
TEXT-ADBENCH: TEXT ANOMALY DETECTION BENCHMARK BASED ON LLMs EMBEDDING

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ABSTRACT

Text anomaly detection is a critical task in natural language processing (NLP), with applications spanning fraud detection, misinformation identification, spam detection and content moderation, etc. Despite significant advances in large language models (LLMs) and anomaly detection algorithms, the absence of standardized and comprehensive benchmarks for evaluating the existing anomaly detection methods on text data limits rigorous comparison and development of innovative approaches. This work performs a comprehensive empirical study and introduces a benchmark for text anomaly detection, leveraging embeddings from diverse pre-trained language models across a wide array of text datasets. Our work systematically evaluates the effectiveness of embedding-based text anomaly detection by incorporating (1) early language models (GloVe, BERT); (2) multiple LLMs (LLaMa-2, LLaMa-3, Mistral, OpenAI (small, ada, large)); (3) multi-domain text datasets (news, social media, scientific publications); (4) comprehensive evaluation metrics (AUROC, AUPRC). Our experiments reveal a critical empirical insight: embedding quality significantly governs anomaly detection efficacy, and deep learning-based approaches demonstrate no performance advantage over conventional shallow algorithms (e.g., KNN, Isolation Forest) when leveraging LLM-derived embeddings. In addition, we observe strongly low-rank characteristics in cross-model performance matrices, which enables an efficient strategy for rapid model evaluation (or embedding evaluation) and selection in practical applications. Furthermore, by open-sourcing our benchmark toolkit that includes all embeddings from different models and code (see <https://github.com/jicongfan/Text-Anomaly-Detection-Benchmark>), this work provides a foundation for future research in robust and scalable text anomaly detection systems.

Keywords Text Anomaly Detection · LLMs · Text Representation · Benchmark

1 Introduction

Anomaly detection (AD) Chandola et al. [2009], Aggarwal [2016], Ruff et al. [2021], broadly defined as the task of identifying patterns that deviates significantly from the majority, is a cornerstone of data analysis and decision-making in different fields. In past few decades, researchers achieved significant progress in medical diagnosis Kononenko [2001], Amato et al. [2013], Bakator and Radosav [2018], Richens et al. [2020], intrusion detection Mukherjee et al. [2002], Tsai et al. [2009], Liao et al. [2013], Khraisat et al. [2019] in cybersecurity, fraud detection Bolton and Hand [2002], Abdallah et al. [2016], Motie and Raahemi [2024] in finance, and fault detection Isermann [2005], Fan et al. [2017, 2022] in industry. While these AD methods commonly excel in structured data type, such as time-series Zamanzadeh Darban et al. [2024], tabular data, images Fernando et al. [2021] and videos Liu et al. [2025], text-based anomaly detection (see the formal definition given by Definition 1 and the corresponding examples) presents challenges

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due to the unstructured, high-dimensional nature of language, complex and diverse anomalies, where anomalies may manifest as subtle semantic inconsistencies, syntactic irregularities, or contextual deviations.

Due to the inherent characteristics of human language, text representation techniques have become a fundamental component of natural language processing (NLP). Early text representation techniques Harris [1954], Sparck Jones [1972], Aizawa [2003] relied heavily on handcrafted features, such as term frequency (TF) and inverse document frequency (IDF), which aimed to quantify the importance of words within documents. These methods, while simple and computationally efficient, treated text as unordered collections of words (i.e., bag-of-words models), failing to capture syntactic structure or semantic relationships. Subsequent developments introduced vector space models, such as Latent Semantic Analysis (LSA) Blei et al. [2003] and Latent Dirichlet Allocation (LDA) Dumais [2004], incorporating co-occurrence patterns and topic distributions to produce more meaningful document embeddings. However, these techniques still struggled to represent contextual meaning and polysemy, limiting their expressiveness in downstream tasks. A major breakthrough occurred with the rise of neural word embeddings, particularly Word2Vec Mikolov et al. [2013], GloVe Pennington et al. [2014a], and FastText Joulin et al. [2016], which mapped words into dense, low-dimensional vectors based on their distributional properties in large corpora. These models significantly improved the semantic fidelity of word representations, but they remained static, assigning each word a single representation regardless of its context. To address this limitation, researchers introduced contextualized word embeddings, such as ELMo Peters et al. [2018], BERT Devlin et al. [2019] and GPT Radford et al. [2018], which generated dynamic representations conditioned on surrounding text. These models marked a paradigm shift in NLP by allowing representations to reflect both syntax and semantics within a specific context. With the advent of large language models (LLMs) such as GPT-series, LLaMA-series and etc., leveraging transformer architectures and pretraining on large-scale text data, text representation based on LLMs exhibits remarkable performance in a wide range of language understanding and generation tasks Naveed et al. [2023], Patil and Gudivada [2024].

However, the integration of the representation technique of LLMs into text anomaly detection remains limited exploration and there is a significant lack for a comprehensive analysis and comparison for existing conventional shallow AD algorithms Schölkopf et al. [1999], Breunig et al. [2000], Liu et al. [2008], deep learning-based AD methods Ruff et al. [2018], Fu et al. [2024], and tailored text AD methods Ruff et al. [2019], Manolache et al. [2021], which has hindered the progress and development of text anomaly detection techniques. We have noticed that there are two related works Li et al. [2024a], Cao et al. [2025] recently that provided some comparison and valuable insights. However, the two works exhibit at least the following limitations: (1) insufficient comparative analysis, with a focus primarily on shallow anomaly detection algorithms; (2) the absence of discussion or comparison regarding different pooling strategies when utilizing text embeddings from large language models (LLMs), despite their critical impact on embedding effectiveness; (3) a narrow evaluation framework, relying on a single performance metric; and (4) a lack of open-source embeddings and code, limiting reproducibility and further research.

To address these gaps, this work introduces Text-ADBench, a comprehensive benchmark for text anomaly detection based on embeddings derived from LLMs. Specifically, we construct a large number of two-stage text AD methods. First, we generate the text embedding using a diverse suite of language models, including early language models (GloVe-6B, BERT), open-source LLMs (LLaMA2-7B, LLaMA3-8B, Mistral-7B) and OpenAI’s text-embedding models (small, ada, large). To aggregate sequential token embeddings into a single vector representation, we utilize three pooling strategies, including “mean”, “end-of-sequence (EOS) token”, and “weighted mean”. Second, we develop anomaly detection tasks by applying these embeddings to a range of AD methods, encompassing both shallow and deep learning-based techniques. The workflow of Text-ADBench is illustrated in Fig. 1. Additionally, we incorporate two specialized text AD methods (CVDD Ruff et al. [2018] and DATE Manolache et al. [2021]) into our comparative analysis. Our experiments are conducted on eight real-world text datasets. The main contributions of this work are summarized as follows.

- We present a comprehensive benchmark for text anomaly detection, addressing the existing gap in leveraging large language models (LLMs) embeddings for this task. Our framework incorporates diverse language models, multiple pooling strategies, a wide range of anomaly detection methods, and comprehensive evaluation metrics
- We conduct further analysis of the results and identify a low-rank property in performance. This finding has two important implications: (1) the detection performance of novel text datasets or AD methods can be reliably predicted using only a subset of performance measurements, and (2) this property enables an efficient strategy for rapid model evaluation (embedding evaluation) and selection in practical applications.
- We release Text-ADBench at <https://github.com/jicongfan/Text-Anomaly-Detection-Benchmark> that including all data, embeddings, and code used in our experiments. We provide an integrated and easy-to-use framework whatever related researchers want to reproduce results or evaluate novel embeddings and methods, which would foster the development of these fields.

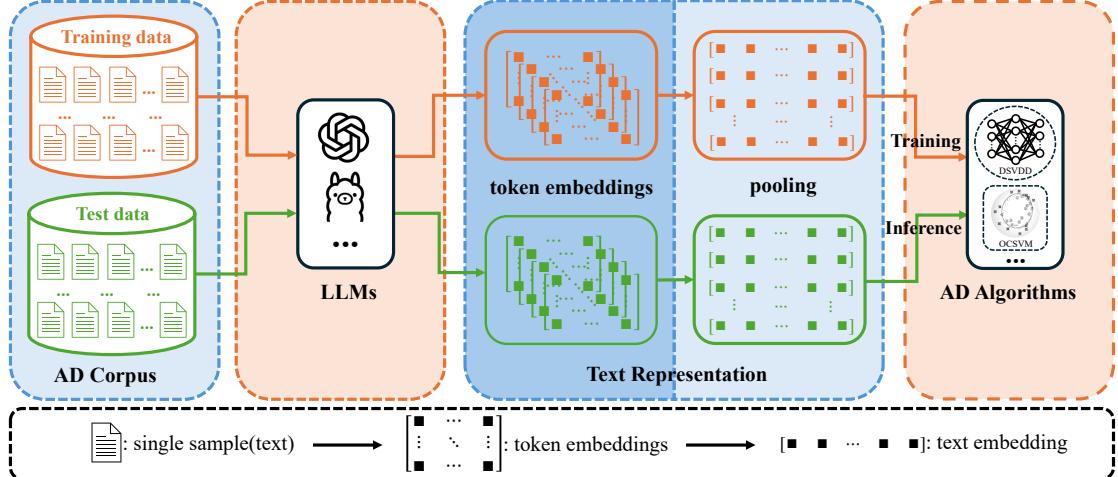


Figure 1: Flowchart of Text-ADBench.

This work serves as a foundational resource for both researchers and practitioners, advancing the text AD field through its methodological rigor and holistic evaluation. By open-sourcing our benchmark framework, precomputed embeddings, we aim to catalyze further research into hybrid pooling strategies, domain adaptation, and efficient LLM utilization for text anomaly detection.

The remainder of this paper is organized as follows: Section 2 reviews related work; Section 3 formulates the problem of text anomaly detection; Section 4 details the specific settings including datasets, LLMs, embedding, AD methods. Section 5 presents experimental results and basic analysis; Section 6 explores the low-rank property of performance; and Section 7 concludes this work and provide future directions.

2 Related Work

2.1 Unsupervised Anomaly Detection

Unsupervised Anomaly Detection (UAD) is a fundamental task in data analysis and decision-making, with broad applications across various domains, such as fault detection in industry, fraud detection in finance, medical diagnosis, and intrusion detection in cybersecurity. Consequently, a flood of unsupervised anomaly detection methods have been proposed in recent decades Schölkopf et al. [1999], Breunig et al. [2000], Liu et al. [2008], Ruff et al. [2018], Deecke et al. [2019], Qiu et al. [2021], Fu et al. [2024], Xiao et al. [2025a], Dai and Fan [2025]. Generally, these UAD methods are grounded in distinct assumptions about data distribution Aggarwal [2016], Pang et al. [2021], Ruff et al. [2021]. For instance, anomalies may reside in low-density regions or exhibit deviations in feature space compared to normal instances. The performance of these methods is often contingent upon the degree of alignment between the input data and the underlying assumptions. Roughly, these methods can be organized into two categories, including conventional machine learning-based shallow algorithms and deep learning-based methods Pang et al. [2021]. Shallow anomaly detection algorithms Schölkopf et al. [1999], Breunig et al. [2000], Liu et al. [2008], Li et al. [2022] typically have a straightforward learning process and exhibit superior interpretability. For instance, OCSVM Schölkopf et al. [1999] learns a maximum-margin hyperplane in a kernel space to separate normal data from the origin. Isolation Forest Liu et al. [2008] builds an ensemble of trees to isolate data points, where anomalies are identified by their shorter average path lengths on these trees. KNN Ramaswamy et al. [2000] defines the anomaly score of a sample as its distance to the k-th nearest neighbor, based on the assumption that anomalies reside in sparser regions of the feature space compared to normal data. Deep learning-based anomaly detection methods Schlegl et al. [2017], Zong et al. [2018], Ruff et al. [2018], Pang et al. [2019], Perera et al. [2019], Goyal et al. [2020], Fan et al. [2022], Qiu et al. [2021], Cai and Fan [2022], Xu et al. [2023a], Fu et al. [2024], Ye et al. [2025] often achieve superior detection performance, particularly in high-dimensional data settings. For instance, AutoEncoder (AE) Hinton and Salakhutdinov [2006] minimizes the reconstruction error on normal data. It assumes that abnormal data cannot be reconstructed well when an autoencoder is trained only on normal data. Naturally, reconstruction error is used as an anomaly score. Deep SVDD Ruff et al. [2018] learns a minimum-radius hypersphere to encompass all the normal data while the unseen abnormal data are expected to fall outside, where its anomaly score is defined by the distance to the hypersphere's center. The PLAD proposed by Cai

and Fan [2022] trains a perturbator to perturb normal data and a classifier to distinguish normal data and perturbed data, leading to an effective decision boundary for anomaly identification.

Note that in addition to UAD methods, there are also a few semi-supervised AD methods Hendrycks et al. [2018], Pang et al. [2018], Akcay et al. [2019], Ruff et al. [2020], Zhou et al. [2021], Pang et al. [2023], Xiao et al. [2025b] that can utilize labeled anomalies to improve the detection performance, since in some scenarios, a few known anomalous samples, though scarce, are available during the training stage.

2.2 Text Representation

Text representation is a fundamental technique of natural language processing (NLP) that transforms unstructured textual data into structured numerical formats, thereby enabling machine learning models to process and analyze linguistic information effectively. The evolution of text representation techniques has undergone several significant stages.

Early text representation techniques primarily relied on statistical and frequency-based approaches. The Bag-of-Words (BOW) model Harris [1954] and Term Frequency-Inverse Document Frequency (TF-IDF) Sparck Jones [1972] represented text as vectors of word frequencies, thereby only preserving the statistical lexical information but neglecting word order. As a result, the BOW model fails to capture semantic relationships between words and lacks contextual understanding. To address the limitations of the BOW model, distributed representations Mikolov et al. [2013], Pennington et al. [2014b] were developed, which encode words as dense vectors in a continuous space. For instance, Word2Vec Mikolov et al. [2013] introduced two architectures, Skip-gram and Continuous Bag-of-Words (CBOW), that capture semantic and syntactic relationships by predicting word contexts. Similarly, GloVe (Global Vectors for Word Representation) Pennington et al. [2014b] integrated global co-occurrence statistics with local context window-based learning. However, despite their advancements, Word2Vec and GloVe produce static and context-free word embeddings, which are unable to effectively handle polysemy and out-of-vocabulary (OOV) words. In 2017, the introduction of Transformer architecture Vaswani et al. [2017] revolutionized text representation by generating context-dependent embeddings. Subsequent models, such as GPT (Generative Pretrained Transformer) Radford et al. [2018] and BERT (Bidirectional Encoder Representations from Transformers) Devlin et al. [2019], leveraged the self-attention mechanism to produce dynamic word representations conditioned on surrounding text, markedly improving performance on downstream NLP tasks. With the advent of LLMs (Large Language Models), recently, the NLP community has begun adopting decoder-only LLMs for text embedding Wang et al. [2023], BehnamGhader et al. [2024a].

2.3 Text Anomaly Detection

In the field of natural language processing, anomaly detection tasks are employed to identify harmful content, spam reviews, and abusive language. A straightforward strategy is to construct pipeline (two-stage) methods by integrating text representation techniques with existing anomaly detection methods. Xu et al. Xu et al. [2023b] systematically estimated such combinations based on SBERT Reimers and Gurevych [2019]. Additionally, several specialized text anomaly detection algorithms Ruff et al. [2019], Manolache et al. [2021], Das et al. [2023] were proposed in recent years. For instance, CVDD Ruff et al. [2018], a self-attention-based model for unsupervised text anomaly detection method, minimizes the weighted cosine distance between the attention-weighted text embeddings and “context vectors”, where it employs self-attention heads to generate “context vectors” that capture diverse semantic themes in normal data and each head produces an orthogonal attention matrix, ensuring independent feature extraction. During the inference stage, anomalies are identified by averaging the cosine distances between the new sample’s embeddings and all “context vectors”. DATE Manolache et al. [2021] trains Transformers using masked language modeling (MLM) and two tailored pretext tasks to capture contextual anomalies. FATE Das et al. [2023], a semi-supervised text anomaly detection method, employs a contrastive objective to adjust anomaly scores. This approach ensures that normal samples cluster around a reference score while anomalies deviate significantly. Additionally, FATE leverages attention mechanisms and multi-instance learning to capture distinctive anomaly behaviors. More recently, Pantin and Marsala Pantin and Marsala [2024] introduced ERLA, a robust ensemble-based anomaly detection method utilizing autoencoders, where each autoencoder incorporates a local robust subspace recovery projection of the original data in its encoding embedding, thereby leveraging the geometric properties of the k-nearest neighbors to optimize subspace recovery and identify anomalous patterns in textual data.

2.4 Anomaly Detection based on LLMs

The remarkable success of large language models (LLMs) in natural language processing has spurred their adaptation to anomaly detection (AD) tasks Su et al. [2024] for further improvement of detection accuracy via their advanced semantic understanding. Current LLM-based AD approaches can be categorized into three paradigms: *(i) prompt-based*

methods Yang et al. [2024], Dong et al. [2024] directly employ pretrained LLMs to perform few-shot or zero-shot learning by designing specialized prompt functions, and **(ii) fine-tuning methods** Gu et al. [2024], Li et al. [2024b] adapt general-purpose LLMs into domain-specific anomaly detectors by fine-tuning them on task-relevant datasets, thereby tailoring their capabilities to the nuances of AD, and **(iii) embedding based methods** Li et al. [2024a], Cao et al. [2025] regard LLMs as feature extractors, generating high-dimensional embeddings that capture high-quality semantic and contextual patterns and then leveraging existing AD algorithms (e.g., OCSVM, Isolation Forest) to detect deviations from normal pattern based on these embeddings.

2.5 Existing Benchmarks for Text Anomaly Detection

There are some notable works Xu et al. [2023b], Bejan et al. [2023], Li et al. [2024a], Yang et al. [2024], Cao et al. [2025] that take effort to text anomaly detection. For instance, Xu et al. Xu et al. [2023b] evaluated 22 AD algorithms on 17 text corpora and mainly analyzed the performance effects of weak supervised signals. To the best of our knowledge, the first text anomaly detection benchmark based on LLMs is NLP-ADBench Li et al. [2024a], where Li et al. evaluated 11 AD algorithms based on embeddings of BERT and OpenAI (text-embedding-3-large) across 8 text corpora. To clearly delineate the different emphases and advantages of existing benchmarks and to further compare them with Text-ADBench, we provide a statistical comparison in Table 1. In summary, this benchmark emphasizes the following three aspects.

- First, while previous works Xu et al. [2023b], Bejan et al. [2023] mainly focus on the embeddings derived from early language models, recent works Li et al. [2024a], Cao et al. [2025] have begun to incorporate embeddings from LLMs, albeit with a limited scope. Considering the rapid advancement of the representation capabilities of LLMs, we compare 33 distinct embeddings for each dataset by integrating embedding models with pooling strategies. Notably, previous works do not compare the impact of different pooling strategies.
- Second, this benchmark identifies a low-rank property in performance matrices and demonstrates that the detection performance of novel text datasets or AD methods can be effectively predicted based on historical performance measurements. This finding enables an efficient strategy for rapid model evaluation (or embedding evaluation) or selection based on the results of this benchmark.
- More importantly, we release all resources used in this benchmark including all original text datasets, embeddings and code. These open-access resources ensures researchers and practitioners can easily end efficient reproduce our results, estimate novel datasets or AD algorithms, thereby fostering progress in the field. Additionally, the released embeddings can be leveraged for other downstream tasks.

Table 1: Comparison among Text-ADBench and existing benchmarks, where “DL” and “TFT” refers to “Deep Learning” and “Tailored for Text”, respectively. Note that the term “# Emb.” denotes the number of distinct embeddings derived from each text dataset.

Benchmark	Datasets	Coverage (numbers)				AD Algorithm Shallow	Type DL	Type TFT	Representation Early LM	Pooling	Open Source Code	Embedding	Performance Matrices	
		Algo.	LLMs	Emb.	Metrics								Analysis	Prediction
Xu et al. Xu et al. [2023b] (2023)	22	17	0	2	1	✓	✓	✗	✓	✗	✗	✗	✗	✗
Bejan et al. Bejan et al. [2023] (2023)	7	4	0	2	2	✓	✗	✓	✓	✗	✓	✗	✗	✗
Li et al. Li et al. [2024a] (2024)	8	11	1	2	1	✓	✓	✓	✓	✗	✓	✗	✗	✗
Yang et al. Yang et al. [2024] (2024)	5	10	2	-	2	✓	✓	✓	✗	✗	✓	✗	✗	✗
Cao et al. Cao et al. [2025] (2025)	6	8	5	8	1	✓	✗	✗	✓	✗	✗	✗	✗	✗
Text-ADBench (ours)	12	12	12	33	2	✓	✓	✓	✓	✓	✓	✓	✓	✓

3 Problem Formulation

Text anomaly detection, considered in this work, aims to identify the text instances that deviate significantly from the majority. The following presents a formal definition.

Definition 1 (Text anomaly detection). *Let $\mathcal{C} = \{s_1, s_2, \dots, s_n\}$ be a corpus of n textual sequences, where all or most sequences are in some unknown normal condition or pattern P . Text anomaly detection aims to learn a detector f from \mathcal{C} that can determine whether a new textual sequence s_{new} is in P or not.*

For instance, if \mathcal{C} is composed of emails, a textual sequence containing spam information should be detected as abnormal. One more example, if \mathcal{C} consists of movie reviews, a review with abusive content would also be detected as abnormal.

In this work, we split the text anomaly detection into two stages. In the first stage, we extract text embeddings based on early language models (GloVe and BERT) and LLMs. Subsequently, in the second stage, we design a general unsupervised anomaly detection task on the text embeddings. Before delving into the details, we first introduce the notation convention as follows.

1. **Text Representation based on Embedding Models** Let \mathbf{M}_{emb} be a language model (e.g., BERT and LLaMA3). We obtain the embeddings $\mathcal{X} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n\}$ of \mathcal{C} as

$$\mathbf{x}_i = \text{Pooling}(\mathbf{M}_{\text{emb}}(s_i)), \quad i = 1, 2, \dots, n, \quad (1)$$

where $\text{Pooling}(\cdot)$ aims to aggregate token-level embeddings of the sequence s_i into a single vector $\mathbf{x}_i \in \mathbb{R}^d$, where d represents the embedding dimension of the language model.

2. **Unsupervised Anomaly Detection** We assume that the \mathcal{X} is drawn from an unknown distribution $\mathcal{D}_{\mathbf{x}} \subseteq \mathbb{R}^d$. A point $\mathbf{x} \in \mathbb{R}^d$ is deemed to be anomalous if $\mathbf{x} \notin \mathcal{D}_{\mathbf{x}}$. Then, the goal of the unsupervised AD is to obtain a decision function $h_{\text{UAD}} : \mathbb{R}^d \rightarrow \{0, 1\}$ by utilizing only \mathcal{X} , such that $h_{\text{UAD}}(\mathbf{x}) = 0$ if $\mathbf{x} \in \mathcal{D}_{\mathbf{x}}$ and $h_{\text{UAD}}(\mathbf{x}) = 1$ if $\mathbf{x} \notin \mathcal{D}_{\mathbf{x}}$. The primary difference among AD methods lies in the design of the decision function $f(\cdot)$.

