Isolation Forest for Anomaly Detection in Raw Vehicle Sensor Data

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Keywords: Anomaly Detection, Data Transfer, Isolation Forest.

Abstract: A vehicle generates data describing its condition and the driver's behavior. Sending data from many vehicles to a backend costs money and therefore needs to be reduced. The limitation to relevant data is inescapable. When using data collected from a vehicle fleet, the normality can be learned and deviations from it identified as abnormal and thus relevant. The idea of learning the normality with the Replicator Neural Network and the Isolation Forest is applied to the identification of anomalies and the reduction of data transfer. It is compared how good the methods are in detecting anomalies and what it means for the traffic between vehicle and backend. It can be shown that the Isolation Forest beats the Replicator Neural Network. When reducing the transfered amount of data to 7%, in average more than 80.63% of the given anomalies are included.

1 INTRODUCTION

In the automotive industry, the usage of data generated by vehicles offers new potential for the future. By collecting and processing the data from many vehicles on a backend, functions like autonomous driving or the improvement of the product in a technical or costumer orientated way can be realized (see Fig. 1) (Gadatsch, 2017).

One challenge in this context is the amount of data. Only in the internal communication system, one vehicle alone produces up to 750 kilobytes per second. Extrapolated to a fleet of 150 vehicles, each driving one hour per day, up to 2.8 terabytes are produced in one week. Transmitting all data from vehicle to backed over air and store it there is not feasible, because of the transmission costs, data loss and the required preprocessing steps in the vehicle. One idea to solve this issue is the focus on anomalies, because they might represent interesting events and they bring new information to the backend. An anomaly can be defined as an *observation that deviates so much from other observations as to arouse suspicion that it was generated by a different mechanism* (Hawkins, 1980).

This paper applies the idea of finding unusual vehicle behavior as deviation from the normality defined by the raw vehicle sensor data from a vehicle fleet. The focus is in the application of the Isolation Forest approach.

The paper is organized as follows: In Sect. 2 different methods for detecting anomalies are introduced. Section 3 explains how the idea of anomaly detection is applied on the vehicles sensor data. Experiments and results are demonstrated in Sect. 4. The paper ends with a conclusion and the description of further research in Sect. 5.

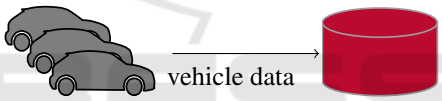


Figure 1: Collection of data via vehicle fleet.

2 STATE OF THE ART

Anomalies are detected in various domains as for example to recognize attacks on a network (intrusion detection) or some kind of fraud regarding credit card transactions. It is also applied in medicine to detect diseases and unusual symptoms. Comparable to anomalies in the vehicle sensor data is the detection of a defect sensor before the system breaks down (Pahuja and Yadav, 2013; Pimentel et al., 2014; Goldstein and Uchida, 2016).

Model-based methods for anomaly detection are one-class Support Vector Machines (SVMs) or Replicator Neural Networks (ReplNN) (Chandola et al., 2009). A newer method is the Isolation Forest (Iforest) (Liu et al., 2008; Liu et al., 2012).

Hofmockel, J. and Sax, E.
Isolation Forest for Anomaly Detection in Raw Vehicle Sensor Data.
In *Proceedings of the 4th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2018)*, pages 411-416
ISBN: 978-989-758-293-6

In the one-class SVM, the smallest possible sphere including all the normal data is found during training. In the application, data points outside of the sphere are detected as abnormal (Tax and Duin, 2004; Schölkopf et al., 2000).

