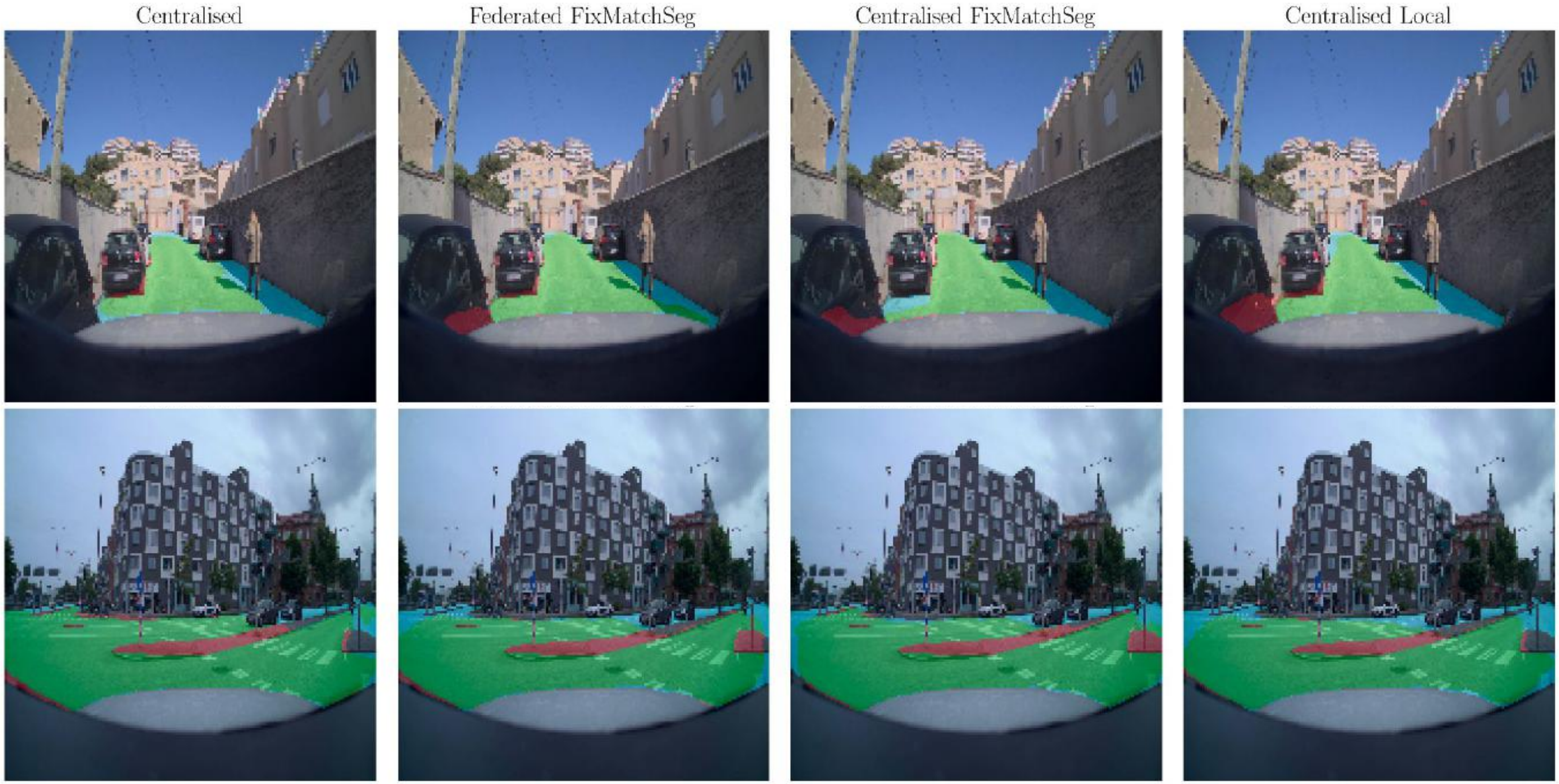
One last thing about our experiment design



