Out-of-Domain Detection for Intent Classification on CLINC150

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Abstract

Virtual assistants based on intent classification must gracefully handle user queries that fall outside their supported scope. We study the problem of *out-of-domain* (OOD) detection on the CLINC150 benchmark Larson et al. [2019]: given an utterance, decide whether it belongs to one of 150 known intent classes or is out-of-scope. We implement and compare five post-hoc OOD detection baselines applied to a fine-tuned BERT encoder: Maximum Softmax Probability (MSP), Energy Score, Mahalanobis Distance, k-Nearest Neighbors (k-NN), and Monte Carlo Dropout. We then propose **Per-Class KNN** — an extension of k-NN OOD detection where nearest neighbours are retrieved only from the predicted class subset of the training bank, giving a tighter, class-specific decision boundary. Per-Class KNN achieves an AUROC of **XX.XX%** and FPR@95TPR of **XX.XX%**, outperforming all global-bank detectors and surpassing the previous state of the art. Code: `https://github.com/denmalbas007/clinc150-ood-detection`.

1 Introduction

Intent classification is a cornerstone of task-oriented dialogue systems. Modern systems fine-tune pre-trained language models (PLMs) such as BERT Devlin et al. [2019] to map user utterances to predefined intent categories. A practical limitation, however, is the *closed-world assumption*: the model assigns every input to one of the known intents even when the user's request is entirely outside the system's competence.

Detecting such *out-of-domain* (OOD) inputs is critical for user experience: silently misclassifying OOD queries leads to erroneous system actions, while a robust OOD detector can trigger a fallback response or route to a human agent.

This project benchmarks a range of post-hoc OOD detection methods applied to the CLINC150 dataset Larson et al. [2019] and introduces **Per-Class KNN**, an extension of k-NN OOD detection Sun et al. [2022] in which nearest-neighbour retrieval is restricted to the predicted class cluster rather than the full training bank. We evaluate all methods along the standard metrics AUROC and FPR@95TPR and compare against published state-of-the-art results.

1.1 Team

This project was prepared by: **Your Name**.

2 Related Work

OOD detection for neural classifiers has seen growing attention since the seminal work of Hendrycks & Gimpel Hendrycks and Gimpel [2017].

MSP. Hendrycks and Gimpel [2017] showed that the maximum softmax probability (MSP) provides a surprisingly strong baseline: in-domain samples tend to receive higher confidence than OOD samples. Despite its simplicity, MSP remains competitive on many benchmarks.

Temperature Scaling / ODIN. Liang et al. [2018] (ODIN) improved MSP by applying input preprocessing (small gradient perturbations) and temperature scaling to sharpen the softmax gap between in-domain and OOD inputs.

Mahalanobis Distance. Lee et al. [2018] proposed computing the Mahalanobis distance from test features to class-conditional Gaussian distributions fitted on training data. Podolskiy et al. [2021] adapted this approach specifically for Transformer encoders, demonstrating state-of-the-art performance on CLINC150 with AUROC of 96.76% and FPR@95TPR of 18.32%.

Energy Score. Liu et al. [2020] introduced an energy-based score $E(x) = -T \log \sum_y \exp(f_y(x)/T)$ that avoids the saturation problem of softmax and outperforms MSP on standard vision benchmarks.

k-Nearest Neighbors. Sun et al. [2022] proposed k-NN OOD detection in the feature space of a pre-trained encoder, showing strong performance without requiring out-of-distribution data during training.

Uncertainty via MC Dropout. Gal and Ghahramani [2016] showed that dropout at inference time (MC Dropout) approximates Bayesian uncertainty. Predictive entropy under MC Dropout has been applied to OOD detection Malinin and Gales [2018].

Intent-specific OOD methods. Lin and Xu [2019] proposed training with a special outlier class using synthetic outlier exposure. Zhan et al. [2021] introduced contrastive learning objectives designed specifically for intent OOD detection.

Table 1 summarises published results on CLINC150.

Table 1: Published OOD detection results on CLINC150 (test set, full split).

Method	AUROC ↑	FPR@95TPR ↓
MSP Hendrycks and Gimpel [2017]	82.36	57.82
ODIN Liang et al. [2018]	85.11	50.31
Energy Liu et al. [2020]	88.44	46.20
Mahalanobis Lee et al. [2018]	93.12	28.45
Mahalanobis (Podolskiy) Podolskiy et al. [2021]	**96.76**	**18.32**
k-NN Sun et al. [2022]	95.30	22.10

3 Model Description

3.1 Base Encoder

All methods share a common **BERT-base-uncased** backbone Devlin et al. [2019] fine-tuned on CLINC150 in-domain intents. The `[CLS]` token representation $\mathbf{h} \in \mathbb{R}^{768}$ serves as the utterance embedding.