Based on the two stages above, the detector f can be formulated as

$$f(s) := h_{\text{UAD}}(\text{Pooling}(\mathbf{M}_{\text{emb}}(s))) \quad (2)$$

The value of $f(s_{\text{new}})$ can determine whether the textual sequence s_{new} is normal or anomalous.

In this work, we consider the combinations of different embedding models, different pooling operations, and different UAD algorithms, leading to a comprehensive evaluation of key techniques for textual anomaly detection.

4 Benchmark Settings

In this section, we will introduce the detailed experimental preparations, including dataset splitting, embedding models, and the anomaly detection methods used in this benchmark.

4.1 Datasets

Different from anomaly detection tasks on images, tabular data, and time series, where there are standard datasets with normal and abnormal samples defined clearly, text anomaly detection presents unique challenges. The richness of natural language allows anomalies to manifest in diverse forms, such as rare topics, unusual language styles, irregular syntax or grammar, and harmful or abusive content. We observe that existing textual AD benchmarks Xu et al. [2023b], Bejan et al. [2023], Li et al. [2024a], Yang et al. [2024], Cao et al. [2025] consistently employ the NLP classification datasets. Aligning with this established methodology, our benchmark utilizes 8 text classification datasets from various NLP domains to construct 14 specialized Text-AD datasets. The statistical information of the Text-AD datasets are shown in Table 2.

Table 2: Statistical information of the Text-AD datasets.

Text-AD Dataset	Domain	# Training Samples	# Test Samples	Anomaly Ratio
20Newsgroups	News	10,419	7,876	0.12
Reuters21578	News	4,435	4,723	0.45
IMDB	Movie Review	10,000	40,000	0.625
SST2	Movie Review	10,000	58,078	0.51
SMS-Spam	Phone Message	3,000	2,534	0.29
Enron	Email	10,000	21,924	0.31
WOS	Paper Abstract	28,918	18,065	0.31
DBpedia14-0	Wikipedia Term	20,000	44,999	0.44
DBpedia14-1	Wikipedia Term	20,000	44,999	0.44
DBpedia14-2	Wikipedia Term	20,000	44,999	0.44
DBpedia14-3	Wikipedia Term	20,000	45,000	0.44
DBpedia14-4	Wikipedia Term	20,000	44,997	0.44

The specific splitting and descriptions of each dataset are summarized below.

- **20Newsgroups**² Lang [1995] is a collection of newsgroup documents. It is organized into 20 different newsgroups, each corresponding to a different topic. Some of the newsgroups are very closely related to each

²<http://qwone.com/jason/20Newsgroups/>

other (e.g., “comp.sys.ibm.pc.hardware / comp.sys.mac.hardware”), while others are highly unrelated (e.g. “misc.forsale / soc.religion.christian”). For constructing the text-AD dataset, class “misc.forsale” is regarded as an abnormal class, and the remaining classes are regarded as normal.

- **Reuters21578**³ Lewis [1997] is a collection of documents that appeared on Reuters newswire in 1987. It is organized into 59 different groups with 21578 samples in the original version. In this work, we use the ApteMod version provided in NLTK Corpora⁴ and classes “earn” and “acq” are regarded as normal, and the remaining are regarded as abnormal.
- **IMDB**⁵ Maas et al. [2011] is a dataset for binary sentiment (“pos” and “neg”) classification containing substantially more data than previous benchmark datasets. For constructing the text-AD dataset, class “pos” is regarded as normal, and “neg” is regarded as the abnormal class.
- **SST2**⁶ Socher et al. [2013] is a corpus with fully labeled parse trees that allows for a complete analysis of the compositional effects of sentiment in language. The corpus is based on the dataset introduced by Pang and Lee (2005) and consists of 11,855 single sentences extracted from movie reviews. It is a binary sentiment classification dataset. In this benchmark, class “1-(positive)” is regarded as the normal class and class “0-(negative)” is regarded as the abnormal class.
- **SMS-Spam**⁷ Almeida et al. [2011] is a public set of SMS labeled messages that have been collected for mobile phone spam research. It has one collection composed by 5,574 English, real and non-encoded messages, tagged according being legitimate or spam. Naturally, legitimate messages are regarded the normal samples, and spam messages are regarded as abnormal samples.
- **Enron**⁸ contains a total of about 0.5M messages from about 150 users, mostly senior management of Enron. We counted the entire dataset and found the two email accounts (“kay.mann@enron.com”, “vince.kaminski@enron.com”) with the most emails under them, both greater than 10,000, as well as many accounts with just 1 email under them. Based on this observation, we use the emails from accounts (“kay.mann@enron.com”, “vince.kaminski@enron.com”) as normal samples and the emails from the accounts with only 1 email as abnormal samples.
- **WOS**⁹ Kowsari et al. [2017] is Web of Science Dataset (WOS-46985). This dataset contains the abstracts of 46,985 published papers that have 7 parent categories, including “Computer Science (CS), Electrical Engineering (ECE), Psychology, Mechanical Engineering (MAE), Civil Engineering (Civil), Medical Science (Medical), and Biochemistry”. For constructing the text-AD dataset, class “Psychology” is regarded as the normal class, and the remaining classes are regarded as abnormal.
- **DBpedia14**¹⁰ Zhang et al. [2015] is constructed by picking 14 non-overlapping classes from DBpedia 2014. Each class contains 40,000 training samples and 5,000 testing samples. We construct five text-AD datasets (DBpedia14-0, DBpedia14-1, DBpedia14-2, DBpedia14-3, DBpedia14-4) based on the original dataset. Specifically, for DBpedia14-0, we use class 0 as the normal class, and the samples from the test set of classes [1, 2, 3, 4] are regarded as abnormal samples. For DBpedia14-1, we use class 1 as the normal class, and the samples from the test set of classes [0, 2, 3, 4] are regarded as abnormal samples. The text-AD datasets (DBpedia14-2, DBpedia14-3, DBpedia14-4) have the same construction process.

4.2 Embedding Models

Text embedding is widely recognized as the foundational and essential step in NLP tasks, as it transforms the semantic content of natural language into a structured vector representation. Over the past several years, the emergence of innovative embedding techniques has consistently propelled the field of NLP forward, significantly advancing the development and applications of NLP techniques.

For instance, researchers at Stanford University advanced the field of word embeddings with the introduction of GloVe (Global Vectors for Word Representation) Pennington et al. [2014a]. GloVe enhanced the capabilities of Word2Vec by incorporating global statistical information across the entire corpus to generate word vectors, which enabled a

³https://raw.githubusercontent.com/nltk/nltk_data/gh-pages/packages/corpora/reuters.zip

⁴https://www.nltk.org/nltk_data/

⁵<http://ai.stanford.edu/amaas/data/sentiment/>

⁶<https://huggingface.co/datasets/stanfordnlp/sst2>

⁷https://huggingface.co/datasets/ucirvine/sms_spam

⁸https://huggingface.co/datasets/Hellisotherpeople/enron_emails_parsed

⁹<https://huggingface.co/datasets/river-martin/web-of-science-with-label-texts>

¹⁰https://huggingface.co/datasets/fancyzhx/dbpedia_14

more nuanced semantic understanding by integrating both local context windows and global corpus statistics. The landscape of NLP was further revolutionized in 2017 with the introduction of the transformer architecture Vaswani et al. [2017], which introduced the self-attention mechanism. Building on this breakthrough, BERT(Bidirectional Encoder Representation from Transformers) Devlin et al. [2019], released in 2018, pioneered context-dependent word embeddings. Unlike earlier models such as Word2Vec and GloVe, which produced statistic, context-free embeddings, BERT leveraged a transformer-based architecture to create dynamic representations that capture the meaning of words based on their surrounding context, considering both preceding and succeeding words within a sentence. With the advent of LLMs (Large Language models), only recently, the NLP community started to adopt decoder-only LLMs for text embedding BehnamGhader et al. [2024a].

In this work, we primarily employ LLMs as embedding models and also consider two classical language models including GloVe and BERT. Detailed information about the embedding models used in this work are summarized in Table 3. Building upon Llama-2-7B-chat Touvron et al. [2023], Mistral-7B-Instruct-v0.2 Jiang et al. [2023] and Llama-3-8B-Instruct AI@Meta [2024], we employ their fine-tuned versions tailored for text embedding from LLM2Vec¹¹ BehnamGhader et al. [2024b]. Additionally, three specialized text embedding models¹² (text-embedding-3-small, text-embedding-ada-002, text-embedding-3-large) from OpenAI are also evaluated in this work. For brevity, we refer to these models as “small, ada, large” in the following sections. Our text representation pipeline involves two sequential stages: (1) extracting token-level embeddings via the embedding models, followed by (2) applying pooling strategies to aggregate the token embeddings into final text representations. As detailed in Table 3, three distinct pooling strategies are evaluated in this benchmark. For each AD dataset, we derive 33 distinct text representations, each generated by varying combinations of embedding models and pooling strategies. Notably, the terms “mntp”¹³, “mntp-unsup-simcse”¹⁴ and “mntp-supervised”¹⁵ denote the different fine-tuning techniques. More details on these fine-tuning techniques can be found in LLM2Vec BehnamGhader et al. [2024b].

Table 3: Basic information of embedding models.

Embedding Models	Pooling	Max Tokens	Dimensions	Parameters	Open Source
GloVe (glove-6B)	Mean	512	300	120M	✓
BERT (large-uncased)	Mean, CLS	512	1024	340M	✓
LLaMA-2(mntp)	Mean, Weighted Mean, EOS	8191	4096	7B	✓
LLaMA-2(mntp-unsup-simcse)	Mean, Weighted Mean, EOS	8191	4096	7B	✓
LLaMA-2(mntp-supervised)	Mean, Weighted Mean, EOS	8191	4096	7B	✓
LLaMA-3(mntp)	Mean, Weighted Mean, EOS	8191	4096	8B	✓
LLaMA-3(mntp-unsup-simcse)	Mean, Weighted Mean, EOS	8191	4096	8B	✓
LLaMA-3(mntp-supervised)	Mean, Weighted Mean, EOS	8191	4096	8B	✓
Mistral(mntp)	Mean, Weighted Mean, EOS	32768	4096	7B	✓
Mistral(mntp-unsup-simcse)	Mean, Weighted Mean, EOS	32768	4096	7B	✓
Mistral(mntp-supervised)	Mean, Weighted Mean, EOS	32768	4096	7B	✓
OpenAI (embedding-3-small)	-	8192	1536	-	✗
OpenAI (embedding-ada-002)	-	8192	1536	-	✗
OpenAI (embedding-3-large)	-	8192	3072	-	✗

4.3 Anomaly Detection Methods

For comprehensive benchmarking, we consider both shallow machine learning-based AD algorithms, deep learning based AD methods and specialized textual AD methods. The details are described below.

Shallow Machine Learning-based AD Algorithms:

- **One-Class SVM (OCSVM)** Schölkopf et al. [1999] OCSVM maps input data to a high-dimensional space by kernel methods and finds a hyperplane that separate normal data from the origin with maximum margin. RBF kernel was used in our experiments.
- **Isolation Forest (IForest)** Liu et al. [2008] IForest isolates instances by building an ensemble of Trees, then anomalies are those instances which have short average path lengths on the Trees.

¹¹<https://github.com/McGill-NLP/llm2vec/tree/main>

¹²<https://platform.openai.com/docs/guides/embeddings>

¹³mntp: masked next token prediction

¹⁴mntp-unsup-simcse: unsupervised contrastive learning

¹⁵mntp-supervised: supervised contrastive learning

- **Local Outlier Factor (LOF)** Breunig et al. [2000] LOF measures the local deviation of the density of each instance with respect to its neighbors. We set the hyperparameter “n_neighbors”=30 in our experiments.
- **Principal Component Analysis (PCA)** Shyu et al. [2003] PCA is a linear dimensionality reduction method that employs matrix decomposition to transform data into a new orthogonal coordinate system defined by its principal components. These principal components are ordered such that the first component captures the maximal variance in the data, with subsequent components representing decreasingly smaller variations. When applied in anomaly detection, PCA projects data onto a lower-dimensional subspace spanned by the top-k eigenvectors. The anomaly score for a new sample is computed as the reconstruction error.
- **K-Nearest Neighbors (KNN)** Ramaswamy et al. [2000] KNN views the anomaly score of a new sample as the distance to its k -th nearest neighbor. We set $k = 3$ in our experiments.
- **Kernel Density Estimation (KDE)** Kim and Scott [2012] KDE is a non-parametric method to estimate the probability density function (PDF) of a dataset. It smooths observed data points using a kernel function to approximate the underlying distribution. When applied in anomaly detection, anomalies are identified as points in low-density regions of the estimated PDF. We use the Gaussian kernel in our experiments.
- **Empirical-Cumulative-distributed-based Outlier Detection (ECOD)** Li et al. [2022] ECOD is a hyperparameter-free outlier detection algorithm based on the empirical cumulative distribution function (ECDF). It employs ECDF to estimate the density of each feature independently and assumes that outliers are located in the tails of the distribution.

Deep Learning-based AD Methods:

- **AutoEncoder (AE)** Hinton and Salakhutdinov [2006] An AutoEncoder is a type of neural network that consists of two parts including an encoder and a decoder. Encoder learns to compress input data into a lower-dimensional representation space and then decoder reconstructs them back to the original data space. When applied in anomaly detection, reconstruction error is a natural selection as the anomaly score.
- **Deep Support Vector Data Description (SVDD)** Ruff et al. [2018] Deep SVDD is a deep one-class learning method that learns a minimal enclosing hypersphere in a latent space to characterize normal data. The anomaly score for a sample is given by the squared Euclidean distance to the hypersphere center in latent space.
- **Dense Projection for Anomaly Detection (DPAD)** Fu et al. [2024] DPAD is a density based method that learns to obtain locally dense low-dimensional representation for training data (normal data). The anomaly score is the KNN score in the low-dimensional space.

Specialized Textual AD Methods:

- **Context Vector Data Description (CVDD)** Ruff et al. [2019] CVDD is a method that builds upon pretrained word embeddings to learn multiple sentence representations (context vector) that capture multiple semantic contexts via the self-attention mechanism and to project the word representations near these context vector by minimizing the cosine distance between them.
- **Detecting Anomalies in Text using ELECTRA (DATE)** Manolache et al. [2021] DATE an end-to-end approach for the discrete text domain that combines a powerful representation learner for Text (ELECTRA) Clark et al. [2020] and an anomaly score is tailed for sequential data.

To evaluate these anomaly detection approaches, for seven shallow and three deep learning based AD methods, we combine them with all 33 text embeddings, which results in 330 distinct two-stage anomaly detection configurations (10 AD methods \times 33 embeddings) per dataset. Regarding the specialized text AD methods, CVDD utilizes word embeddings from GloVe and BERT, and DATE operates directly on raw text inputs without requiring pretrained embeddings.

4.4 Evaluation Metrics

For a holistic evaluation, this work utilizes both AUROC (Area Under the Receiver Operating Characteristic curve) and AUPRC (Area Under the Precision-Recall curve) to measure detection performance. AUROC is more suitable for scenarios where the number of positive and negative samples is relatively balanced or where high classification accuracy is required for both types of samples. It can comprehensively reflect the performance of the model. AUPRC is more suitable for scenarios with imbalanced positive and negative samples, especially where high precision and recall are required for the identification of positive samples. It can better reflect the model’s predictive ability for the minority class. The experiments on DBpedia14 were conducted on Intel(R) Xeon(R) Gold 5117 CPU @ 2.00GHz with 4 \times

NVIDIA GeForce RTX 4090 GPUs, Python 3.8, and all other experiments all were conducted Intel(R) Xeon(R) CPU E5-2678 v3 @ 2.50GHz with 4× NVIDIA GeForce RTX 3090 GPUs, Python 3.8. We report the average results over five runs.

5 Experimental results

Table 4: Average AUROC(%) of all two-stage methods. The top two results on each dataset are marked in **bold** (top, second).

Embedding	Pooling	20News.	Reuters.	IMDB	SST2	SMS	Enron	WOS	DBp.0	DBp.1	DBp.2	DBp.3	DBp.4
GloVe	Mean	56.26	76.26	46.97	48.95	40.26	65.22	45.94	76.89	87.70	81.03	85.07	82.46
BERT	CLS	55.73	60.05	45.27	53.99	41.84	60.11	47.62	85.41	85.96	77.30	74.33	74.19
LLaMA-2 (mntp)	Mean	54.89	80.33	45.40	54.25	51.77	59.88	48.19	83.41	85.92	83.66	82.48	82.00
	EOS	47.40	64.82	48.90	53.26	62.18	57.73	48.49	66.25	72.31	65.09	72.45	69.68
	Weighted Mean	51.95	61.16	48.03	52.29	56.07	60.36	47.15	66.95	74.54	72.93	80.45	80.20
LLaMA-2 (mntp-unsup-simcse)	Mean	51.15	61.10	48.21	52.18	60.52	59.18	46.61	65.45	73.26	71.01	78.46	78.25
	EOS	59.30	92.49	48.19	64.56	79.80	82.89	59.22	92.66	98.00	88.81	97.01	94.72
	Weighted Mean	52.26	86.72	49.41	62.91	78.64	74.76	44.81	78.22	91.18	81.15	94.99	91.85
LLaMA-2 (mntp-supervised)	Mean	53.02	85.27	49.93	63.11	84.83	72.49	44.87	77.34	90.86	79.05	94.11	90.97
	EOS	57.53	90.41	51.74	68.61	91.40	82.74	67.18	88.16	97.59	84.21	94.88	95.22
	Weighted Mean	56.81	89.84	53.38	71.35	78.93	80.53	49.95	83.96	97.20	87.67	93.44	93.50
LLaMA-3 (mntp)	Mean	54.59	88.55	53.13	69.40	84.67	80.11	50.95	82.39	96.49	86.69	92.69	92.91
	EOS	62.57	82.40	45.53	56.90	90.86	74.07	55.80	76.92	89.09	87.06	95.20	90.57
	Weighted Mean	56.82	85.16	47.40	58.54	72.42	70.57	45.89	66.82	82.35	83.03	93.84	89.98
LLaMA-3 (mntp-unsup-simcse)	Mean	54.59	81.82	47.72	59.11	80.20	67.15	46.30	67.44	82.70	81.68	93.16	90.05
	EOS	54.35	77.95	47.36	58.47	89.98	81.19	55.76	63.48	78.27	64.78	75.43	72.86
	Weighted Mean	48.68	86.53	49.26	60.56	78.63	72.96	42.38	64.76	86.10	80.40	94.79	91.02
LLaMA-3 (mntp-supervised)	Mean	46.56	84.57	49.42	60.17	86.78	70.13	43.35	66.28	85.92	79.62	94.03	90.56
	EOS	62.17	89.04	52.98	67.22	90.70	80.01	56.24	87.97	97.31	82.84	91.48	92.61
	Weighted Mean	60.06	92.21	50.63	69.56	86.64	79.87	63.59	87.30	98.16	90.85	95.11	96.04
Mistral (mntp)	Mean	62.19	71.77	50.60	68.84	86.28	79.98	62.76	87.37	97.88	89.90	94.57	95.42
	EOS	71.99	76.96	43.67	58.10	87.77	80.89	59.08	79.32	90.56	86.33	91.47	88.10
	Weighted Mean	64.55	74.79	50.63	55.39	78.32	70.94	46.56	69.48	83.72	81.16	92.50	88.31
Mistral (mntp-unsup-simcse)	Mean	50.97	76.25	54.13	64.70	84.21	73.95	40.38	63.85	80.40	69.78	85.89	81.87
	EOS	56.89	85.30	52.79	64.78	84.88	89.53	63.80	79.68	94.45	75.24	86.40	82.07
	Weighted Mean	51.04	78.63	53.92	64.58	76.65	75.98	39.71	65.20	81.42	72.29	87.38	82.09
Mistral (mntp-supervised)	Mean	50.97	76.25	54.13	64.70	84.21	73.95	40.38	63.85	80.40	69.78	85.89	81.87
	EOS	53.07	88.51	56.46	71.12	83.70	81.25	60.27	87.57	95.57	88.31	94.46	91.52
	Weighted Mean	50.88	91.10	50.67	71.98	65.36	84.37	52.86	83.67	94.65	87.77	92.47	90.17
OpenAI-3-small	-	55.61	91.10	51.69	66.50	57.88	74.08	58.52	91.20	94.34	88.10	93.08	91.64
OpenAI-ada-002	-	61.51	88.66	51.60	65.49	77.54	78.12	60.28	86.05	92.45	87.58	93.05	92.54
OpenAI-3-large	-	51.84	92.10	54.78	67.60	65.41	77.55	63.31	92.52	94.15	88.03	93.43	91.58

Table 4 and Table 5 report average AUROC (%) and AUPRC (%) on all two-stage detectors across different embeddings and datasets, respectively. Depending on the results of Table 4 and Table 5, we have the following observations and analysis:

- Across all datasets, the top two performing results originate from the detectors utilizing LLM-derived embeddings. This indicates that LLM-based embeddings boost the performance for two-stage anomaly detection frameworks and exhibit marked advantages over traditional embedding methods such as GloVe and BERT for text anomaly detection tasks.
- No single LLM-derived embedding universally outperforms others across all datasets. This suggests that the optimal choice of embedding model may depend on specific dataset characteristics or task requirements.
- The results of AUPRC (%) in Table 5 reveals that the embedding models from OpenAI perform much better than other embedding models, which suggests that the models from OpenAI achieve both high precision and high recall, a critical advantage in the scenarios where false negatives are costly.

To observe the effect of different pooling strategies across all datasets, we compute the row-wise averages based on Table 4 to get the mean performance of each embedding-pooling combination across all datasets. We visualize these aggregated mean results for the LLaMA-2, LLaMA-3, and Mistral in Figure 2, enabling direct comparison for the overall effectiveness of different pooling strategies, where “EOS” exhibits significant advantages over “Mean” and “Weighted Mean” in most cases. In addition, we also notice that “Mean” and “Weighted Mean” have quite similar performance in

Table 5: Average AUPRC(%) of all two-stage methods. The top two results on each dataset are marked in **bold** (top, second).