While training a Replicator Neural Network, a prediction function $f(x)$ is learned, such that the difference between training point $\mathbf{x} \in \mathbb{R}^d$, and its reconstructed output $f(\mathbf{x}) = \tilde{\mathbf{x}}$, $\tilde{\mathbf{x}} \in \mathbb{R}^d$ is minimized for all $\mathbf{x} \in T$, with T describing the training data and d the number of features. The weights are learned with normal data and in the application the reconstruction error of test data point $\mathbf{x}_{test}$ characterizes its anomaly score. The reconstruction error is calculated as the mean squared difference between the original value and its reconstruction (Dau et al., 2014; Hawkins et al., 2002):

$$||\mathbf{x}_{test} - \tilde{\mathbf{x}}_{test}||_2^2. \quad (1)$$

The Isolation Forest approach assumes that anomalies are easier to isolate from the rest of the data than normal instances (see Fig. 2) (Liu et al., 2008; Liu et al., 2012).

Many binary trees are generated using different subsamples of the training data T. Hereby splitting feature and splitting value are chosen randomly (uniform distribution). The only parameters to define are the number of trees (t) and the subsampling size (ψ).

As exemplary shown in Fig. 3, the tree where the splitting value differentiates between normal and abnormal is more likely to be generated. That is why the expected path length of an abnormal data point is shorter than the path length of normal instances. Accordingly for the example (Liu et al., 2008; Liu et al., 2012):

$$P(T_1) < P(T_2) \implies E(h_2) < E(h_0) < E(h_1), \quad (2)$$

with $P(T_i)$ describing the probability of tree T_i and $E(h_i)$ as the expected path length (h_i) of data point x_i, $i \in \{0,1,2\}$:

$$E(h_i) = P(h(x_i) = 1) \cdot 1 + P(h(x_i) = 2) \cdot 2. \quad (3)$$

The average path length of the test data point $\mathbf{x}_{test}$ overall generated trees is used to calculate the anomaly score. The smaller the score, the higher the probability of being an anomaly (Liu et al., 2008; Liu et al., 2012).

3 OUR CONTRIBUTION

For the anomaly detection in vehicle sensor data, the concept of one-class classification is employed. Therefore data items are collected on the backend and

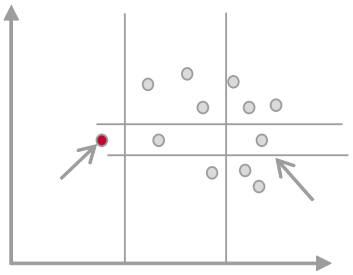


Figure 2: Isolation approach.

by assuming that most of them are normal, a reference model is learned (compare Fig. 1). In the application phase, the model is applied in the vehicle to detect deviations from the normal behavior as anomalies (Chandola et al., 2009). This approach ensures that after the training phase, data transfered between vehicle and backend is restricted to unusual situations not or rarely seen on the backend (see Fig. 4).

The paper analyses if the Isolation Forest is suitable to detect anomalies in raw vehicle sensor data with the aim of reducing data transfer. For comparison, a Replicator Neural Network is trained and tested additionally.

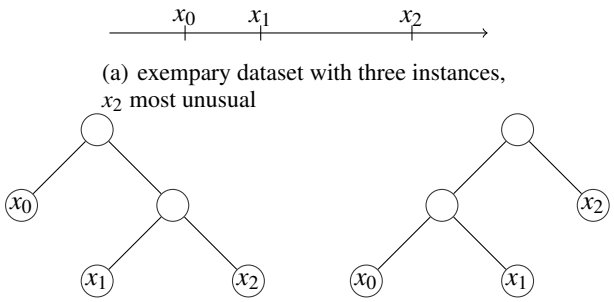
4 EXPERIMENTS AND RESULTS

To evaluate the methods for detecting anomalies in raw vehicle sensor data, different datasets are used. Based on data collected by a vehicle fleet, the model describing the normality is trained. Hereby it is assumed that most of the data are normal, but the ground truth is not known. For evaluation, different rides with enforced anomalies like an accident, full breaking or overspeed are under consideration. These rides are completely labeled.

The analyzed data are the signals transfered via the internal communication system in the vehicle, more concrete via the Controller Area Network (CAN-bus) (Winzker, 2017). These signals like velocity, longitudinal/lateral acceleration, steering angle/velocity, information about opened windows or brake pressure describe driving and vehicle behavior.