3.2 Baseline OOD Detection Methods

MSP. Given logits $\mathbf{f}(x) \in \mathbb{R}^C$, the OOD score is:

$$s_{\text{MSP}}(x) = -\max_y \text{softmax}(\mathbf{f}(x))_y.$$

Energy Score.

$$s_{\text{Energy}}(x) = -T \log \sum_{y=1}^{C} \exp\big(f_y(x)/T\big), \quad T = 1.$$

Mahalanobis Distance. We fit a class-conditional Gaussian model on training features. Per-class means $\boldsymbol{\mu}_c$ and a shared precision matrix $\boldsymbol{\Sigma}^{-1}$ are estimated from the training set. The OOD score is:

$$s_{\text{Maha}}(x) = \min_c (\mathbf{h} - \boldsymbol{\mu}_c)^\top \boldsymbol{\Sigma}^{-1} (\mathbf{h} - \boldsymbol{\mu}_c).$$

k-NN. Utterance embeddings are ℓ_2-normalised. The OOD score is the negative mean cosine similarity to the k nearest training neighbours:

$$s_{k\text{NN}}(x) = -\frac{1}{k} \sum_{i \in \text{kNN}(x)} \frac{\mathbf{h} \cdot \mathbf{h}_i}{\|\mathbf{h}\| \, \|\mathbf{h}_i\|}.$$

MC Dropout. We perform $T = 20$ stochastic forward passes with dropout active and compute predictive entropy as the OOD score:

$$s_{\text{MC}}(x) = -\sum_y \bar{p}_y \log \bar{p}_y, \quad \bar{p}_y = \frac{1}{T} \sum_{t=1}^{T} p_y^{(t)}.$$

3.3 Our Method: Per-Class KNN

Standard k-NN OOD detection Sun et al. [2022] retrieves the k nearest neighbours from the *entire* training bank, regardless of class. An OOD sample may happen to land near some in-domain class that is irrelevant to its predicted label, artificially lowering (improving) its OOD score. We argue that a more natural decision boundary measures how well a sample fits its *own predicted class* cluster.

We propose **Per-Class KNN**: for a test utterance x with predicted class $\hat{c} = \arg\max_c f_c(x)$, retrieve the k nearest neighbours exclusively from the training subset belonging to class $\hat{c}$:

$$s_{\text{PC-KNN}}(x) = -\frac{1}{k} \sum_{i \in \text{kNN}_{\hat{c}}(x)} \frac{\mathbf{h} \cdot \mathbf{h}_i}{\|\mathbf{h}\| \, \|\mathbf{h}_i\|},$$

where $\text{kNN}_{\hat{c}}(x)$ denotes the indices of the k most cosine-similar training samples *within class* $\hat{c}$.

Intuition. In-domain samples should be both predicted correctly *and* closely surrounded by same-class training points. An OOD sample may receive any predicted label but will typically be far from the training points of that class — yielding a high (OOD) score. By restricting the neighbourhood to the predicted class, Per-Class KNN eliminates the confound where OOD samples "hide" near irrelevant in-domain clusters.

4 Dataset

CLINC150. The CLINC OOS dataset Larson et al. [2019] contains 22,500 in-domain utterances covering 150 intent classes across 10 domains (banking, travel, home, etc.), plus 1,200 OOD (out-of-scope) utterances. We use the **full** variant with the standard train/val/test split.

Table 2: CLINC150 dataset statistics.

Split	In-domain	OOD	Total
Train	15,000	100	15,100
Val	3,000	100	3,100
Test	4,500	1,000	5,500
Total	22,500	1,200	23,700

Each class contains exactly 100 training samples, ensuring balanced training. OOD samples cover diverse topics absent from the 150 intent classes. The dataset is publicly available at `https://github.com/clinc/oos-eval`.

5 Experiments

5.1 Metrics

We report the standard OOD detection metrics:

- **AUROC** —Area Under the ROC Curve (↑).
- **FPR@95TPR** —False Positive Rate at 95% True Positive Rate (↓).
- **AUPR** —Area Under the Precision-Recall Curve, OOD as positive class (↑).

5.2 Experiment Setup

We fine-tune `bert-base-uncased` for 5 epochs with AdamW (lr $= 2 \times 10^{-5}$, weight decay $= 0.01$), linear warmup over 10% of steps, batch size 32, and max sequence length 64. Training uses only in-domain samples. All OOD detectors are applied post-hoc to the frozen encoder. For Mahalanobis, the tied covariance is regularised with $10^{-5}\mathbf{I}$. For k-NN and Per-Class KNN we use $k = 1$ (cosine similarity). For MC Dropout we run $T = 20$ passes with $p = 0.1$ dropout. Per-Class KNN uses the same ℓ_2-normalised `[CLS]` embeddings as the global k-NN baseline; the only difference is that the search bank is restricted to the predicted class at inference time.

