A Robust Autoencoder Ensemble-Based Approach for Anomaly Detection in Text

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Abstract

In this work, a robust autoencoder ensemblebased approach designed to address anomaly detection in text corpora is introduced. Each autoencoder within the ensemble incorporates a local robust subspace recovery projection of the original data in its encoding embedding, leveraging the geometric properties of the knearest neighbors to optimize subspace recovery and identify anomalous patterns in textual data. The evaluation of such an approach needs an experimental setting dedicated to the context of textual anomaly detection. Thus, beforehand, a comprehensive real-world taxonomy is introduced to distinguish between independent anomalies and contextual anomalies. Such a study to identify clearly the kinds of anomalies appearing in a textual context aims at addressing a critical gap in the existing literature. Then, extensive experiments on classical text corpora have been conducted and their results are presented that highlights the efficiency, both in robustness and in performance, of the robust autoencoder ensemble-based approach when detecting both independent and contextual anomalies. Diverse range of tasks, including classification, sentiment analysis, and spam detection, across eight different corpora, have been studied in these experiments.

1 Introduction

Anomaly detection (Chandola et al., 2009; Ruff et al., 2021) and outlier detection (Hawkins, 1980; Hodge and Austin, 2004; Zhang, 2013; Aggarwal, 2017a) are tasks aiming to estimate whether an observation is normal or not. Both of these tasks are referring to similar characteristics, and the terms anomaly and outlier are interchangeable in this paper. Several works have been devoted to study and categorise the different characteristics of an anomaly, and three principal kinds of anomalies can be noted: independent, contextual and collective. Defining a taxonomy for anomalies is crucial

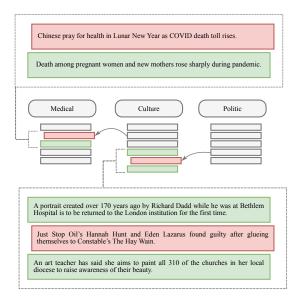


Figure 1: Presentation of the studied problem with three documents topics: medical, culture and politic. Under each topic we represent a textual document with colored rectangles. Gray and green are inliers and red ones are anomalies. The detailed documents are the abstract of the news articles taken from sources like Reuters, New York times, BBC, ... The first scenario is the apparition of a culture-related document in a medical feed, and the second scenario is a political document in the culture feed.

while the task to find anomalies lacks dedicated datasets. Such issue often leads practitioners to introduce an artificial contamination to produce anomalies into datasets. With the emergence of new machine learning methods and the availability of many datasets and corpora, anomaly detection can be addressed through many approaches (Beggel et al., 2020; He et al., 2021; Goodge et al., 2023), however, in most cases, models are based on one-class classification (OCC) (Khan and Madden, 2014; Ruff et al., 2018; Sohn et al., 2021).

Performing anomaly detection on textual data is less common than on many other types of data (images, time series and medical) but it comes with several useful applications that helps discerning wrong web content, hateful messages, spam or also errors in news feed. One of the main difficulties in this domain is the reproduction of experimental protocols and results from the literature (Bejan et al., 2023). Indeed, there is a great difference between tackling independent outliers and contextual outliers (Mahapatra et al., 2012; Fouché et al., 2020; Bejan et al., 2023) using semantic in text. For the former, anomaly classifier needs to differentiate two kinds of documents that come from unrelated topics (eg. sports and computer) but for the latter, they needs to detect a topic contaminated with another "sibling" (see Fig. 1 for examples of this difference). It appears that most of the recent works contaminate corpora without addressing the problem of which kind of anomaly/outlier is added in this process (Manevitz and Yousef, 2001; Kannan et al., 2017; Ruff et al., 2019a; Lai et al., 2020).

In this paper, based on recent literature, we address the problem of taxonomy after defining two kinds of anomaly: independent and contextual. Those anomalies are dependent of any semantic hierarchy and we propose in the experiments section to detail furthermore how they are benchmarked. For tackling both kind of anomalies, we propose a novel ensemble-based approach built with a robust autoencoder.

