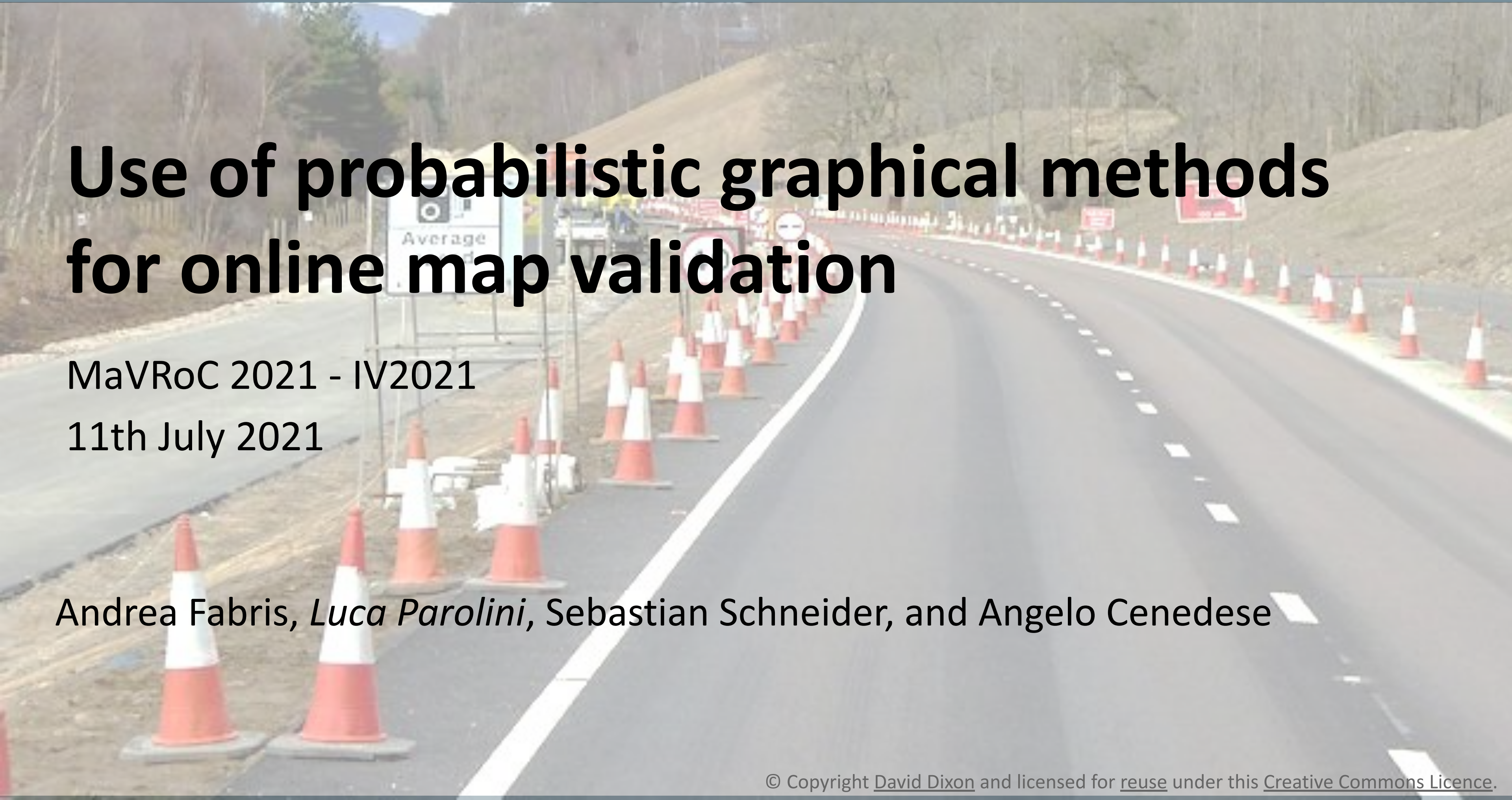

Use of probabilistic graphical methods for online map validation

MaVRoC 2021 - IV2021

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Andrea Fabris, *Luca Parolini*, Sebastian Schneider, and Angelo Cenedese

