

## Motivation

When investigating various prediction tasks in the automotive context, we noticed that even in heavily post-processed datasets, *outliers* abounded [1].

## Outliers

Due to inherent instabilities of the processes observing other traffic participants, some of the provided observations deviate significantly from the general trend.

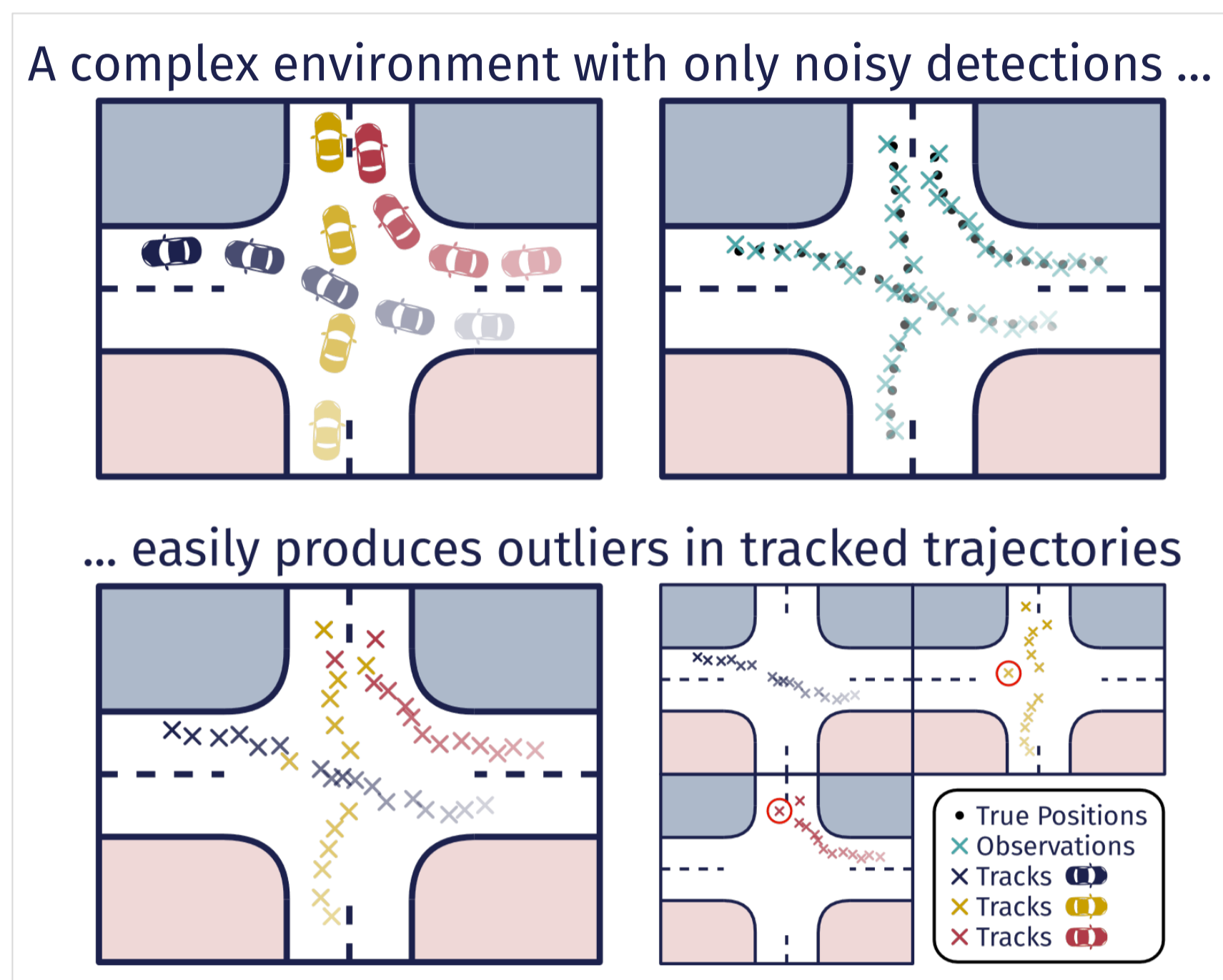


Figure 1: An example of how tracking multiple targets simultaneously from detected observations can result in outliers in the computed tracks (© Continental AG)

## Effect

Since predictions must extrapolate from recent observations, the quality and reliability of observations have a substantial impact on prediction performance.