Embedding	Pooling	20News.	Reuters.	IMDB	SST2	SMS	Enron	WOS	DBp.0	DBp.1	DBp.2	DBp.3	DBp.4
GloVe	Mean	13.62	83.03	59.97	51.77	26.40	39.46	29.55	71.45	82.95	75.84	81.68	77.87
BERT	CLS	14.51	66.85	59.59	54.69	25.07	38.22	30.71	82.73	81.00	72.35	68.03	66.32
LLaMA-2 (mntp)	EOS	10.99	75.29	61.57	54.04	38.91	39.29	29.66	56.95	64.90	58.91	67.42	63.20
	Mean	12.31	72.68	60.86	53.47	38.03	37.47	28.99	56.74	66.76	65.35	77.06	73.65
	Weighted Mean	12.15	72.37	61.02	53.25	43.37	37.19	28.65	56.02	66.11	63.95	75.18	71.15
LLaMA-2 (mntp-unsup-simcse)	EOS	14.69	93.86	60.98	62.97	57.42	64.46	38.03	90.79	97.47	86.86	96.33	92.88
	Mean	12.78	88.45	61.47	62.98	59.27	52.26	28.30	71.08	88.06	77.33	93.84	88.99
	Weighted Mean	13.01	87.46	61.76	62.86	68.98	51.36	28.27	70.44	88.16	74.64	92.81	87.80
LLaMA-2 (mntp-supervised)	EOS	16.44	93.34	63.17	66.15	77.74	64.81	45.06	84.99	96.63	83.42	94.39	93.76
	Mean	16.00	93.05	64.39	69.89	57.70	59.51	32.04	80.70	96.40	85.42	92.26	92.09
	Weighted Mean	16.67	92.28	64.26	67.85	66.43	59.85	32.63	79.16	95.58	84.22	91.06	91.29
LLaMA-3 (mntp)	EOS	18.43	85.76	59.26	57.55	78.56	56.45	35.15	67.60	82.73	82.22	92.94	86.25
	Mean	14.53	87.69	60.23	59.10	46.72	47.12	29.02	56.89	75.39	77.99	92.22	85.68
	Weighted Mean	13.97	85.18	60.37	59.30	56.77	45.10	28.88	57.53	76.42	76.86	91.41	85.93
LLaMA-3 (mntp-unsup-simcse)	EOS	13.28	82.85	60.27	57.92	77.25	66.06	36.67	57.35	71.57	58.27	68.15	65.09
	Mean	12.07	88.82	61.28	60.82	58.63	51.45	27.78	57.52	82.19	78.73	93.93	89.08
	Weighted Mean	11.53	87.49	61.26	60.21	70.42	50.34	27.96	58.80	82.46	76.84	92.98	88.22
LLaMA-3 (mntp-supervised)	EOS	18.38	93.08	64.30	66.75	81.73	63.40	35.55	86.77	96.76	77.69	88.92	90.01
	Mean	18.90	94.93	63.07	68.39	75.57	63.20	42.54	84.23	97.62	89.40	94.20	95.11
	Weighted Mean	17.24	94.09	63.04	67.86	74.50	63.32	41.61	84.61	97.37	88.10	93.43	94.43
Mistral (mntp)	EOS	23.38	84.77	57.89	57.71	72.76	65.53	38.72	73.90	86.92	84.52	90.61	85.90
	Mean	16.84	79.46	62.53	55.88	54.97	46.45	29.20	59.40	74.81	74.21	89.55	81.57
	Weighted Mean	16.08	77.65	62.55	55.52	58.02	44.84	29.25	57.82	74.88	72.74	88.81	81.92
Mistral (mntp-unsup-simcse)	EOS	15.65	89.32	63.84	62.75	68.35	78.10	41.85	74.75	91.78	72.03	84.83	79.31
	Mean	12.37	83.75	64.48	63.99	57.76	57.44	26.60	57.14	76.79	66.83	84.69	78.56
	Weighted Mean	12.32	82.29	64.60	63.76	69.51	56.85	26.66	56.55	76.26	63.28	82.76	77.12
Mistral (mntp-supervised)	EOS	14.20	92.42	67.12	68.78	67.82	67.41	38.98	84.36	94.50	86.62	93.57	90.07
	Mean	12.55	94.15	62.69	70.39	42.49	66.87	33.17	79.29	93.36	84.55	90.88	88.17
	Weighted Mean	12.53	92.84	62.93	69.54	48.78	66.84	33.05	77.46	93.25	83.42	89.67	86.33
OpenAI-3-small	-	19.04	95.35	65.29	67.93	38.38	52.64	40.09	92.24	96.27	89.35	94.94	92.76
OpenAI-ada-002	-		21.83	93.08	64.43	66.24	54.38	59.43	42.37	83.67	92.01	88.47	94.99
OpenAI-3-large	-		17.58	96.10	66.96	69.12	42.00	56.88	45.75	91.64	93.02	83.55	93.88

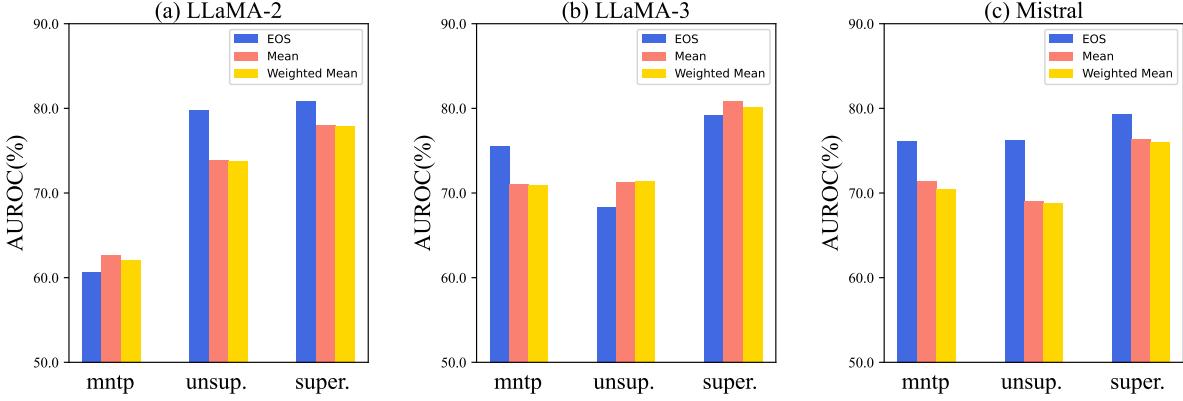


Figure 2: The average AUROC(%) across all datasets. The “unsup.” and “super.” correspond to the embedding models with “mntp-unsup-simcse” and “mntp-supervised”, respectively.

all cases. Figure 3 presents the average AUROC ranking across different LLM-derived embeddings. The visualization reveals that embeddings fine-tuned using the “mntp-supervised” approach (denoted as -3-) consistently achieve superior ranking positions compared to other embeddings. This finding aligns with the results reported in BehnamGhader et al. [2024b], where representations fine-tuned by “mntp-supervised” achieved state-of-the-art performance on the Massive Text Embedding Benchmark (MTEB).

Table 6 summarizes detection performance (AUROC%) of different AD methods across all datasets. Notably, CVDD, a specialized text anomaly detection method, operates directly on token-level embedding rather than aggregated

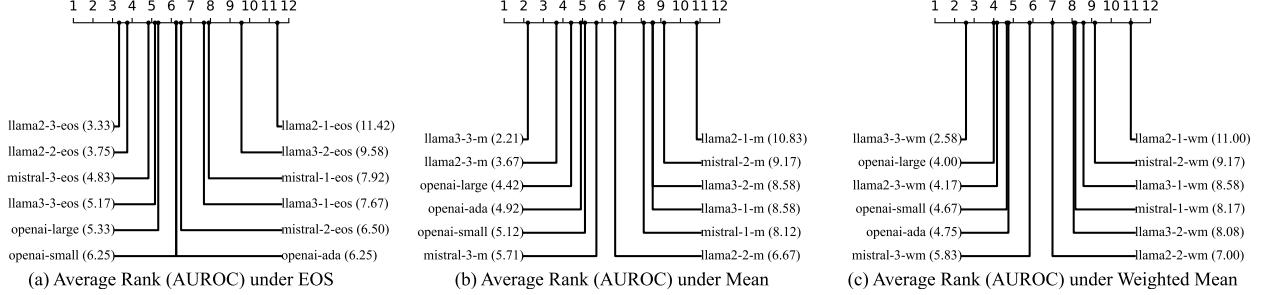


Figure 3: Performance comparison of different embeddings from LLMs. Note that “llama2-1, llama3-1, mistral-1” denote those corresponding embedding models with “mntp”, and “llama2-2, llama3-2, mistral-2” denote those corresponding embedding models with “mntp-unsup-simcse” and “llama2-3, llama3-3, mistral-3” denote those corresponding embedding models with “mntp-supervised”. The plots (a), (b), (c) compare the average AUROC from all the embedding models under EOS, Mean, and Weighted Mean, respectively.

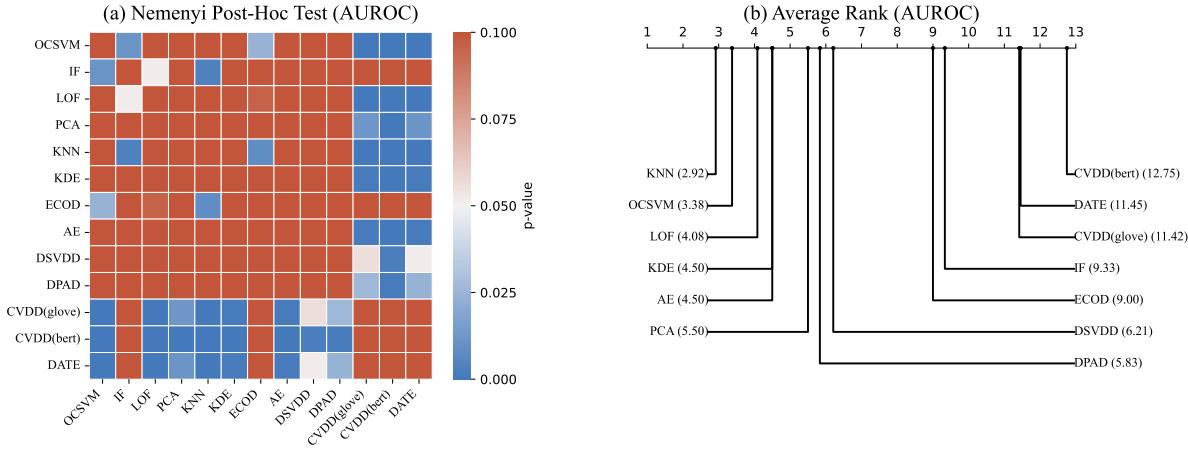


Figure 4: Performance comparison of different AD methods. In plot (a), a pair of methods with $p\text{-value} > 0.05$ indicates no statistically significant difference in their detection performance at the 95% confidence level.

sentence-level representations. Due to computational constraints associated with processing all token embeddings from LLMs, the experiments on CVDD were limited to conventional embeddings, specifically GloVe and BERT. Furthermore, DATE, another text-specific AD method, requires access to raw text data rather than precomputed embeddings. Figure 4 presents a comprehensive comparison of AD methods based on the results from Table 6 and two-stage AD methods only use the “best” results. In Figure 4, plot (a), a heatmap visualization of p-values derived from the Nemenyi post-hoc test, and plot (b), an average rank diagram where lower rank indicates better performance. Depending on the results of Table 6 and Figure 4, we have the following observations:

- Analyzing the “best” results of all two-stage AD methods, deep learning based detectors (AE, DSVDD, DPAD) exhibit no advantage over conventional “shallow” algorithms(OCSVM, IForest, LOF, KNN, KDE) when using LLM-derived embeddings. This finding suggests that (1) the high-quality representations from LLMs effectively encode textual nuances, enabling conventional algorithms to achieve competitive even better detection performance directly in the input space; and (2) the added complexity of deep anomaly detectors may be unnecessary when leveraging such high-quality text representation.
- When utilizing the embedding from GloVe and BERT, CVDD exhibits a slight advantage over two-stage AD methods including conventional shallow and deep learning based methods.
- No single method universally outperforms others across all datasets. Across all datasets, the average performance of KNN outperforms all others methods.

To further evaluate the performance of two-stage AD methods on different text embeddings, we visualize the heatmaps of AUROC(%) across all datasets in Figure 5. This visualization clearly demonstrates that LLM-derived embeddings

Table 6: Comparison among different AD methods. The top two results for each dataset are marked in **bold** (top, second). Note that “mean” denotes the average performance on all embeddings and “best” refers to the best performance across all embeddings.

Methods	20News.	Reuters.	IMDB	SST2	SMS	Enron	WOS	DBp.0	DBp.1	DBp.2	DBp.3	DBp.4	Avg
OCSVM (GloVe)	55.88	76.85	46.35	46.38	48.02	63.12	52.49	82.33	91.59	85.27	87.97	86.64	68.57
OCSVM (BERT)	52.80	80.74	45.11	51.94	54.87	53.26	53.09	81.63	82.06	80.26	75.88	76.02	65.64
OCSVM (mean)	55.69	85.33	49.47	63.04	81.94	73.90	51.52	79.87	90.66	83.74	91.14	89.98	74.69
OCSVM (best)	72.74	99.22	62.97	85.22	94.66	99.24	69.13	98.70	99.87	95.83	99.46	98.89	89.66
IForest (GloVe)	56.09	78.21	46.76	44.69	33.43	62.45	38.61	77.03	88.37	83.18	82.11	82.12	64.42
IForest (BERT)	55.17	80.79	45.34	50.73	46.89	54.83	50.35	78.96	77.26	76.38	72.88	72.27	63.49
IForest (mean)	54.42	80.39	48.20	55.86	72.32	64.73	48.01	70.05	83.63	73.82	82.84	81.24	67.96
IForest (best)	71.87	94.08	54.68	66.90	92.83	75.01	62.69	84.70	95.89	84.84	93.48	89.15	80.51
LOF (GloVe)	60.16	84.54	49.31	58.73	44.65	67.86	64.93	86.25	96.57	87.29	97.15	92.22	74.14
LOF (BERT)	58.86	89.45	47.75	58.66	56.05	76.18	59.02	91.35	95.04	92.97	96.42	93.65	76.28
LOF (mean)	54.87	80.66	54.30	64.83	77.35	81.31	62.12	87.77	94.73	90.42	96.73	94.26	78.28
LOF (best)	70.79	93.86	64.66	71.96	93.62	94.52	73.27	99.30	99.89	97.91	99.81	99.22	88.23
PCA (GloVe)	56.36	77.77	46.51	44.79	34.60	62.64	39.30	78.19	90.11	83.39	83.69	83.09	65.04
PCA (BERT)	54.21	80.45	44.59	51.45	50.44	55.01	49.05	80.39	80.88	78.62	70.94	72.75	64.06
PCA (mean)	55.66	83.99	48.02	57.57	78.04	65.66	48.11	77.04	88.63	80.97	88.73	87.43	71.65
PCA (best)	73.68	99.13	56.58	69.76	95.01	79.23	67.61	98.50	99.83	94.18	99.02	98.42	85.91
KNN (GloVe)	59.90	82.75	46.74	48.68	35.43	73.63	33.74	79.83	89.22	83.86	92.02	85.92	67.64
KNN (BERT)	55.61	83.61	47.65	59.00	33.36	61.86	37.77	87.41	92.76	89.61	95.96	93.23	69.82
KNN (mean)	59.40	85.34	56.82	68.89	74.57	78.89	56.09	84.32	93.50	86.97	95.10	93.02	77.74
KNN (best)	74.56	96.58	73.44	80.11	94.61	92.78	80.91	99.19	99.90	97.54	99.64	99.24	90.71
KDE (GloVe)	55.99	75.96	46.37	45.23	41.38	63.57	47.93	81.04	90.89	84.03	85.17	84.82	66.86
KDE (BERT)	53.90	78.06	44.29	51.32	51.41	54.88	49.52	80.11	79.44	77.28	69.22	71.38	63.40
KDE (mean)	56.04	84.09	48.84	62.06	81.43	71.38	48.67	78.68	89.24	81.94	89.55	88.47	73.37
KDE (best)	73.18	99.04	61.74	84.67	95.38	99.11	68.70	98.59	99.84	94.03	98.99	98.40	89.31
ECOD (GloVe)	55.42	64.57	42.95	43.83	32.81	58.58	36.11	65.91	76.42	74.83	69.89	70.75	57.67
ECOD (BERT)	52.41	66.28	39.24	48.39	32.27	51.93	43.80	71.79	70.92	71.73	56.43	63.34	55.71
ECOD (mean)	53.05	71.35	40.10	51.79	59.89	61.85	43.24	64.61	79.13	72.60	79.69	79.91	63.10
ECOD (best)	71.97	93.74	48.10	57.75	89.95	75.51	63.07	91.73	99.57	87.13	96.97	95.86	80.95
AE (GloVe)	55.60	80.93	48.66	49.60	31.25	69.41	40.26	79.30	89.48	83.76	91.06	86.25	67.13
AE (BERT)	54.84	83.64	46.87	57.39	42.61	59.28	41.25	90.65	94.50	93.38	96.35	94.07	71.24
AE (mean)	57.28	87.62	53.86	71.12	75.08	87.45	56.29	85.17	94.24	88.99	95.77	93.68	78.88
AE (best)	71.51	98.75	59.17	80.95	94.37	98.72	75.89	98.32	99.75	97.14	99.71	99.15	89.45
DSVDD (GloVe)	49.77	57.92	47.72	53.47	64.28	56.91	56.32	56.61	68.34	57.31	66.49	61.66	58.07
DSVDD (BERT)	54.49	71.45	46.19	51.35	89.43	54.60	49.32	81.18	91.28	84.91	93.83	88.91	71.41
DSVDD (mean)	54.32	80.11	49.49	58.62	76.25	70.74	52.04	70.89	84.70	74.30	87.78	81.38	70.05
DSVDD (best)	68.32	99.12	54.06	67.80	92.98	85.81	59.92	98.27	99.87	95.31	99.69	99.26	85.03
DPAD (GloVe)	57.43	83.08	48.31	54.09	36.78	73.99	49.69	82.42	96.02	87.38	95.19	91.17	71.30
DPAD (BERT)	56.64	88.87	46.96	62.26	60.38	79.74	48.70	90.67	92.02	91.41	96.92	94.38	75.75
DPAD (mean)	56.36	82.95	51.32	67.58	76.57	86.76	54.23	78.27	88.81	81.59	90.13	86.90	75.12
DPAD (best)	73.41	94.56	57.02	78.36	95.02	97.43	66.74	93.53	99.25	93.59	99.62	98.61	87.26
CVDD (GloVe)	62.60	86.48	46.66	51.71	49.00	69.38	50.51	91.26	97.13	74.83	92.03	82.14	71.14
CVDD (BERT)	54.98	51.76	47.64	46.83	44.80	52.86	40.23	57.24	61.44	56.21	55.69	52.47	51.85
DATE	51.47	-	48.56	56.96	72.89	71.67	56.36	79.61	85.92	77.18	84.14	78.31	69.37

outperform conventional embedding techniques (GloVe and BERT) in most cases, with particularly pronounced improvements in semantic anomaly detection tasks.

6 Low-rank analysis and prediction

To systematically analyze the performance properties across datasets, we conduct singular value decomposition (SVD) on the performance matrices (AUROC on each dataset) (Table 8 to Table 19) where each performance matrix (or table) is a holistic evaluation of detection performance on one dataset across all text embeddings (rows) and AD algorithms (columns). Let $\mathbf{P} \in \mathbb{R}^{m \times n}$ be the performance matrix and σ_i denotes the i -th singular value, where $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n > 0$, m denotes the number of embeddings, n denotes the number of AD algorithms, and $n \leq m$. Figure 6 presents the cumulative contribution ratio of the singular values across all datasets, where the cumulative contribution ratio (ccr) is defined by $ccr(j) = (\sum_{i=1}^j \sigma_i) / (\sum_{i=1}^n \sigma_i)$.

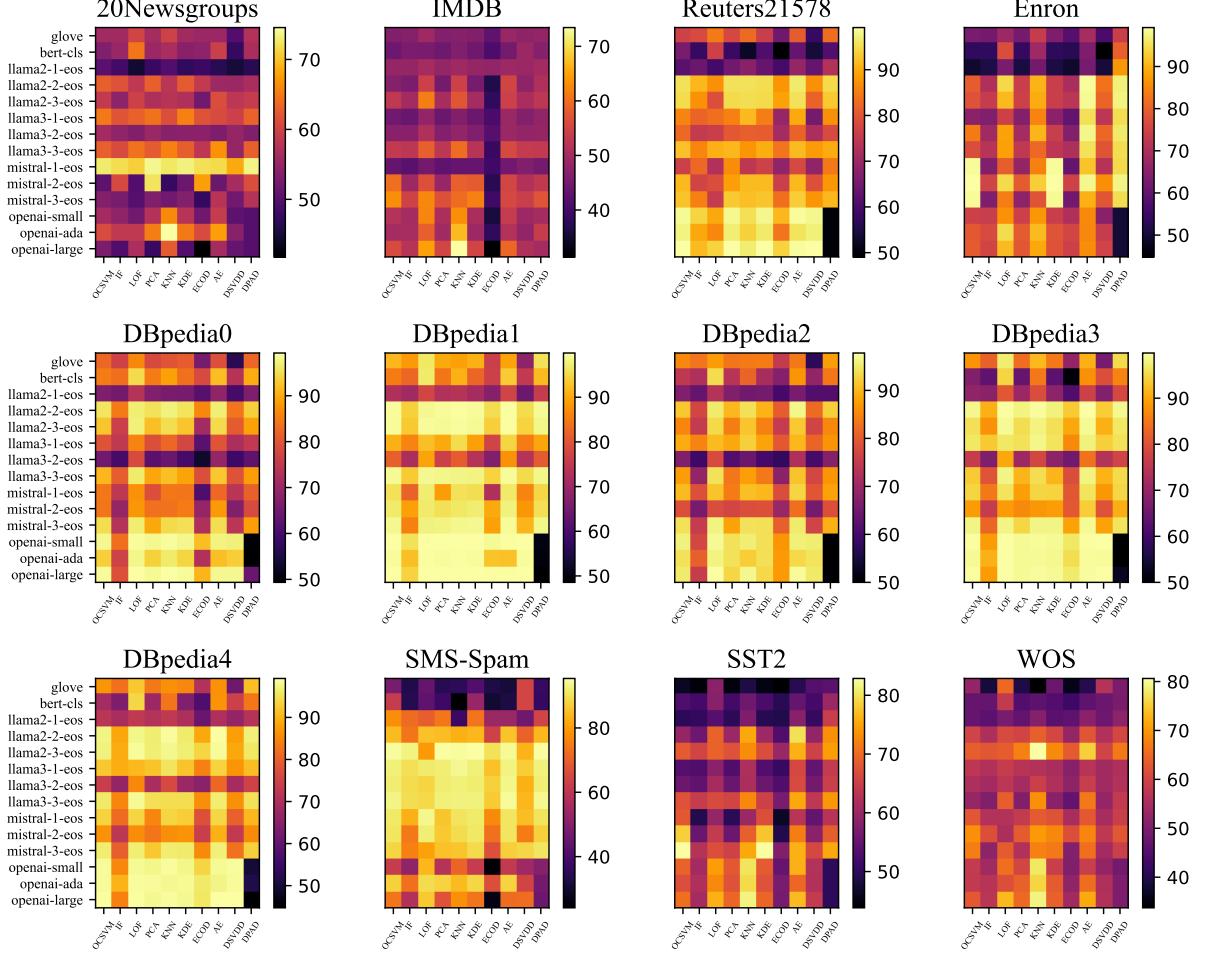


Figure 5: The heatmap of AUROC(%) of each two-stage AD method with different text embeddings. Note that “llama2-1, llama3-1, mistral-1” denote those corresponding “mntp” models, “llama2-2, llama3-2, mistral-2” denote those corresponding “mntp-unsup-simcse” models and “llama2-3, llama3-3, mistral-3” denote those corresponding “mntp-supervised” models.