The need of map validation

Safety is a core feature that autonomous-driving vehicles (ADVs) aim for

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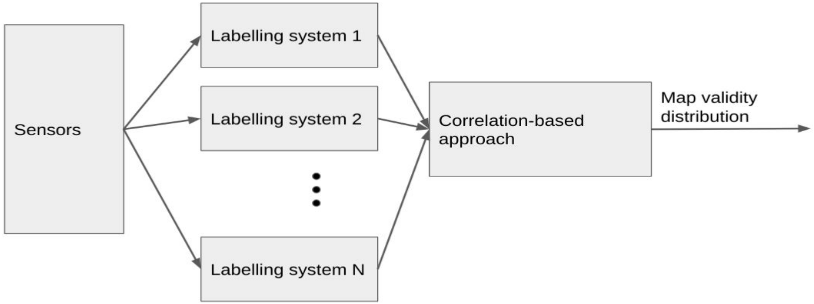
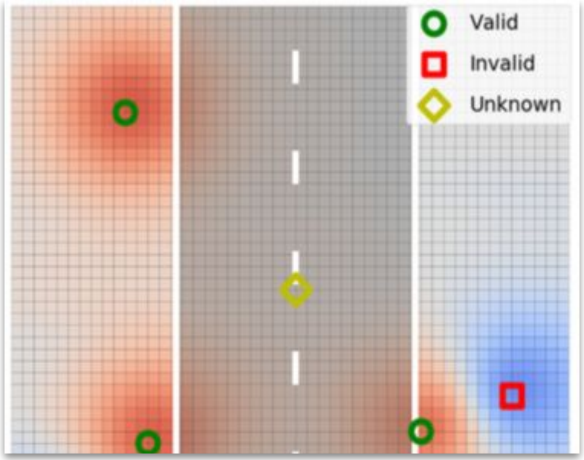
Maps are sensors whose

- field of view (FOV) is not affected by traffic conditions
- measurements have unknown and potentially extensive latency, e.g., days, or weeks

Proposed probabilistic framework

- The vehicle is equipped with multiple sensors
- Each sensor observes parts of the road
- Different algorithms fused data from the sensors and provide an estimation of the map validity on certain areas
- We call these algorithms *labelling systems*
- A correlation-based approach fuses the results from the different algorithms[1]





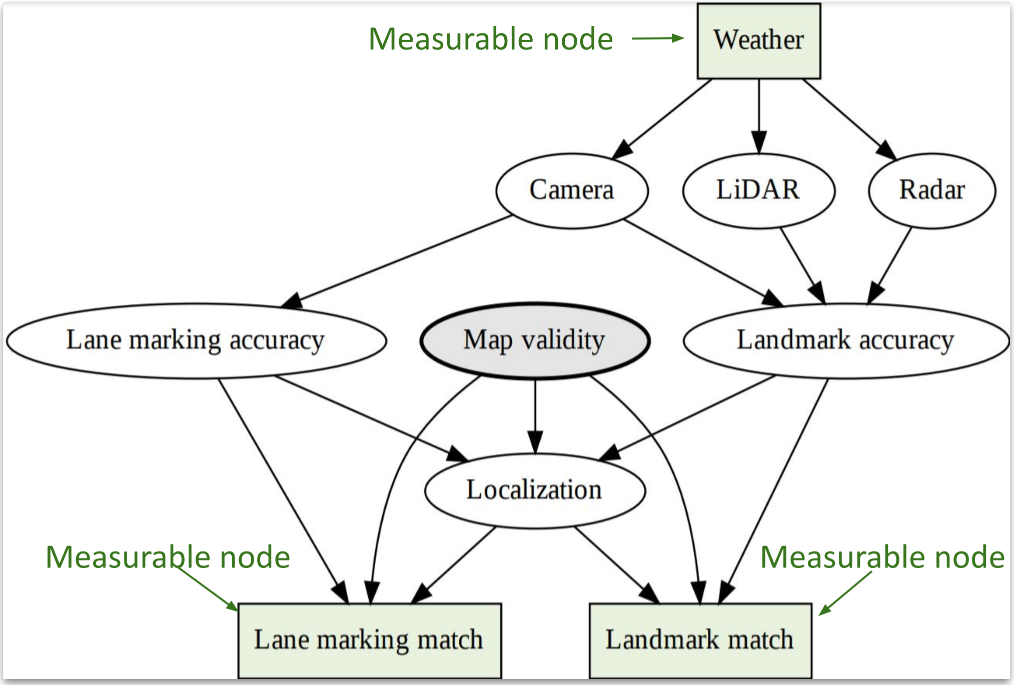
[1] Correlation-Based Approach to Online Map Validation, Fabris et al., MaVRoC 2020