This paper is composed as follows. In Section 2, recent works are presented. In Section 3, our approach to build an Ensemble robust subspace local recovery encoder is introduced with a description of its properties. Several experiments are presented in Section 4. Finally, Section 6 concludes and presents some future work.

2 Related works

Recent advances in word embedding with language models like BERT (Devlin et al., 2019) or RoBERTa (Liu et al., 2019), and large language models such as Llama (Touvron et al., 2023) and OPT (Zhang et al., 2022) have shown promising characteristics for anomaly detection. However, only few methods of the literature propose their use (Manolache et al., 2021; Ruff et al., 2019a). Other methods like One-Class Support Vector Machine (OCSVM) (Schölkopf et al., 2001) and Textual Outlier using Nonnegative Matrix Factorization (TONMF) (Kannan et al., 2017) rely on a TF-IDF representation. Surprinsinly, recent methods are not using outlier ensemble methods (Aggarwal and

Sathe, 2015; Zhao et al., 2019a; Zimek et al., 2014) for performing anomaly/outlier detection with text data. Their usage in both Mixture of Experts (Du et al., 2022) and ensemble approach (Briskilal and Subalalitha, 2022) in various NLP tasks highlights that anomaly detection in text data misses important approaches.

AutoEncoders (AE) have been widely used for anomaly/outlier detection with high-dimensional data (Chen et al., 2017; Kieu et al., 2019) and are also successful with other kind of data (An and Cho, 2015; Chen et al., 2018; Lai et al., 2020; Zhou and Paffenroth, 2017; Beggel et al., 2020). The risk of using autoencoders with language models leads to the apparition of degenerate solution in the learning step. Robust properties are needed in such scenario for handling the manifold collapse phenomenon (Wang and Wang, 2019). Such issue can be mitigated using robust projections in the learned space of the autoencoder (eigenfunction decomposition (Bengio et al., 2004), ...). The Robust Subspace Recovery (Lerman and Maunu, 2018; Rahmani and Atia, 2017) is a robust manifold learning technique that map inlier distributions in a subspace where anomalies/outliers are at the edge. An autoencoder based on such an approach (Lai et al., 2020) encodes observation from the input space in a robust subspace. One problem of such autoencoder is the difficulty to address scenarios with features that present similar range values (problem of entanglement). This entanglement is especially more difficult with contextual anomalies where documents shares similar semantic properties. Such problem can be tackled using a local projection from the nearest neighbours in the latent representation space. Several manifold learning approaches like locally linear embedding (LLE) (Roweis and Saul, 2000), neighbourhood components analysis (NCA) (Goldberger et al., 2004) or soft nearest neighbours (SNN) (Frosst et al., 2019) can help to mitigate it.

In this paper we introduce an ensemble-based approach with randomly connected autoencoders. We also present a new autoencoder, robust subspace local recovery autoencoder (RLAE), that performs robust subspace representation with local neighbouring recovery. In this approach, called Ensemble robust subspace Local recovery Autoencoder (ErLA), a RLAE ensemble, it can be seen as an ensemble of several subspace that aims to find normal data with different *manifolds*. It is based on the hypothesis that one distribution is highly contam-

inated, and that inliers lies in a low-dimensional subspace.

3 ErLA: Ensemble robust subspace Local recovery Autoencoder

This section presents our approach ErLA and a description of its properties. While robust subspace recovery autoencoders have successfully tackled anomaly detection in text corpora, they lack locality and geometry awareness for mitigating disentanglement and manifold collapse in transformer-based language models. Thus, we introduce RLAE which integrates locality in the latent representation through a local neighbouring method.

The section is structured with a presentation of the randomly connected autoencoders, followed by a presentation of RSR loss. We then introduce the locally linear embedding loss term of ErLA before presenting its ensemble method. Finally, we present the representation of text.

3.1 Randomly Connected One-Class Autoencoder

Instead of using fully connected autoencoders, we propose to use randomly connected autoencoders. In the case of RSRAE, it is a novel approach and allow us to build ensemble autoencoders with different base detectors.