2500 Validation frames

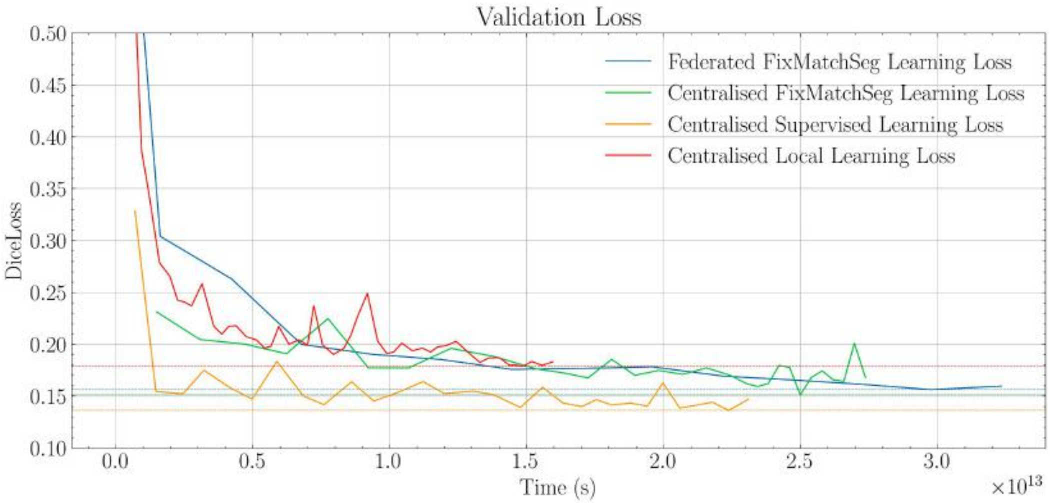
Federated Splits are uniformly random from a balanced dataset → IID assumption

$$D = \frac{2 \cdot \sum_{i=1}^{N} y_i \cdot \hat{y}_i}{\sum_{i=1}^{N} y_i + \sum_{i=1}^{N} \hat{y}_i}, \quad \text{Dice Loss} = 1 - D$$