As evidenced by Figure 6, the cumulative contribution ratio of the first two singular values ($ccr(2)$) exceeds 0.90 on most datasets. This demonstrates that the AUROC matrices possess strongly low-rank characteristics. This finding has two important implications: (1) the detection performance of novel text datasets or anomaly detection methods can be reliably predicted using only a subset of performance measurements, and (2) this property enables an efficient strategy for rapid model evaluation (embedding evaluation) and selection in practical applications.

To further verify the low-rank characteristics of the AUROC matrices (Table 8 to Table 19), we construct the matrix completion task using the performance matrices. Specifically, for every AUROC matrix, we construct matrix completion Candes and Recht [2012], Fan et al. [2019] tasks by MCAR (missing completely at random) mechanism with missing rate $\in \{0.5, 0.6, 0.7\}$. We use matrix factorization and non-convex optimization techniques Chi [2018] to recover the missed entries of the performance matrices. Formally, we consider a rank-constrained least-squares problem:

$$\min_{\Phi \in \mathbb{R}^{m \times n}} \|\mathcal{P}_\Omega(\Phi - \mathbf{P})\|_F^2, \quad \text{s.t. } \text{rank}(\Phi) \leq r, \quad (3)$$

where $\mathbf{P} \in \mathbb{R}^{m \times n}$ denotes the performance matrix with m rows (text embeddings) and n columns (AD algorithms), Ω consists of the locations of observed entries and the observation operator $\mathcal{P}_\Omega : \mathbb{R}^{m \times n} \rightarrow \mathbb{R}^{m \times n}$ as

$$[\mathcal{P}_\Omega(\mathbf{P})]_{ij} = \begin{cases} \mathbf{P}_{ij}, & (i, j) \in \Omega \\ 0, & \text{otherwise} \end{cases}. \quad (4)$$

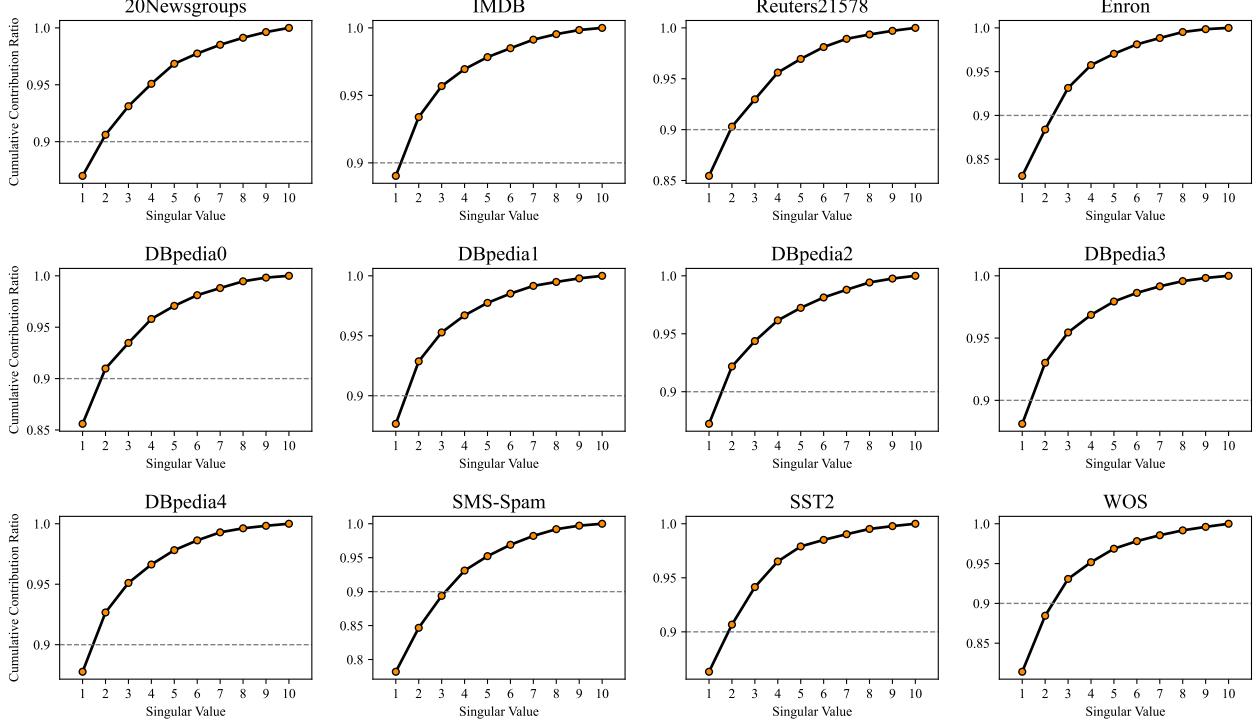


Figure 6: The cumulation contribution ratio of singular value of detection performance (AUROC) across all datasets.

Invoking the low-rank factorization $\Phi = \mathbf{U}\mathbf{V}^T$, where $\mathbf{U} \in \mathbb{R}^{m \times r}$ and $\mathbf{V} \in \mathbb{R}^{n \times r}$, we can rewrite (3) as an unconstrained optimization problem:

$$\min_{\mathbf{U}, \mathbf{V}} \|\mathcal{P}_\Omega(\mathbf{U}\mathbf{V}^T - \mathbf{P})\|_F^2. \quad (5)$$

In our experiments, we set $r = 1$ and utilize the singular value decomposition technique to initialize the $\mathbf{U} = \mathbf{U}_0 \Sigma_0^{1/2}$ and $\mathbf{V} = \mathbf{V}_0 \Sigma_0^{1/2}$, where $\mathbf{U}_0 \Sigma_0 \mathbf{V}_0^T$ is the best rank- r approximation of $\mathcal{P}_\Omega(\mathbf{P})$. The normalized Mean Absolute Percentage Error (MAPE), as defined in Equation (6), is employed to quantify the accuracy of the prediction.

$$\text{MAPE} = \frac{1}{k} \sum_{i=1}^k \left| \frac{p_i - \hat{p}_i}{p_i} \right|, \quad (6)$$

where $p_i, \hat{p}_i \in \mathbb{R}$ denote the missing (or unknown) values of detection performance and the corresponding recovered (or predicted) values, respectively. The k denotes the number of unknown values, and the missing rate is $\text{mr} = k/mn$.

The recovery results are reported in Table 7, where most of the recovery errors are below 0.1. The results verify the feasibility of a rapid model evaluation (embedding evaluation) and selection in practical applications based on the empirical evaluations in this benchmark. Take the 20Newsgroups dataset as an example, we use 50% entries of the AUROC performance matrix (see Table 8) to predict other values and show the result of six AD methods on six embeddings in Figure 7. We can see that the predictions are close to the real performance values. That means, a rapid and relatively accurate prediction of the performance of the new pairs (text embedding, AD method) can be obtained based on some observed results from this benchmark, which guides an efficient and reliable model evaluation (embedding evaluation) and selection.

7 Conclusion

In this work, we present Text-ADBench, a comprehensive benchmark for text anomaly detection, which both considers shallow and deep AD approaches, constructs abundant two-stage text AD methods by concatenating LLMs with different pooling strategies and estimates the detection accuracy across eight datasets. Experimental results reveal that (i) LLM-based embeddings boost the detection performance for these two-stage AD methods and “EOS” pooling

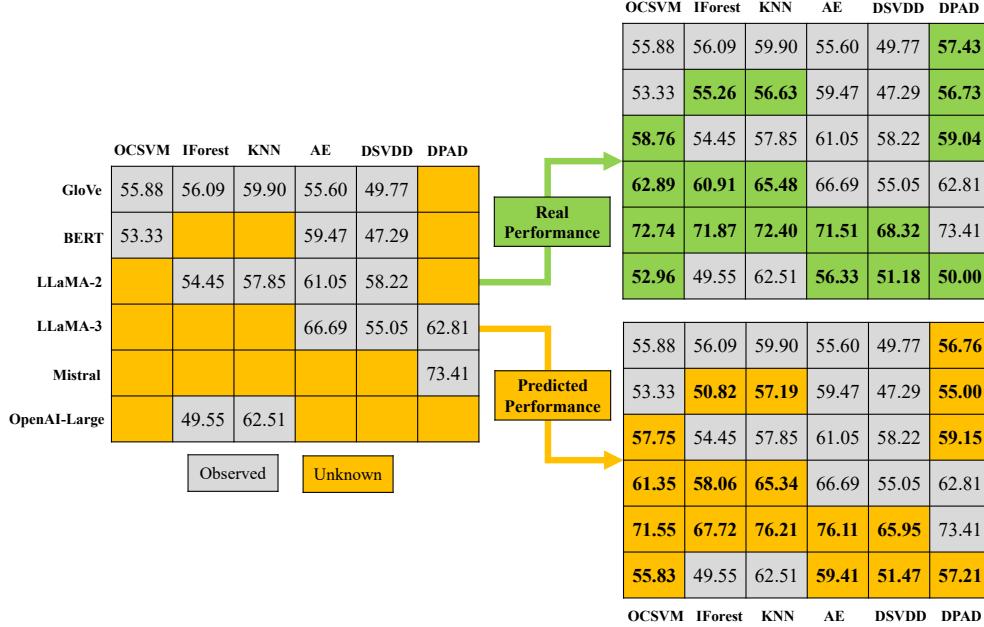


Figure 7: The visualization of AUROC performance prediction on the 20Newsgroups dataset, where the missing rate is 0.5. The prediction process is completed in 1.88 seconds, while the actual performance evaluation requires 5099.50 seconds.

Table 7: Recovery performance (MAPE) across all datasets in the setting of MCAR. Note that ‘mr’ denotes missing rate.

	20News.	IMDB	Enton	Reuters.	DBp.0	DBp.1	DBp.2	DBp.3	DBp.4	SMS-SPAM	SST2	WOS
mr=0.5	0.0348	0.0254	0.0419	0.0380	0.0357	0.0375	0.0301	0.0279	0.0286	0.0698	0.0336	0.0570
mr=0.6	0.0431	0.0460	0.0624	0.0404	0.0433	0.0452	0.0438	0.0344	0.0433	0.0828	0.0482	0.0749
mr=0.7	0.0746	0.0535	0.1233	0.0684	0.0787	0.0795	0.0661	0.0589	0.0753	0.1534	0.0771	0.1282

exhibits significant advantages over “Mean” and “Weighted Mean” in most cases, and (ii) deep learning based detectors (AE, DSVDD, DPAD) exhibit no advantage over conventional “shallow” algorithms (OCSVM, IForest, KNN, LOF, KDE) when using LLM-derived embeddings, and (iii) the average performance of KNN outperforms all other methods, although no single method universally outperforms other across all datasets. Furthermore, we analyze the performance matrices across datasets and find strongly low-rank characteristics, which enables an efficient strategy for rapid model evaluation (embedding evaluation) and selection in practical applications by using the historical estimation from Text-ADBench.

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Table 8: Average AUROC(%) on 20Newsgroups. The best results are marked in **bold**.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	55.88	56.09	60.16	56.36	59.90	55.99	55.42	55.60	49.77	57.43	56.26
BERT	CLS	53.33	55.26	64.69	55.50	56.63	54.03	54.34	59.47	47.29	56.73	55.73
	Mean	52.80	55.17	58.86	54.21	55.61	53.90	52.41	54.84	54.49	56.64	54.89
LLaMA-2 (mntp)	EOS	50.34	48.51	44.65	47.76	49.60	47.07	47.84	46.56	45.08	46.57	47.40
	Mean	57.73	51.73	51.06	53.31	49.92	54.96	52.76	49.34	49.99	48.66	51.95
	Weighted Mean	57.49	51.05	50.27	52.93	49.36	54.23	52.41	47.51	48.49	47.79	51.15
LLaMA-2 (mntp-unsup-simcse)	EOS	62.87	61.58	58.53	62.84	58.16	62.38	58.74	55.69	55.60	56.63	59.30
	Mean	48.36	49.17	49.70	50.27	59.76	51.34	48.28	54.71	54.54	56.44	52.26
	Weighted Mean	49.07	53.43	48.44	51.19	59.91	52.20	49.22	55.03	55.02	56.74	53.03
LLaMA-2 (mntp-supervised)	EOS	58.76	54.45	59.81	56.97	57.85	57.09	52.09	61.05	58.22	59.04	57.53
	Mean	52.37	50.39	56.44	54.85	68.25	55.07	51.98	64.36	56.01	58.41	56.81
	Weighted Mean	52.81	52.91	56.70	54.90	68.61	55.04	51.96	64.62	55.60	58.11	57.13
LLaMA-3 (mntp)	EOS	64.87	61.85	62.98	64.39	61.12	65.39	61.66	60.73	59.64	63.07	62.57
	Mean	56.78	54.21	54.59	56.13	59.78	58.09	53.46	56.84	58.48	59.89	56.83
	Weighted Mean	55.01	52.59	52.73	54.18	56.27	56.51	51.75	53.52	57.07	56.29	54.59
LLaMA-3 (mntp-unsup-simcse)	EOS	56.19	54.69	53.46	55.46	53.86	54.12	54.23	53.16	54.98	53.31	54.35
	Mean	45.40	48.45	46.00	45.76	52.27	46.84	43.63	49.65	54.34	54.42	48.68
	Weighted Mean	43.75	40.98	45.34	43.63	49.93	44.73	41.58	47.93	54.45	53.31	46.56
LLaMA-3 (mntp-supervised)	EOS	62.89	60.91	64.37	62.32	65.48	62.76	58.42	66.69	55.05	62.81	62.17
	Mean	56.77	57.46	64.29	57.19	68.83	57.62	54.25	66.26	56.08	61.88	60.06
	Weighted Mean	54.98	52.65	62.84	55.14	67.38	55.57	52.30	64.81	53.43	59.95	57.91
Mistral (mntp)	EOS	72.74	71.87	70.79	73.68	72.40	73.18	71.97	71.51	68.32	73.41	71.99
	Mean	66.07	66.54	59.40	66.17	67.03	69.00	63.94	62.30	61.46	63.56	64.55
	Weighted Mean	64.60	63.53	57.32	64.29	64.03	67.08	62.18	59.96	59.78	59.18	62.20
Mistral (mntp-unsup-simcse)	EOS	50.49	60.63	49.75	72.13	47.56	51.66	67.61	51.58	56.42	61.03	56.89
	Mean	50.49	49.25	48.71	48.63	54.34	50.22	47.54	52.94	54.12	54.19	51.04
	Weighted Mean	50.68	49.99	49.06	48.68	53.77	50.29	47.57	52.65	53.06	53.91	50.97
Mistral (mntp-supervised)	EOS	53.66	52.78	50.09	53.35	52.03	53.61	47.48	57.82	52.10	57.78	53.07
	Mean	55.51	46.15	46.68	47.31	59.08	53.51	44.75	55.35	48.74	51.67	50.88
	Weighted Mean	55.18	48.75	45.39	46.87	58.30	53.17	44.34	54.91	49.47	51.07	50.75
OpenAI-3-small	-	56.21	54.65	52.08	57.52	66.17	57.85	51.91	59.08	50.59	50.00	55.61
OpenAI-ada-002	-	60.79	58.61	58.62	65.32	74.56	64.94	60.85	67.56	53.84	50.00	61.51
OpenAI-3-large	-	52.96	49.55	56.77	47.58	62.51	49.73	41.77	56.33	51.18	50.00	51.84

Table 9: Average AUROC(%) on Enron.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	63.12	62.45	67.86	62.64	73.63	63.57	58.58	69.41	56.91	73.99	65.22
BERT	CLS	53.74	53.72	76.81	54.28	68.02	53.49	52.78	63.68	44.82	79.74	60.11
LLaMA-2 (mntp)	Mean	53.26	54.83	76.18	55.01	61.86	54.88	51.93	59.28	54.60	76.96	59.88
	EOS	49.45	51.32	63.05	50.81	62.33	51.07	49.14	62.76	50.53	86.86	57.73
	Weighted Mean	53.25	57.01	75.37	54.82	65.48	53.28	52.89	63.47	52.50	75.49	60.36
LLaMA-2 (mntp-unsup-simcse)	EOS	79.37	70.29	93.97	73.96	90.00	73.96	69.56	98.72	82.24	96.87	82.89
	Mean	66.36	64.54	75.49	65.92	79.29	66.77	60.60	96.50	78.66	93.51	73.96
	Weighted Mean	62.76	62.23	73.83	62.02	77.20	62.67	56.72	96.07	77.46	93.92	72.29
LLaMA-2 (mntp-supervised)	EOS	77.73	73.46	90.54	74.64	89.13	73.96	71.92	98.34	80.39	97.27	82.63
	Mean	72.64	71.80	89.83	72.30	84.22	71.79	69.74	98.10	78.61	96.26	80.53
	Weighted Mean	72.18	70.57	89.84	71.67	85.30	71.04	68.78	98.27	76.99	96.43	80.15
LLaMA-3 (mntp)	EOS	65.56	64.01	74.72	64.44	84.38	65.51	60.31	94.98	72.05	94.72	75.67
	Mean	62.76	62.63	76.23	63.19	75.43	63.50	59.38	87.32	66.59	88.66	69.63
	Weighted Mean	58.53	59.51	72.36	58.66	71.95	58.71	55.18	85.99	63.28	87.29	67.34
LLaMA-3 (mntp-unsup-simcse)	EOS	83.39	68.32	88.18	68.99	90.19	73.90	64.50	97.69	80.84	95.88	81.19
	Mean	64.98	62.56	75.92	63.12	77.73	64.95	56.47	94.95	76.24	92.65	73.86
	Weighted Mean	61.01	58.90	74.23	58.55	74.75	59.90	52.26	94.54	74.84	92.29	70.13
LLaMA-3 (mntp-supervised)	EOS	76.73	71.47	87.94	72.70	80.99	72.37	70.04	95.00	78.12	94.70	79.91
	Mean	76.73	71.13	87.94	72.70	80.99	72.37	70.04	95.00	76.83	94.94	79.62
	Weighted Mean	76.73	71.66	87.94	72.70	80.99	72.37	70.04	95.00	77.57	94.83	79.89
Mistral (mntp)	EOS	98.59	64.01	79.51	66.56	84.17	98.50	60.53	91.67	71.18	94.22	80.89
	Mean	68.90	63.21	76.57	63.60	74.84	66.84	59.02	83.59	67.56	85.28	70.94
	Weighted Mean	66.16	59.70	74.99	60.55	71.16	62.31	57.39	81.00	64.72	84.42	69.34
Mistral (mntp-unsup-simcse)	EOS	99.24	75.01	94.14	79.23	92.78	99.11	74.83	97.76	85.81	97.43	89.53
	Mean	97.55	57.20	76.67	57.84	77.89	78.38	51.44	94.24	74.39	94.25	75.75
	Weighted Mean	97.59	53.20	75.89	53.52	75.20	76.75	48.21	93.33	72.42	93.38	73.67
Mistral (mntp-supervised)	EOS	98.47	63.79	83.80	65.75	78.17	98.38	61.87	89.47	78.20	94.57	81.26
	Mean	98.39	68.29	89.60	71.18	83.33	95.51	67.86	96.65	77.04	95.88	84.77
	Weighted Mean	98.43	68.67	88.62	69.93	83.02	96.88	66.40	96.45	75.92	95.60	84.14
OpenAI-3-small	-	74.64	73.79	86.20	74.50	86.77	74.01	70.52	85.30	65.05	50.00	73.98
OpenAI-ada-002	-	78.75	76.39	94.52	78.84	90.82	78.13	75.51	84.88	73.35	50.00	78.03
OpenAI-3-large	-	79.01	75.35	90.90	78.50	88.76	77.98	74.41	85.51	75.09	50.00	77.55

Table 10: Average AUROC(%) on IMDB.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	46.35	46.76	49.31	46.51	46.74	46.37	42.95	48.66	47.72	48.31	46.97
BERT	CLS	44.33	45.77	45.66	44.46	46.31	44.40	40.95	45.12	48.91	46.76	45.27
LLaMA-2 (mntp)	Mean	45.11	45.34	47.75	44.59	47.65	44.29	39.24	46.87	46.19	46.96	45.40
	EOS	48.36	48.33	50.26	48.33	49.32	48.33	48.10	49.20	48.90	49.83	48.90
	Weighted Mean	46.58	47.22	49.44	46.70	49.39	47.03	46.07	49.45	48.34	50.11	48.03
LLaMA-2 (mntp-unsup-simcse)	EOS	46.81	45.85	54.24	45.19	54.25	45.31	36.69	55.03	47.54	50.96	48.19
	Mean	47.02	47.93	54.04	47.11	56.24	47.05	40.53	55.06	48.73	50.39	49.51
	Weighted Mean	47.95	47.23	54.95	48.11	55.54	48.04	41.90	55.10	49.29	51.17	49.93
LLaMA-2 (mntp-supervised)	EOS	52.96	49.81	61.47	50.41	57.19	50.04	38.27	54.25	50.49	52.53	51.74
	Mean	50.70	50.66	57.43	49.84	70.00	49.87	36.92	62.78	51.28	54.36	53.38
	Weighted Mean	50.62	49.70	57.68	49.71	69.58	49.76	36.86	62.01	50.82	54.53	53.13
LLaMA-3 (mntp)	EOS	44.69	43.88	48.10	43.96	46.39	44.07	40.66	48.87	46.64	48.05	45.53
	Mean	45.31	45.56	50.65	45.51	50.82	45.57	40.46	51.42	48.06	50.65	47.40
	Weighted Mean	45.82	45.68	51.25	46.07	50.43	46.07	41.47	51.50	48.34	50.59	47.72
LLaMA-3 (mntp-unsup-simcse)	EOS	47.15	47.01	51.15	46.52	48.09	46.23	42.05	48.92	48.02	48.45	47.36
	Mean	47.21	46.62	53.39	47.43	57.03	47.62	39.07	54.22	49.16	50.80	49.26
	Weighted Mean	47.57	48.13	53.43	47.81	55.85	47.99	39.76	53.70	49.40	50.61	49.43
LLaMA-3 (mntp-supervised)	EOS	53.22	52.45	58.45	52.58	59.94	52.09	39.02	55.60	53.36	53.12	52.98
	Mean	45.68	46.96	55.31	45.91	68.50	45.94	35.48	60.64	49.38	52.50	50.63
	Weighted Mean	45.83	46.36	55.18	46.07	68.54	46.10	35.20	60.44	49.03	53.02	50.58
Mistral (mntp)	EOS	43.55	42.30	44.95	42.96	43.61	43.44	39.85	44.56	46.37	45.07	43.67
	Mean	49.30	49.24	53.55	49.12	53.51	49.59	44.37	54.63	49.89	53.13	50.63
	Weighted Mean	49.54	48.71	53.65	49.36	53.00	49.78	44.95	54.36	50.07	52.57	50.60
Mistral (mntp-unsup-simcse)	EOS	60.00	49.21	56.65	48.48	58.41	57.97	37.61	55.18	51.41	53.01	52.79
	Mean	53.44	51.29	58.19	51.71	59.78	52.94	46.47	58.36	52.54	54.46	53.92
	Weighted Mean	53.75	52.36	58.93	52.08	58.87	53.21	46.92	57.98	52.53	54.63	54.13
Mistral (mntp-supervised)	EOS	62.97	54.68	62.49	56.58	59.78	61.74	39.73	55.53	54.06	57.02	56.46
	Mean	52.80	47.19	54.34	44.50	63.85	49.12	34.83	57.37	49.56	53.15	50.67
	Weighted Mean	53.44	48.84	54.47	45.03	63.61	49.85	35.07	57.01	50.21	53.14	51.07
OpenAI-3-small	-	51.72	49.98	62.25	50.70	63.05	50.55	35.90	53.48	49.23	50.00	51.69
OpenAI-ada-002	-	49.98	50.40	58.47	49.49	66.97	49.26	38.19	51.47	48.14	53.66	51.60
OpenAI-3-large	-	56.02	51.94	64.66	55.10	73.44	54.99	31.40	59.17	51.13	50.00	54.79

