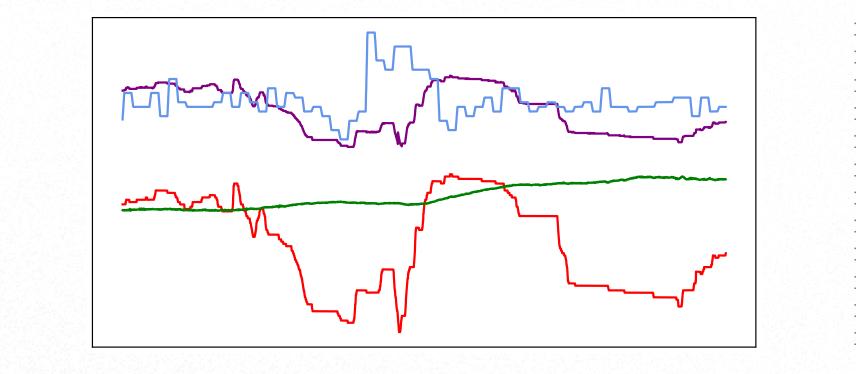
Anomaly detection in CAN with TCN

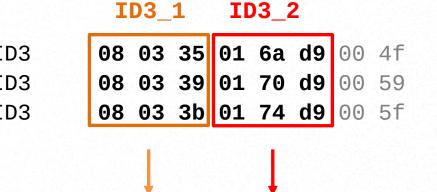
Background

Modern cars are full of embedded controllers (ECUs), which are connected by internal networks, like CAN (Controller Area Network). ECUs communicate with each other mostly periodically, and signals are encoded in CAN messages. One message type usually contains more signals.



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ID1							00			
ID2	05	c8	00	0f	00	00	92	3C		
ID3	08	03	35	01	6a	d9	00	4f		ID3
ID1	00	00	00	00	00	00	00	6a		ID3
ID2	05	c 8	00	0f	00	00	92	3c		ID3
ID3	08	03	39	01	70	d9	00	59		
ID1	00	00	00	00	00	00	00	6a		
ID2	05	c2	00	0f	00	00	92	36		
ID1	00	00	00	00	00	00	00	6a		
ID3	08	03	3b	01	74	d9	00	5f		
ID2	05	c2	00	0f	00	00	92	36		
ID1	00	00	00	00	00	00	00	6a		

ID2	05	c8	00	0f	00	00	92	3c	
ID3	08	03	35	01	6a	d9	00	4f	
ID1	00	00	00	00	00	00	00	6a	
ID2	05	c8	00	0f	00	00	92	3c	
ID3	08	03	39	01	70	d9	00	59	
ID1	00	00	00	00	00	00	00	6a	
ID2	05	c2	00	0f	00	00	92	36	
ID1	00	00	00	00	00	00	00	6a	
ID3	08	03	3b	01	74	d9	00	5f	
ID2	05	c2	00	0f	00	00	92	36	
	I	D3	1	ID	32				



Message preprocessing

Step 1) Filter on message ID. Messages with the same ID will contain multiple signals.

Step 2) Signal extraction from messages. Slicing masks are calculated with the analysis of bit flip rate.

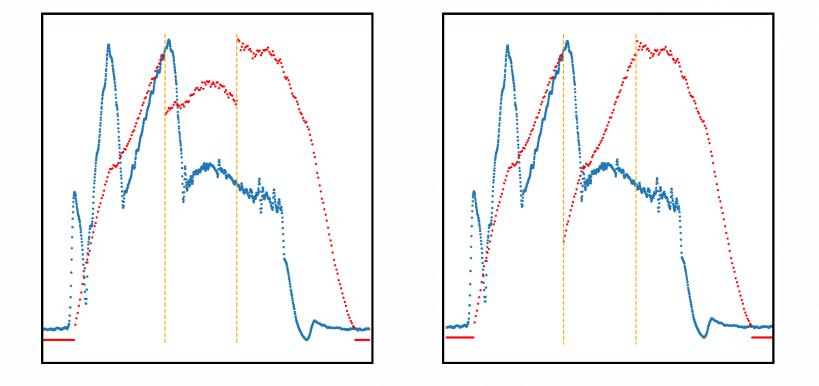
Step 3) Create input dataset. Input data will contain these individual signals from all message types. Missing values are filled with zeros.



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ID3_1	ID3_2	ID1_1	
0.531725	0.607422	0.112845	
0.531728	0.607422	0.112828	
0.531730	0.607422	0.112810	

Problem Malicious modification of these messages must be detected for the safety of the vehicle.