4.1 Evaluation criteria

For the comparison of the Replicator Neural Network and the Isolation Forest, the database X is split as shown in Fig. 5. The training data $T \subset X$ are assumed to be normal and used to learn the reference model. The validation data $V \subset X \setminus T$ is sampled from the same database as the training data and is therefore also meant to be mostly normal. The proportion



(a) exempary dataset with three instances, x_2 most unusual

(b) Tree T_1, $P(T_1) = D_{01}/D_{02}$

(c) Tree T_2, $P(T_2) = D_{12}/D_{02}$

Figure 3: Example for understanding Isolation Forest, D_{ij} is the distance from data point x_i to point x_j with $D_{01} < D_{12}$, (Liu et al., 2012).

of detected anomalies in the validation data (γ) shows how good the model generalizes and if it can be used to reduce the data transfer:

$$\gamma = \frac{|V'|}{|V|}, \tag{4}$$

with V' describing the validation data detected as anomaly.

Based on its anomaly score, an instance is predicted as abnormal if the score succeeds a defined border τ.:

$$score > \tau \rightarrow \text{ anomaly.} \tag{5}$$

For τ, the 95%-quantile of the anomaly scores of the training data ($S(T)$) is used because it ensures that 95% of the training data are classified as normal, while the 5% most exceptional training data get ignored. Thus, the assumption of exclusively normal training data gets defused:

$$\tau_{Q_{95}} = Q_{95}(S(T)). \tag{6}$$

The border is also applied to classify the labeled test data and to calculate *Recall* (fraction of correctly detected anomalies among real anomalies) and *Precision* (fraction of correctly detected anomalies among detected anomalies). Their harmonic mean is the *F-Score* (Bekkar et al., 2013):

$$F\text{-}Score = 2\frac{Recall \cdot Precision}{Recall + Precision}. \tag{7}$$

Additionally, the Area Under the Curve (AUC) resulting from the Receiver-Operating-Characteristic curve (ROC-curve) is calculated, because for this purpose no concrete border needs to be set (Fawcett, 2006). It can be evaluated if the anomaly score in general is

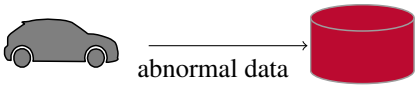


Figure 4: Reduction to anomalies in application phase.

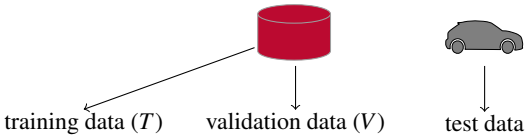


Figure 5: Usage of given data.

suitable to sort the data points by normality and the methods can be compared. The analysis is limited to the test data completely labeled (see Fig. 5).

4.2 Database

Different datasets are used for evaluation. Table 1 clarifies that the nine test cases differentiate in the amount of given data for training, the number of analyzed signals d and the enforced anomalies within the test ride. The sampling rate is 100 milliseconds.

4.3 Results

The following section compares the Replicator Neural Network with the Isolation Forest. The Replicator Neural Network consists of one hidden layer with d neurons (Tóth and Gosztolya, 2004; Dau et al., 2014). Our experiments have revealed that for the Isolation Forest, $t = 256$ and $\psi = 256$ are the settings which can't be improved by further increase.

Table 2 shows the AUC for the different use cases presented in Table 1. It can be identified that especially the accidents can be perfectly separated from the remaining data due to an AUC equals 1. The Table clarifies that the Isolation Forest has an high average AUC of 0.9080 which beats the ReplNN. In all test cases the Isolation Forest achieves an AUC above 0.83. The only exception is test case $K8$. Here the Replicator Neural Network performs better, but also not well. Reason could be that for the high dimension ($d = 353$), the amount of training data is not enough.

Table 1: Database for evaluation.