Table 11: Average AUROC(%) on Reuters21578.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	76.85	78.21	84.54	77.77	82.75	75.96	64.57	80.93	57.92	83.08	76.26
BERT	CLS	65.90	58.08	76.69	58.43	52.54	60.90	49.07	63.65	54.05	61.18	60.05
LLaMA-2 (mntp)	Mean	80.74	80.79	89.45	80.45	83.61	78.06	66.28	83.64	71.45	88.87	80.33
	EOS	62.17	64.19	59.43	65.07	67.87	63.69	59.71	69.37	63.61	73.05	64.82
	Weighted Mean	56.63	64.05	61.33	60.15	65.36	55.25	51.87	72.80	57.44	66.75	61.16
LLaMA-2 (mntp-unsup-simcse)	EOS	95.38	91.17	86.94	95.37	95.48	95.03	87.49	96.42	87.06	94.56	92.49
	Mean	88.38	85.75	82.98	86.88	88.28	87.17	69.20	91.01	93.85	93.73	86.72
	Weighted Mean	86.85	82.27	80.99	85.55	87.56	86.01	67.09	90.01	93.00	93.40	85.27
LLaMA-2 (mntp-supervised)	EOS	94.91	87.13	78.69	94.63	95.00	94.57	89.01	95.48	81.75	92.90	90.41
	Mean	93.01	86.39	80.14	93.74	93.45	93.97	80.80	95.82	87.85	93.22	89.84
	Weighted Mean	91.79	84.43	78.29	92.80	92.61	93.17	78.40	94.96	86.85	92.19	88.55
LLaMA-3 (mntp)	EOS	85.68	81.94	83.20	85.15	91.29	84.94	69.60	89.73	65.39	87.03	82.40
	Mean	87.78	87.23	88.00	88.29	90.27	85.52	70.45	91.42	71.72	90.90	85.16
	Weighted Mean	83.23	84.13	86.00	83.58	88.53	79.73	65.95	89.88	68.13	89.07	81.82
LLaMA-3 (mntp-unsup-simcse)	EOS	82.44	75.30	75.92	80.25	81.38	80.89	71.27	81.72	72.18	78.12	77.95
	Mean	88.81	86.12	82.93	87.32	86.69	87.51	72.88	89.19	92.31	91.53	86.53
	Weighted Mean	86.65	84.48	81.57	84.96	85.76	85.77	68.92	87.91	89.82	89.89	84.57
LLaMA-3 (mntp-supervised)	EOS	92.05	85.86	90.48	91.02	87.55	90.04	83.79	91.49	88.21	89.91	89.04
	Mean	95.15	89.31	85.14	95.43	94.43	95.37	86.48	96.14	91.00	93.68	92.21
	Weighted Mean	94.20	87.61	83.18	94.64	93.21	94.61	85.08	95.44	88.59	92.97	90.95
Mistral (mntp)	EOS	76.36	82.49	72.82	86.65	74.52	76.81	68.80	77.98	68.81	84.37	76.96
	Mean	83.02	73.65	85.07	71.73	78.16	74.15	51.18	80.69	70.46	79.78	74.79
	Weighted Mean	79.11	67.31	84.11	67.05	75.84	68.29	51.52	79.00	68.48	77.02	71.77
Mistral (mntp-unsup-simcse)	EOS	91.31	77.16	78.51	88.63	91.46	91.46	76.21	91.32	79.13	87.85	85.30
	Mean	82.74	69.52	77.99	72.18	82.54	82.56	52.60	85.73	90.93	89.49	78.63
	Weighted Mean	80.27	67.28	76.98	68.18	80.85	80.14	51.16	84.49	85.46	87.65	76.25
Mistral (mntp-supervised)	EOS	92.27	85.17	75.34	92.81	91.92	92.50	83.30	93.17	87.50	91.08	88.51
	Mean	96.03	85.75	83.32	94.96	94.16	96.27	81.86	96.07	88.45	94.15	91.10
	Weighted Mean	94.63	80.60	80.77	93.60	92.50	94.99	78.34	94.93	89.51	92.52	89.24
OpenAI-3-small	-	98.28	94.08	89.56	98.19	95.15	97.98	91.06	98.75	97.96	50.00	91.10
OpenAI-ada-002	-	97.36	89.57	86.28	96.76	93.65	96.40	83.91	95.60	97.05	50.00	88.66
OpenAI-3-large	-	99.22	91.51	93.86	99.13	96.58	99.04	93.74	98.81	99.12	50.00	92.10

Table 12: Average AUROC(%) on SMS-SPAM.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	48.02	33.43	44.65	34.60	35.43	41.38	32.81	31.25	64.28	36.78	40.26
BERT	CLS	61.94	33.87	43.46	37.87	24.09	53.32	30.65	32.28	64.43	36.44	41.84
LLaMA-2 (mntp)	Mean	54.87	46.89	56.05	50.44	33.36	51.41	32.27	42.61	89.43	60.38	51.77
	EOS	77.78	72.10	69.49	74.03	37.45	73.46	53.77	53.72	46.29	63.70	62.18
	Weighted Mean	83.29	78.76	57.48	78.45	24.03	79.76	55.17	23.46	49.16	31.14	56.07
LLaMA-2 (mntp-unsup-simcse)	EOS	84.47	73.75	85.16	84.62	82.78	83.84	63.55	85.56	70.46	83.84	79.80
	Mean	81.30	69.30	78.38	81.35	85.65	83.29	51.53	85.92	79.59	90.06	78.64
	Weighted Mean	90.15	77.71	82.54	90.03	89.54	91.15	67.09	90.14	77.15	92.77	84.83
LLaMA-2 (mntp-supervised)	EOS	94.66	92.83	79.26	95.01	94.61	95.38	89.95	94.04	83.25	95.02	91.40
	Mean	81.31	75.32	71.73	83.60	86.17	84.04	63.34	88.26	68.52	87.06	78.94
	Weighted Mean	88.52	82.91	73.14	90.55	91.40	90.92	75.79	92.04	70.33	91.06	84.67
LLaMA-3 (mntp)	EOS	92.22	89.65	91.47	91.78	93.96	92.14	85.26	92.63	86.98	92.53	90.86
	Mean	76.28	69.36	71.61	71.36	76.02	80.55	50.00	67.66	85.48	75.86	72.42
	Weighted Mean	85.66	78.23	74.60	81.86	84.55	88.40	62.24	76.60	85.39	84.51	80.20
LLaMA-3 (mntp-unsup-simcse)	EOS	91.73	89.18	88.12	91.52	92.30	91.61	87.39	93.21	82.83	91.93	89.98
	Mean	78.70	70.04	79.80	78.66	83.08	81.52	54.77	80.07	90.05	89.63	78.63
	Weighted Mean	89.12	82.52	79.30	88.98	90.44	90.84	71.52	88.28	92.98	93.87	86.79
LLaMA-3 (mntp-supervised)	EOS	92.98	89.27	88.63	92.30	92.43	92.57	86.64	94.37	83.90	93.86	90.70
	Mean	88.38	83.92	83.94	88.12	90.71	88.51	76.90	91.60	82.33	92.01	86.64
	Weighted Mean	88.49	82.51	80.21	88.33	91.05	88.73	77.01	91.87	81.95	92.64	86.28
Mistral (mntp)	EOS	91.19	82.91	93.62	85.86	90.31	91.28	77.19	90.52	84.68	90.14	87.77
	Mean	87.73	76.24	89.00	80.09	77.92	85.22	59.60	69.45	79.48	78.45	78.32
	Weighted Mean	87.05	78.91	89.90	81.99	76.55	84.70	63.97	72.57	84.97	83.58	80.42
Mistral (mntp-unsup-simcse)	EOS	90.57	74.40	91.78	86.37	89.20	90.86	72.87	90.42	74.88	87.41	84.88
	Mean	86.56	62.12	77.74	69.28	80.45	85.71	44.16	82.17	90.03	88.29	76.65
	Weighted Mean	93.31	74.03	81.37	83.82	88.78	92.96	59.97	89.13	90.83	87.94	84.21
Mistral (mntp-supervised)	EOS	88.10	75.49	80.83	85.18	85.82	88.77	66.90	87.21	88.33	90.42	83.71
	Mean	67.30	56.11	68.55	60.83	65.23	65.35	38.87	73.20	77.94	80.23	65.36
	Weighted Mean	72.84	69.16	68.22	71.76	69.69	71.85	47.77	76.31	76.61	84.21	70.84
OpenAI-3-small	-	61.90	51.99	83.73	58.73	70.73	61.47	24.67	60.85	54.70	50.00	57.88
OpenAI-ada-002	-	87.52	72.89	89.00	87.78	84.46	88.38	66.59	87.85	63.97	46.97	77.54
OpenAI-3-large	-	73.78	58.06	86.32	67.39	77.96	73.45	26.93	72.12	72.48	45.65	65.41

Table 13: Average AUROC(%) on SST2.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	46.38	44.69	58.73	44.79	48.68	45.23	43.83	49.60	53.47	54.09	48.95
BERT	CLS	52.93	51.93	58.17	51.82	55.93	52.40	49.58	55.04	51.98	60.13	53.99
LLaMA-2 (mntp)	Mean	51.94	50.73	58.66	51.45	59.00	51.32	48.39	57.39	51.35	62.26	54.25
	EOS	49.80	50.25	53.66	49.80	57.31	49.37	48.97	58.31	50.41	64.76	53.26
	Weighted Mean	49.30	48.99	54.87	48.44	55.45	48.39	47.83	56.74	50.29	62.60	52.29
LLaMA-2 (mntp-unsup-simcse)	EOS	59.54	55.85	69.28	60.01	75.26	60.30	52.98	79.73	59.35	73.34	64.56
	Mean	56.08	54.24	69.40	56.10	74.60	56.22	50.87	80.42	57.77	73.43	62.91
	Weighted Mean	56.33	55.41	68.69	56.75	74.28	57.03	51.18	80.11	58.95	72.38	63.11
LLaMA-2 (mntp-supervised)	EOS	68.26	65.75	69.25	67.43	73.06	66.84	59.87	75.91	65.34	74.43	68.61
	Mean	69.42	66.90	71.96	69.76	79.30	69.87	59.56	80.95	67.80	78.00	71.35
	Weighted Mean	67.63	65.33	69.90	67.63	76.72	67.58	58.33	79.01	65.51	76.34	69.40
LLaMA-3 (mntp)	EOS	53.44	53.01	58.52	53.01	61.97	53.29	50.71	66.14	54.67	64.20	56.90
	Mean	53.34	52.50	61.56	52.86	65.73	53.18	49.74	71.71	56.56	68.17	58.54
	Weighted Mean	54.01	53.22	60.36	53.98	66.88	54.55	50.38	72.34	56.09	69.29	59.11
LLaMA-3 (mntp-unsup-simcse)	EOS	55.67	54.47	61.22	55.28	61.80	55.53	53.08	66.40	56.37	64.89	58.47
	Mean	54.18	52.57	64.17	53.40	71.01	54.25	48.57	78.33	57.43	71.68	60.56
	Weighted Mean	54.26	53.52	63.34	54.02	68.19	54.59	50.35	76.12	57.32	69.94	60.17
LLaMA-3 (mntp-supervised)	EOS	67.37	64.56	66.66	65.65	72.67	65.23	57.07	75.38	63.72	73.93	67.22
	Mean	68.40	65.00	69.25	68.05	77.93	68.46	56.30	79.29	65.78	77.17	69.56
	Weighted Mean	67.93	63.80	68.28	67.27	76.67	67.53	56.26	78.47	65.22	76.93	68.84
Mistral (mntp)	EOS	68.11	49.06	59.58	49.75	60.00	67.15	46.48	63.11	54.85	62.90	58.10
	Mean	57.58	49.75	61.80	49.23	59.01	50.04	47.23	64.01	53.35	61.93	55.39
	Weighted Mean	58.85	48.24	60.76	47.80	58.34	50.29	45.61	63.02	53.43	62.23	54.86
Mistral (mntp-unsup-simcse)	EOS	78.33	55.41	64.16	55.57	68.95	77.53	48.89	71.74	58.47	68.78	64.78
	Mean	76.40	51.94	65.86	52.15	72.60	73.37	47.95	77.75	56.58	71.19	64.58
	Weighted Mean	76.84	51.12	65.90	52.85	72.66	74.02	47.98	76.92	57.85	70.89	64.70
Mistral (mntp-supervised)	EOS	82.86	62.85	67.00	65.44	75.32	82.57	57.75	75.92	66.17	75.35	71.12
	Mean	85.22	60.37	70.55	63.38	79.46	84.67	53.42	79.77	64.61	78.36	71.98
	Weighted Mean	84.58	58.70	69.98	62.82	78.02	83.96	53.60	78.47	65.03	76.54	71.17
OpenAI-3-small	-	69.22	61.05	74.36	68.21	80.11	68.29	55.22	76.10	62.47	50.00	66.50
OpenAI-ada-002	-	66.86	61.98	72.88	67.42	79.33	67.43	56.94	69.61	62.43	50.00	65.49
OpenAI-3-large	-	70.49	61.21	76.14	69.56	81.38	69.48	56.76	76.90	64.13	50.00	67.61

Table 14: Average AUROC(%) on WOS.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	52.49	38.61	64.93	39.30	33.74	47.93	36.11	40.26	56.32	49.69	45.94
BERT	CLS	47.15	47.21	58.02	45.24	46.23	45.26	42.84	46.73	47.94	49.57	47.62
	Mean	53.09	50.35	59.02	49.05	37.77	49.52	43.80	41.25	49.32	48.70	48.19
LLaMA-2 (mntp)	EOS	47.46	46.17	49.46	46.92	50.92	45.99	46.68	51.51	48.03	51.74	48.49
	Mean	51.40	48.20	49.87	47.89	44.30	49.80	45.72	41.10	46.66	46.57	47.15
	Weighted Mean	50.81	46.20	49.01	47.56	43.84	49.00	45.80	40.44	47.12	46.34	46.61
LLaMA-2 (mntp-unsup-simcse)	EOS	59.93	55.46	60.92	59.98	63.82	60.33	52.78	62.55	56.07	60.37	59.22
	Mean	43.21	40.96	63.18	37.96	44.43	37.21	32.79	47.23	48.75	52.38	44.81
	Weighted Mean	43.55	40.89	61.41	38.99	43.46	38.17	34.00	46.54	49.30	52.43	44.87
LLaMA-2 (mntp-supervised)	EOS	63.75	62.69	63.58	67.61	80.63	68.70	63.07	75.20	59.79	66.74	67.18
	Mean	42.33	44.13	71.32	38.35	62.02	37.53	33.12	61.07	51.96	57.71	49.95
	Weighted Mean	43.48	45.23	71.22	40.30	62.89	39.56	34.94	61.45	52.09	58.34	50.95
LLaMA-3 (mntp)	EOS	57.53	56.04	58.65	56.68	56.21	55.15	51.04	56.67	54.18	55.83	55.80
	Mean	46.21	40.74	64.35	39.34	41.85	38.43	32.59	51.39	51.10	52.91	45.89
	Weighted Mean	46.47	43.61	61.57	40.70	41.70	39.55	34.43	51.18	51.50	52.25	46.30
LLaMA-3 (mntp-unsup-simcse)	EOS	55.43	54.32	57.35	54.56	59.02	55.75	52.04	58.71	54.23	56.24	55.77
	Mean	39.86	35.45	67.20	32.38	41.82	31.03	28.28	47.85	48.64	51.26	42.38
	Weighted Mean	41.18	38.75	64.85	34.76	41.69	33.31	30.64	47.64	48.72	51.93	43.35
LLaMA-3 (mntp-supervised)	EOS	52.83	50.45	63.67	50.43	69.22	51.45	46.91	66.72	52.78	57.94	56.24
	Mean	57.58	56.96	68.03	58.56	80.91	60.32	52.28	75.89	59.92	65.48	63.59
	Weighted Mean	57.09	53.65	67.86	57.88	80.45	59.60	51.82	75.11	58.97	65.12	62.76
Mistral (mntp)	EOS	62.76	56.11	56.25	58.24	63.09	62.29	55.07	62.98	54.97	59.00	59.08
	Mean	45.85	43.45	58.23	45.42	43.69	39.01	39.31	50.99	48.41	51.22	46.56
	Weighted Mean	46.08	47.59	56.45	45.30	42.62	39.85	39.57	50.21	47.35	50.24	46.53
Mistral (mntp-unsup-simcse)	EOS	69.13	61.76	55.32	63.37	70.04	68.34	61.41	68.10	57.69	62.82	63.80
	Mean	35.26	32.69	66.85	29.61	39.89	25.44	27.66	46.58	45.95	47.14	39.71
	Weighted Mean	35.84	35.69	65.07	31.09	39.67	26.82	29.11	46.36	46.95	47.20	40.38
Mistral (mntp-supervised)	EOS	67.36	51.96	63.23	56.02	67.46	66.76	50.75	65.73	54.28	59.12	60.27
	Mean	53.03	44.95	66.33	42.45	63.01	48.78	37.68	62.63	52.41	57.38	52.87
	Weighted Mean	53.01	46.27	66.04	42.53	62.26	48.95	37.85	61.62	51.993	56.95	52.75
OpenAI-3-small	-	58.28	54.04	65.73	60.26	77.54	58.95	50.42	58.66	52.45	48.87	58.52
OpenAI-ada-002	-	57.94	56.71	61.64	64.10	75.75	63.28	52.17	65.50	55.66	50.00	60.28
OpenAI-3-large	-	62.88	57.12	73.27	64.90	78.96	64.10	54.21	71.66	55.96	49.99	63.31

Table 15: Average AUROC(%) on DBpedia-0.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	82.33	77.03	86.25	78.19	79.83	81.04	65.91	79.30	56.61	82.42	76.89
BERT	CLS	84.94	83.48	94.62	84.91	88.83	83.56	78.23	91.72	73.72	90.05	85.41
LLaMA-2 (mntp)	Mean	81.63	78.96	91.35	80.39	87.41	80.11	71.79	90.65	81.18	90.67	83.41
	EOS	66.76	65.36	73.55	66.98	66.16	65.87	62.14	69.01	59.94	66.76	66.25
	Weighted Mean	71.12	67.53	75.38	68.81	64.65	68.76	60.57	64.77	64.68	63.27	66.95
LLaMA-2 (mntp-unsup-simcse)	EOS	95.81	84.70	96.94	95.58	97.19	95.72	86.18	96.90	84.03	93.53	92.66
	Mean	74.23	68.99	89.01	73.36	90.10	74.03	58.97	91.77	68.61	93.10	78.22
	Weighted Mean	73.66	68.05	87.25	72.96	88.96	73.46	60.43	90.74	66.59	91.35	77.35
LLaMA-2 (mntp-supervised)	EOS	92.60	76.40	97.15	91.94	95.01	92.53	71.28	94.77	80.94	88.98	88.16
	Mean	85.12	70.96	96.43	84.64	95.57	85.43	67.99	95.08	69.66	88.76	83.96
	Weighted Mean	82.66	70.59	95.45	82.01	94.07	82.87	65.51	93.65	70.64	86.41	82.39
LLaMA-3 (mntp)	EOS	79.66	75.02	85.66	79.01	82.40	77.65	62.42	79.92	72.24	75.25	76.92
	Mean	67.77	61.99	78.51	64.46	72.96	64.46	49.11	75.34	59.41	74.14	66.82
	Weighted Mean	67.23	63.40	79.63	64.99	72.87	64.01	52.51	75.60	60.46	73.72	67.44
LLaMA-3 (mntp-unsup-simcse)	EOS	64.99	59.96	78.33	62.28	64.22	60.07	53.30	69.45	59.06	63.10	63.48
	Mean	57.96	52.51	77.22	55.97	72.86	56.43	39.12	79.26	68.53	87.71	64.76
	Weighted Mean	60.54	54.98	78.71	58.64	73.21	58.85	44.32	79.66	67.49	86.36	66.28
LLaMA-3 (mntp-supervised)	EOS	91.28	81.33	96.52	89.50	91.92	89.30	79.18	92.78	79.51	88.42	87.97
	Mean	89.58	75.19	97.70	88.85	97.10	89.57	72.66	95.77	76.45	90.12	87.30
	Weighted Mean	90.05	74.91	97.39	89.40	96.54	90.10	75.55	95.25	75.27	89.26	87.37
Mistral (mntp)	EOS	84.28	74.80	87.38	79.19	84.40	84.09	60.87	82.58	74.01	81.65	79.33
	Mean	73.53	64.10	78.53	66.68	78.63	71.00	53.56	75.60	62.50	70.67	69.48
	Weighted Mean	72.03	63.49	77.92	64.06	76.14	68.74	53.46	73.52	62.46	67.64	67.95
Mistral (mntp-unsup-simcse)	EOS	84.17	69.58	87.92	83.64	83.72	84.88	69.46	88.11	67.04	78.28	79.68
	Mean	62.80	57.52	75.63	56.29	73.78	61.24	49.01	77.50	63.44	74.81	65.20
	Weighted Mean	61.06	55.33	74.31	55.30	71.51	59.71	49.57	75.98	62.69	73.02	63.85
Mistral (mntp-supervised)	EOS	95.09	73.39	96.62	89.64	94.79	95.24	72.87	95.15	74.24	88.68	87.57
	Mean	92.75	69.24	96.86	79.56	95.32	91.00	65.31	96.01	63.39	87.23	83.67
	Weighted Mean	91.19	67.42	96.15	77.83	93.97	89.39	64.72	95.04	63.79	71.38	81.09
OpenAI-3-small	-	98.23	83.36	98.86	98.18	98.86	98.12	91.73	97.52	97.12	50.00	91.20
OpenAI-ada-002	-	93.55	76.89	97.77	93.76	96.55	94.05	73.06	92.03	93.44	49.35	86.05
OpenAI-3-large	-	98.70	79.29	99.30	98.50	99.19	98.59	91.03	98.32	98.27	63.99	92.52