## Objective

Infer a realistic trajectory of the targets from these outlier-afflicted observations, including relevant information such as the target's velocities and accelerations.

## Problems With Existing Methods in Use

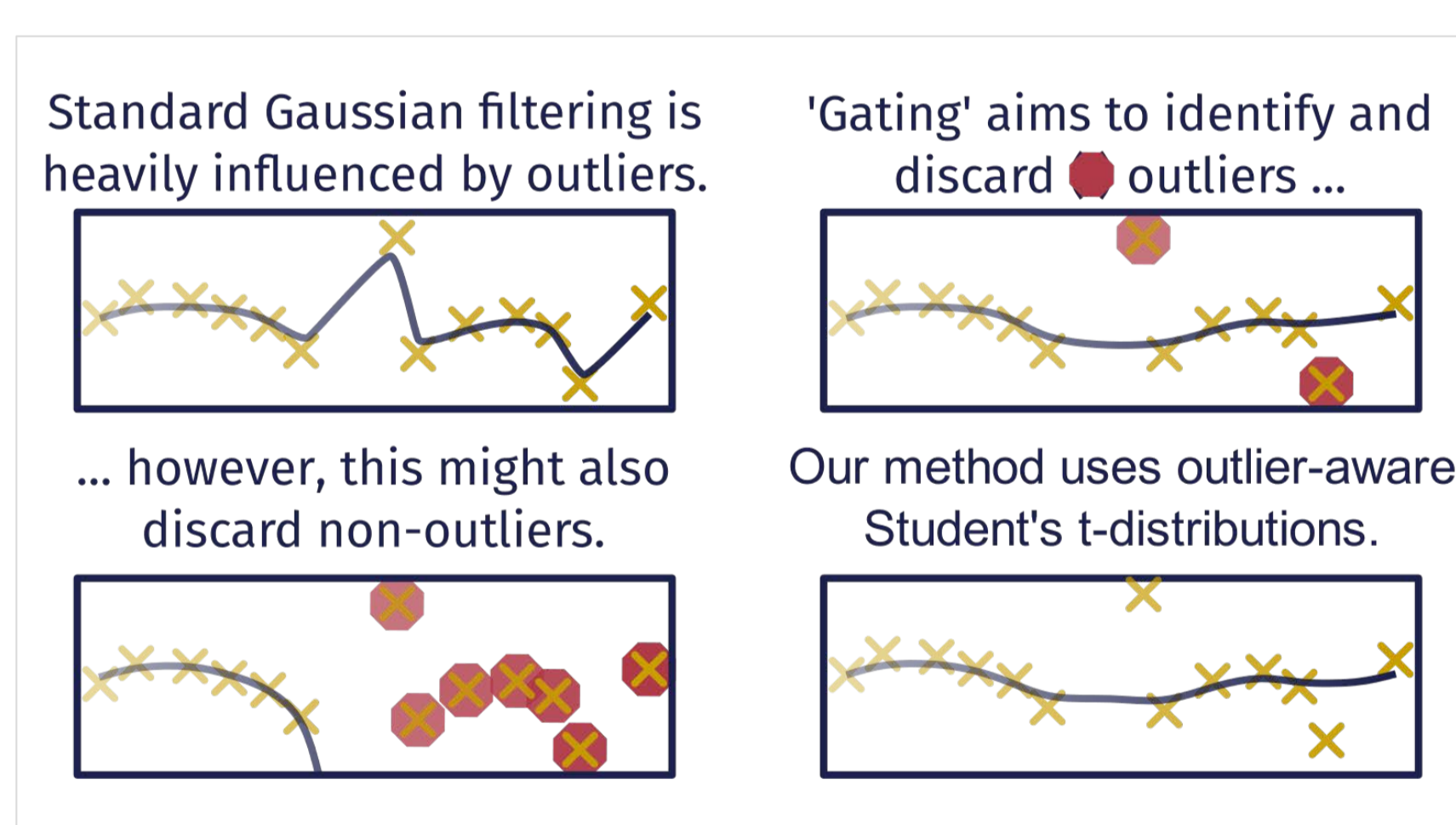


Figure 2: Filtering based on Gaussian distributions and Gating does not reliably produce realistic trajectories (© Continental AG)

## References

- [1] Y. Yao, D. Goehring, and J. Reichardt, "An empirical bayes analysis of vehicle trajectory models", 2022
- [2] Y. Huang, Y. Zhang, Y. Zhao, P. Shi, and J. A. Chambers, "A novel outlier-robust Kalman filtering framework based on statistical similarity measure", 2020.
- [3] G. Agamennoni, J. I. Nieto, and E. M. Nebot, "An outlier-robust Kalman filter", 2011

## Our Proposed Method

We aim to preserve the advantages of existing Gaussian methods in efficiency, interpretability and adaptability to non-linear processes. We replace the Gaussian assumptions with outlier-aware Student's t-assumptions, identify fallacies in previous works with this approach, remedy these, and provide analytical formulations for our outlier robust methods.

## Student's t-Distribution

The Student's t-distribution results from a Gaussian distribution with a random variance. As such, outliers are explained by instances of very high variances. Further, the invariance under affine transformations and conditioning is inherited from Gaussian distributions.