A labelling system based on probabilistic graphical model

- Nodes represent random variables
- Edges represent direct influences between random variables

- Information coming from heterogeneous sources can be fused in a common probabilistic framework
- Efficient encoding of high-dimensional distributions[1]

- Nodes can be measurable, or hidden
  - Weather, Lane marking match, and Landmark match are measurable nodes



[1] Probabilistic Graphical Models: Principles and Techniques, Koller and Friedman

Example of prior and conditional distributions

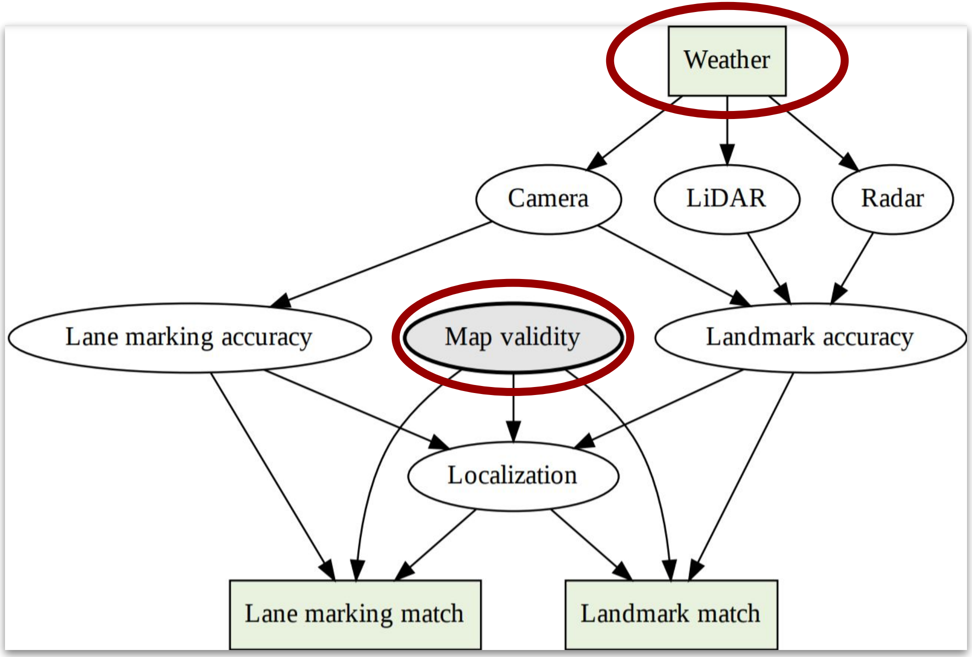
Prior distributions

Weather

Value	Probability
Cooperative	0.5
Non-cooperative	0.5

Map validity

Value	Probability
Valid	0.8
Invalid	0.2



All other distributions available in code at https://github.com/lparolin/mavroc_2021