Table 16: Average AUROC(%) on DBpedia-1.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	91.59	88.37	96.57	90.11	89.22	90.89	76.42	89.48	68.34	96.02	87.70
BERT	CLS	85.12	82.64	96.96	84.38	90.72	82.31	76.57	93.64	75.22	92.02	85.69
LLaMA-2 (mntp)	Mean	82.06	77.26	95.04	80.88	92.76	79.44	70.92	94.50	91.28	95.08	85.92
	EOS	72.70	70.78	77.46	72.85	73.51	71.59	67.31	77.05	64.28	75.58	72.31
	Weighted Mean	78.29	77.44	84.46	77.84	73.07	75.90	67.14	71.41	69.54	70.32	74.54
LLaMA-2 (mntp-unsup-simcse)	EOS	99.36	94.23	98.87	99.29	99.57	99.17	95.50	99.68	95.37	98.98	98.00
	Mean	91.62	85.06	96.51	91.27	97.89	90.92	75.64	98.86	84.71	99.35	91.18
	Weighted Mean	91.55	84.60	95.31	91.00	97.60	90.76	77.20	98.57	83.08	98.94	90.86
LLaMA-2 (mntp-supervised)	EOS	99.24	93.39	99.26	99.06	99.41	99.09	94.00	99.65	94.31	98.47	97.59
	Mean	99.02	92.20	99.34	98.94	99.47	98.97	93.46	99.74	91.65	99.18	97.20
	Weighted Mean	98.59	90.42	99.00	98.48	99.34	98.54	91.94	99.64	90.16	98.81	96.49
LLaMA-3 (mntp)	EOS	91.01	85.87	92.29	90.23	95.34	89.26	77.18	94.66	85.20	89.82	89.09
	Mean	80.39	76.92	91.91	79.08	92.66	77.83	62.68	94.02	77.41	90.59	82.35
	Weighted Mean	81.00	77.90	92.25	79.69	92.03	78.23	65.85	93.47	76.69	89.88	82.70
LLaMA-3 (mntp-unsup-simcse)	EOS	81.52	72.13	89.55	76.58	81.08	73.44	66.64	87.63	73.42	80.69	78.27
	Mean	84.90	79.02	93.02	83.65	93.64	84.31	63.48	96.40	84.63	97.93	86.10
	Weighted Mean	86.15	78.86	91.60	84.76	93.30	85.33	67.97	96.06	78.25	96.88	85.92
LLaMA-3 (mntp-supervised)	EOS	98.90	93.60	98.73	98.33	98.28	98.07	94.34	99.15	95.22	98.46	97.31
	Mean	99.45	94.13	99.64	99.37	99.78	99.38	95.29	99.75	95.51	99.25	98.16
	Weighted Mean	99.36	93.42	99.43	99.29	99.69	99.31	95.44	99.68	94.20	99.00	97.88
Mistral (mntp)	EOS	96.03	81.95	97.14	88.69	96.01	95.67	72.63	96.80	86.03	94.69	90.56
	Mean	85.54	77.75	93.35	78.44	92.88	80.27	66.97	92.60	82.60	86.82	83.72
	Weighted Mean	85.26	74.54	93.26	77.45	92.01	80.11	67.72	91.90	82.20	86.57	83.10
Mistral (mntp-unsup-simcse)	EOS	96.91	89.10	96.90	95.84	96.64	97.11	90.26	97.84	88.17	95.70	94.45
	Mean	82.61	68.12	89.88	72.22	90.87	80.24	59.96	93.49	82.63	94.13	81.42
	Weighted Mean	81.05	67.34	88.65	71.63	89.72	78.88	61.55	92.83	79.31	93.01	80.40
Mistral (mntp-supervised)	EOS	98.70	85.69	97.86	97.90	98.61	98.76	89.27	99.17	91.36	98.35	95.57
	Mean	99.36	84.70	99.36	96.78	99.44	99.22	84.83	99.66	84.52	98.59	94.65
	Weighted Mean	99.21	84.99	98.93	96.10	99.29	99.05	84.15	99.56	84.45	98.41	94.41
OpenAI-3-small	-	99.81	95.89	99.85	99.78	99.86	99.77	99.09	99.55	99.81	50.00	94.34
OpenAI-ada-002	-	99.33	92.45	99.69	99.35	99.63	99.31	92.75	92.57	99.48	49.94	92.45
OpenAI-3-large	-	99.87	94.48	99.89	99.83	99.90	99.84	99.57	99.67	99.87	48.56	94.15

Table 17: Average AUROC(%) on DBpedia-2.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	85.27	83.18	87.29	83.39	83.86	84.03	74.83	83.76	57.31	87.38	81.03
BERT	CLS	74.38	72.29	93.54	73.46	81.22	71.48	67.47	86.61	69.06	83.49	77.30
LLaMA-2 (mntp)	Mean	80.26	76.38	92.97	78.62	89.61	77.28	71.73	93.38	84.91	91.41	83.66
	EOS	66.84	63.97	73.12	66.84	65.10	65.68	60.01	66.17	61.51	61.69	65.09
	Weighted Mean	77.94	76.14	84.42	76.70	72.00	74.73	67.44	65.56	67.48	66.92	72.93
LLaMA-2 (mntp-unsup-simcse)	EOS	91.55	76.95	95.02	89.97	93.93	89.72	80.26	96.38	82.01	92.33	88.81
	Mean	78.48	72.24	91.36	78.01	89.49	77.70	67.63	94.41	68.62	93.59	81.15
	Weighted Mean	75.82	68.91	91.12	75.03	89.09	74.74	63.90	93.55	66.04	92.27	79.05
LLaMA-2 (mntp-supervised)	EOS	84.92	74.84	93.14	84.19	91.30	84.45	75.18	91.81	76.86	85.37	84.21
	Mean	89.62	75.58	97.45	88.93	94.80	89.24	78.65	95.88	75.91	90.64	87.67
	Weighted Mean	88.65	73.82	97.05	87.88	94.80	88.25	77.30	95.17	73.50	90.45	86.69
LLaMA-3 (mntp)	EOS	88.90	84.84	90.38	88.47	92.36	88.14	79.83	89.97	81.23	86.44	87.06
	Mean	81.14	79.00	90.45	81.48	89.25	79.20	73.15	91.79	75.44	89.44	83.03
	Weighted Mean	80.62	78.41	90.48	79.85	88.48	78.50	69.85	90.37	74.53	85.76	81.68
LLaMA-3 (mntp-unsup-simcse)	EOS	66.82	59.22	77.74	61.74	64.43	60.04	57.90	72.31	60.26	67.38	64.78
	Mean	80.14	74.68	87.21	78.89	84.98	78.95	71.00	90.39	67.80	89.99	80.40
	Weighted Mean	79.17	71.97	87.73	77.33	85.45	77.52	68.29	90.46	67.73	90.59	79.62
LLaMA-3 (mntp-supervised)	EOS	87.34	68.89	94.21	83.58	87.64	83.65	68.01	91.19	77.15	86.73	82.84
	Mean	92.93	80.54	97.91	91.96	97.54	92.46	81.73	96.58	85.96	90.91	90.85
	Weighted Mean	92.43	76.96	97.62	91.41	97.12	92.01	80.08	96.15	84.63	90.57	89.90
Mistral (mntp)	EOS	90.46	78.65	91.07	84.02	90.74	89.99	78.01	92.84	79.47	88.08	86.33
	Mean	83.52	75.35	91.04	76.09	90.05	78.12	67.50	91.18	74.23	84.52	81.16
	Weighted Mean	83.98	73.31	91.23	74.66	88.97	78.16	65.20	89.69	73.24	82.73	80.12
Mistral (mntp-unsup-simcse)	EOS	78.43	65.80	78.17	76.89	78.23	78.61	69.70	82.59	65.59	78.43	75.24
	Mean	72.22	62.69	79.31	65.42	76.27	70.72	60.51	85.28	68.39	82.13	72.29
	Weighted Mean	68.43	60.36	79.05	61.66	74.03	66.83	57.06	83.96	66.63	79.75	69.78
Mistral (mntp-supervised)	EOS	94.16	75.20	95.98	87.90	94.24	94.03	80.71	95.07	76.60	89.21	88.31
	Mean	94.30	74.90	96.87	86.51	95.24	93.38	78.98	97.14	70.80	89.60	87.77
	Weighted Mean	93.93	73.10	96.87	85.31	95.54	92.86	77.72	96.99	69.49	89.69	87.15
OpenAI-3-small	-	95.83	77.10	96.96	94.18	95.41	93.99	86.62	95.64	95.31	50.00	88.10
OpenAI-ada-002	-	94.20	80.73	96.05	94.16	92.06	93.92	87.07	93.26	94.32	50.00	87.58
OpenAI-3-large	-	95.15	75.31	97.79	92.95	96.64	93.15	87.13	97.05	94.84	50.25	88.03

Table 18: Average AUROC(%) on DBpedia-3.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	87.97	82.11	97.15	83.69	92.02	85.17	69.89	91.06	66.49	95.19	85.07
BERT	CLS	67.87	63.44	94.62	64.36	85.11	63.13	51.13	87.72	79.72	86.22	74.33
LLaMA-2 (mntp)	Mean	75.88	72.88	96.42	70.94	95.96	69.22	56.43	96.35	93.83	96.92	82.48
	EOS	69.63	68.89	80.81	70.94	79.30	69.28	61.81	77.33	68.06	78.44	72.45
	Weighted Mean	81.68	82.60	90.70	82.64	82.90	80.83	71.28	78.73	75.17	77.98	80.45
LLaMA-2 (mntp-unsup-simcse)	EOS	98.52	91.07	99.52	98.02	99.28	97.76	93.74	99.71	93.79	98.69	97.01
	Mean	95.15	88.32	99.48	95.08	99.21	94.92	86.74	99.68	91.68	99.62	94.99
	Weighted Mean	94.43	88.46	99.32	94.13	99.38	94.04	83.96	99.62	88.23	99.51	94.11
LLaMA-2 (mntp-supervised)	EOS	95.87	87.82	98.84	95.72	98.02	95.80	90.23	98.99	90.89	96.66	94.88
	Mean	94.54	82.80	99.55	94.11	98.78	94.25	83.03	99.60	90.02	97.75	93.44
	Weighted Mean	93.61	81.93	99.47	93.12	98.96	93.29	81.69	99.53	87.74	97.59	92.69
LLaMA-3 (mntp)	EOS	96.56	93.48	96.65	95.99	98.33	96.13	87.10	97.68	94.09	95.98	95.20
	Mean	93.31	91.62	98.98	93.31	99.03	91.35	84.11	99.28	89.18	98.19	93.84
	Weighted Mean	93.59	89.09	98.71	92.64	98.96	91.69	80.99	99.02	89.18	97.74	93.16
LLaMA-3 (mntp-unsup-simcse)	EOS	76.36	67.48	90.21	71.02	78.37	69.11	65.69	84.28	74.08	77.67	75.43
	Mean	94.99	90.25	98.76	94.43	98.39	94.44	88.34	99.07	90.37	98.84	94.79
	Weighted Mean	94.79	87.39	98.57	93.80	98.69	94.02	86.13	99.10	88.85	98.97	94.03
LLaMA-3 (mntp-supervised)	EOS	93.77	80.49	98.11	91.52	95.54	91.50	79.30	98.02	91.44	95.16	91.48
	Mean	96.56	85.35	99.78	95.87	99.64	95.96	85.80	99.71	94.20	98.21	95.11
	Weighted Mean	96.17	84.75	99.73	95.24	99.64	95.35	83.28	99.67	94.88	97.02	94.57
Mistral (mntp)	EOS	94.69	85.16	96.14	89.28	94.75	94.38	80.82	96.20	88.45	94.81	91.47
	Mean	94.67	87.76	98.53	90.32	98.79	89.94	79.43	98.97	89.64	96.95	92.50
	Weighted Mean	95.02	86.60	98.31	89.23	98.49	91.01	76.39	98.48	88.46	95.93	91.79
Mistral (mntp-unsup-simcse)	EOS	88.88	76.12	88.74	87.11	88.50	89.02	80.95	93.96	80.06	90.71	86.40
	Mean	87.74	76.16	94.93	79.56	93.72	85.18	71.12	97.63	90.91	96.82	87.38
	Weighted Mean	86.46	72.79	95.93	76.88	93.81	83.30	68.24	97.56	87.75	96.18	85.89
Mistral (mntp-supervised)	EOS	98.14	82.72	98.23	94.92	98.13	98.06	89.56	98.94	89.69	96.16	94.46
	Mean	97.08	78.75	98.90	89.69	98.48	96.22	79.09	99.44	89.94	97.08	92.47
	Weighted Mean	97.00	77.61	99.03	87.84	98.77	95.96	75.91	99.47	88.26	96.90	91.68
OpenAI-3-small	-	99.47	88.72	99.73	99.02	99.05	98.99	96.65	99.50	99.64	50.00	93.08
OpenAI-ada-002	-	98.97	91.13	99.77	98.84	99.00	98.75	95.60	99.26	99.18	50.00	93.05
OpenAI-3-large	-	99.46	88.82	99.81	98.95	99.33	98.90	96.97	99.42	99.69	52.96	93.43

Table 19: Average AUROC(%) on DBpedia-4.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	86.64	82.12	92.22	83.09	85.92	84.82	70.75	86.25	61.66	91.17	82.46
BERT	CLS	68.96	63.59	93.78	67.67	82.68	64.06	57.37	86.37	74.36	83.02	74.19
LLaMA-2 (mntp)	Mean	76.02	72.27	93.65	72.75	93.23	71.38	63.34	94.07	88.91	94.38	82.00
	EOS	71.83	69.48	72.80	71.09	72.77	69.98	60.90	70.17	66.53	71.23	69.68
	Weighted Mean	85.18	82.91	89.40	84.03	79.83	82.68	74.62	75.26	72.24	75.87	80.20
LLaMA-2 (mntp-unsup-simcse)	EOS	97.43	88.44	97.72	96.30	98.78	96.16	88.80	98.91	87.72	96.91	94.72
	Mean	92.43	87.34	96.54	92.33	97.64	92.34	84.28	98.58	78.40	98.61	91.85
	Weighted Mean	92.05	85.47	95.88	91.97	97.71	92.03	83.33	98.34	74.56	98.32	90.97
LLaMA-2 (mntp-supervised)	EOS	97.04	89.15	98.54	96.56	97.95	96.61	93.54	98.43	88.73	95.64	95.22
	Mean	95.95	83.52	98.73	95.58	97.78	95.72	87.47	98.71	85.29	96.22	93.50
	Weighted Mean	95.17	84.63	98.37	94.70	97.92	94.87	85.52	98.45	83.35	96.15	92.91
LLaMA-3 (mntp)	EOS	92.05	89.42	90.54	91.60	95.28	91.77	84.06	93.35	86.54	91.08	90.57
	Mean	88.88	87.18	95.54	88.77	96.54	87.22	81.80	97.10	82.94	93.81	89.98
	Weighted Mean	89.43	87.75	95.12	89.13	96.14	88.25	81.75	96.56	82.35	94.02	90.05
LLaMA-3 (mntp-unsup-simcse)	EOS	73.74	66.52	85.02	69.60	76.21	67.38	65.19	80.80	69.16	74.95	72.86
	Mean	91.37	86.63	95.26	90.81	96.02	91.03	84.40	97.43	80.17	97.12	91.02
	Weighted Mean	91.30	86.73	94.78	90.79	96.24	91.16	83.58	97.30	76.66	97.04	90.56
LLaMA-3 (mntp-supervised)	EOS	95.96	84.73	98.22	94.82	94.75	94.71	85.64	96.31	85.91	95.08	92.61
	Mean	98.28	88.03	99.22	97.69	99.24	97.75	92.08	98.93	91.95	97.26	96.04
	Weighted Mean	98.05	86.61	98.92	97.57	99.12	97.65	91.01	98.71	89.72	96.89	95.42
Mistral (mntp)	EOS	93.33	81.38	93.52	84.66	93.63	92.76	77.53	93.86	80.03	90.32	88.10
	Mean	88.83	83.05	95.74	84.23	96.29	84.09	77.68	96.60	83.66	92.92	88.31
	Weighted Mean	89.74	81.42	95.47	84.30	95.87	85.79	77.06	95.88	83.76	93.99	88.33
Mistral (mntp-unsup-simcse)	EOS	86.20	72.20	85.42	82.71	85.82	86.43	73.96	89.74	72.96	85.27	82.07
	Mean	84.02	70.93	91.94	75.91	90.49	82.12	68.83	95.10	77.17	84.42	82.09
	Weighted Mean	82.48	70.17	92.89	74.03	90.45	80.30	67.09	94.69	74.71	91.93	81.87
Mistral (mntp-supervised)	EOS	96.34	79.86	96.59	92.16	96.30	96.25	85.23	96.83	82.43	93.21	91.52
	Mean	96.57	75.56	97.72	88.28	97.39	95.73	78.00	98.32	80.15	93.94	90.17
	Weighted Mean	96.28	74.55	97.64	86.88	97.51	95.30	75.78	98.25	77.31	84.70	88.42
OpenAI-3-small	-	98.60	84.79	98.33	97.68	98.72	97.63	93.60	98.39	98.64	50.00	91.64
OpenAI-ada-002	-	98.46	89.91	98.69	98.42	98.04	98.40	95.86	97.40	98.57	51.67	92.54
OpenAI-3-large	-	98.89	84.20	98.87	98.17	98.74	98.12	95.67	99.15	99.26	44.73	91.58

Table 20: Average AUPRC(%) on DBpedia-0.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	75.71	70.37	81.18	71.46	78.23	74.33	57.78	76.00	49.73	79.74	71.45
BERT	CLS	80.55	80.16	94.03	81.80	88.41	78.31	74.76	91.09	70.10	88.12	82.73
LLaMA-2 (mntp)	Mean	75.26	73.05	89.84	73.91	84.82	73.11	64.81	88.09	78.47	88.49	78.99
	EOS	56.67	55.17	67.82	56.49	58.53	55.56	51.91	58.88	51.03	57.48	56.95
	Weighted Mean	58.97	55.13	72.02	56.11	54.86	56.08	49.52	54.88	56.32	53.51	56.74
LLaMA-2 (mntp-unsup-simcse)	EOS	94.68	81.07	96.03	94.25	96.33	94.43	81.18	96.07	81.45	92.40	90.79
	Mean	63.24	59.69	83.47	62.01	84.27	62.60	48.93	87.45	68.42	90.69	71.08
	Weighted Mean	63.40	59.51	81.40	62.32	82.92	62.71	50.39	86.75	66.20	88.81	70.44
LLaMA-2 (mntp-supervised)	EOS	89.72	70.60	96.73	88.21	94.73	89.20	61.68	94.48	78.06	86.44	84.99
	Mean	81.71	64.93	95.92	80.78	94.67	81.66	61.00	94.43	64.95	86.94	80.70
	Weighted Mean	79.14	64.78	94.85	78.18	93.05	79.12	59.13	92.88	66.17	84.27	79.16
LLaMA-3 (mntp)	EOS	68.72	64.56	79.29	67.88	75.63	65.35	50.81	72.98	64.43	66.37	67.60
	Mean	54.94	51.43	69.99	52.30	61.18	52.12	41.88	66.09	52.83	66.13	56.89
	Weighted Mean	54.16	52.46	72.65	52.58	61.92	51.10	43.51	67.94	53.23	65.73	57.53
LLaMA-3 (mntp-unsup-simcse)	EOS	57.75	53.28	72.57	55.06	59.06	54.01	48.35	64.11	52.72	56.62	57.35
	Mean	47.79	44.59	68.90	46.25	62.68	46.39	36.73	70.97	67.30	83.62	57.52
	Weighted Mean	49.88	46.69	71.77	48.16	63.20	48.10	39.06	72.30	66.63	82.18	58.80
LLaMA-3 (mntp-supervised)	EOS	90.61	78.77	96.21	88.64	92.29	88.65	75.71	93.15	76.48	87.20	86.77
	Mean	87.01	69.91	96.93	85.78	96.33	86.77	66.12	95.22	69.91	88.33	84.23
	Weighted Mean	87.94	69.85	96.62	86.84	95.82	87.79	69.86	94.77	69.17	87.42	84.61
Mistral (mntp)	EOS	80.92	66.88	83.21	71.28	81.21	80.64	50.76	77.67	70.74	75.73	73.90
	Mean	62.47	54.29	67.56	56.39	67.18	60.21	46.17	64.68	52.95	62.05	59.40
	Weighted Mean	60.11	53.73	69.17	53.15	64.73	57.10	45.33	63.33	52.65	58.92	57.82
Mistral (mntp-unsup-simcse)	EOS	79.77	63.05	83.92	79.71	78.99	80.73	60.25	84.27	63.50	73.31	74.75
	Mean	52.76	49.51	66.80	47.96	63.55	51.16	42.89	69.32	59.91	67.52	57.14
	Weighted Mean	52.11	48.24	66.61	48.00	61.74	50.76	43.77	68.77	59.21	66.33	56.55
Mistral (mntp-supervised)	EOS	94.61	66.74	95.02	85.98	94.39	94.49	63.31	94.62	68.58	85.85	84.36
	Mean	89.39	62.21	95.71	72.26	93.90	86.90	56.45	94.92	56.56	84.61	79.29
	Weighted Mean	87.70	61.09	94.99	70.76	92.53	85.14	56.64	93.98	57.24	74.53	77.46
OpenAI-3-small	-	97.51	79.64	98.41	97.51	98.38	97.36	88.64	96.02	96.67	72.22	92.24
OpenAI-ada-002	-	89.37	71.41	96.86	89.66	95.36	90.06	63.80	84.13	89.96	66.10	83.67
OpenAI-3-large	-	97.70	74.32	98.85	97.58	98.50	97.51	85.41	96.95	97.60	71.94	91.64