Centralised
Federated FixMatchSeg
Centralised FixMatchSeg
Centralised Local

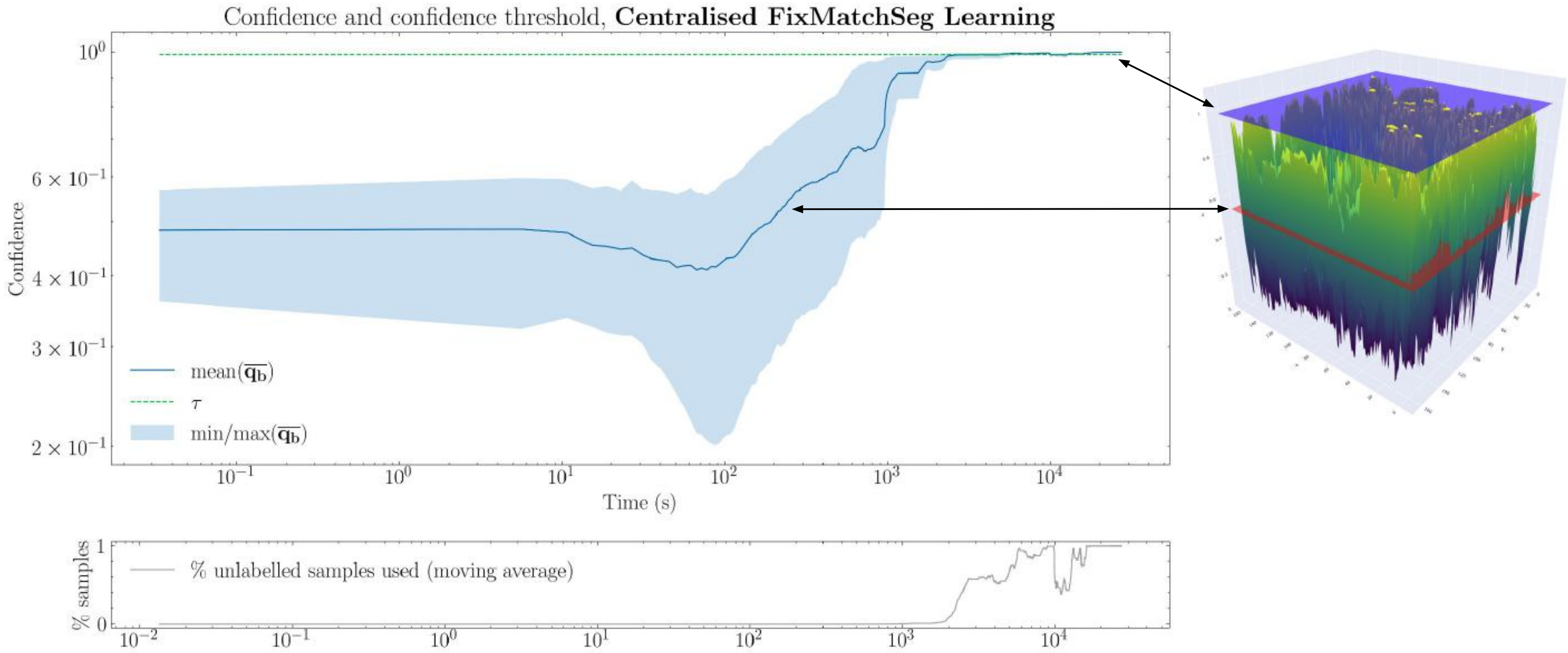
Our experiment setup and design

- Similar curves
- Focus on general shape
- Early convergence



Model (# labelled images, # unlabelled images)	min DiceLoss
Centralised Supervised Learning (5100, 0)	**0.136**
Federated FixMatchSeg Learning (100, 5000)	0.156
Centralised FixMatchSeg Learning (100, 5000)	0.151
Centralised Local Learning (100, 0)	0.179