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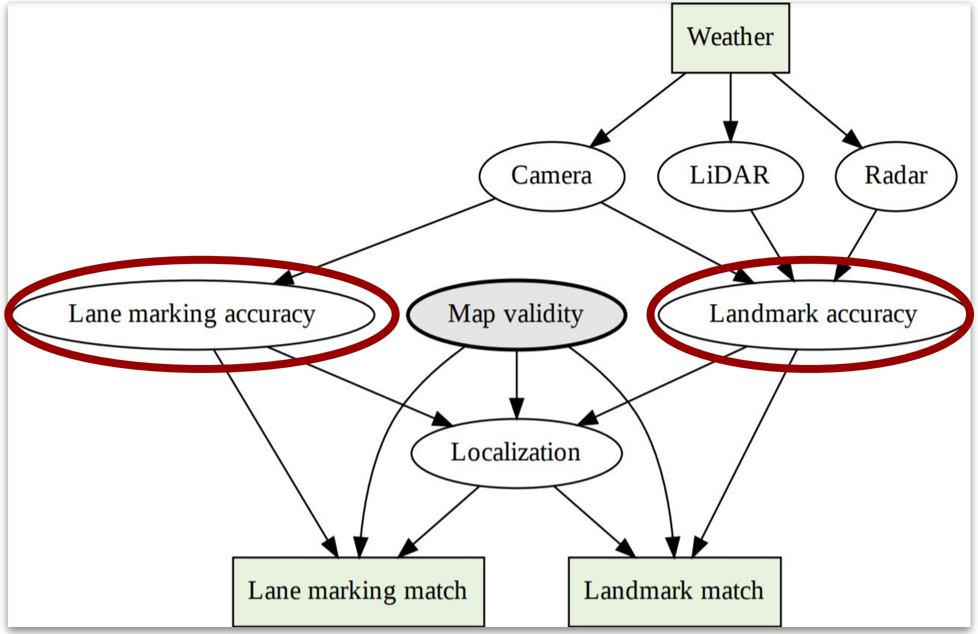
Conditional probabilities of high accuracy

Variable	Camera	RaDAR	LiDAR	Probability
Lane marking	nominal	-	-	0.85
	degraded	-	-	0.3
Landmark	nominal	nominal	nominal	0.95
	degraded	nominal	nominal	0.8
	nominal	degraded	nominal	0.8
	degraded	degraded	nominal	0.4
	nominal	nominal	degraded	0.7
	degraded	nominal	degraded	0.4
	nominal	degraded	degraded	0.5
	degraded	degraded	degraded	0.01



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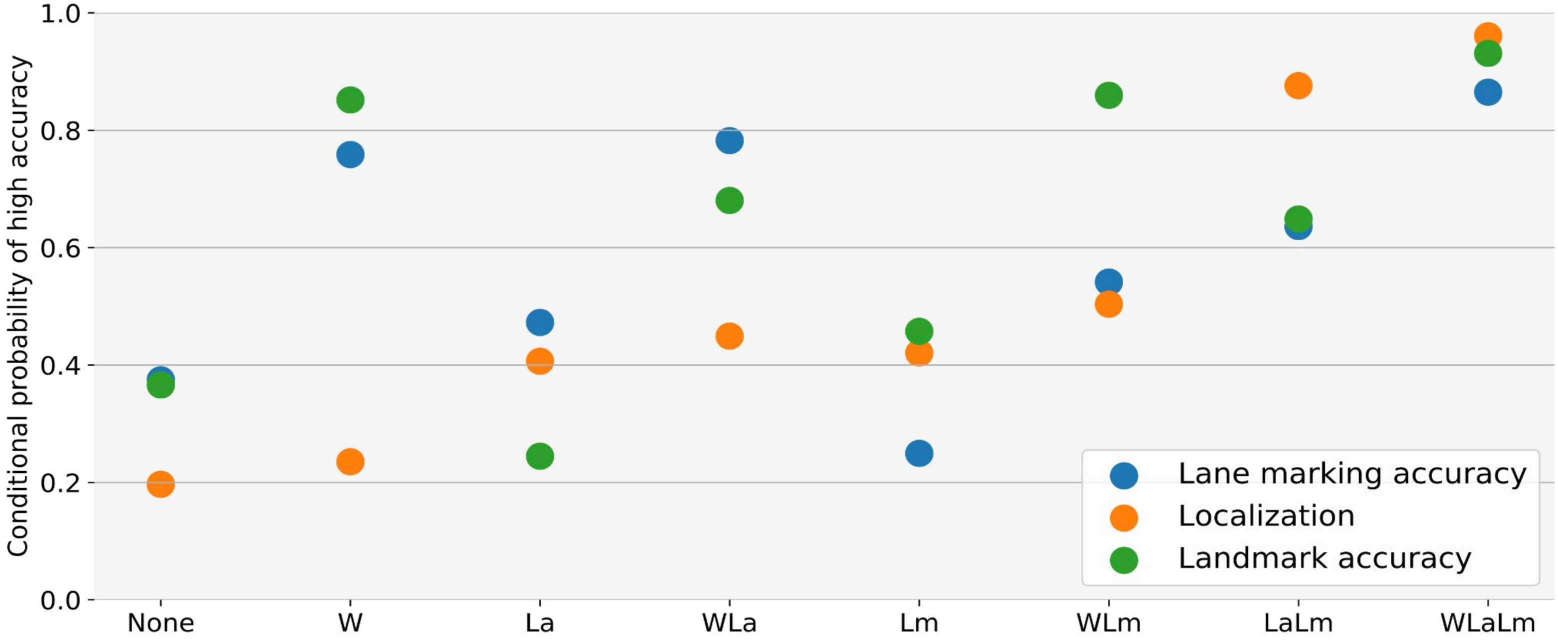
Posterior probabilities for different measured values