Let X be a dataset of N instances such as $X = \{x_1, ..., x_N\}$. Each instance has D dimensions which correspond to its attributes: $x_i = \{x_1, ..., x_D\}$. An Autoencoder is a neural networks in which the encoder \mathcal{E} maps an instance x_i in a latent representation noted $z_i = \mathcal{E}(x_i) \in \mathbb{R}^e$ of dimension e. The RSR layer is a linear transformation $\mathbf{A} \in \mathbb{R}^{d \times e}$ that reduces the dimension to d. We denote \hat{z}_i the representation of z_i through the RSR layer, such as $\hat{z}_i = \mathbf{A}z_i \in \mathbb{R}^d$. The decoder \mathcal{D} maps \hat{z}_i to \hat{x}_i in the original space D. The matrix \mathbf{A} and the parameters of \mathcal{E} and \mathcal{D} are obtained with the minimization of a loss function.

Similarly to (Chen et al., 2017) we introduce autoencoders with random connection such as we increase the variance of our model. In the autoencoders ensemble each autoencoder has a random probability of having several of its connections to be cut. Thus, we set the probability of disconnection with a random rate in [0.2, 0.5].

3.2 Robust Subspace Recovery Layer

We present the RSR AutoEncoder that aims to robustly and nonlinearly reduce the dimension of the original data (Lerman and Maunu, 2018). The RSR layer maps the inliers around their original locations and the outliers far from their original locations. The loss function minimises the sum of the autoencoder loss function noted L_{AE} with the RSR loss function noted L_{RSR} .

$$L_{AE}^{p}(\mathcal{E}, \mathbf{A}, \mathcal{D}) = \sum_{i=1}^{N} ||\mathbf{x}_{i} - \hat{\mathbf{x}}_{i}||_{2}^{p}$$
 (1)

which is the $l_{2,p}-norm$ based loss function for p>0.

For performing the subspace recovery, we denote two terms that have different roles in the minimisation process. The first term enforces the RSR layer to be robust (PCA estimation) and the second enforces the projection to be orthogonal:

$$L_{RSR}^{q}(\mathbf{A}) = \lambda_1 \sum_{i=1}^{N} ||\mathbf{z}_i - \mathbf{A}^{\mathrm{T}} \hat{\mathbf{z}}_i||_2^q$$
$$+ \lambda_2 \sum_{i=1}^{N} ||\mathbf{A} \mathbf{A}^{\mathrm{T}} - \mathbf{I}_d||_f^q \quad (2)$$

with \mathbf{A}^{\top} the transpose of \mathbf{A} , \mathbf{I}_d the $d \times d$ matrix and $||\cdot||_f$ the Frobenius norm. λ_1 and λ_2 are hyperparameters and q=1 is corresponding to the optimal $l_{p,q}$ norm (Maunu et al., 2019). If we simplify Equation 2 we have:

$$L_{RSRAE}(\mathcal{E}, \mathbf{A}, \mathcal{D}) = \lambda_1 L_{AE}^1(\mathcal{E}, \mathbf{A}, \mathcal{D}) + \lambda_2 L_{RSR}^1(\mathbf{A})$$
(3)

3.3 Robust local embedding

Locally Linear Embedding (LLE) (Roweis and Saul, 2000; Chen and Liu, 2011) is a popular dimensionality reduction technique that aims to preserve the local geometry of the data in a lowerdimensional subspace. It is based on the assumption that data points in a local neighbourhood can be linearly represented by their neighbouring data points. The LNE term in the loss function encourages the autoencoder to learn representations that preserve the relationships between data points in their local neighbourhoods. By doing so, it helps to project the Euclidean distance with its neighbours in the learned subspace. Based on Equation 2, the reconstruction loss function of RSRAE enforces robustness with ${\cal L}^1_{AE}$ and the orthogonality with L_{RSR}^1 . Because the learned representation of the encoder is compressed in a e dimension space, the locality of the subspace is not handled.