Model confidence & details



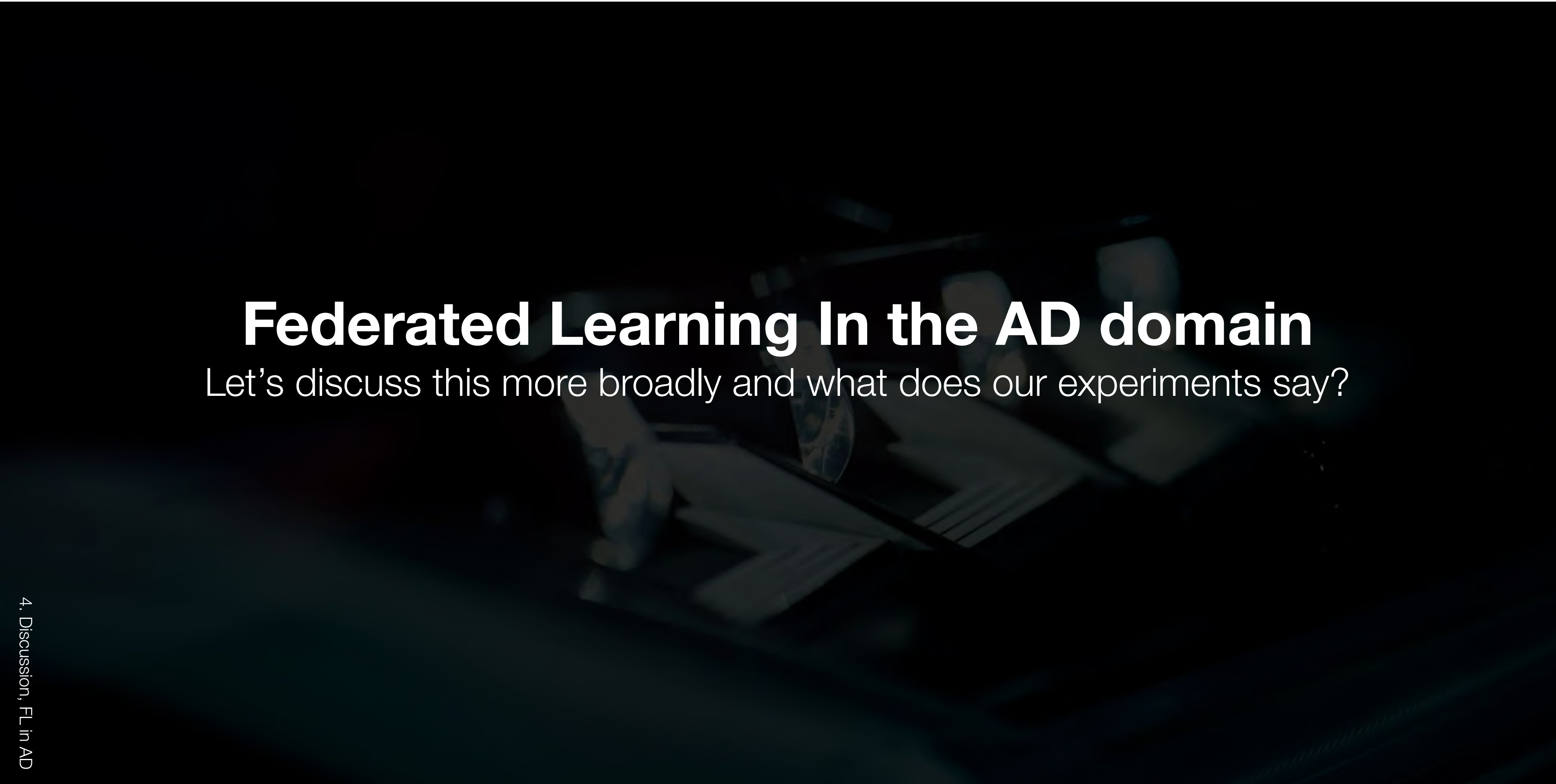
Discussion: Insights and Limitations

Similar losses across all models

Simplification of the true problem

Future Research Questions:

- Will increasing labelled data diminish the value of unlabelled data?
- Could more capable encoders or larger image sizes differentiate model performance?
- Will our findings remain valid in more complex segmentation scenarios (cars, pedestrians, etc)?