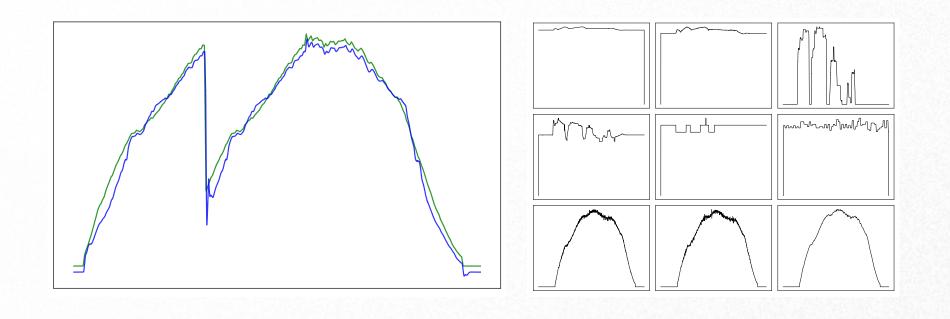
Solution

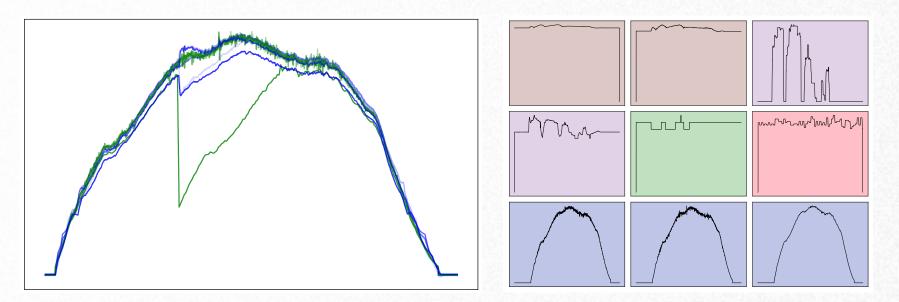


The used dataset contains ~2,5 hours of traffic (~5,5 million messages) from different driving scenarios. Six different modification attacks were performed on the traces. During each attack only one signal is modified.

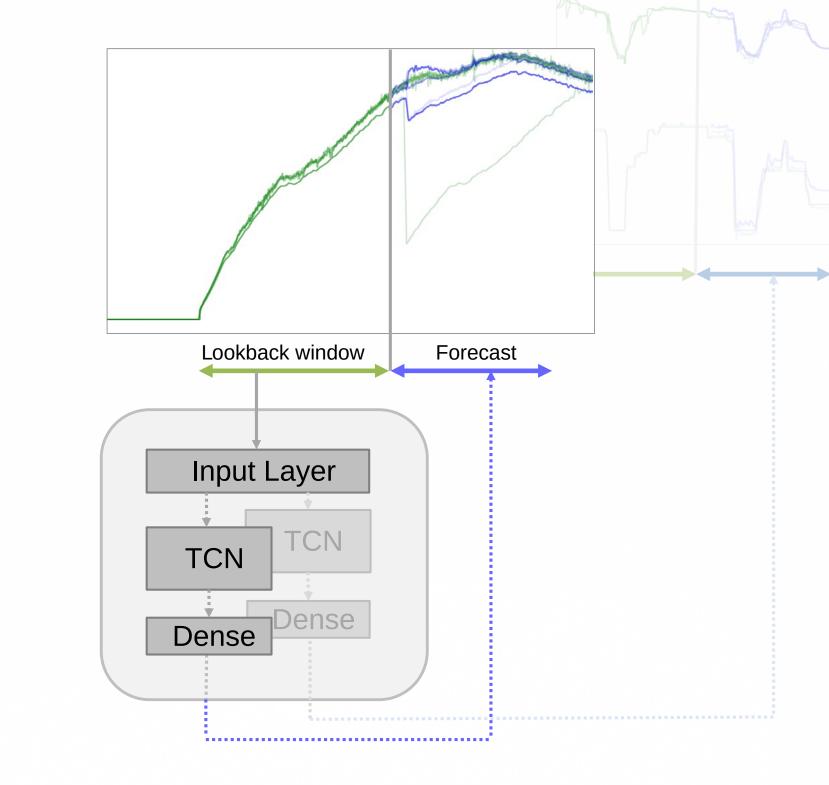
Correlation

Signals are grouped by their correlation. A multi-channel model is trained on each of these groups, where one channel corresponds to one signal.