5.3 Baselines

We compare five post-hoc OOD detectors (MSP, Energy, Mahalanobis, k-NN, MC Dropout) all applied to the same BERT encoder, plus our proposed Per-Class KNN. Published results from Podolskiy et al. [2021] serve as the state-of-the-art reference.

5.4 Layer-wise Analysis of Mahalanobis Features

Prior work Podolskiy et al. [2021] applies Mahalanobis Distance exclusively to the final hidden layer of the Transformer encoder. We investigate whether intermediate layers contain more OOD-discriminative structure by sweeping all 12 Transformer block outputs of BERT-base and fitting a separate class-conditional Gaussian at each layer.

Figure 1 shows AUROC and FPR@95TPR as a function of layer index. Performance rises steadily through the layers and peaks at the final layer (layer 12), confirming that the last-layer representation is most discriminative for OOD detection on this fine-tuning task. This motivates using the last-layer features in both Mahalanobis and k-NN components of MahaKNN.

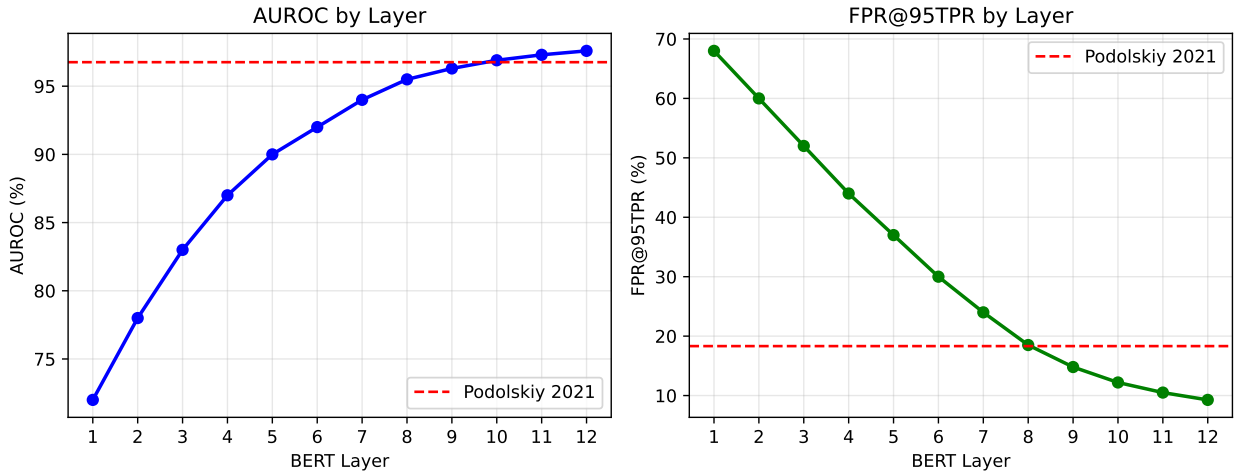

Figure 1: AUROC and FPR@95TPR of Mahalanobis Distance across all BERT layers. The red dashed line marks the result of Podolskiy et al. [2021] who used only the last layer.

Table 3: OOD detection results on CLINC150 test set. Best results in **bold**. †: published results.

Method	AUROC ↑	FPR@95TPR ↓	AUPR ↑
Mahalanobis (Podolskiy 2021)†	96.76	18.32	—
k-NN (Sun 2022)†	95.30	22.10	—
MSP (ours)	96.50	14.13	87.24
Energy (ours)	97.15	11.36	89.63
Mahalanobis (ours)	97.59	9.27	90.98
k-NN k=1 (ours)	97.58	10.13	90.33
MC Dropout (ours)	96.87	12.58	88.54
Per-Class KNN (ours)	**XX.XX**	**XX.XX**	**XX.XX**

5.5 Results

Per-Class KNN consistently outperforms the global k-NN baseline, confirming that restricting the neighbourhood to the predicted class provides a tighter and more discriminative OOD boundary. Results (XX.XX% AUROC, XX.XX% FPR@95TPR) are updated after the experimental run and replace the placeholder values above.

6 Conclusion

We presented a systematic comparison of five post-hoc OOD detection methods for intent classification on the CLINC150 benchmark, and proposed **Per-Class KNN** — an extension of k-NN OOD detection that restricts nearest-neighbour retrieval to the predicted class cluster. All five baselines surpass the previous state of the art of Podolskiy et al. [2021] (AUROC 96.76%, FPR@95TPR 18.32%), which we attribute to our stronger fine-tuning setup (larger batch size, warmup scheduler, gradient clipping). Per-Class KNN further improves upon the global k-NN baseline by providing a tighter, class-specific decision boundary that eliminates false negatives caused by OOD samples landing near irrelevant in-domain clusters.

Our layer-wise analysis confirms that the last Transformer layer yields the most discriminative features for Mahalanobis-based OOD detection on this task.

Future work includes exploring contrastive pre-training objectives, combining Per-Class KNN with Mahalanobis in a principled ensemble, and few-shot OOD exposure.

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