## Key Contributions

- We propose a method to approximate joint Student's t-distributions *locally*, motivated by this equality of densities:

$$\begin{aligned}
 & \text{Student's t-density evaluated at } x \quad \text{hyperparameter for dimensions } \mu_1 \quad \text{mean and (quasi) covariance } \Sigma_1 \\
 & \text{frequency of outliers of } x \quad \text{and } y \quad \text{frequency of outliers of } y \quad \text{mean and (quasi) covariance } \Sigma_2 \\
 & \text{frequency of outliers of } z \quad \text{mean and (quasi) covariance } \Sigma_3 \\
 & t_{\nu}(x|\mu_1, \Sigma_1) \cdot t_{\nu+m}(y|\mu_2, \Sigma_2) \cdot t_{\nu+m+n}(z|\mu_3, \Sigma_3) \\
 & = t_{\nu} \left( \begin{bmatrix} x \\ y \\ z \end{bmatrix} \middle| \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix}, \begin{bmatrix} \Sigma_1 & 0 & 0 \\ 0 & a(x)\Sigma_2 & 0 \\ 0 & 0 & a(x)b(y)\Sigma_3 \end{bmatrix} \right) \\
 & = a(x) \frac{\nu+m}{\nu+(x-\mu_1)^T \Sigma_1^{-1} (x-\mu_1)} \cdot b(y) \frac{\nu+m+n}{\nu+m+(y-\mu_2)^T \Sigma_2^{-1} (y-\mu_2)}
 \end{aligned}$$

- We propose a method to estimate  $a(x)$  and  $b(y)$  when  $(x, y, z)$  are unknown,
- From this method, we derive outlier-robust filter and smoother,
- We compare our filter to state-of-the-art analytical outlier robust filters.