Weather	Non-cooperative	Cooperative	Non-cooperative	Cooperative	Non-cooperative	Cooperative	Non-cooperative	Cooperative
Lane marking match	Not detected	Not detected	Detected	Detected	Not detected	Not detected	Detected	Detected
Landmark match	Not detected	Not detected	Not detected	Not detected	Detected	Detected	Detected	Detected

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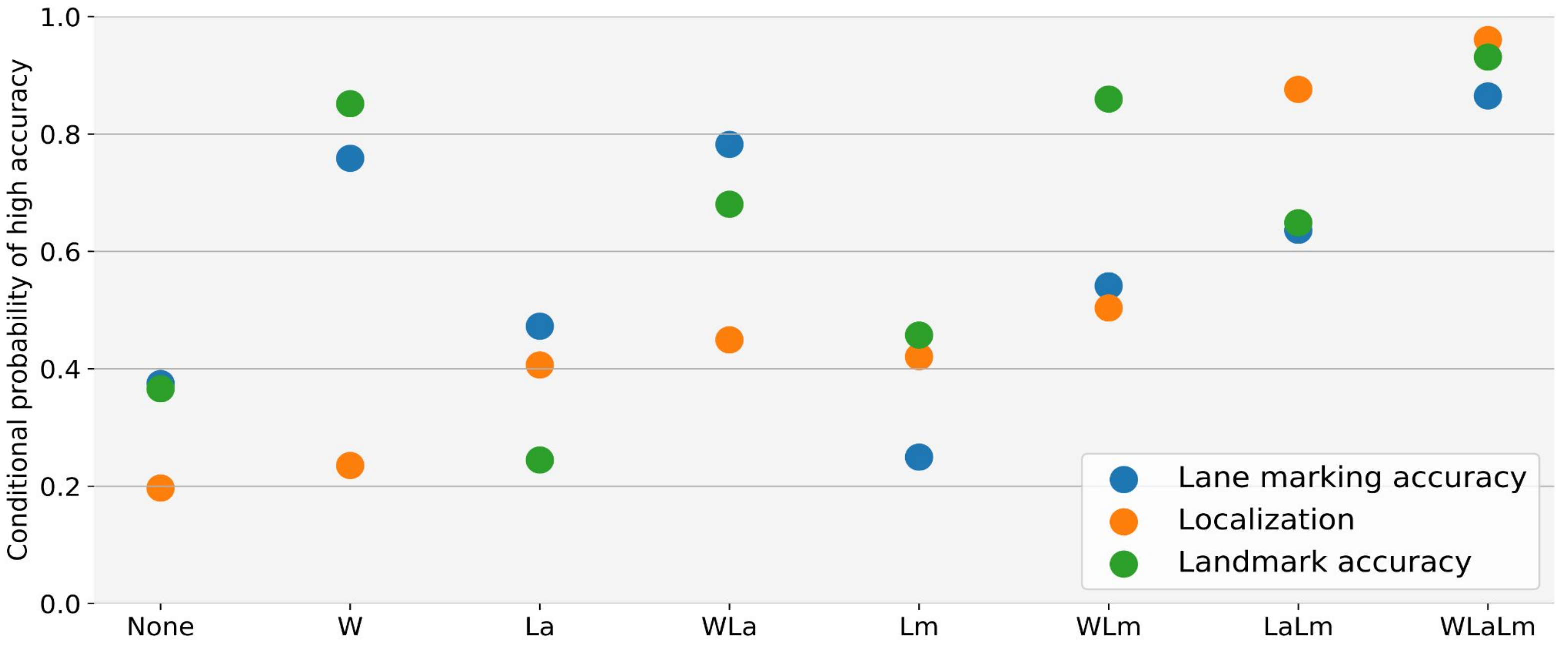