Table 21: Average AUPRC(%) on DBpedia-1.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	86.75	82.24	94.89	84.35	88.16	85.55	66.30	87.44	59.01	94.85	82.95
BERT	CLS	76.32	76.46	96.13	77.89	89.81	72.45	68.87	92.51	70.44	89.13	81.00
	Mean	72.73	68.32	94.03	72.09	89.50	69.72	61.34	91.53	90.35	93.37	80.30
LLaMA-2 (mntp)	EOS	64.35	62.71	70.95	64.42	68.97	63.06	59.05	70.60	56.56	68.32	64.90
	Mean	68.26	68.19	82.69	68.43	65.65	64.93	58.36	65.44	62.92	62.75	66.76
	Weighted Mean	67.72	66.05	82.57	67.03	65.76	64.30	59.28	64.95	59.89	63.56	66.11
LLaMA-2 (mntp-unsup-simcse)	EOS	99.19	93.01	97.80	99.10	99.42	98.93	94.22	99.53	94.74	98.74	97.47
	Mean	87.69	79.81	94.78	87.08	96.93	86.30	66.54	98.23	84.16	99.09	88.06
	Weighted Mean	88.51	79.98	92.00	87.65	96.64	87.10	69.58	97.97	83.38	98.75	88.16
LLaMA-2 (mntp-supervised)	EOS	98.64	91.44	98.82	98.35	99.33	98.42	90.69	99.56	93.23	97.86	96.63
	Mean	98.45	90.34	98.90	98.32	99.30	98.33	91.45	99.61	90.38	98.96	96.40
	Weighted Mean	97.99	88.19	98.26	97.83	99.19	97.89	89.79	99.52	88.64	98.51	95.58
LLaMA-3 (mntp)	EOS	83.34	78.38	86.21	82.66	92.76	80.23	66.02	92.08	80.44	85.20	82.73
	Mean	69.38	67.33	90.48	68.65	88.81	65.74	53.38	91.86	70.86	87.36	75.39
	Weighted Mean	71.73	69.22	90.65	70.99	88.68	67.88	56.64	91.65	69.84	86.87	76.42
LLaMA-3 (mntp-unsup-simcse)	EOS	72.76	64.13	84.03	67.20	77.27	65.14	57.85	84.48	69.24	73.59	71.57
	Mean	78.88	72.05	90.79	77.04	91.35	77.54	57.06	94.99	84.99	97.25	82.19
	Weighted Mean	81.46	72.85	88.87	79.52	91.18	79.94	61.44	94.85	78.24	96.30	82.46
LLaMA-3 (mntp-supervised)	EOS	98.63	91.99	98.27	97.98	98.19	97.75	92.91	99.03	94.73	98.10	96.76
	Mean	99.19	92.67	99.48	99.05	99.68	99.09	93.90	99.65	94.47	99.00	97.62
	Weighted Mean	99.15	92.12	99.14	99.02	99.60	99.06	94.29	99.57	92.98	98.74	97.37
Mistral (mntp)	EOS	94.78	74.90	96.18	82.58	94.81	94.28	60.89	95.39	83.53	91.91	86.92
	Mean	73.76	64.77	91.37	64.29	88.01	65.77	54.26	88.52	76.74	80.57	74.81
	Weighted Mean	75.00	62.49	90.42	64.71	87.25	67.33	55.76	88.09	76.99	80.74	74.88
Mistral (mntp-unsup-simcse)	EOS	95.05	85.81	95.04	92.77	94.69	95.24	82.87	96.35	86.50	93.43	91.78
	Mean	76.51	60.69	87.10	64.58	87.51	73.20	52.84	91.09	81.76	92.67	76.79
	Weighted Mean	76.03	60.73	85.11	65.51	86.34	73.13	55.61	90.69	77.89	91.61	76.26
Mistral (mntp-supervised)	EOS	98.72	82.23	96.14	97.58	98.64	98.76	85.79	99.07	90.12	97.92	94.50
	Mean	98.94	81.36	99.02	95.94	99.23	98.73	81.73	99.47	80.84	98.31	93.36
	Weighted Mean	98.85	82.36	98.17	95.33	99.09	98.62	81.85	99.38	80.78	98.10	93.25
OpenAI-3-small	-	99.72	94.78	99.78	99.67	99.79	99.65	98.53	98.85	99.73	72.22	96.27
OpenAI-ada-002	-	98.73	90.29	99.55	98.78	99.50	98.72	88.16	82.64	99.08	64.63	92.01
OpenAI-3-large	-	99.50	86.86	99.69	99.38	99.68	99.39	98.10	97.07	99.54	51.02	93.02

Table 22: Average AUPRC(%) on DBpedia-2.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	80.80	77.57	80.46	77.45	81.23	78.55	66.27	81.66	49.44	84.95	75.84
BERT	CLS	65.89	65.82	92.59	66.89	80.41	62.54	60.92	85.11	64.15	79.17	72.35
LLaMA-2 (mntp)	Mean	72.93	69.45	92.30	71.37	88.32	68.77	64.33	91.91	83.29	89.92	79.26
	EOS	59.23	56.31	70.00	59.26	61.23	57.93	52.93	59.69	55.93	56.55	58.91
	Weighted Mean	68.74	67.64	83.10	67.97	65.10	64.80	58.11	57.88	59.78	60.39	65.35
LLaMA-2 (mntp-unsup-simcse)	EOS	90.13	72.78	94.16	88.24	93.55	87.99	75.20	95.82	79.57	91.20	86.86
	Mean	72.71	66.34	88.87	71.83	87.22	71.49	60.70	93.31	67.99	92.80	77.33
	Weighted Mean	69.35	62.07	88.28	68.09	86.00	67.73	56.58	92.01	65.00	91.25	74.64
LLaMA-2 (mntp-supervised)	EOS	84.89	72.15	92.71	83.99	90.96	84.24	74.35	91.33	74.64	84.93	83.42
	Mean	87.62	70.22	97.21	86.44	94.91	86.89	73.23	95.49	72.32	89.83	85.43
	Weighted Mean	86.51	68.50	96.70	85.26	94.65	85.78	72.05	94.59	68.76	89.43	84.22
LLaMA-3 (mntp)	EOS	83.54	79.07	87.28	82.84	90.40	82.43	71.68	87.28	75.51	82.18	82.22
	Mean	74.25	72.49	88.23	75.22	86.38	71.73	65.70	90.20	68.81	86.93	77.99
	Weighted Mean	73.81	72.61	88.56	73.77	85.63	71.31	62.93	88.54	68.65	82.80	76.86
LLaMA-3 (mntp-unsup-simcse)	EOS	58.41	51.81	73.50	53.66	59.23	52.69	50.26	68.65	54.12	60.34	58.27
	Mean	78.13	71.77	86.20	76.79	84.10	76.83	68.32	89.46	66.50	89.24	78.73
	Weighted Mean	75.70	67.31	85.99	73.56	83.57	73.77	63.61	88.95	66.50	89.42	76.84
LLaMA-3 (mntp-supervised)	EOS	81.23	61.06	92.78	75.94	85.27	76.25	57.49	89.62	74.66	82.59	77.69
	Mean	91.92	77.23	97.59	90.51	97.22	91.09	78.16	96.27	84.12	89.91	89.40
	Weighted Mean	91.22	72.61	97.23	89.66	96.75	90.40	75.79	95.84	82.13	89.37	88.10
Mistral (mntp)	EOS	89.95	74.33	91.18	80.78	90.30	89.42	73.13	92.12	77.06	86.92	84.52
	Mean	74.95	66.29	88.66	65.98	85.55	67.25	58.35	87.74	66.96	80.37	74.21
	Weighted Mean	75.04	63.23	88.60	64.12	84.03	67.21	55.95	85.84	65.40	78.00	72.74
Mistral (mntp-unsup-simcse)	EOS	77.22	59.67	75.84	72.47	77.09	77.36	62.71	80.77	62.16	75.05	72.03
	Mean	65.70	54.88	75.10	57.32	70.50	63.59	52.47	82.80	65.93	80.06	66.83
	Weighted Mean	60.17	52.27	74.74	52.62	66.31	58.04	48.66	80.45	63.03	76.56	63.28
Mistral (mntp-supervised)	EOS	93.35	70.83	95.09	86.16	93.55	93.09	77.55	94.28	74.09	88.26	86.62
	Mean	92.47	68.73	96.33	81.21	94.65	91.12	71.04	96.61	64.66	88.69	84.55
	Weighted Mean	91.63	66.34	96.25	78.16	94.74	89.97	67.99	96.41	64.20	88.48	83.42
OpenAI-3-small	-	95.13	73.48	96.57	93.18	95.37	93.04	84.27	95.12	95.12	72.22	89.35
OpenAI-ada-002	-	93.23	79.13	95.80	93.09	92.55	92.83	85.63	92.03	93.68	66.76	88.47
OpenAI-3-large	-	91.52	60.66	95.83	88.18	94.46	88.46	80.80	91.25	91.93	52.44	83.55

Table 23: Average AUPRC(%) on DBpedia-3.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	84.38	76.84	95.78	79.43	91.92	81.01	62.90	90.64	59.40	94.51	81.68
BERT	CLS	56.39	53.00	93.20	53.46	82.94	52.16	43.97	85.30	77.76	82.14	68.03
LLaMA-2 (mntp)	Mean	66.65	64.37	95.57	62.22	94.78	59.65	49.25	95.26	93.68	96.31	77.77
	EOS	63.53	62.92	75.98	64.98	76.56	62.93	56.63	71.37	64.98	74.34	67.42
	Weighted Mean	77.93	78.58	89.65	78.81	79.86	76.45	67.97	76.15	71.52	73.70	77.06
LLaMA-2 (mntp-unsup-simcse)	EOS	98.11	89.27	99.29	97.48	99.15	97.17	91.99	99.62	92.87	98.37	96.33
	Mean	93.58	85.59	99.12	93.39	98.82	93.21	83.83	99.48	91.94	99.45	93.84
	Weighted Mean	92.69	85.52	98.84	92.18	98.93	92.08	80.69	99.39	88.50	99.31	91.81
LLaMA-2 (mntp-supervised)	EOS	95.27	86.85	98.52	95.03	97.86	95.09	89.64	98.80	90.48	96.35	94.39
	Mean	93.62	78.90	99.39	92.83	98.66	92.98	79.76	99.49	89.48	97.46	92.26
	Weighted Mean	92.23	77.64	99.28	91.17	98.78	91.37	77.18	99.39	86.37	97.23	91.06
LLaMA-3 (mntp)	EOS	94.47	90.85	94.28	93.65	97.67	93.77	81.94	96.89	91.36	94.49	92.94
	Mean	90.97	89.47	98.51	91.29	98.50	88.50	80.95	98.98	87.38	97.67	92.22
	Weighted Mean	91.48	86.49	97.85	90.54	98.46	89.30	77.54	98.69	86.65	97.06	91.41
LLaMA-3 (mntp-unsup-simcse)	EOS	67.67	59.24	87.12	61.72	74.28	60.58	56.15	82.43	71.07	71.19	68.15
	Mean	93.80	88.44	98.35	93.12	98.00	93.14	86.48	98.81	90.62	98.53	93.93
	Weighted Mean	93.53	84.96	97.40	92.32	98.26	92.55	83.77	98.81	89.52	98.68	92.98
LLaMA-3 (mntp-supervised)	EOS	91.23	74.75	97.44	87.79	95.00	87.92	72.76	97.57	90.91	93.81	88.92
	Mean	96.08	82.14	99.72	95.00	99.57	95.06	82.75	99.65	94.02	97.98	94.20
	Weighted Mean	95.59	81.61	99.66	94.03	99.57	94.12	78.80	99.61	94.69	96.66	93.43
Mistral (mntp)	EOS	94.11	83.63	95.48	88.25	94.15	93.81	78.45	95.78	88.18	94.24	90.61
	Mean	91.69	83.24	97.71	86.06	97.86	84.67	73.51	98.34	86.42	95.97	89.55
	Weighted Mean	92.24	82.24	97.17	84.75	97.37	86.68	70.45	97.63	85.01	94.59	88.81
Mistral (mntp-unsup-simcse)	EOS	88.34	71.99	88.17	85.23	88.06	88.41	76.69	93.27	78.86	89.28	84.83
	Mean	85.15	71.33	93.98	75.44	91.81	81.86	66.00	97.08	90.69	96.29	84.69
	Weighted Mean	82.84	66.60	94.76	71.57	91.05	78.81	62.22	96.88	87.29	95.53	82.76
Mistral (mntp-supervised)	EOS	97.69	80.41	97.72	93.90	97.72	97.54	87.66	98.65	88.67	95.71	93.57
	Mean	96.16	74.42	98.62	87.00	98.14	95.06	74.35	99.26	89.07	96.70	90.88
	Weighted Mean	95.92	72.71	98.75	84.00	98.38	94.56	69.62	99.28	87.06	96.46	89.67
OpenAI-3-small	-	99.32	86.90	99.64	98.76	98.97	98.73	95.93	99.36	99.56	72.27	94.94
OpenAI-ada-002	-	98.74	90.35	99.70	98.57	98.93	98.47	95.12	98.80	99.00	72.26	94.99
OpenAI-3-large	-	99.31	86.90	99.75	98.69	99.25	98.63	96.48	98.89	99.60	61.25	93.88

Table 24: Average AUPRC(%) on DBpedia-4.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	81.18	76.63	88.21	77.48	84.59	78.97	63.42	85.14	53.68	89.41	77.87
BERT	CLS	54.95	53.48	91.63	55.20	80.75	50.06	46.91	83.62	69.06	77.50	66.32
LLaMA-2 (mntp)	Mean	63.21	60.98	91.18	60.88	90.85	58.34	52.17	91.38	87.34	92.40	74.87
	EOS	64.64	61.95	68.04	63.36	66.47	62.36	53.91	64.18	62.12	64.99	63.20
	Weighted Mean	77.58	75.28	87.56	76.42	74.47	73.87	64.98	70.43	65.76	70.10	73.65
LLaMA-2 (mntp-unsup-simcse)	EOS	96.38	84.68	96.88	94.76	98.37	94.60	84.25	98.50	84.37	96.00	92.88
	Mean	88.61	82.70	94.43	88.29	96.25	88.19	78.58	97.80	77.16	97.88	88.99
	Weighted Mean	88.12	80.58	92.67	87.80	96.22	87.78	77.58	97.45	72.26	97.50	87.80
LLaMA-2 (mntp-supervised)	EOS	95.53	86.69	97.93	94.91	97.56	94.95	90.97	98.07	86.18	94.80	93.76
	Mean	94.81	80.36	98.06	94.31	97.60	94.45	84.81	98.40	82.43	95.63	92.09
	Weighted Mean	93.79	81.21	97.57	93.17	97.58	93.36	82.50	98.09	80.14	95.49	91.29
LLaMA-3 (mntp)	EOS	87.73	85.19	84.18	87.17	93.16	87.17	78.02	91.04	80.95	87.86	86.25
	Mean	83.17	81.68	93.55	83.42	94.67	80.78	74.83	95.87	77.27	91.52	85.68
	Weighted Mean	84.41	83.17	91.88	84.26	94.21	82.77	75.13	95.26	76.27	91.93	85.93
LLaMA-3 (mntp-unsup-simcse)	EOS	63.32	57.09	82.21	58.58	70.83	57.31	54.35	77.00	63.63	66.61	65.09
	Mean	89.01	83.72	93.67	88.25	95.02	88.41	81.21	96.62	78.72	96.16	89.08
	Weighted Mean	88.63	82.89	92.28	87.86	95.08	88.21	79.80	96.38	75.06	95.99	88.22
LLaMA-3 (mntp-supervised)	EOS	93.65	80.20	97.59	91.88	93.84	91.93	79.57	95.63	82.51	93.33	90.01
	Mean	97.83	85.28	98.87	97.06	99.07	97.17	90.11	98.73	90.28	96.74	95.11
	Weighted Mean	97.60	83.74	98.40	96.94	98.93	97.08	88.95	98.49	87.83	96.31	94.43
Mistral (mntp)	EOS	92.25	76.55	93.23	81.31	92.57	91.63	72.25	93.09	77.12	89.02	85.90
	Mean	80.48	73.23	93.55	74.16	93.20	73.03	67.28	94.33	77.10	89.34	81.57
	Weighted Mean	82.42	71.93	92.55	75.00	92.51	76.52	67.23	93.26	77.29	90.45	81.92
Mistral (mntp-unsup-simcse)	EOS	85.05	66.72	83.64	78.77	84.71	85.15	67.26	88.29	70.74	82.82	79.31
	Mean	79.73	64.80	89.41	69.63	87.45	77.02	62.07	93.68	75.25	86.61	78.56
	Weighted Mean	77.22	62.70	88.99	66.63	86.46	74.15	59.51	92.89	72.63	90.07	77.12
Mistral (mntp-supervised)	EOS	95.71	76.27	95.25	90.71	95.71	95.58	82.85	96.35	79.82	92.45	90.07
	Mean	95.55	71.23	97.15	85.45	96.96	94.52	73.18	97.99	76.50	93.18	88.17
	Weighted Mean	95.11	69.45	96.96	82.96	97.03	93.85	69.47	97.92	73.20	87.36	86.33
OpenAI-3-small	-	98.09	81.37	96.59	96.90	98.40	96.83	91.47	97.37	98.33	72.22	92.76
OpenAI-ada-002	-	97.94	88.21	97.99	97.85	97.79	97.86	94.83	92.09	98.14	68.95	93.16
OpenAI-3-large	-	98.48	81.20	98.10	97.54	98.49	97.51	94.24	98.76	98.99	48.41	91.17

Table 25: Average AUPRC(%) on WOS.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	31.51	25.02	45.53	25.09	23.64	28.64	24.04	26.10	36.96	29.00	29.55
BERT	CLS	29.69	29.99	38.01	29.06	30.06	28.99	27.90	30.19	31.78	31.39	30.71
	Mean	53.09	30.56	38.03	29.62	25.45	29.96	27.22	26.73	31.84	30.13	32.26
LLaMA-2 (mntp)	EOS	28.92	28.53	30.28	28.83	30.58	28.37	28.79	31.11	29.96	31.24	29.66
	Mean	30.87	29.41	31.08	28.98	27.53	29.89	28.17	26.33	29.00	28.61	28.99
	Weighted Mean	30.45	28.33	30.55	28.85	27.25	29.47	28.22	25.71	29.28	28.38	28.65
LLaMA-2 (mntp-unsup-simcse)	EOS	38.17	35.56	39.46	37.97	42.25	38.12	33.04	40.98	35.59	39.13	38.03
	Mean	26.58	25.76	40.63	24.32	26.71	24.04	22.77	28.52	31.04	32.62	28.30
	Weighted Mean	26.71	25.64	39.34	24.72	26.42	24.39	23.14	28.31	31.46	32.54	28.27
LLaMA-2 (mntp-supervised)	EOS	41.67	41.00	39.60	44.35	61.23	45.26	40.51	54.19	37.75	45.02	45.06
	Mean	26.32	27.50	49.36	24.62	37.38	24.27	22.88	38.23	32.98	36.86	32.04
	Weighted Mean	26.87	28.16	49.32	25.41	38.66	25.08	23.48	38.94	33.10	37.28	32.63
LLaMA-3 (mntp)	EOS	35.73	34.80	38.07	34.96	36.77	33.94	31.60	36.94	33.71	35.02	35.15
	Mean	27.58	25.43	41.89	24.66	26.26	24.33	22.65	31.01	33.41	32.93	29.02
	Weighted Mean	27.57	26.46	39.01	25.12	26.23	24.69	23.16	30.95	33.66	32.00	28.88
LLaMA-3 (mntp-unsup-simcse)	EOS	36.61	35.50	36.96	36.20	39.69	36.90	34.47	39.30	34.21	36.85	36.67
	Mean	25.05	23.63	45.34	22.59	25.76	22.23	21.58	28.87	30.93	31.77	27.78
	Weighted Mean	25.54	24.79	43.07	23.28	25.80	22.85	22.16	28.89	31.12	32.12	27.96
LLaMA-3 (mntp-supervised)	EOS	32.39	31.37	40.34	30.69	45.62	31.29	28.75	43.89	33.00	35.97	35.55
	Mean	36.77	36.70	43.71	36.90	62.51	38.19	32.49	56.01	37.74	44.33	42.54
	Weighted Mean	36.09	33.82	43.77	36.08	61.52	37.31	31.92	55.05	36.91	43.67	41.61
Mistral (mntp)	EOS	41.87	36.28	35.50	38.09	42.10	41.41	35.74	42.33	35.45	38.44	38.72
	Mean	28.00	27.37	36.12	28.36	26.94	25.03	25.68	30.83	31.08	32.63	29.20
	Weighted Mean	28.10	29.51	34.82	28.25	26.57	25.44	25.76	30.39	30.50	33.11	29.25
Mistral (mntp-unsup-simcse)	EOS	46.73	40.62	32.22	41.56	47.56	45.86	39.90	45.92	36.91	41.23	41.85
	Mean	23.52	22.77	44.12	21.91	24.90	20.96	21.44	27.94	29.60	28.84	26.60
	Weighted Mean	23.73	23.80	41.61	22.32	24.95	21.25	21.81	27.98	30.15	28.96	26.66
Mistral (mntp-supervised)	EOS	44.47	32.89	40.36	35.54	44.93	43.46	31.88	44.02	34.15	38.06	38.98
	Mean	31.23	28.32	43.12	26.89	38.44	29.15	24.84	39.50	33.63	36.56	33.17
	Weighted Mean	31.28	29.00	43.11	26.88	37.91	29.26	24.87	38.74	33.31	36.13	33.05
OpenAI-3-small	-	36.87	34.33	40.96	38.33	57.87	36.87	30.76	34.67	33.36	56.90	40.09
OpenAI-ada-002	-	37.03	36.27	37.29	41.80	55.00	41.14	32.47	41.39	35.58	65.73	42.37
OpenAI-3-large	-	41.83	37.42	50.02	43.63	61.09	42.63	34.44	51.49	37.26	57.73	45.75

Table 26: Average AUPRC(%) on SST2.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	48.76	47.88	60.76	47.94	51.37	48.01	47.34	51.96	57.41	56.31	51.77
BERT	CLS	53.33	53.00	57.23	52.81	56.73	52.85	51.49	55.72	54.52	59.24	54.69
LLaMA-2 (mntp)	Mean	52.39	51.76	57.69	52.02	57.90	51.91	50.49	56.52	53.76	60.52	54.50
	EOS	51.25	51.52	54.59	51.14	56.92	50.89	50.55	58.29	52.29	62.98	54.04
	Weighted Mean	50.93	50.65	55.74	50.18	55.74	50.29	49.84	57.48	52.58	61.24	53.47
LLaMA-2 (mntp-unsup-simcse)	EOS	58.39	55.96	67.03	58.43	71.81	58.41	53.16	76.37	60.25	69.90	62.97
	Mean	57.56	55.53	68.62	57.48	72.00	57.56	53.50	77.38	59.68	70.48	62.98
	Weighted Mean	57.33	56.28	67.83	57.47	71.56	57.56	53.40	77.05	60.53	69.60	62.86
LLaMA-2 (mntp-supervised)	EOS	65.79	63.93	65.37	64.92	69.68	64.38	58.96	72.44	64.67	71.36	66.15
	Mean	68.73	66.20	69.40	68.76	76.86	69.02	59.38	77.93	67.34	75.24	69.89
	Weighted Mean	66.82	64.44	67.20	66.45	74.09	66.54	58.12	75.92	65.33	73.64	67.85
LLaMA-3 (mntp)	EOS	55.20	54.64	58.17	54.67	61.13	54.91	53.12	64.89	55.91	62.91	57.55
	Mean	55.11	54.24	61.87	54.74	64.08	54.86	52.41	69.33	58.29	66.11	59.10
	Weighted Mean	55.32	54.66	59.58	55.27	65.01	55.59	52.70	69.98	57.56	67.31	59.30
LLaMA-3 (mntp-unsup-simcse)	EOS	55.73	54.91	59.83	55.29	60.09	55.43	53.99	64.23	57.20	62.55	57.92
	Mean	55.87	54.02	64.04	54.94	68.59	55.47	51.46	75.04	59.66	69.14	60.82
	Weighted Mean	55.54	54.65	63.09	54.84	66.18	55.18	52.16	73.52	59.28	67.66	60.21
LLaMA-3 (mntp-supervised)	EOS	67.52	64.57	65.43	65.72	70.51	65.54	58.28	73.81	63.76	72.35	66.75
	Mean	67.99	64.34	67.52	67.44	75.48	67.82	57.17	76.70	64.79	74.60	68.39
	Weighted Mean	67.70	63.21	66.81	66.93	74.18	67.21	57.19	76.19	64.63	74.59	67.86
Mistral (mntp)	EOS	64.76	51.30	58.21	51.78	59.38	63.94	49.48	61.70	55.86	60.67	57.71
	Mean	57.15	51.24	61.53	50.75	58.20	52.03	49.44	62.21	55.55	60.71	55.88
	Weighted Mean	57.83	50.50	60.07	50.02	57.72	52.73	48.56	61.43	55.81	60.48	55.52
Mistral (mntp-unsup-simcse)	EOS	74.50	55.19	61.85	54.09	65.91	73.43	49.87	68.59	58.93	65.14	62.75
	Mean	72.69	53.82	65.79	54.33	69.94	70.00	51.22	74.57	58.62	68.93	63.99
	Weighted Mean	72.67	53.18	65.05	54.62	69.59	70.11	51.09	73.64	59.47	68.20	63.76
Mistral (mntp-supervised)	EOS	79.81	61.59	64.52	62.99	71.83	79.50	57.27	72.87	65.25	72.12	68.78
	Mean	82.74	60.07	68.49	62.28	76.65	82.03	54.84	76.45	65.06	75.30	70.39
	Weighted Mean	81.97	58.75	68.08	61.70	74.97	81.29	54.90	75.37	64.93	73.48	69.54
OpenAI-3-small	-	67.77	61.04	71.04	67.22	77.75	67.32	55.83	71.69	63.72	75.95	67.93
OpenAI-ada-002	-	64.27	61.13	69.52	64.78	76.34	64.64	56.86	65.86	63.08	75.95	66.24
OpenAI-3-large	-	68.75	61.39	73.62	68.44	79.29	68.27	57.46	72.77	65.21	75.95	69.12