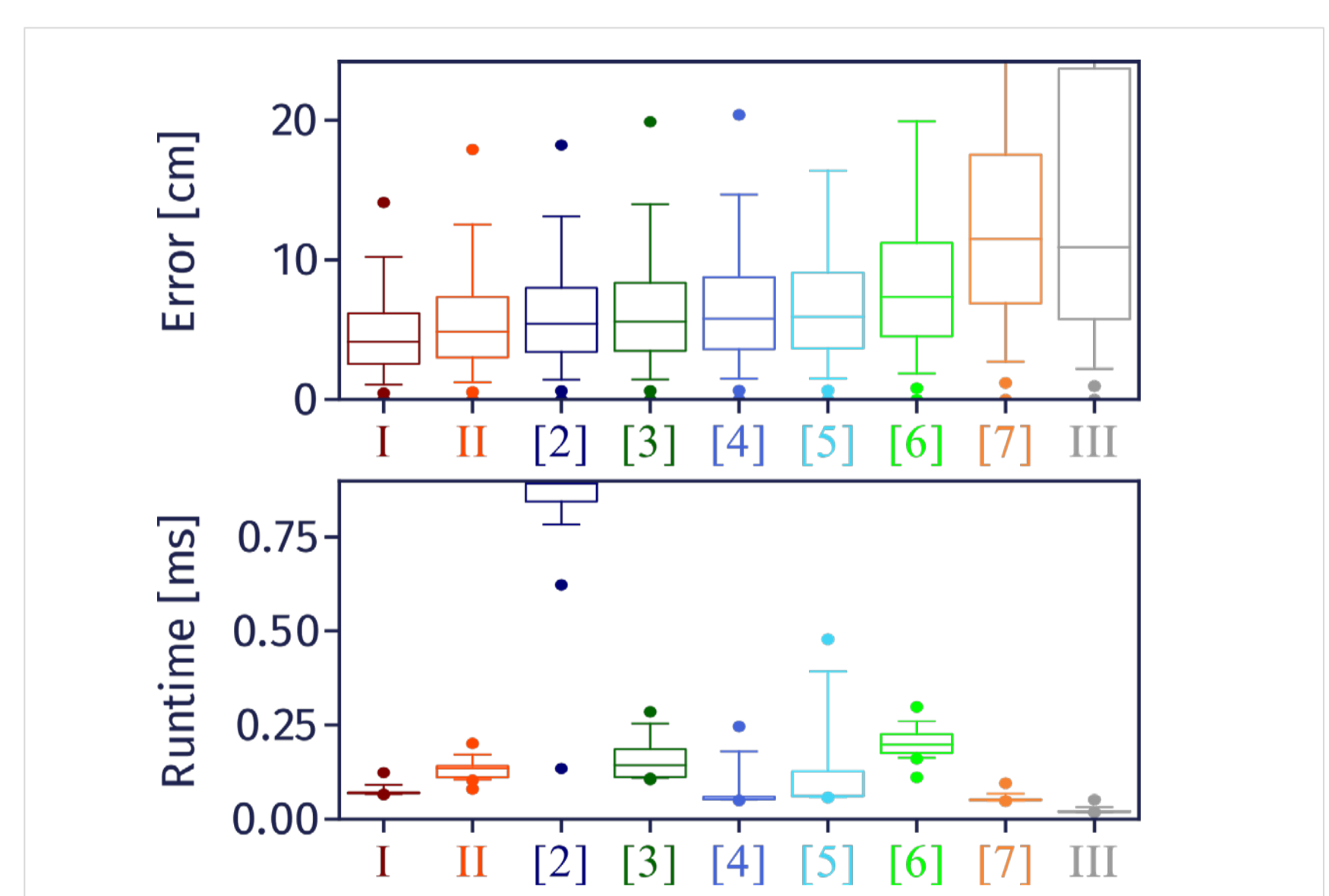


Figure 3: Comparison with comparable filters on challenging simulated tracking tasks. (© Continental AG)

- [4] G. Chang, "Robust Kalman filtering based on Mahalanobis distance as outlier judging criterion", 2014
- [5] G. Chang, "Kalman filter with both adaptivity and robustness", 2014.
- [6] S. Sarkka and A. Nummenmaa, "Recursive noise adaptive Kalman filtering by variational Bayesian approximations", 2009
- [7] M. Roth, "Kalman filters for nonlinear systems and heavy-tailed noise", 2013.

## Partners



## External partners



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