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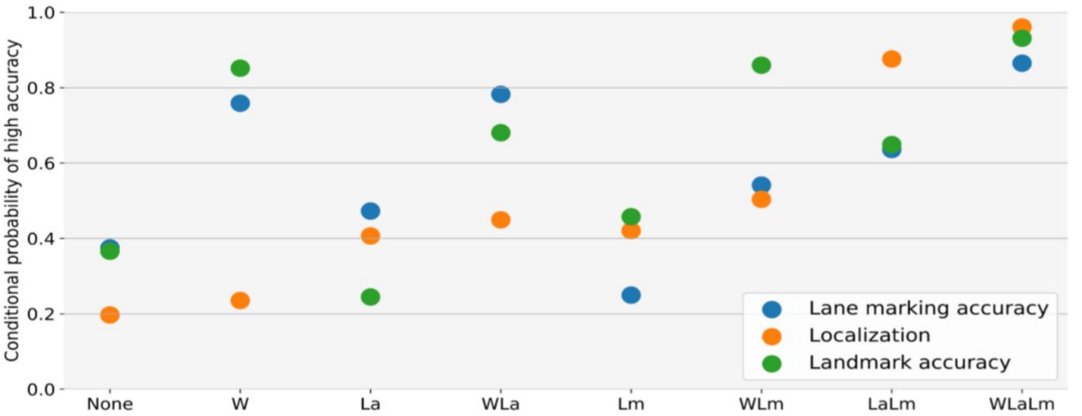
Landmark match	Not detected	Not detected	Not detected	Not detected	Detected	Detected	Detected	Detected
Prob. of valid map	**0.403**	**0.246**	**0.864**	**0.675**	**0.859**	**0.721**	**0.998**	**0.999**

Defining a map classifier

- A classifier maps measured values onto the set {*Valid, Invalid*}
- We focus on a classifier that depends on the posterior distribution of map valid only
    - A map is valid if the posterior distribution of map valid is larger than the threshold λ



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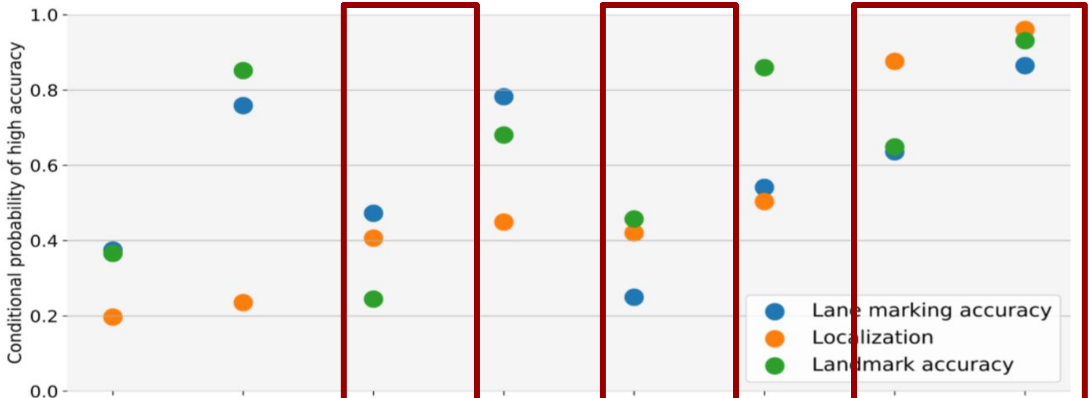