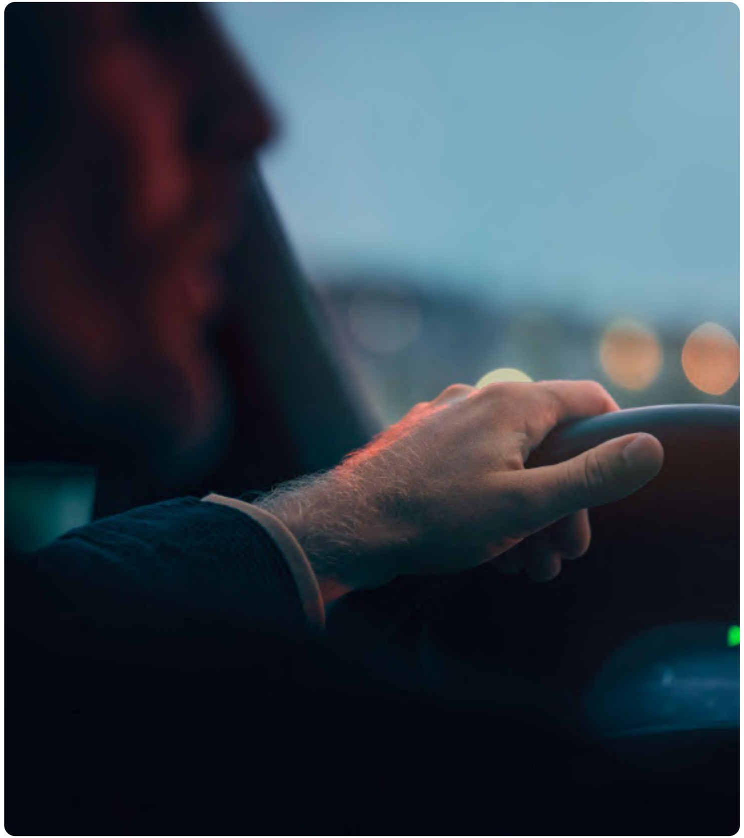


Federated Learning In the AD domain

Let’s discuss this more broadly and what does our experiments say?

Discussion: Insights and Limitations

- FL aligns with data minimisation principles.
- Native FL does not directly guarantee privacy in the face of malicious clients.
- FL holds promise as a potential solution if the challenges outlined in our thesis can be overcome.



Discussion: Insights and Limitations

- Previous work's assumption: Abundance of labelled data on client vehicles.
- Real-world challenge: Need for localised learning on the vehicle.
- Implemented semi-supervised learning for road segmentation and imitation learning for trajectory prediction.

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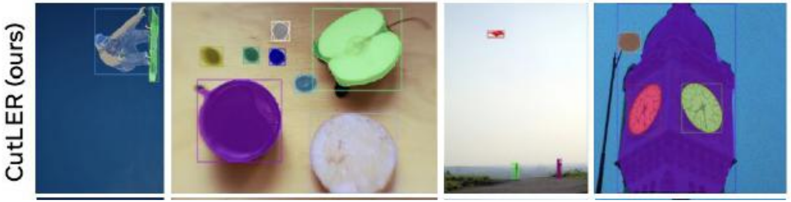
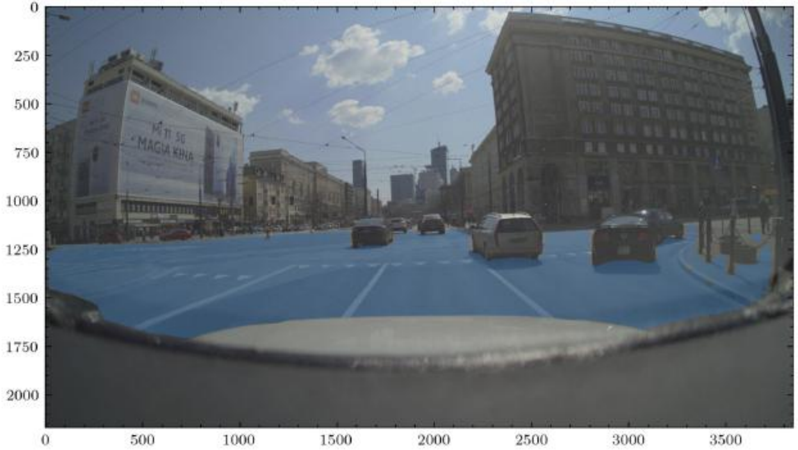
What is next?

Unsupervised Visual Representation Learning





Emerging Properties in Self-Supervised Vision Transformers

Conclusion

Concluding Remarks

Explored Federated Learning in Autonomous Driving

Emphasised the potential of unlabelled data

Adopted semi-supervised learning and imitation learning in FL

Future direction: Unsupervised models in FL for AD

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Towards Federated Fleet Learning

Reimagining Autonomous Driving: A Study of Federated Learning Using Unannotated Data

Big thanks to: Zenseact & AI Sweden, Our supervisors, William Ljungberg, Pavel Lutskov.


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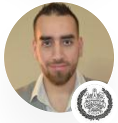
DEPARTMENT OF ELECTRICAL ENGINEERING
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2023
www.chalmers.se

Alexander Viala Bellander
alexander@vialabellander.se



Yazan Ghafir
ghafir@chalmers.se

Thank you!

Presentation, Zenseact, 2023-06-15

Alexander Viala Bellander & Yazan Ghafir