For tackling this problem, we propose to introduce a third term to L_{RLAE} based on a local neighbours embedding (LNE). Given a set of data points $\{\mathbf{x}_i\}_{i=1}^N$ in the input space, the goal of LNE is to find a lower-dimensional representation $\{\mathbf{z}_i\}_{i=1}^N$ in the output space (the subspace learned by the autoencoder) such that the local relationships between data points are preserved. We note:

$$L_{LNE}(\mathbf{A}) = \sum_{i=1}^{N} \left\| \mathbf{x}_{i} - \sum_{j \in \mathcal{N}_{i}} w_{ij} \mathbf{x}_{j} \right\|_{2}^{2}$$
 (4)

where \mathcal{N}_i represents the set of indices of the knearest neighbours of $\mathbf{x_i}$ (excluding $\mathbf{x_i}$ itself) and w_{ij} are the weights assigned to the neighbouring observations $\mathbf{x_j}$ in the reconstruction of $\mathbf{x_i}$. The weights w_{ij} can be computed using the least squares method to minimize the reconstruction error: $\min_{\mathbf{w_i}} \left\| \mathbf{x_i} - \sum_{j \in \mathcal{N}_i} w_{ij} \mathbf{x_j} \right\|_2^2$ subject to the constraint $\sum_{j \in \mathcal{N}_i} w_{ij} = 1$.

The LNE term encourages the autoencoder to find a representation for each data point as a combination of its k-nearest neighbours in the input space. With minimisation of the LNE term in the loss function, the autoencoder learns to preserve the local linear relationships, which ultimately helps to project the Euclidean distance with its neighbours. The reconstruction errors of LNE is measured by the cost function:

$$L_{LNE}(\mathbf{A}) = \sum_{i=1}^{N} \sum_{j \in \mathcal{N}_i} w_{ij} \|\mathbf{A}\mathbf{x}_i - \mathbf{A}\mathbf{x}_j\|_2^2 \quad (5)$$

The weight w_j assigned to the neighbour x_{ij} in the local reconstruction of x_i is determined based on its corresponding distances. The inclusion of the LNE term in the loss function encourages the autoencoder to preserve the local geometric structure of the data in the learned subspace.

Finally, the RLAE cost function is measured as follows:

$$L_{RLAE}(\mathcal{E}, \mathbf{A}, \mathcal{D}) = L_{RSRAE}(\mathcal{E}, \mathbf{A}, \mathcal{D}) + \lambda_3 L_{LNE}(\mathbf{A})$$
 (6)

The parameter λ_3 controls the influence of the LNE term on the overall loss. Because it controls the influence of locality of the manifold, the term is preferred to be low for avoiding degenerate results.

3.4 Ensemble Learning

The main idea behind ensemble methods is that a combination of several models, also called *base detectors*, and their outputs is more robust than usage of a single model. Such robustness can be observed against the bias-variance tradeoff and also for tackling the issue of overfitting.

Although the possibility to combine multiple base detectors is intuitive, the design of such approaches needs special attention regarding normalisation of outputs. In ErLA, we use the reconstruction error of each autoencoders and then we normalise each base detector scores through the standard deviation of one unit. We then take the median value for each observation.

3.5 Text Representation

Recent works (Ruff et al., 2019a; Manolache et al., 2021) have recorded their results on BERT-based language models. Thus, we use RoBERTa (Liu et al., 2019) for text representation. The ErLA model is not based on the self-attention mechanism, such as for (Ruff et al., 2019a; Manolache et al., 2021), and we use the implementation of (Reimers and Gurevych, 2019).

4 Experiments

In this section we present several experiments on both independent anomalies and contextual anomalies. We present all corpora and how we perform this study. The section is structured as follows: i) presentation of the experimental protocol for tackling independent and contextual anomalies; ii) presentation of all corpora and their principal characteristics; iii) complete description of experiment settings; iv) results of conducted benchmarks.