	None	W	La	WLa	Lm	WLm	LaLm	WLaLm
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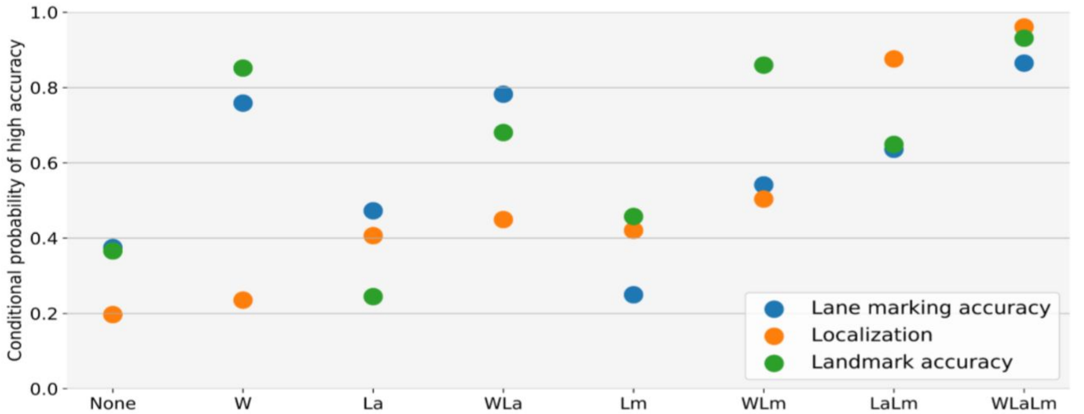

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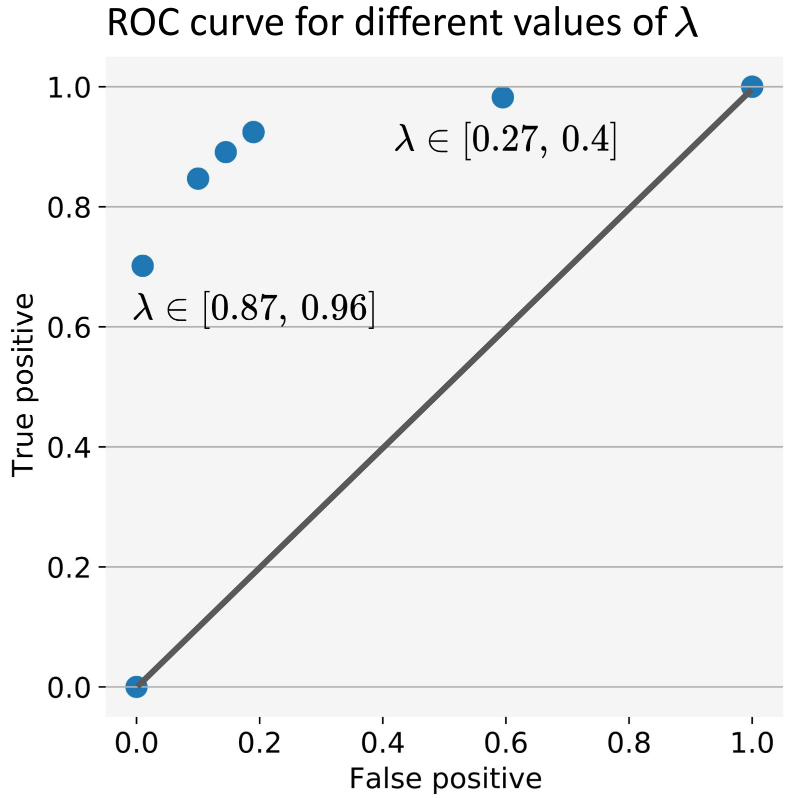
When $\lambda = 1.0$, then the map is always estimated to be invalid

The receiver operating characteristic (ROC) curve

- Pairs of True Positive Rate (TPR), False Positive Rate (FPR) for different values of λ
  - TPR: Probability of declaring the map valid, when it is
  - FPR: Probability of declaring the map valid, when it is not
- Expected shape for a binary classifier
- The PGM results relatively insensitive towards the choice of the threshold λ