Id	Driving time for training [h]	d	Anomalies in test ride
K1	36	137	accident
K2	36	31	accident
K3	47	239	accident
K4	47	45	accident
K5	41	71	enforced anomalies as drive with open doors, full breaking, overspeed, ...
K6	71	106	enforced anomalies as drive with open doors, full breaking, close window with pinched book, ...
K7	27	353	Electronic Stability Control (ESC) intervention
K8	22	353	ESC intervention
K9	55	161	Antilock Braking System (ABS) intervention

Shown by the remaining test cases, the Isolation Forest provides a score, which is a suitable measurement to sort data points by their normality.

When regarding the proportion of detected anomalies in the validation data (γ), the Isolation Forest sticks out to generalize quite well. The value of $\gamma = 0.0696$ fits the border $\tau_{Q_{95}}$. When 95% of the training data are classified as normal, 94.1% of the validation data are also predicted to be normal. The Replicator Neural Network with $\gamma = 0.237$ tends to overfit and can not generally be applied to different data than the training data. Accordingly, when applying the trained Isolation Forest in vehicles, only 6.96% of the data are identified as abnormal and transmitted to the backend. The reduction of data transfer is guaranteed. *Recall* and *Precision* explain that in average 80% of the anomalies are detected and transfered, but only 31.45% of the data are really abnormal. The classification with the fixed threshold $\tau_{Q_{95}}$ is not reliable and additionally the anomaly score needs to be taken into account.

Figure 6 in the Appendix demonstrates which anomalies are detected by the Isolation Forest with threshold $\tau_{Q_{95}}$. It can be seen that especially the accidents and safety interventions are identified. Less extreme driving situations (e.g. full braking or overspeed) are not categorized to be abnormal. Events like window opening rear left are predicted as anomaly because they are rare in the training data T.

In summary, the results show that the amount of data transfered from vehicle to backend can be reduced while ensuring that most of the abnormal situations are included. Furthermore, when considering the anomaly score, the most abnormal situations can directly be identified.

5 CONCLUSION

The paper introduces the idea of anomaly detection to reduce the data transfer between vehicle and backend. The investigations show that the anomaly score yield by the Isolation Forest can be used to identify very unusual situations and delivers better results than the Replicator Neural Network. The definition of a score-based border distinguishing between normal and abnormal is difficult and depends on the use case.

By reducing data transfer to data detected as abnormal, up to 93% of traffic can be saved. Hereby it is ensured that most of the actual anomalies are transmitted as well. The wrongly classified data points can then be separated on the backend by their smaller anomaly score.

The next steps will be further improvements of the model. The investigation so far was reduced to static events. Since the vehicle produces time dependent data, an extension is necessary. Features describing the time series need to be extracted.

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Table 2: Comparison: Replicator Neural Network vs. Isolation Forest.

			$\tau = Q_{95}(S(X))$					
	AUC		γ		*Recall*		*Precision*	
	ReplNN	Iforest	ReplNN	Iforest	ReplNN	Iforest	ReplNN	Iforest
K1	1.0000	1.0000	0.2762	0.0444	1.0000	1.0000	0.0167	0.0270
K2	1.0000	1.0000	0.0912	0.1347	1.0000	1.0000	0.0909	0.0769
K3	1.0000	1.0000	0.5634	0.1773	1.0000	1.0000	0.0182	0.1429
K4	1.0000	0.9895	0.0699	0.0103	1.0000	1.0000	0.0400	0.3333
K5	0.7500	0.9356	0.1249	0.0833	0.7500	0.5833	0.6000	0.7778
K6	0.8126	0.8813	0.1192	0.0266	0.8182	0.5455	0.1765	0.5455
K7	0.8600	1.0000	0.6716	0.0693	1.0000	1.0000	0.3846	0.4545
K8	0.6690	0.5267	0.0998	0.0372	0.3590	0.1282	0.1458	0.4167
K9	0.8065	0.8387	0.1138	0.0430	1.0000	1.0000	0.0476	0.0556
mean	0.8776	**0.9080**	0.2367	**0.0696**	0.8808	**0.8063**	0.1689	**0.3145**