4.1 Experimental protocol

A large number of contributions have settled anomaly/outlier taxonomies (Hawkins, 1980; Hodge and Austin, 2004; Zhang, 2013; Aggarwal, 2017b; Ruff et al., 2019a) several types of outliers have been proposed in the literature: Point anomaly, Conditional/Contextual anomaly and Collective/Group anomaly. A similar taxonomy can be applied to textual data. Consequently, various types of outliers frequently coexist within the documents of a given corpus. The definition of a topic can be assimilated to the subject matter that a document addresses. Depending on the document type, there may be multiple subtopics within a broader cate-

Algorithm 1 TAC: Textual Anomaly Contamination

```
Require: Inlier topic \zeta, corpus X, split size l, con-
    tamination rate \nu
Ensure: 0 < l \le N
    c \leftarrow l\nu
    i \leftarrow 0
    Initialize empty matrix Z
    \mathcal{A} \leftarrow \{\mathbf{x}_j \times \mathbf{y}_j \in \mathbf{X} \times \mathbf{Y} | \forall j \in [0, N], \mathbf{y}_j \neq \zeta\}
    X_{\zeta} \leftarrow \{X \setminus A\}
                                                      ▶ Inlier Matrix
    while |\mathbf{Z}| < c \operatorname{do}
         if Parent(y_i) \neq Parent(\zeta) then
                Append(x_i, y_i) to Z
         end if
         i \leftarrow i + 1
    end while
    Fill Z with X_{\zeta} until |Z| = l
    return Shuffle(Z)
```

gory (e.g., a sports topic that encompasses football and tennis). Thus, accounting for this hierarchical structure introduces a form of contextual anomaly. These contextual outliers may appear unremarkable in isolation but are considered outliers when associated with a small subset of the corpus.

Collective anomaly poses challenges in terms of formalisation due to the contextual nature of textual data. To illustrate this, consider a legal document mentioning a football player, which would be anomalous if incorrectly appearing in a sports-related corpus. Point outliers represent observations that lack any meaningful relationship with other topics. Specifically, anomaly topics and inlier topics have different hierarchical parents within the category structure. Let a labelled document of a corpus $(x,y) \in X \times \mathcal{Y}$ and ζ be the inlier category, and its corresponding subset $X_{\zeta} \subseteq X$. We define \mathcal{A} the subset of all anomalies such as $\mathcal{A} \subset X$. We have:

$$\mathcal{A} = X \backslash X_{\mathcal{C}} \tag{7}$$

Regarding \mathcal{A} , we can make the distinction with two different constraints. We note P(y) the direct parent of y in a given hierarchy. First, an observation x_i is considered to be an anomaly if its parent topic is different of inlier parent topics such as:

$$\mathcal{A}_{p}(\zeta) = \{ P(\zeta) \neq P(y) | (a, y) \in \mathcal{A} \times Y \}$$
 (8)

The second constraint corresponds to documents that do not lie in X_{ζ} but share the same parent topic

Dataset	Topics	Hierarchy
20 Newsgroups	20	Yes
DBpedia 14	14	Yes
Reuters-21578	90	No
Web of Science	134	Yes
Enron	2	No
SMS Spam	2	No
IMDB	2	No
SST2	2	No

Table 1: Presentation of datasets from the literature on outlier detection and the inherent tasks. We describe these corpora by indicating the existence of a topic hierarchy in the labels of the original corpus.

as ζ . These observations are identified as another kind of anomaly: contextual anomaly. We write:

$$\mathcal{A}_c(\zeta) = \{ P(\zeta) = P(y) | (a, y) \in \mathcal{A} \times Y, \mathcal{A} \setminus \mathcal{A}_p \}$$
(9)

4.2 Data

Although there are dedicated datasets for outlier detection, such as ODDS or UCI, they mainly provide multidimensional data, time series and computer vision data. Applications such as spam detection and text classification have a rich set of corpora available. Recent work (Lai et al., 2020; Ruff et al., 2019a; Kannan et al., 2017; Mahapatra et al., 2012) uses classification datasets such as Reuters-21578¹ and 20 Newsgroups² with a dedicated preparation in order to compare their approaches.

