



# **Outlier Explanation and Visualization for Supporting the Use of Outlier Detection in Internal Auditing**

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**Disclaimer**

The results, opinions and conclusions expressed in this thesis are not necessarily those of Volkswagen Aktiengesellschaft.

## **Abstract**

Internal auditing faces multiple challenges caused by the growing amounts of data stemming from ongoing digital transformation. New techniques are therefore being evaluated for their application in auditing, one of which is outlier detection. Able to uncover irregularities without requiring domain knowledge about a system, outlier detection has already been applied in a number of auditing studies. Most identify outlier detection as only a first step, however, highlighting the key challenge of turning detected outliers into audit findings. Addressing this challenge, this work explores how outlier explanation and visualization can help auditors derive actual findings from potential findings. To adequately assess auditing's requirements, two workshops with internal auditors were conducted. Based on the deduced requirements, three existing outlier explanation methods were selected for their potential suitability in internal auditing. These methods were further adapted, leading to a total of six different approaches. To gauge their performance for explanation, the approaches were then benchmarked on several datasets with both injected and real outliers. This quantitative evaluation identified suitable explanation approaches. For a qualitative evaluation, one suitable approach was combined with a visualization and a detection method to create a prototype. This prototype was then applied to and refined over two different audits to determine the general suitability of the approach for auditing. Subsequently, a focus group was conducted to collect feedback from auditors regarding the suitability of the visualization and possible further extensions to it. Both quantitative and qualitative evaluations show that the developed approach can facilitate the application of outlier detection for internal auditing through outlier explanation and visualization and can, thus, help auditors to address the proliferation of data and to reduce risks by uncovering previously overlooked problems.

## **Zusammenfassung**

Die Interne Revision steht durch die von der digitalen Transformation verursachte steigende Datenmenge vor zahlreichen Herausforderungen. Daher werden neue Technologien für ihren Einsatz in der Revision evaluiert, eine davon ist die Anomaliedetektion. Anomaliedetektion ist in der Lage, Unregelmäßigkeiten aufzudecken, ohne dass Fachwissen über ein System erforderlich ist, und wurde bereits in einer Reihe von Studien in der Revision eingesetzt. In den meisten Studien wird die Erkennung von Anomalien jedoch nur als ein erster Schritt gesehen, wobei die größere Herausforderung darin besteht, erkannte Anomalien in Prüfungsfeststellungen zu überführen. Die vorliegende Arbeit befasst sich mit dieser Herausforderung und untersucht, wie die Erklärung und Visualisierung von Anomalien den Revisoren dabei helfen kann, aus potenziellen Feststellungen tatsächliche Prüfungsfeststellungen abzuleiten. Um die Anforderungen der Revision adäquat zu bewerten, wurden zwei Workshops mit internen Revisoren durchgeführt. Auf Basis der abgeleiteten Anforderungen wurden drei bestehende Anomalie-Erklärungsmethoden auf ihre potenzielle Eignung für die Interne Revision hin untersucht. Diese Methoden wurden weiter angepasst, so dass sich insgesamt sechs verschiedene Ansätze ergaben. Um die Leistungsfähigkeit der Erklärungsansätze zu beurteilen, wurden diese anschließend an mehreren Datensätzen mit sowohl injizierten als auch echten Anomalien einem Benchmarking unterzogen. Durch diese quantitative Evaluation wurden geeignete Erklärungsansätze identifiziert. Für eine qualitative Evaluation wurde einer der geeigneten Ansätze mit einer Visualisierung und einer Erkennungsmethode kombiniert, um einen Prototyp zu erstellen. Dieser wurde anschließend in zwei verschiedenen Revisionsprüfungen angewandt und weiterentwickelt, um die generelle Eignung des Ansatzes für die Revision zu ermitteln. Anschließend wurde eine Fokusgruppe genutzt, um Rückmeldungen von Revisoren bezüglich der Eignung der Visualisierung und möglicher Erweiterungen zu sammeln. Sowohl die quantitative als auch die qualitative Evaluation zeigen, dass der entwickelte Ansatz die Anwendung von Anomaliedetektion für die Interne Revision durch die Erklärung und Visualisierung von Anomalien erleichtert und somit den Revisoren helfen kann, die wachsende Datenmenge zu bewältigen und Risiken zu reduzieren, indem bisher nicht erkannte Probleme aufgedeckt werden.

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## List of Acronyms and Abbreviations

ATON	Attention-guided triplet deviation network for outlier interpretation
ALSO	Attribute-wise learning and scoring outliers
AP	Average precision
ARP	Average R-precision
AUPR	Area under the precision-recall curve
AUROC	Area under the ROC curve
CD	Critical difference
cLSA	Continuous local search algorithm
COIN	Contextual outlier interpretation
COPOD	Copula-based outlier detection
DBN	Deep belief nets
DBSCAN	Density-based spatial clustering of applications with noise
DFKI	Deutsches Forschungszentrum für Künstliche Intelligenz
EL	Embedding layer
EM	Expectation maximization
FPR	False positive rate
GASP	Group-wise attribute selection and prediction
GD	Gower distance
GMM	Gaussian mixture models
HBOS	Histogram-based outlier scoring
IForest	Isolation forest
IIA	Institute of internal auditors
IndEnt	Individual entropy
IOF	Inverse occurrence frequency
IQR	Interquartile range
kNN	K-nearest neighbor
LIME	Local interpretable model-agnostic explanations
LODI	Local outlier detection with interpretation
LOF	Local outlier factor
LOGP	Local outliers with graph projection
MAD	Median absolute deviation
MIXATON	Mixed-type ATON
MIXMAD	Mixed data multilevel anomaly detection
MNIST	Modified National Institute of Standards and Technology
Mv.RBM	Multivariate RBM
NLP	Natural language processing
OAMiner	Outlying aspect miner
OC-SVM	One-class SVM
ODDS	Outlier detection datasets

OE	One-hot encoding
PCA	Principal component analysis
PCP	Parallel coordinate plot
RBF	Radial basis function
RBM	Restricted Boltzmann machines
ReLU	Rectified linear unit
RMSE	Root-mean squared error
ROC	Receiver operating characteristic
RPA	Robotic process automation
SHAP	Shapley additive explanations
SMSE	Standardized mean square error
SPAD	Simple univariate probabilistic anomaly detector
SVM	Support vector machine
TPR	True positive rate
UCI	University of California Irvine

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