Conclusion and Future Research

- PGMs can be effectively used for map validation purposes
    - Expert judgment must be used in order to find suitable trade-offs between model complexity and accuracy
- Data from vastly heterogeneous sources can be fused in a common probabilistic framework
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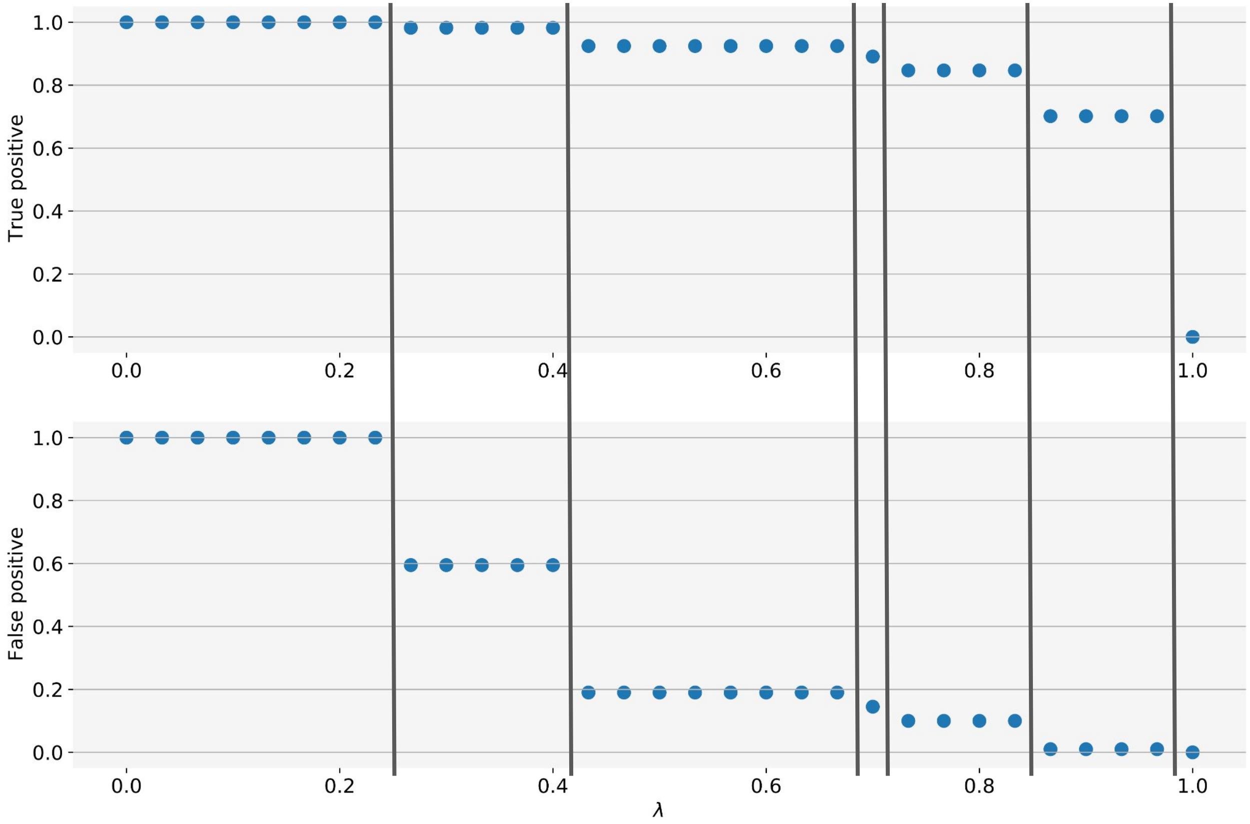
- Data from vastly heterogeneous sources can be fused in a common probabilistic framework
  - The network provides the posterior distribution for all variables in the model
- PGMs require fewer data for the tuning of the parameters compared with deep learning techniques
  - Some of these data can be learned from experiments, others may require expert judgment
  - Internal nodes have clear probabilistic meaning
- Comparison against other methods, e.g., based on neural network, still missing

Additional slides

TPR and FPR as function of threshold parameter



TPR and FPR values have jumps due to the discrete nature of the RVs we used in the model