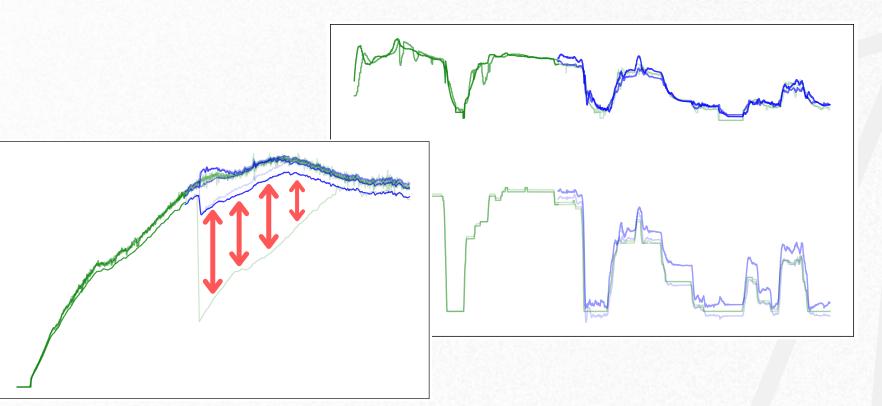
Predicting one signal at a time would not necessarily result in a detectable anomaly. However, the prediction of a



group of signals will depend on their correlation, thus an attack in only one signal will alter the prediction of the whole group. This causes a more significant anomaly.

Model

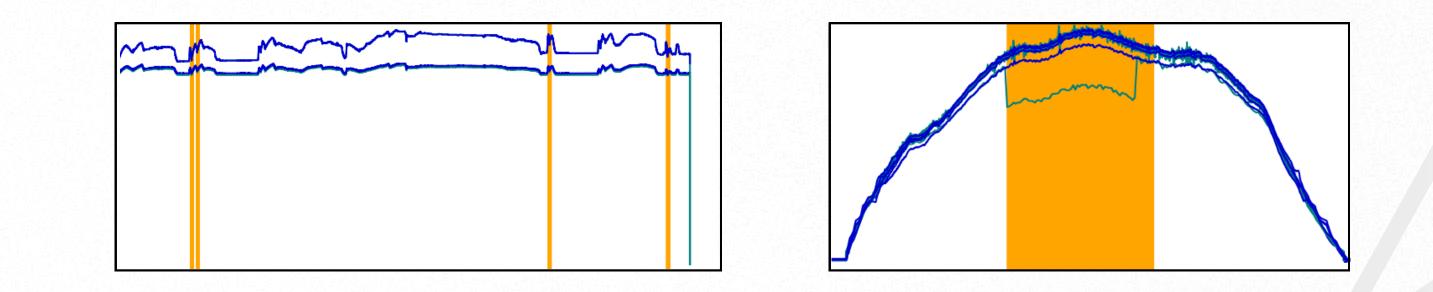
During training, the model receives the relevant signals in a sliding window through an input layer, which passes the correlated signals to a TCN layer. The TCN is composed of four dilatation layers, and predicts next value for each signal in the group by training on the values in the sliding



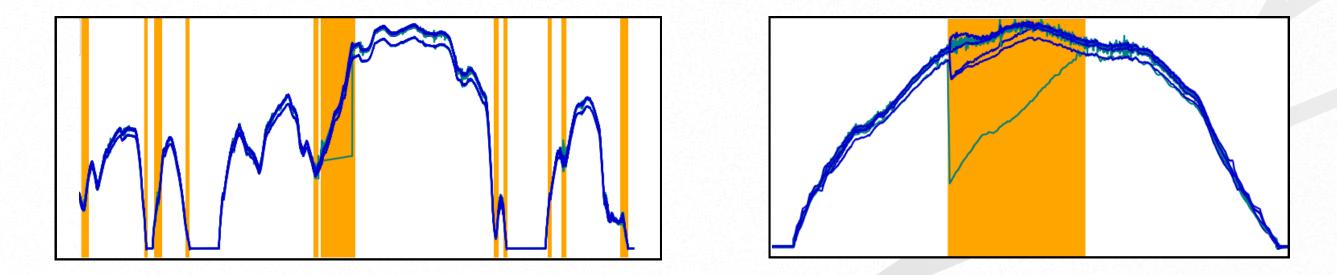
window. The TCN layer is followed by a Dense layer, which produces the output corresponding to the group size.

Anomaly detection is done by comparing the prediction with the actual value.

Results



Predicting a group of signals allows us to detect attacks that modify the signal in a way that would otherwise be normal. Using this method, we were able to detect the majority of attacks, but attacks of different lengths were problematic. Choosing the right evaluation window size is an important task in the detection process.



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Conclusion

- CAN anomalies could be efficiently detected with TCN networks.
- Grouping signals based on correlation improves anomaly detection and reduces the required resources.
- Finding the proper window and threshold values is essential for high accuracy and low FPR results.