We use the corpus presented in the section and for each available category, we apply the preparation of independent outliers and contextual outliers with TAC (Algorithm 1). To be fair with each method and each dataset, we set the size of the preparation subset to 350 and the results are averaged over 10 of runs. The data is pre-processed by removing lower case and stop words. The train part of each corpus is used for training and evaluation. The TF-IDF model is applied to the whole corpus and only tokens that appear at least three times are kept in the vocabulary. In a first step, we set $\nu=0.10$.

20 Newsgroups. For 20 Newsgroups we separate the subtopics into seven main topics: computer, forsale, motors, politics, religion, science, sports.

http://www.daviddlewis.com/resources/ testcollections/reuters21578/

²http://qwone.com/~jason/20Newsgroups/

Independent anomalies ($\nu = 0.1$)								
Model	20New.	Reuters	WOS	DBpedia	Enron	SMS Sp.	IMDB	SST2
OCSVM	0.884	0.851	0.876	0.962	0.687	0.683	0.539	0.575
OC-AE	0.630	0.721	0.655	0.599	0.484	0.683	0.517	0.499
RandAE	0.622	0.689	0.636	0.575	0.466	0.687	0.503	0.486
RSRAE	0.669	0.768	0.731	0.634	0.518	0.642	0.540	0.577
CVDD	0.781	0.895	0.948	0.958	0.629	0.717	0.513	0.562
RLEA	0.792	0.829	0.843	0.840	0.611	0.657	0.521	0.542
ErLA	0.907	0.926	0.939	0.983	0.713	0.813	0.560	0.594

Contextua	l anomalies	$(\nu = 0.1)$	
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Model	20New.		Reuters		WOS		DBpedia	
	AP	AUC	AP	AUC	AP	AUC	AP	AUC
OCSVM	0.220	0.681	0.471	0.755	0.599	0.889	0.566	0.882
OC-AE	0.175	0.592	0.351	0.683	0.162	0.577	0.334	0.714
RandAE	0.164	0.579	0.337	0.662	0.147	0.544	0.319	0.694
RSRAE	0.177	0.584	0.340	0.729	0.214	0.623	0.260	0.660
CVDD	0.131	0.613	0.481	0.824	0.623	0.916	0.646	0.919
RLEA	0.201	0.642	0.420	0.757	0.334	0.738	0.368	0.747
ErLA	0.325	0.718	0.609	0.880	0.687	0.921	0.840	0.951

Table 2: Results of state of the art models for independent and contextual anomalies with the contamination rate $\nu=0.10$. Area under ROC (AUC) is the default evaluation metric for independent contamination, and Average Precision (AP) is also added for contextual contamination. The experimental study is performed on Distill RoBERTA. Each result is performed on test split prepared through Algorithm 1.

We do not count the topic "forsale" for contextual outliers because it has no subtopics.

Reuters-21578. The Reuters-21578 corpus contains documents associated with several topics. We delete all these documents to keep only those associated with a single topic. We reorganise the topics in order to obtain a hierarchy, based on the work of (Toutanova et al., 2001). Thus, four parent themes are created: commodities, finance, metals and energy. We apply TAC to the eight topics that have the greatest number of training documents.

DBpedia 14. For DBpedia 14 we create the topic hierarchy based on the ontology provided³ and has six parent topics.

Web Of Science. Web of Science is often used as a reference for hierarchical classification and provides three levels of topic hierarchy. The third level topics are distributed among the corresponding first level parents. Thus, seven parent topics are present and for child topics that are associated with more than one parent, we keep the largest set of children and delete the others.