Table 27: Average AUPRC(%) on SMS-SPAM.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	26.52	22.75	25.21	23.05	23.86	24.57	22.44	22.00	49.75	23.83	26.40
BERT	CLS	32.75	21.45	28.19	22.44	19.23	27.88	20.63	21.01	34.94	22.18	25.07
LLaMA-2 (mntp)	Mean	28.47	25.40	30.48	26.59	21.24	26.97	20.99	23.91	74.98	33.71	31.27
	EOS	56.19	48.91	41.10	50.68	22.32	49.64	30.43	28.45	25.98	35.36	38.91
	Weighted Mean	63.63	56.71	30.73	54.21	19.45	57.92	30.47	19.16	27.26	20.75	38.03
LLaMA-2 (mntp-unsup-simcse)	EOS	61.66	50.00	63.14	61.91	61.57	59.93	36.33	64.90	50.76	63.95	57.42
	Mean	62.99	46.33	48.39	61.06	64.61	64.74	29.74	65.77	69.10	79.97	59.27
	Weighted Mean	79.89	57.05	54.27	78.50	74.56	80.91	42.13	75.06	62.38	85.07	68.98
LLaMA-2 (mntp-supervised)	EOS	84.45	80.54	50.55	85.05	84.44	86.20	69.80	83.95	66.07	86.31	77.74
	Mean	60.93	53.46	41.79	64.26	66.77	64.70	36.08	69.68	49.51	69.85	57.70
	Weighted Mean	72.32	62.84	42.60	75.99	77.48	76.51	48.46	78.71	50.19	79.22	66.43
LLaMA-3 (mntp)	EOS	82.54	74.90	77.28	79.21	85.08	80.84	62.23	82.88	78.11	82.48	78.56
	Mean	48.64	42.12	40.25	41.28	46.30	53.41	27.09	39.11	80.10	48.88	46.72
	Weighted Mean	63.85	51.23	43.49	54.51	58.34	68.75	34.05	49.34	79.84	64.32	56.77
LLaMA-3 (mntp-unsup-simcse)	EOS	80.98	75.79	68.32	80.48	81.12	80.69	70.80	83.18	69.99	81.10	77.25
	Mean	57.89	46.62	54.39	56.49	59.68	59.59	32.27	55.07	85.59	78.69	58.63
	Weighted Mean	73.86	63.81	52.10	72.90	73.87	76.10	45.45	69.05	89.69	87.39	70.42
LLaMA-3 (mntp-supervised)	EOS	87.20	79.38	73.64	85.61	85.59	85.94	73.28	88.27	71.90	86.45	81.73
	Mean	80.35	69.59	66.37	79.66	82.28	80.11	59.53	82.63	72.60	82.60	75.57
	Weighted Mean	80.25	67.09	57.96	79.71	82.72	80.12	59.12	82.78	71.62	83.67	74.50
Mistral (mntp)	EOS	77.70	61.84	87.20	65.32	76.59	77.94	48.68	78.38	76.39	77.55	72.76
	Mean	68.80	51.29	71.74	54.98	48.62	64.86	32.43	38.91	63.48	54.56	54.97
	Weighted Mean	65.89	54.45	74.03	58.65	46.02	63.07	35.36	41.51	74.71	66.47	58.02
Mistral (mntp-unsup-simcse)	EOS	77.92	49.97	79.25	69.17	75.09	78.38	45.10	76.93	59.67	72.02	68.35
	Mean	67.61	39.54	51.01	46.39	54.71	66.82	26.13	56.59	86.00	82.81	57.76
	Weighted Mean	83.56	52.81	57.07	69.16	71.18	83.39	36.67	70.82	86.68	83.77	69.51
Mistral (mntp-supervised)	EOS	73.02	54.45	61.60	69.16	68.55	73.90	48.16	72.51	78.85	78.03	67.82
	Mean	38.66	33.45	44.74	38.33	37.60	37.32	23.82	46.16	65.17	59.67	42.49
	Weighted Mean	45.98	48.04	43.99	52.08	42.87	45.54	28.78	51.40	61.39	67.71	48.78
OpenAI-3-small	-	33.86	29.66	66.32	31.71	42.08	33.22	19.34	32.84	30.04	64.73	38.38
OpenAI-ada-002	-	63.49	48.74	67.03	63.55	60.52	64.81	36.99	66.92	39.20	32.56	54.38
OpenAI-3-large	-	44.12	34.80	65.74	37.84	51.06	43.22	19.89	41.39	44.83	37.07	42.00

Table 28: Average AUPRC(%) on Reuters21578.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	84.40	84.32	86.11	84.53	87.87	83.97	75.58	87.37	68.23	87.91	83.03
BERT	CLS	67.87	64.83	83.76	64.11	65.62	64.13	58.90	69.48	60.42	69.37	66.85
	Mean	82.12	82.44	92.20	81.75	87.02	79.84	71.82	87.01	82.39	90.75	83.73
LLaMA-2 (mntp)	EOS	76.00	76.47	69.21	77.28	73.92	76.74	73.87	75.79	76.00	77.65	75.29
	Mean	72.41	75.13	73.37	73.73	72.38	71.49	68.02	78.75	68.66	72.81	72.68
	Weighted Mean	72.38	75.38	72.96	73.83	72.24	71.96	68.32	73.98	69.47	73.22	72.37
LLaMA-2 (mntp-unsup-simcse)	EOS	95.64	92.78	90.29	95.62	96.33	95.27	88.33	97.07	91.50	95.81	93.86
	Mean	88.99	87.31	86.94	87.30	89.34	87.28	74.16	92.17	96.04	94.97	88.45
	Weighted Mean	88.05	84.49	85.66	86.46	88.77	86.49	73.00	91.39	95.40	94.88	87.46
LLaMA-2 (mntp-supervised)	EOS	96.33	90.37	85.10	96.11	97.01	96.05	91.61	97.39	88.14	95.32	93.34
	Mean	94.93	89.93	87.57	95.18	95.97	95.19	86.36	97.49	92.37	95.51	93.05
	Weighted Mean	94.39	88.56	86.19	94.76	95.44	94.89	85.19	96.94	91.52	94.88	92.28
LLaMA-3 (mntp)	EOS	87.96	85.53	86.73	87.88	92.44	87.31	74.79	91.52	74.10	89.32	85.76
	Mean	89.44	88.82	90.67	89.72	90.85	87.49	75.96	92.53	79.37	92.04	87.69
	Weighted Mean	86.10	86.41	89.34	86.16	89.62	83.18	72.19	91.39	76.59	90.77	85.18
LLaMA-3 (mntp-unsup-simcse)	EOS	85.72	80.32	81.40	83.25	86.27	83.96	76.75	86.52	80.93	83.34	82.85
	Mean	90.13	87.92	88.05	88.33	88.72	88.24	77.47	91.17	94.85	93.31	88.82
	Weighted Mean	88.75	86.77	87.05	86.77	88.07	87.06	75.00	90.27	92.99	92.20	87.49
LLaMA-3 (mntp-supervised)	EOS	94.97	89.83	94.94	93.98	92.89	93.41	89.10	95.18	92.99	93.54	93.08
	Mean	96.88	92.35	91.75	96.86	96.61	96.78	89.91	97.75	94.54	95.88	94.93
	Weighted Mean	96.26	90.88	90.64	96.30	95.79	96.23	88.97	97.32	93.13	95.40	94.09
Mistral (mntp)	EOS	85.42	87.24	81.89	90.52	84.50	85.56	77.16	86.44	79.52	89.43	84.77
	Mean	83.79	77.66	90.04	75.48	82.27	77.54	61.81	84.78	77.38	83.89	79.46
	Weighted Mean	81.61	72.97	89.65	72.16	81.48	74.20	61.98	84.14	75.92	82.37	77.65
Mistral (mntp-unsup-simcse)	EOS	93.80	82.86	84.58	91.27	93.71	93.81	82.21	93.63	86.30	91.08	89.32
	Mean	86.03	76.53	85.31	78.52	85.82	85.26	66.56	88.21	93.69	91.60	83.75
	Weighted Mean	84.72	75.24	84.77	76.05	85.02	83.98	64.90	87.55	90.15	90.52	82.29
Mistral (mntp-supervised)	EOS	95.64	88.88	83.58	95.17	95.46	95.78	87.37	96.11	92.06	94.20	92.42
	Mean	97.70	89.84	89.21	96.60	96.62	97.80	87.06	97.74	92.70	96.26	94.15
	Weighted Mean	96.74	85.92	87.43	95.63	95.47	96.91	84.73	96.97	93.47	95.17	92.84
OpenAI-3-small	-	98.79	95.85	93.30	98.75	97.20	98.58	93.02	98.20	98.61	81.16	95.35
OpenAI-ada-002	-	98.17	92.22	90.86	97.62	95.85	97.36	86.44	93.20	97.95	81.16	93.08
OpenAI-3-large	-	99.52	93.80	96.38	99.43	98.18	99.38	95.33	98.36	99.45	81.16	96.10

Table 29: Average AUPRC(%) on IMDB.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	59.62	59.62	62.26	59.50	59.62	59.62	57.34	60.77	60.38	60.98	59.97
BERT	CLS	59.02	59.64	59.57	58.94	60.02	59.19	56.97	59.39	62.74	60.45	59.59
	Mean	58.52	58.70	61.10	58.24	60.29	58.07	55.39	59.87	59.81	59.88	58.99
LLaMA-2 (mntp)	EOS	61.30	61.22	62.38	61.30	61.69	61.36	61.09	61.60	61.64	62.11	61.57
	Mean	60.30	60.38	61.40	60.27	61.23	60.57	59.92	61.26	61.37	61.91	60.86
	Weighted Mean	60.53	60.52	61.84	60.47	61.33	60.78	60.14	61.32	61.36	61.96	61.02
LLaMA-2 (mntp-unsup-simcse)	EOS	59.52	59.14	65.87	58.66	64.56	58.63	54.35	65.64	61.06	62.37	60.98
	Mean	59.80	60.34	65.22	59.68	65.02	59.66	55.75	65.30	61.84	62.09	61.47
	Weighted Mean	60.25	59.90	65.85	60.17	64.75	60.16	56.39	65.37	62.14	62.57	61.76
LLaMA-2 (mntp-supervised)	EOS	63.15	61.64	71.39	60.90	67.06	60.61	54.33	65.46	63.53	63.65	63.17
	Mean	62.26	62.64	68.26	61.50	74.37	61.52	53.82	70.51	63.71	65.35	64.39
	Weighted Mean	62.25	61.97	68.42	61.47	74.17	61.49	53.85	70.06	63.52	65.42	64.26
LLaMA-3 (mntp)	EOS	58.50	58.08	61.20	58.08	59.74	58.14	56.36	61.36	60.43	60.75	59.26
	Mean	58.80	58.94	62.60	58.86	61.90	58.91	56.02	62.97	60.99	62.27	60.23
	Weighted Mean	59.05	58.87	62.93	59.12	61.66	59.14	56.54	62.92	61.25	62.23	60.37
LLaMA-3 (mntp-unsup-simcse)	EOS	59.57	59.75	63.77	59.23	60.89	59.10	57.13	61.49	61.16	60.61	60.27
	Mean	59.94	59.57	64.40	59.97	65.21	60.04	55.05	64.48	61.78	62.31	61.28
	Weighted Mean	60.00	60.26	64.29	60.05	64.60	60.12	55.30	64.11	61.78	62.07	61.26
LLaMA-3 (mntp-supervised)	EOS	63.81	63.68	69.31	63.06	68.75	62.75	55.51	66.63	64.99	64.49	64.30
	Mean	59.23	60.14	67.79	59.17	74.23	59.16	53.23	70.69	62.44	64.65	63.07
	Weighted Mean	59.36	59.79	67.60	59.30	74.12	59.29	53.11	70.46	62.38	64.98	63.04
Mistral (mntp)	EOS	57.59	57.09	59.22	57.35	57.66	57.52	55.71	58.28	59.90	58.61	57.89
	Mean	61.57	61.61	64.62	61.53	64.07	61.70	58.81	65.18	62.14	64.08	62.53
	Weighted Mean	61.79	61.35	64.80	61.71	63.81	61.85	59.25	64.99	62.26	63.71	62.55
Mistral (mntp-unsup-simcse)	EOS	67.81	61.45	67.25	60.69	67.14	66.53	54.89	65.41	63.34	63.92	63.84
	Mean	64.12	62.88	67.74	63.00	67.53	63.73	59.61	67.39	63.95	64.85	64.48
	Weighted Mean	64.25	63.60	68.19	63.19	67.14	63.86	59.83	67.19	63.80	64.90	64.60
Mistral (mntp-supervised)	EOS	71.63	65.36	71.56	66.39	69.71	70.77	55.88	66.90	65.43	67.58	67.12
	Mean	63.51	60.36	66.10	58.42	69.91	61.39	52.85	67.11	62.50	64.72	62.69
	Weighted Mean	63.88	61.53	66.13	58.81	69.75	61.82	53.02	66.82	62.81	64.77	62.93
OpenAI-3-small	-	62.69	61.83	72.47	61.90	70.79	61.77	53.42	64.98	61.77	81.25	65.29
OpenAI-ada-002	-	61.87	62.27	69.91	61.37	73.20	61.21	54.76	62.70	60.73	76.26	64.43
OpenAI-3-large	-	64.63	62.85	73.06	63.92	77.58	63.75	51.36	68.31	62.91	81.25	66.96

Table 30: Average AUPRC(%) on Enron.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	37.93	36.93	40.82	37.03	44.10	38.10	34.42	41.41	34.71	49.17	39.46
BERT	CLS	32.16	32.18	57.63	32.31	41.17	31.81	31.74	37.95	27.95	57.25	38.22
LLaMA-2 (mntp)	Mean	31.62	31.79	57.16	31.83	35.86	31.86	30.67	34.47	34.99	52.55	37.28
	EOS	34.63	34.84	44.46	34.71	36.72	35.47	33.59	39.80	32.79	65.89	39.29
	Weighted Mean	32.36	33.56	57.62	32.55	37.46	32.05	31.93	36.79	32.99	47.38	37.47
LLaMA-2 (mntp-unsup-simcse)	EOS	54.05	44.27	83.79	46.85	72.03	46.89	42.63	95.97	66.67	91.42	64.46
	Mean	38.49	37.37	49.46	37.91	49.34	38.35	34.83	89.67	63.77	83.36	52.26
	Weighted Mean	36.62	36.34	51.16	35.72	47.99	35.92	32.97	89.19	62.83	84.83	51.36
LLaMA-2 (mntp-supervised)	EOS	55.39	47.70	78.19	47.78	73.45	45.84	44.82	96.12	65.16	93.65	64.81
	Mean	44.31	44.35	71.67	43.44	59.99	42.76	41.61	94.61	61.62	90.76	59.51
	Weighted Mean	44.89	43.73	72.18	43.52	64.10	42.57	41.42	95.27	59.66	91.11	59.85
LLaMA-3 (mntp)	EOS	43.86	42.10	54.53	42.32	66.56	42.59	39.57	89.34	56.05	87.60	56.45
	Mean	36.76	36.60	54.71	36.99	46.04	36.78	34.72	71.43	44.84	72.35	47.12
	Weighted Mean	34.17	34.73	53.76	34.26	43.67	33.80	32.40	70.51	43.06	70.64	45.10
LLaMA-3 (mntp-unsup-simcse)	EOS	67.41	46.72	74.17	46.90	74.98	52.98	43.72	94.54	69.06	90.13	66.06
	Mean	38.74	36.92	51.74	37.09	47.95	37.94	33.32	86.17	62.29	82.33	51.45
	Weighted Mean	37.01	34.93	53.45	34.61	46.58	35.06	31.28	86.20	62.23	82.01	50.34
LLaMA-3 (mntp-supervised)	EOS	58.44	48.15	75.28	49.34	61.85	48.50	46.40	91.00	65.31	89.76	63.40
	Mean	58.44	48.20	75.28	49.34	61.85	48.50	46.40	91.00	62.76	90.18	63.20
	Weighted Mean	58.44	48.50	75.28	49.34	61.85	48.50	46.40	91.00	63.96	89.96	63.32
Mistral (mntp)	EOS	94.16	40.55	60.58	41.59	64.22	93.79	37.99	80.67	55.98	85.80	65.53
	Mean	42.34	36.85	55.35	36.87	45.61	39.65	34.17	62.80	44.85	65.97	46.45
	Weighted Mean	40.89	34.49	57.19	34.88	43.04	36.54	33.24	60.47	42.85	64.79	44.84
Mistral (mntp-unsup-simcse)	EOS	97.30	53.27	84.83	56.86	80.74	96.84	51.76	93.32	73.20	92.87	78.10
	Mean	89.95	33.26	50.40	33.26	47.74	61.91	30.34	84.12	58.23	85.15	57.44
	Weighted Mean	90.04	31.22	53.07	31.26	46.20	62.02	29.05	83.05	58.46	84.15	56.85
Mistral (mntp-supervised)	EOS	94.47	40.33	69.56	40.91	57.48	94.00	38.50	82.82	67.20	88.87	67.41
	Mean	92.61	40.60	70.03	41.95	55.81	88.20	39.76	90.56	60.06	89.10	66.87
	Weighted Mean	92.87	41.47	69.11	41.19	56.01	90.10	38.92	90.44	59.61	88.68	66.84
OpenAI-3-small	-	46.08	47.25	67.22	45.77	62.80	45.32	42.15	61.19	42.70	65.93	52.64
OpenAI-ada-002	-	52.83	51.17	84.73	52.33	74.67	50.96	48.17	61.25	52.28	65.92	59.43
OpenAI-3-large	-	51.20	48.38	76.08	50.12	67.18	49.62	45.96	62.01	52.27	65.94	56.88

Table 31: Average AUPRC(%) on 20Newsgroups.

Embedding	Pooling	OCSVM	IForest	LOF	PCA	KNN	KDE	ECOD	AE	DSVDD	DPAD	Avg
GloVe	Mean	13.13	13.61	14.79	13.52	15.12	13.16	13.22	13.46	12.16	14.07	13.62
BERT	CLS	13.26	13.82	21.37	13.90	14.39	13.44	13.63	15.17	11.60	14.50	14.51
LLaMA-2 (mntp)	Mean	13.09	13.74	16.96	13.47	13.84	13.32	12.98	13.98	14.34	14.80	14.05
	EOS	11.46	11.13	10.56	10.83	11.70	10.55	10.89	11.07	10.57	11.10	10.99
	Weighted Mean	13.89	12.18	12.80	12.41	11.77	12.82	12.33	11.79	11.59	11.56	12.31
LLaMA-2 (mntp-unsup-simcse)	EOS	15.61	16.01	13.98	15.43	14.46	15.19	13.84	14.16	14.10	14.11	14.69
	Mean	11.63	11.82	11.53	12.03	14.61	12.27	11.54	13.32	14.51	14.52	12.78
	Weighted Mean	11.84	13.01	11.14	12.26	14.55	12.55	11.73	13.31	14.82	14.88	13.01
LLaMA-2 (mntp-supervised)	EOS	16.31	13.70	19.20	14.99	16.62	14.98	12.94	21.36	16.41	17.91	16.44
	Mean	13.36	12.48	15.30	14.01	22.88	14.01	12.99	23.73	14.48	16.74	16.00
	Weighted Mean	13.98	13.41	15.99	14.50	25.15	14.45	13.36	24.81	14.30	16.78	16.67
LLaMA-3 (mntp)	EOS	19.05	17.70	18.89	18.93	18.55	18.92	17.24	18.49	16.70	19.87	18.43
	Mean	14.17	13.48	13.69	14.10	15.36	14.45	13.23	14.69	16.12	16.01	14.53
	Weighted Mean	13.78	13.43	13.16	13.67	14.65	14.08	12.90	13.83	15.23	14.97	13.97
LLaMA-3 (mntp-unsup-simcse)	EOS	13.33	13.15	13.84	12.94	13.92	12.72	12.62	13.96	13.46	12.86	13.28
	Mean	11.16	11.79	10.88	11.21	12.52	11.44	10.71	12.37	14.64	13.98	12.07
	Weighted Mean	10.72	9.984	10.74	10.71	11.78	10.94	10.26	11.76	14.54	13.88	11.53
LLaMA-3 (mntp-supervised)	EOS	18.02	16.92	22.38	17.26	20.32	17.47	14.78	24.17	13.87	18.58	18.38
	Mean	16.13	16.64	23.24	16.21	26.00	16.46	14.49	25.72	15.33	18.78	18.90
	Weighted Mean	15.11	13.41	20.47	15.05	23.70	15.26	13.57	23.88	14.02	17.94	17.24
Mistral (mntp)	EOS	24.22	23.74	22.74	23.39	23.67	24.48	21.89	24.32	19.67	25.73	23.38
	Mean	17.49	17.97	14.57	17.64	17.42	18.54	16.73	15.86	15.45	16.70	16.84
	Weighted Mean	16.88	16.61	15.27	16.81	16.07	17.50	16.12	15.02	15.18	15.35	16.08
Mistral (mntp-unsup-simcse)	EOS	13.34	16.78	13.02	23.25	12.48	13.71	19.31	13.73	14.42	16.50	15.65
	Mean	11.93	11.78	11.39	11.63	12.94	11.87	11.37	12.79	14.55	13.45	12.37
	Weighted Mean	11.99	12.03	11.38	11.69	12.66	11.93	11.42	12.67	13.94	13.54	12.32
Mistral (mntp-supervised)	EOS	13.75	13.78	14.55	13.80	13.26	13.73	11.39	17.79	13.56	16.40	14.20
	Mean	13.36	10.94	11.13	11.17	15.12	12.72	10.58	15.39	12.22	12.87	12.55
	Weighted Mean	13.25	11.66	10.78	11.18	14.63	12.64	10.59	15.30	12.62	12.64	12.53
OpenAI-3-small	-	14.41	14.25	11.85	15.16	21.53	15.25	12.88	16.37	12.60	56.08	19.04
OpenAI-ada-002	-	16.11	15.47	14.53	18.66	29.65	18.30	16.12	19.60	13.78	56.08	21.83
OpenAI-3-large	-	12.88	12.09	14.03	11.30	19.36	11.96	9.939	15.59	12.59	56.08	17.58