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APPENDIX

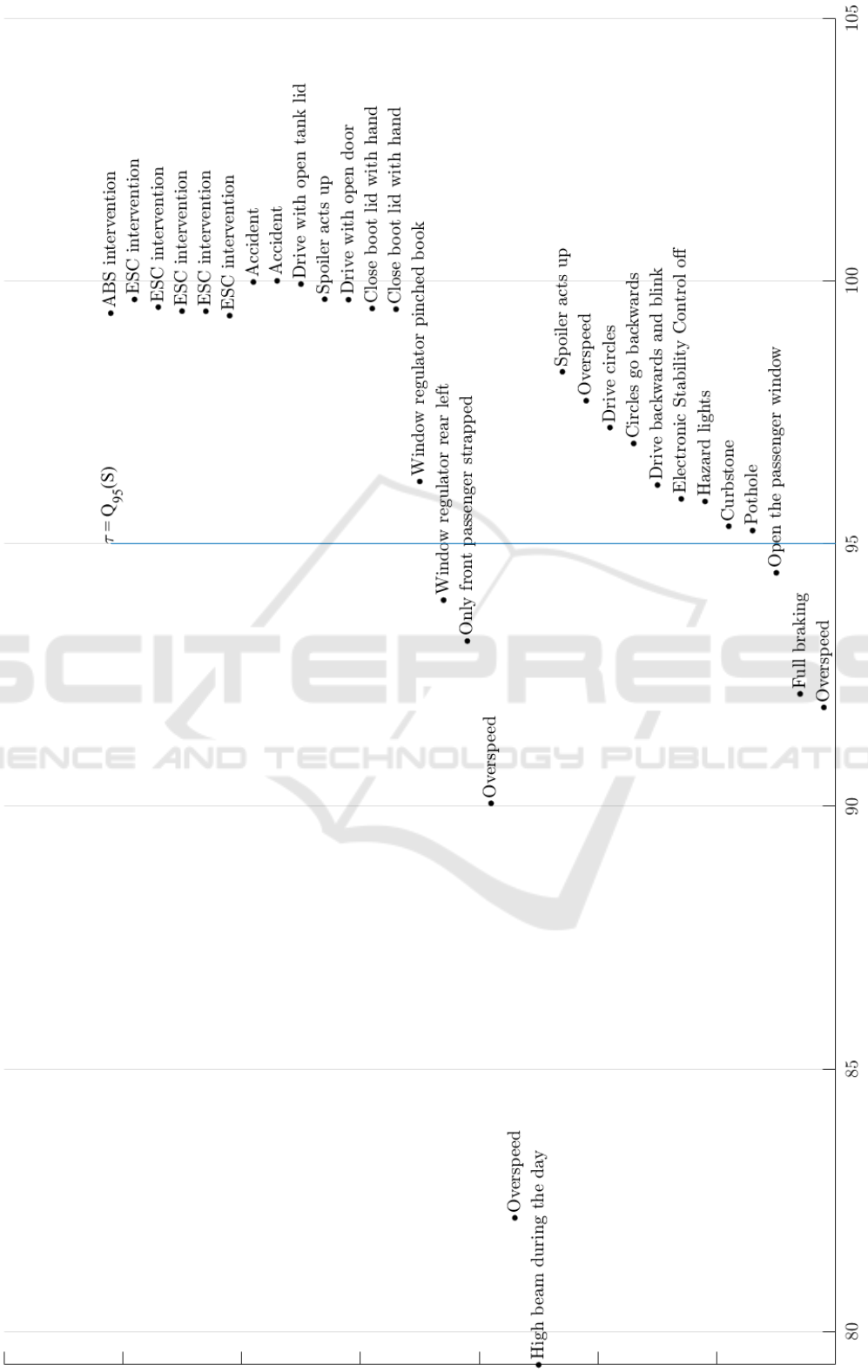

Figure 6: Detected anomalies sorted by anomaly score.