4.3 Setup

We use TAC for preparing contextual contamination on each candidate inliers possible with $\nu=0.1$ (TAC1) and a split size of min(|D|, 1000). All results are performed on AUROC and AUPRC reference works from the previous section. We integrate results of one-class autoencoder (OC-AE) and we also benchmark results on a randomly connected autoencoder ensemble (RandAE) (Chen et al., 2017). The architecture is similar to (Chen et al., 2017) and the autoencoders are following their settings. We also keep the number of runs for each corpus and each split contamination to 10.

Implementation For ErLA and RandAE we setup similarly than with the autoencoder and we set the number of base predictors to 20. We provide the code of our approach⁴ using the PyOD base implementation (Zhao et al., 2019b). We propose an implementation based on the *BaseDetector* of PyOD so each of the compared model can be accordingly tested. Randomly connected neural networks can be difficult to implment. Thus, we have implemented three version of our randomly connected autoencoder: one with setting the prune con-

³mappings.dbpedia.org/server/ontology/classes/

⁴https://github.com/jrmip/ErLA/

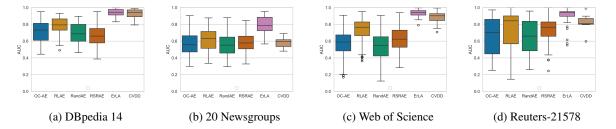


Figure 2: Results of our experimental study with $\nu=0.1$, split size of 350 and number of base detector of 25. The performance metric is AUROC (AC) and the text representation is RoBERTA.

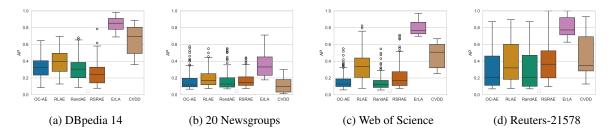


Figure 3: Boxplots of results of our experimental study with $\nu=0.1$, split size of 350 and number of base detector of 25. The performance metric is AUPRC (AP) and the text representation is RoBERTA.

nections to 0 before each backpropagation, another one with the usage of PyTorch built-in prune module and finally a version with Torch-Pruning (Fang et al., 2023). Based on our experiments, we use the built-in Pytorch module for reproducibility. Additionally, we also set hyperparameters $\lambda_1=0.1$, $\lambda_2=0.1$ and $\lambda_3=0.05$. For avoiding manifold collapse problem and degenerates solutions, we advise that $\lambda_3<\lambda_1$. We set the latent dimension of the LNE layer to 32. On the other hand, we set the epoch number to 50 and random connection probability between [0.2,0.5].

Baseline We propose to compare our approach against OCSVM(Schölkopf et al., 2001), a simple one-class autoencoder (OC-AE), RSRAE(Lai et al., 2020) and an ensemble autoencoder model RandAE based on (Chen et al., 2017). For OCSVM OC-AE we use the implementation from PyOD(Zhao et al., 2019b) and for RSRAE we use our PyTorch implementation of their code. All our results approximate theirs. We rigorously follow the guidelines provided by (Lai et al., 2020).

Alternatively, we propose to use a variant of Algorithm 1 considering $P(y) = P(\zeta)$ for independent contamination. Finally we propose to benchmark our results on corpora presented in Table 1.

We also display CVDD (Ruff et al., 2019b) results with several adaptations. In this approach, CVDD learn on all the training corpus instead of

the training split. Considering this property, we use their implementation knowing the approach has advantage against other baseline models.

4.4 Results

We propose to present our results on three principal points: independent contamination, contextual contamination and robustness of model scores. Table 2 displays results on TAC1 (contamination of 0.1) and independent contamination. We can see that ErLA is outperforming all models. While the results are similar, our approach is notably standing over the others on SMS Spam and Reuters-21578. Thus, our ensemble method presents success for semantic related, spam and sentiment corpora.

Table 2 displays the experimental results conducted with our approach ErLA. We observe that our approach is outperforming others model with AUROC metric and AUPRC metric. We can see that usage of ErLA allow to mitigate unstable decision of the original RSRAE. We can also see significant difference of performance with Web of Science corpus and Reuters-21578. Additionally, we can observe that the original one-class autoencoder highly benefits from randomly connection and ensemble technique, as it close the gap with other models.

While our performances are competitive, the principal purpose of tackling outlier detection with ensemble methods is to mitigate the bias-variance

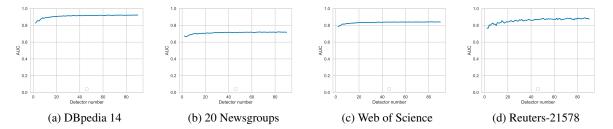


Figure 4: Number of base detectors considering AUC performances on contextual contamination.

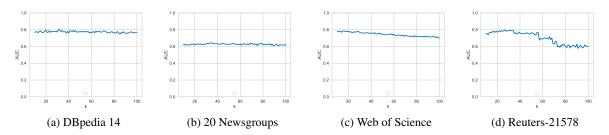


Figure 5: Number of k-nearest neighbours for one RLAE considering AUC performances on contextual contamination and latent dimension of 32.

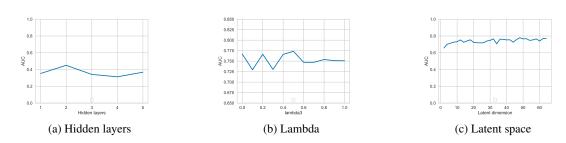


Figure 6: Study of RLAE hyperparameter: hidden layers number, lambda3 regulating local recovery term and latent space dimension.

trade-off. We propose to compare the model results with box-plots, similarly to the previous chapter. The main objective of our contribution is to robust outlier scores for contextual outliers with text. The Figure 2 and the Figure 3 displays an outperforming results from our approach. We can see that the variance of our model is noticeable as the box variance are always smaller than its competitors. Also, the min and max possible scores are close from the median scores, concluding to see that our approach is more efficient, more robust and can handle well language model like RoBERTA.

We can note that reference results are considerably different from ours. The principal reason is due the the contamination process for performing experimental study. We can observe that the literature contaminate both independent anomalies and contextual anomalies without distinctive analysis.

5 Discussion

In this section we propose an observation of various properties of our autoencoder RLAE and its impact inside ErLA (ensemble).

Base detector number The Figure 4 displays the performance impact against the base detector number in ErLA. We can see that starting from 30, there is not substantial gains to increase the number of base detector in the ensemble. While it can slowly increase AUC, it considerably increase the computation time. 20 is then a concrete spot.

Number of local neighbours In Figure 5 we display the impact of the hyperparameter k in RLAE. As stated in the Reuters-21578 results, we can see that this hyperparameter needs to be wisely picked. While a low value seems to be preferable, we can see that our autoencoder is still robust against this hyperparameter.

Parameters In Figure 6 is presented sensibility to three hyperparemeter that impact the learning step: number of hidden layer, the λ_3 parameter and the size of latent space in the ErLA model. While variance is tackled in ensemble methods, hidden layers are not a highly sensible parameter considering the computation/performance tradeoff. In Section 4 the hyperparameter $\lambda_3 < \lambda_1$ is set to 0.05. The curve is the AUC performance against λ_3 for $\lambda_1 = 0.1$. Finally, the learned embedding inside RLAE should be preferably lower than the output dimension of the autoencoder.

6 Conclusion

In this work we have introduced ErLA, an ensemble approach with robust autoencoders, optimized through LNE for tackling contextual anomaly in text. Conducted experiments demonstrate that our approach outperform all baseline method with less variance.

One perspective is to study the integration of attention head for mitigating the black box problem of our model. It is common, recently, to display text with their corresponding temperature, thanks to recent language model based on transformers.

The representation of text is a key concept that we want to investigate in the near future. Our approach has proven state of the art results and a great robustness against two kinds of outliers and with a small amount of available documents.

Furthermore, we have displayed that reference contributions have not put sufficient effort to the contamination process in their protocol. One promising perspective is to propose an unsupervised approach for generating different kinds of outliers. Also, our work mainly focuses on the semantic structure of text but syntax is also a promising direction.

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